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## *Editorial Board*

# FOREWORD

Azerbaijan State University of Economics (UNEC) with great pleasure announces the publication of the inaugural issue (Vol.2, No.1) of the Journal of Economics and Management Advances (JEMA). JEMA is established with the aim of contributing to the advancement of knowledge in economics, business, finance, and management sciences by creating a platform for high-quality academic exchange.

The journal welcomes original research articles, review papers, and short communications written in English that address contemporary theoretical and practical issues in the economic and managerial fields. Our focus is to publish work that is not only methodologically sound but also relevant to current global and regional economic realities.

JEMA operates on the principles of academic integrity, transparency, and open science. Manuscripts submitted for consideration must be original, not previously published or under review elsewhere, and must be approved by all contributing authors. In line with our commitment to open access, all articles published in JEMA are freely available to read, download, distribute, and cite without subscription barriers. We believe that the dissemination of knowledge should be unrestricted and accessible to all.

Beyond article publications, the journal also aims to inform and engage the academic community by highlighting significant scholarly events such as conferences, workshops, and research initiatives that shape the future of the disciplines we represent.

We warmly invite researchers, practitioners, and scholars to contribute their work to JEMA and to take part in this new academic endeavor. Manuscripts can be submitted through our official portal at 100, and further information about the journal, including editorial policies and current issues, is available at journals.unec.edu.az.

We extend our sincere gratitude to all authors, reviewers, and editorial board members for their valuable contributions and dedication. We look forward to growing this platform together and making a meaningful impact in the field of economics and management studies.

***Sincerely,***
***Editorial Board***

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# Economic Growth Assessment through Tourism Development Using the Type-2 Fuzzy Multi-Criteria Decision-Making Method

**Abstract**
Tourism development plays a significant role in stimulating economic growth by promoting investment, job creation, and regional development. Assessing the impact of tourism on economic growth involves complex decision-making processes characterized by uncertainty, subjectivity, and imprecise expert judgments. To address these challenges, this study proposes a framework for evaluating the economic growth of tourism development using a Type-2 fuzzy set method. The proposed approach utilizes linguistic expert judgments and models the associated uncertainty using Type 2 fuzzy sets. This allows for a more realistic representation of ambiguities compared to traditional Type-1 fuzzy methods. Key tourism-related criteria, including infrastructure development, service quality, accessibility, investment intensity, and socioeconomic impacts, are systematically analyzed and weighed within the framework. The aggregation and defuzzification processes enable the prioritization of tourism development factors according to their contribution to economic growth. A case study serves to validate the applicability and effectiveness of the methodology. The results demonstrate that the Type-2 fuzzy logic approach yields more robust and reliable estimates, thereby supporting policymakers and stakeholders in developing effective tourism development strategies that promote sustainable economic growth in the face of uncertainty.

**Keywords**: Fuzzy Numbers, Type-2 Fuzzy Sets, Multi-Criteria Decision-Making, Economic Growth, Tourism Development

## Introduction

Tourism has become one of the most influential sectors of the global economy, acting as a catalyst for economic growth, employment, foreign exchange earnings, and regional development. The expansion of tourism activities stimulates demand in various sectors, including transportation, accommodation, food services, construction, and culture. Consequently, tourism development is frequently integrated into national and regional economic strategies, particularly in developing and transition economies striving for sustainable growth pathways. The relationship between tourism development and economic growth is neither linear nor uniform. The economic impact of tourism depends on a multitude of interdependent factors, such as infrastructure quality, accessibility, investment intensity, service standards, environmental sustainability, and social inclusion. These factors often interact in complex ways and are influenced by external conditions, including political frameworks, market volatility, and global uncertainty. Therefore, assessing tourism's contribution to economic growth requires a comprehensive and systematic evaluation framework capable of processing multidimensional and uncertain information. Traditional methods of economic evaluation rely heavily on quantitative indicators such as gross domestic product, employment rate, or tourism revenue. While these indicators are important, they are insufficient to assess qualitative aspects of tourism development, such as service quality, stakeholder satisfaction, institutional effectiveness, and sociocultural impact. Furthermore, many tourism-related evaluations are based on expert knowledge and subjective assessments, which are inherently imprecise and ambiguous. This limitation underscores the need for advanced decision-making methods that can effectively integrate quantitative and qualitative information. In recent years, multi-criteria decision-making (MCDM) methods have become widely adopted for addressing complex evaluation problems with numerous, often conflicting, criteria. Different studies applied to these topics.

Tourism is widely recognized as a key driver of economic growth, contributing to employment generation, foreign exchange earnings, and regional development (Balaguer & Cantavella-Jordá, 2010; Brida et al., 2014). The tourism-led growth hypothesis suggests that growth in tourism activity can stimulate broader economic performance through multiplier effects and intersectoral linkages (Balaguer & Cantavella-Jordá, 2010). Empirical studies indicate that tourism positively impacts macroeconomic indicators, although the magnitude of this effect varies depending on structural characteristics, investment levels, and policy environments (Tang & Jang, 2009). Traditional econometric approaches, such as input–output models and panel data analysis, provide important quantitative insights but often overlook qualitative dimensions such as service quality, governance effectiveness, and social inclusiveness (Brida et al., 2014; Garau & Pavan, 2018). Given the multi-faceted nature of tourism development, multi-criteria decision-making (MCDM) methods have become popular for assessing tourism performance, competitiveness, and policy alternatives (Chang, 1996; Chen, 2000; Kahraman et al., 2003). Methods such as the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), TOPSIS, and VIKOR allow systematic evaluation of multiple interrelated criteria. Among these, AHP developed by Saaty (1980) is widely used due to its structured pairwise comparison mechanism and ability to decompose complex problems hierarchically.

However, traditional AHP relies on precise numerical inputs, which may fail to capture the uncertainty and subjectivity inherent in expert-based assessments (Kahraman et al., 2003). To address the vagueness and imprecision of expert judgments, fuzzy logic has been integrated into MCDM methods (Zadeh, 1965). Fuzzy AHP and fuzzy TOPSIS enable the representation of linguistic variables and uncertain information, allowing decision-makers to evaluate qualitative and quantitative factors simultaneously (Chang, 1996; Chen, 2000; Kahraman et al., 2003). Fuzzy approaches have been applied to tourism destination selection, sustainability evaluation, service quality assessment, and investment prioritization (Garau & Pavan, 2018). Despite these advances, most tourism-related fuzzy studies employ type-1 fuzzy sets, which assume precise membership functions and may underestimate the higher-order uncertainty present in real-world decision-making (Dubois & Prade, 1980; Castillo & Melin, 2008). Type-2 fuzzy sets extend the conventional fuzzy framework by incorporating uncertainty directly into the membership functions, providing a more flexible and realistic representation of ambiguous and inconsistent expert judgments (Mendel, 2001; Castillo & Melin, 2008; Mendel & John, 2002). Interval type-2 fuzzy sets, in particular, balance modeling power and computational feasibility, making them suitable for complex decision-making contexts (Mendel & John, 2002; Wang & Yu, 2015). Type-2 fuzzy MCDM methods have been successfully applied in engineering management, risk assessment, and strategic planning, demonstrating improved stability and robustness of results compared to type-1 fuzzy approaches (Mendel, 2001; Mendel & John, 2002; Kahraman et al., 2015). Although type-2 fuzzy decision-making has shown effectiveness in various fields, its application in tourism development and economic growth assessment remains limited. Most studies either rely on econometric methods or type-1 fuzzy frameworks, which may inadequately capture uncertainty in expert judgments (Kahraman et al., 2015; Wang & Yu, 2015).

This gap motivates the present study to develop a type-2 fuzzy MCDM framework for evaluating tourism development factors contributing to economic growth. By integrating linguistic assessments, uncertainty modeling, and robust prioritization, the proposed approach aims to support more reliable policy-making and strategic planning in tourism-driven economic development. Among these methods, fuzzy logic-based approaches have proven particularly effective in modeling the uncertainty and ambiguity inherent in human reasoning. While fuzzy type-1 approaches are popular, they require precise membership functions and can oversimplify the uncertainty introduced by experts. In contrast, fuzzy type-2 decision methods extend the traditional fuzzy framework by allowing for uncertainties within the membership functions themselves, thus enabling a more robust representation of linguistic estimates and expert opinions. The application of type-2 fuzzy methods is particularly relevant in the context of tourism-related decision-making, where data scarcity, subjective assessments, and a dynamic environment prevail. Given higher-order uncertainties, type-2 fuzzy models increase the reliability of evaluation results and reduce the risk of biased or inconsistent decisions. Despite these advantages, the application of type-2 fuzzy decision methods to estimate tourism-related economic growth remains limited in the existing literature, revealing a significant research gap. To address this gap, this study develops a framework for estimating economic growth through tourism development using type-2 fuzzy decision methods. The proposed framework systematically identifies and evaluates key tourism development criteria based on expert assessments in linguistic form. By using type-2 fuzzy sets, the methodology can effectively account for uncertainty, ambiguity, and variability in expert opinions. The resulting weights and rankings enable a structured evaluation of tourism development factors regarding their contribution to economic growth.

This study makes four contributions. First, it provides a comprehensive and flexible framework for evaluating tourism-related economic growth under uncertainty. Second, the study demonstrates the applicability and benefits of decision-making methods based on type-2 fuzzy sets for complex socioeconomic valuation problems. Third, it provides decision support for policymakers and stakeholders who wish to prioritize tourism development initiatives. Finally, the study contributes to the growing literature on advanced multi-criteria decision-making methods based on fuzzy sets in tourism economics.

## 1. Preliminaries

**Definition 1.** Mathematical models that combine linguistic variables with standard arithmetic operations form the basis of the algebra of fuzzy numbers. In many decision-making contexts, experts express their assessments using imprecise terms like "approximately 0," "close to 1," or "around 10," which correspond to fuzzy numbers. Among the different types, triangular fuzzy numbers are the most used in practical applications. A triangular fuzzy number graphical depiction is illustrated in Fig. 1.

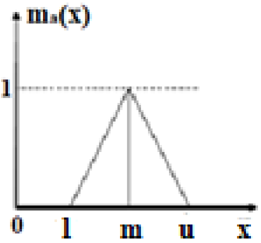


Fig. 1. Triangular type-1 fuzzy set

The membership function of a triangular fuzzy number (TFN) is usually defined in a piecewise linear form. Let a triangular fuzzy number be denoted as

$$\tilde{A} = (l, m, u) \qquad (1)$$

where, $l$ is the lower bound (minimum value), $m$ is the modal value (most likely), $u$ is the upper bound (maximum value). The membership function $\mu_{\tilde{A}}(x)$is defined as:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l \\ \frac{x-l}{m-l}, & l \le x \le m \\ \frac{u-x}{u-m}, & m \le x \le u \\ 0, & x > u \end{cases} \qquad (2)$$

For $x < l$or $x > u$, the membership is 0 (outside the range). Between $l$and $m$, membership increases linearly from 0 to 1. Between $m$and $u$, membership decreases linearly from 1 to 0.
Definition 1. A type-1 fuzzy set $A$ within the universe $X$ is defined by a membership function and can be represented as follows [17]:

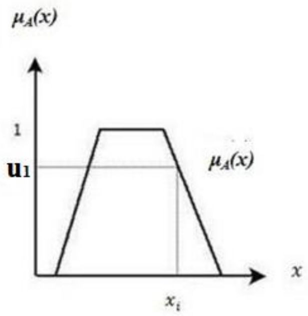


Figure 1. Trapezoidal type-1 fuzzy set

$$A = \{(x, \mu_A(x)) \mid \forall x \in X, \mu_A(x) \in [0,1]\}$$

**Definition 2.** A type 2 fuzzy set $\tilde{A}$ is characterized by a fuzzy membership function $\mu_{\tilde{A}}(x,u)$ in the universe $X$ where $x \in X$ and $u \in J_X, J_X \subseteq [0,1]$ is shown as follows [17]:

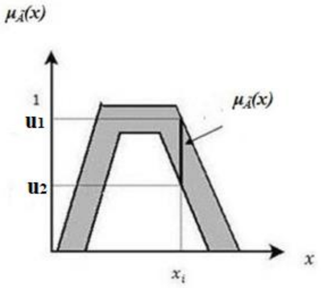


Figure 2. Trapezoidal type-2 fuzzy set

$$\tilde{A} = \{(x, u, \mu_{\tilde{A}}(x,u)) \mid \forall x \in X, u \in [0,1]\}$$

**Definition 3.** Suppose that $\tilde{A} = \sum_i \mu_{\tilde{A}}(x_i)/x_i$ and $\tilde{B} = \sum_j \mu_{\tilde{B}}(x_j)/x_j$ are fuzzy sets included in the set X. According to Zadeh's extension principle [18]

$$\tilde{A} * \tilde{B} = \left(\sum_i \mu_{\tilde{A}}(x_i)/x_i\right) * \left(\sum_j \mu_{\tilde{B}}(x_j)/x_j\right) = \sum_{i,j} \left(\mu_{\tilde{A}}(x_i) \wedge \mu_{\tilde{B}}(x_j)\right) / \left(x_i * x_j\right) \quad (3)$$

The extension principle enables the generalization of the classical function $f$ from a set $X$ to a fuzzy set $A$ on $X$. For each element $x$ in $A$, the degree of membership in the fuzzy set $f(A)$ is defined by applying the function $f$ to the degree of membership of $x$ in $A$.

$$\mu_{f(A)}(y) = \sup_{x \in X, f(x)=y} \mu_A(x) \quad (4)$$

This means the membership function of the fuzzy set $f(A)$ at $y$ is maximum membership degree of all elements $x$ in $A$ such that $f(x) = y$. The Extension Principle also applies to set operations. The union of two fuzzy sets $A$ and $B$ is given below.

$$\mu_{A \cup B}(x) = \max(\mu_A(x), \mu_B(x)) \quad (5)$$

The **intersection** is given below.

$$\mu_{A \cap B}(x) = \min(\mu_A(x), \mu_B(x)) \quad (6)$$

The **complement** of a fuzzy set is given below.

$$\mu_{\neg} A(x) = 1 - \mu_A(x) \quad (7)$$

**Definition 4.** If $\mu_{\tilde{A}}(x)$ and $\mu_{\tilde{B}}(x)$ are membership degrees of type-2 fuzzy sets $\tilde{A}$ and $\tilde{B}$ of the fuzzy set $J \in [0,1]$, then

$$\mu_{\tilde{A}}(x) = f(u_1)/u_1 + f(u_2)/u_2 + \cdots + f(u_n)/u_n = \sum_i f(u_i)/u_i, \quad u_i \in J \quad (8)$$

$$\mu_{\tilde{B}}(x) = g(w_1)/w_1 + g(w_2)/w_2 + \cdots + g(w_m)/w_m = \sum_j f(w_j)/w_j, \quad w_j \in J \quad (9)$$

where $f$ and $g$ are membership functions.

**Definition 5.** The union and intersection of type-2 fuzzy sets are defined as below [18]:

$$\tilde{A} \cup \tilde{B} \Leftrightarrow \mu_{\tilde{A} \cup \tilde{B}}(x) = \mu_{\tilde{A}}(x) \cup \mu_{\tilde{B}}(x) = \left(\sum_i f(u_i)/u_i\right) \cup \left(\sum_i f(w_j)/w_j\right) = \\ = \sum_{i,j} \left(f(u_i) \vee g(w_j)\right) / \left(u_i \vee w_j\right) \quad (10)$$

$$\tilde{A} \cap \tilde{B} \Leftrightarrow \mu_{\tilde{A} \cap \tilde{B}}(x) = \mu_{\tilde{A}}(x) \cap \mu_{\tilde{B}}(x) = \left(\sum_i f(u_i)/u_i\right) \cap \left(\sum_i f(w_j)/w_j\right) = \\ = \sum_{i,j} \left(f(u_i) \wedge g(w_j)\right) / \left(u_i \wedge w_j\right) \quad (11)$$

## 3. Case Study Example: Economic Growth Assessment through Tourism Development

The assessment is based on expert opinions from academia, tourism management, and economic planning. In this study, the problem is formulated as a multi-criteria decision-making problem in which several tourism development alternatives are evaluated based on a set of relevant criteria. Let $A = \{A_1, A_2, ..., A_m\}$ denote the set of tourism development alternatives. In this research, four alternatives are considered: $A_1$ - Urban Tourism Development, $A_2$ - Eco-Tourism Development, $A_3$ - Cultural and Heritage Tourism Development, $A_4$ - Adventure Tourism Development. These alternatives represent different strategic directions that governments and stakeholders may adopt to enhance tourism activity and stimulate economic growth. The alternatives are evaluated according to a set of criteria $C = \{C_1, C_2, ..., C_n\}$ that reflect the main factors influencing tourism-related economic development. Based on an extensive literature review and expert consultation, the tourism development criteria influencing economic growth are grouped into the following main categories: $C_1$ - Tourism Infrastructure (transportation, accommodation capacity, facilities), $C_2$ - Investment and Financial Support (public and private investment, incentives), $C_3$ - Service Quality and Human Resources (staff skills, service standards), $C_4$ - Accessibility and Connectivity (transport access, digital connectivity). These criteria reflect both quantitative and qualitative aspects of tourism development and are suitable for evaluation using a fuzzy-based decision-making approach.

The objective of the problem is to determine the most suitable tourism development alternative that maximizes economic growth by considering the relative importance of these criteria. Since expert evaluations of criteria importance and alternative performance are often expressed using linguistic assessments such as “high,” “medium,” or “low,” uncertainty and ambiguity arise in the decision-making process. To effectively handle this uncertainty, the present study employs a multi-criteria decision-making framework based on Type-2 fuzzy sets. Type-2 fuzzy sets provide a more flexible and accurate representation of linguistic judgments by capturing higher-order uncertainty associated with expert opinions. The experts provide pairwise comparisons of the criteria using predefined linguistic terms. Each linguistic term is represented by an Interval Type-2 fuzzy number to capture uncertainty and variability in expert judgments. The assessments from each expert are combined through suitable Type-2 fuzzy aggregation operators to form the final fuzzy pairwise comparison matrices.

**Table 1.** Linguistic terms modeled using Type-2 fuzzy set values

| Linguistic terms | Linguistic values of type-2 fuzzy sets for linguistic terms | |
|---|---|---|
| | First-order membership function | Second-order membership function |
| Extremal Low | (0.1,0.2,0.3;0.3) | (0.15,0.25,0.35;0.35) |
| Very Low | (0.2,0.3,0.4;0.4) | (0.25,0.35,0.45;0.45) |
| Medium | (0.3,0.4,0.5;0.5) | (0.35,0.45,0.55;0.55) |
| High | (0.4,0.5,0.6;0.6) | (0.45,0.55,0.65;0.65) |
| Very High | (0.5,0.6,0.7;0.7) | (0.55,0.65,0.75;0.75) |
| Extremal High | (0.6,0.7,0.8;0.8) | (0.65,0.75,0.85;0.85) |

Within this framework, experts provide pairwise comparisons and performance evaluations for the alternatives with respect to the defined criteria. These evaluations are represented using Type-2 fuzzy numbers and processed through the decision-making model to calculate criteria weights and determine the overall ranking scores of the alternatives. The alternative with the highest-ranking score is considered the most appropriate tourism development strategy for promoting economic growth. The fuzzy values of the alternatives and the weights of the criteria are determined as in Table 2.

**Table 2.** Fuzzy values of alternatives and weights of criteria

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ |
|---|---|---|---|---|
| $w_j$ | (0.2,0.3,0.4,0.4; 0.25,35,0.45;0.45) | (0.4,0.5,0.6,0.6;0.55,0.65,0.75;0.75) | (0.3,0.4,0.5,0.5;0.55,0.65,0.75;0.75) | (0.5,0.6,0.7,0.7; 0.55,0.65,0.75,0.75) |
| $A_1$ | (0.2,0.3,0.4,0.4; 0.25,35,0.45;0.45) | (0.4,0.5,0.6,0.6;0.55,0.65,0.75;0.75) | (0.3,0.4,0.5,0.5;0.55,0.65,0.75;0.75) | (0.5,0.6,0.7,0.7;0.55, 0.65,0.75,0.75) |
| $A_2$ | (0.6,0.7,0.8,0.8; 0.7,0.8,0.9,0.9) | (0.2,0.3,0.4,0.4; 0.25,35,0.45;0.45) | (0.5,0.6,0.7,0.7;0.55,0.65,0.75,0.75) | (0.3,0.4,0.5,0.5;0.55, 0.65,0.75;0.75) |
| $A_3$ | (0.3,0.4,0.5,0.5;0.55,0.65,0.75;0.75) | (0.4,0.5,0.6,0.6;0.55,0.65,0.75;0.75) | (0.6,0.7,0.8,0.8; 0.7,0.8,0.9,0.9) | (0.5,0.6,0.7,0.7; 0.55,0.65,0.75,0.75) |
| $A_4$ | (0.5,0.6,0.7,0.7;0.55,0.65,0.75,0.75) | (0.6,0.7,0.8,0.8; 0.7,0.8,0.9,0.9) | (0.3,0.4,0.5,0.5;0.55,0.65,0.75;0.75) | (0.4,0.5,0.6,0.6;0.55, 0.65,0.75;0.75) |

The crisp weights $w_j$ for the criteria $C_j\,(j=1,2,3,4)$ were calculated by applying formula (12), which consolidates the aggregated fuzzy evaluations into precise numerical values, thereby quantifying the relative importance of each criterion in the decision-making process.

$$R(C_i)=\frac{1}{2}\left\{\frac{1}{3}\frac{c_i^3(b_i-a_i)+c_i(b_i^3-a_i^3)-a_ib_i(b_i^2-a_i^2)}{c_i^2(b_i-a_i)+c_i(b_i^2-a_i^2)-a_ib_i(b_i-a_i)}+\frac{b_i(a_i^{'}+2b_i^{'}+c_i^{'})}{2}\right\} \tag{12}$$

The weights of the criteria are normalized using formula (13), ensuring that the sum of all criteria weights equals one. This normalization process converts the calculated weights into comparable proportions, allowing for a consistent and balanced assessment of each criterion's relative importance in the overall decision-making framework.

$$w_j=\frac{R(w_j)}{\sum_{j=1}^{n}R(w_j)} \tag{13}$$

So, the crisp weight $R(C_1)$ for the criterion $C_1$ is determined as shown below, providing a precise numerical representation of its relative importance within the set of criteria considered in the decision-making process.

$$R(C_i)=\frac{1}{2}\left\{\frac{1}{3}\frac{0.3_i^3(0.4-0.2)+0.3(0.4^3-0.2^3)-0.2\times0.4(0.4^2-0.2^2)}{0.3^2(0.4-0.2)+0.3(0.4^2-0.2^2)-0.2\times0.4(0.4-0.2)}+\frac{0.4(0.25+2\times0.45+0.35)}{2}\right\}=0.20$$

Similarly, calculations are carried out for the remaining criteria, applying the same procedure to determine their respective crisp weights. This ensures that all criteria are quantitatively evaluated, allowing for a comprehensive and consistent comparison of their relative importance in the decision-making process.

$$R(C_2)=0.50,\quad R(C_3)=0.40,\quad R(C_4)=0.54$$

$$\sum R(w_j)=0.20+0.50+0.40+0.54=1.64$$

The weight of each criterion is calculated as follows, providing a precise quantification of its relative importance. This calculation allows for a systematic and consistent evaluation of all criteria, ensuring that their contributions to the overall decision-making process are properly balanced and comparable

$$w_1=\frac{0.20}{1.64}=0.12,\quad w_2=\frac{0.50}{1.64}=0.30,\quad w_3=\frac{0.40}{1.64}=0.25,\quad w_4=\frac{0.54}{1.64}=0.33$$

The ranking weights for the alternatives $A_i\ (i=1,2,3,4)$ are determined using formula (14), which aggregates the evaluated criteria weights and their respective performance scores.

$$R_{w_j}(A_i)=\sum_{j=1}^{n} w_j R(S_{ij}) \qquad (14)$$

This calculation provides a quantitative basis for ranking the alternatives, allowing decision-makers to identify the most preferred options in a systematic and consistent manner.

$$R_w(A_{11}^L)=0.11,\quad R_w(A_{11}^U)=0.13;\qquad R_w(A_{12}^L)=0.45,\quad R_w(A_{12}^U)=0.6;$$

$$R_w(A_{13}^L)=0.3,\quad R_w(A_{13}^U)=0.5;\qquad R_w(A_{14}^L)=0.6,\quad R_w(A_{14}^U)=0.64$$

$$Rank(A_1^L)=\frac{1}{n(n-1)}\times\left(\sum P(A_1^L)+\frac{n}{2}-1\right)=\frac{1}{12}(1.45+1)=0.21$$

$$Rank(A_1^U)=\frac{1}{n(n-1)}\times\left(\sum P(A_1^U)+\frac{n}{2}-1\right)=0.24$$

$$Rank(A_1)=\frac{Rank(A_1^L)+Rank(A_1^U)}{2}=\frac{0.21+0.24}{2}=0.225$$

We also apply these calculations to the other alternatives, following the same systematic procedure. This ensures that all alternatives are evaluated consistently across all criteria, allowing for a comprehensive comparison and enabling the identification of the most favorable option based on their aggregated ranking weights

$$Rank(A_2)=\frac{Rank(A_2^L)+Rank(A_2^U)}{2}=\frac{0.20+0.23}{2}=0.215$$

$$Rank(A_3)=\frac{Rank(A_3^L)+Rank(A_3^U)}{2}=\frac{0.23+0.26}{2}=0.245$$

$$Rank(A_4) = \frac{Rank(A_4^L) + Rank(A_4^U)}{2} = \frac{0.23 + 0.26}{2} = 0.24$$

Finally, all alternatives are ranked based on their calculated $R_{w_j}(A_i)$ values, and the alternative with the highest $R_{w_j}(A_i)$ is identified as the most favorable choice. This ranking reflects a comprehensive assessment of all criteria and ensures that the decision-making process selects the option with the greatest overall suitability and preference.

$$Rank(A_1) = 0.225, \quad Rank(A_2) = 0.215, \quad Rank(A_3) = 0.245, \quad Rank(A_4) = 0.24$$

$$A_3 > A_4 > A_1 > A_2$$

Based on the calculated ranking values, it is determined that the most favorable alternative is $A_3$, while the least preferred alternative is $A_2$. This result reflects the comprehensive evaluation of all criteria and demonstrates the effectiveness of the applied decision-making methodology in distinguishing between the alternatives according to their overall performance.

## Conclusion

This study introduces a comprehensive framework for assessing the economic impact of tourism development by employing a multi-criteria decision-making (MCDM) approach grounded in Type-2 fuzzy sets. Tourism development is a complex phenomenon influenced by a variety of interrelated economic, social, and infrastructural factors, whose evaluation is often hindered by uncertainty, subjectivity, and imprecise expert judgments. To effectively address these challenges, the proposed methodology leverages Type-2 fuzzy sets, which capture higher-order uncertainties and provide a more nuanced and realistic representation of linguistic assessments compared to conventional Type-1 fuzzy approaches. The framework systematically identifies, quantifies, and evaluates the critical criteria that drive tourism development and contribute to economic growth. By integrating expert knowledge within a structured decision-making process, the model generates robust weights and rankings for each tourism development factor, allowing for reliable prioritization. The results highlight that tourism infrastructure, socioeconomic impacts, and investment intensity are the primary drivers of economic growth, while factors such as service quality and accessibility also have substantial effects. These findings underscore the advantages of incorporating Type-2 fuzzy sets into MCDM, as they enhance the reliability, consistency, and stability of assessment outcomes under conditions of uncertainty. The proposed model offers valuable insights for policymakers and tourism stakeholders, enabling data-driven decisions and strategic planning for sustainable economic growth. The study has certain limitations. The analysis relies on expert opinions, which may introduce variability depending on the selected experts or regional context. Future research could expand the model by integrating dynamic datasets, hybrid Type-2 fuzzy approaches, or comparative evaluations with alternative decision-making methods. Additionally, applying the framework across diverse countries, tourism segments, or development scenarios would further validate its adaptability and generalizability. It makes a significant contribution by bridging tourism economics with advanced fuzzy decision-making techniques, offering a practical, reliable, and systematic tool for evaluating tourism-driven economic growth in environments characterized by uncertainty and imprecision.

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## Section ECONOMICS

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# Examining the Territorial Differences in the Visegrad Countries, with Special Reference to the Region Type Model

**Abstract**
The aim of the study is to examine the NUTS3 level areas of the Visegrad countries using the region type model. By applying the region model, the regions of the Visegrad countries that are performing exceptionally well and have a positive impact on neighbouring regions can be highlighted. The region-type model is often found in the literature but is not widely used. Using the region type model, regions are grouped according to two dimensions (GDP per capita and population density). An important factor in defining the research period was to reduce the negative impact of the 2008 crisis. Thus, the research period is 2014 to 2019, where can be described as the "last year of peace". The region type study with the values of the capitals was analysed. The results show Prague as a knowledge hub region and Budapest and Warsaw as cosmopolitan regions for all the periods studied. The region type classification of the Czech Republic can be considered homogeneous in 2014, but the regions return to their original equilibrium status in 2019 for the Visegrad region. The results show that the region type analysis and the convergence studies can be put in parallel.

**Keywords:** *territorial inequalities, regio model, competitiveness, economic growth*

**Introduction**
Economic and social processes (migration, population concentration, globalization) have contributed to increasing territorial disparities. Territorial disparities can result from social, economic, and environmental components. Nowadays, economic competition has come to the fore for municipalities, regions, and countries (Káposzta, 2014; Lengyel, 2006).
The conceptualization of territorial inequalities has evolved in different stages since the 1900s. Initially, the economic factors appeared that was most important in the science of geography, but the spatial approach also came into focus from the 1950s onwards (Rey, 2004; Jackson, 2004). The definition of spatial inequalities underwent a paradigm shift in the first half of the 20th century, as the spatial distribution of natural and social phenomena became the focus (Győri, 2005). Following the paradigm change, economic studies focused on spatial processes and their interactions (Nagy, 2006), but since the 1990s, the combined use of space and time emerged (Szendi, 2017).
The aim of the study is to bring to the fore the classification of the NUTS3 level areas of the Visegrad countries based on the European Region Model. The European Region Model is a regional competitiveness model, which can be applied to focus on the more competitive areas within the greater region.

**Literature review**

Territorial inequality can arise from various economic, social and natural factors. Throughout history, territorial inequality has increased due to the impact of various economic crises and world wars.

Three types of regional inequality can be distinguished, measured by different indicators: economic (GDP per capita), social (living standards, employment, unemployment) (Wishlade & Yuill, 1997, Molle, 2007; Kutscherauer et al, 2010), territorial (infrastructure, innovation). Studies have shown that these inequalities are generated between centres and peripheries (Poledniková, 2014).

The recognition of spatiality can be traced back to ancient times and since the 1900s we can observe four stages of development in the definitions. Territorial inequality initially appeared in geographical sciences and spatiality has come into focus since the 1950s. Christaller focused on economic aspects (Rey, 2004; Jackson, 2004), which developed into spatial science (Probáld, 2007). In the first half of the 20th century, the discussion of territorial inequalities underwent a paradigm shift, as social and natural factors and, as a result, spatial distributions and modeling also came to the fore (Győri, 2005). In economic studies, the characteristics of inequalities were present without considering space and time, however, spatial social and economic inequalities also appeared in the focus of studies (Kocziszky, 2011). Nemes-Nagy's (1990) definition included the difference in opportunities and economic dependence and independence, which together affect the development of regions. However, according to Enyedi's (1996) definition, a certain degree of difference between regions always exists because the local characteristics of the regions do not necessarily have a positive effect on economic development, while Faluvégi (2000) stated that more than one indicator is needed to examine territorial inequalities to obtain more reliable results.

Based on the literature, territorial inequality can be formulated as follows: 'Social, environmental, and economic territorial disparities are the result of the combination of space and time, and of different processes and interactions. The extent of disparities is caused by different conditions and resources, which contribute to the economic growth of national economies. By focusing on the 'quantitative revolution', the extent, temporal variation and spatial distribution of disparities have become measurable, which allows the actuality of territorial disparities to be maintained." (Zapreskó-Farkas, 2023c p. 6)

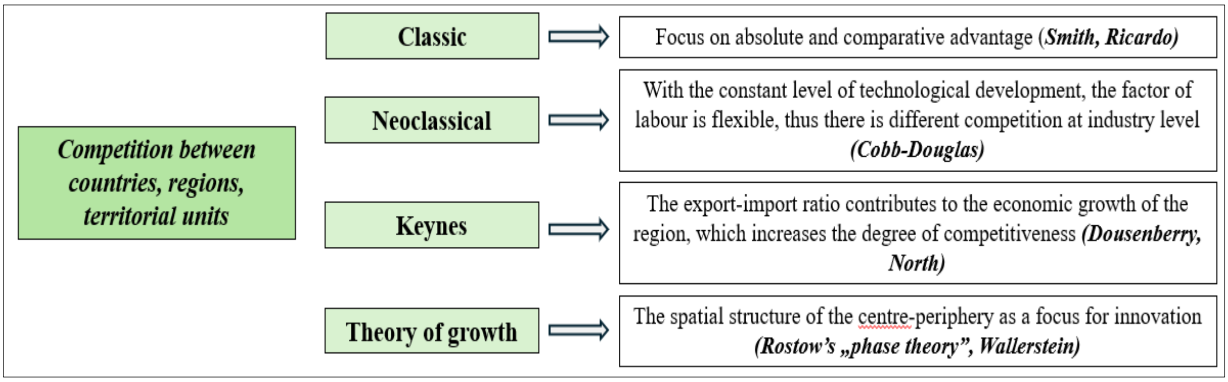
Territorial disparities, centre-periphery interactions and the ongoing process of globalization have brought economic competition to the fore. The competition between companies, regions and countries is aimed at gaining a position to be comparable with each other (Lengyel, 2006).

Porter (1990) argues that competitiveness is more simply understood at the company's level because it includes resources, investment, innovation and welfare at the level of national economies (Wren, 2001; Kitson et al, 2004). However, Aiginger (2006) defined competitiveness as "the ability of a country or region to generate wealth" (Lengyel 2016, p. 146). In further research, the author focuses on social and ecological factors to improve competitiveness (Aiginger & Firgo, 2015). A new approach to the measurement of competitiveness emerged after the 2008 crisis, as the notion of well-being came into focus alongside economic growth and social progress (Stiglitz et al., 2010).

Figure 1. illustrates the economic approaches to competitiveness. Macro-level competitiveness, which can be determined by the combined effect of the concentration of companies, the level of productivity, the standard of living and income factors in the relationship between countries, regions and settlements. Among the classical growth theories, the models of Smith (1776) and Ricardo (1817) stand out. Smith prioritized absolute (lower import ratio and products produced from own resources),

while Ricardo prioritized comparative (specializing in products produced with absolute advantage, which reduces the relative price of the product) advantages (Camagni, 2002). Among the neoclassical theories, the Cobb-Douglas (1934) model stands out, according to which the capital and labor factors are flexible, while technological development remains unchanged. Among the Keynesian growth theories, the export-based model of Duensenberry (1950) and North (1955) can be highlighted. The goal of export-based models is economic growth, which can be achieved through the combined effect of consumption, investment, government spending and the export-import ratio. Among the center-periphery theories, Rostow (1960) (phase theory) and Wallerstein (1974) models (Metcalfe & Ramlogan, 2007) can be highlighted.

**Figure 1.** An economics approach to competitiveness




**Source:** own editing based on Camagni, 2002; Metcalfe & Ramlogan, 2007; Poreisz, 2018

In conclusion, a parallel can be drawn between competitiveness and economic theories. Economic models help to illustrate competitiveness at the regional level.

## Materials and methods

The European Region model is used in this study. There is a large literature on the role of region types in territorial competition. The European Union examined the factors affecting regional competitiveness between 2007 and 2013 (Martin et al, 2003).

The European Union's region types of model groups regions according to two dimensions (population density, GDP per capita). Theoretical types include productive sector regions, economics of scale regions, knowledge centre regions; while basic types include rest regions, rural regions, balanced regions, dynamic regions, special city regions, cosmopolitan regions.

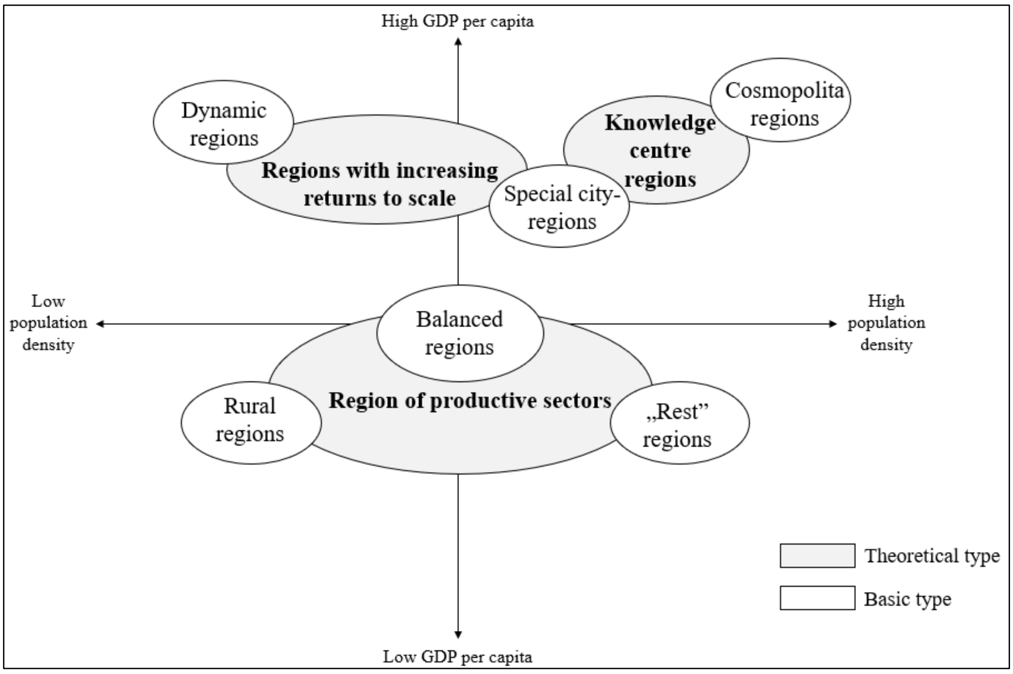
The group of productive sectors includes regions with a medium income level. The main competitive advantage of the regions is the use of cheap input and available cheap labor market at the company level. In addition, the human resources are suitable for the creation of the assembly sites of multinational companies. The regions belonging to this group have a medium population density and an average GDP per capita.

Areas with a high per capita GDP and medium population density can be called regions with increasing returns to scale. Their competitive advantage is ensured by the relatively higher qualification of human resources and the easier availability of suppliers. The well-being of the areas belonging to this group is ensured by the few main industries present in the region.

The regions belonging to the knowledge center have a high per capita GDP and population density.

The region absorbs the highly and well-educated workforce, which means that a high level of research, development and innovation can be found. The high quality of human resources and openness to international relations can be considered as a competitive advantage.

**Figure 2.** European Region Type Model




**Source:** own editing based on Martin et al, 2003 and Fenyővári & Lukovics, 2008

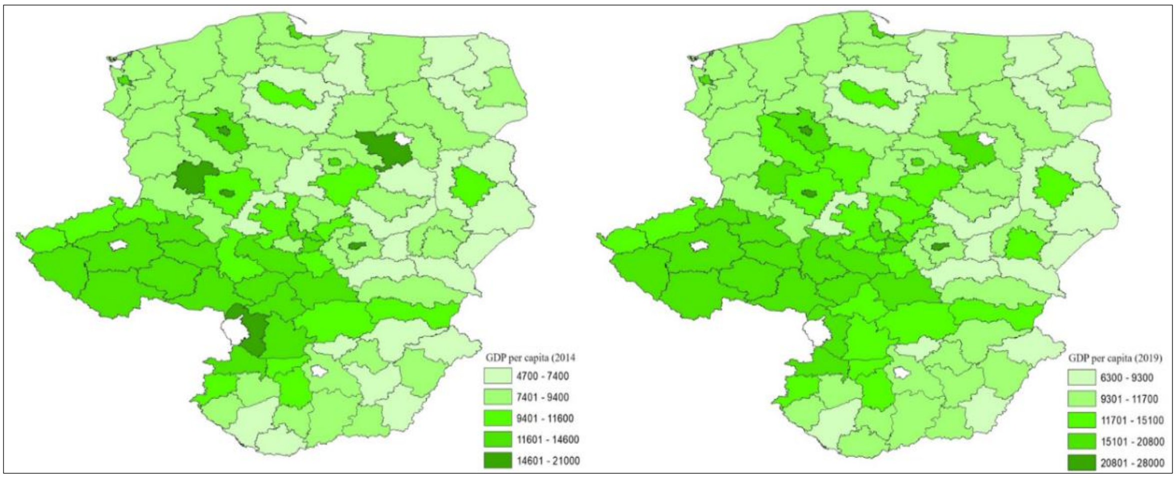
Regions in the balanced category are characterised by a medium level of population density and GDP per capita. Rural regions have lower population densities and GDP per capita, but "resting" regions have higher GDP per capita with low population densities. Compared to balanced regions, special city-regions have relatively higher GDP per capita and population density. Dynamic regions have high GDP per capita and low population density; however, cosmopolitan regions have high levels of both. The main difference between a special city region and a cosmopolitan region is presumably the research and development and innovation rate. It is likely that the cosmopolitan region will outperform on these factors. On this basis, it can be argued that the region has a high quality and educationally advanced human resource base.

This study examines the NUTS3 level (115 regions) of the Visegrad countries. Based on the region type model, I focus on GDP per capita and population density in 2014 and 2019. The aim of the study is to focus on the regions with a competitive advantage in the V4 based on the classification of the region type model.

## Results

Previous studies have shown a similar trend in the development of the V4 countries, which can be explained by foreign direct investment and connection to the European Union (Csaba, 2014; Farkas, 2017; Fábián & Pogátsa, 2016; Lengyel & Kotosz, 2018). In terms of GDP per capita (PPS, USD), the Czech Republic increased from 58% to 78%, Slovakia from 44% to 72.5%, Poland from 42% to 64.5% and Hungary from 51% to 63.5% compared to the EU15 Member States between 2000 and 2015. It can be concluded that the V4 countries are undergoing a strong economic catching-up process (Lengyel & Kotosz, 2018).

**Figure 3.** Regional differences in the Visegrad countries; NUTS3 (GDP per capita; euro; 2014, 2019)

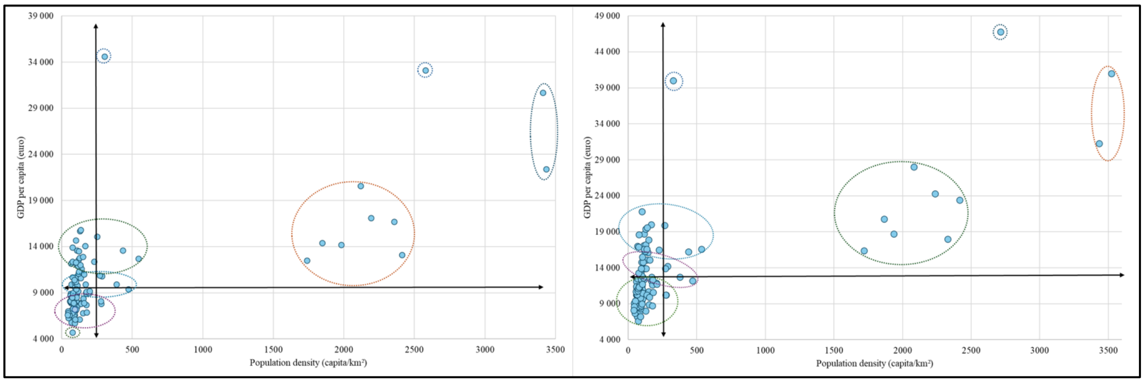



**Source:** own editing based on eurostat data

Figure 3 illustrates the spatial distribution of regional differences in the Visegrad countries (excluding capitals[1]) based on GDP per capita. The figure shows that the Czech Republic stands out at the level of the greater region, as all its regions have high GDP per capita. Nógrád has the lowest GDP per capita (4700 euro in 2014; 6300 euro in 2019), while Warsaw has the highest (31400 euro in 2014; 41000 euro in 2019) in the years under analysis.

The figure 4 shows the distribution of NUTS3 level areas in the Visegrad countries by region type model in 2014 and 2019. In the analysis, the annual average of the region type model indicators (GDP per capita and population density) is used as the model origin.[2] The difference between the two periods examined is that the trend line is steeper in 2019 than in 2014, suggesting that income inequality has increased in terms of GDP per capita.

**Figure 4.** Distribution of NUTS3 level areas in the Visegrad countries based on the European Region Type model (2014, 2019)




**Source:** own editing based on eurostat data

[1] GDP per capita in Bratislava is 34600 euro in 2014 and 39900 euro in 2019; in Prague 33100 euro in 2014 and 46800 euro in 2019; in Warsaw 31200 euro in 2014 and 41000 euro in 2019; in Budapest 22400 euro in 2014 and 31000 in 2019.

[2] The average GDP per capita is 10327 euro in 2014 and 13623 euro in 2019; while the average population density is 324 km² in 2014 and 326 km² in 2019.

I examined the correlation between the coefficients (GDP per capita and population density) that show table 1. The significance value is 0.000 at both time points examined and the strength of the relationship between them is $R^2$ (2014) = 0.668 and $R^2$(2019) = 0.720. There is a relatively strong positive relationship between the variables at both time points examined.

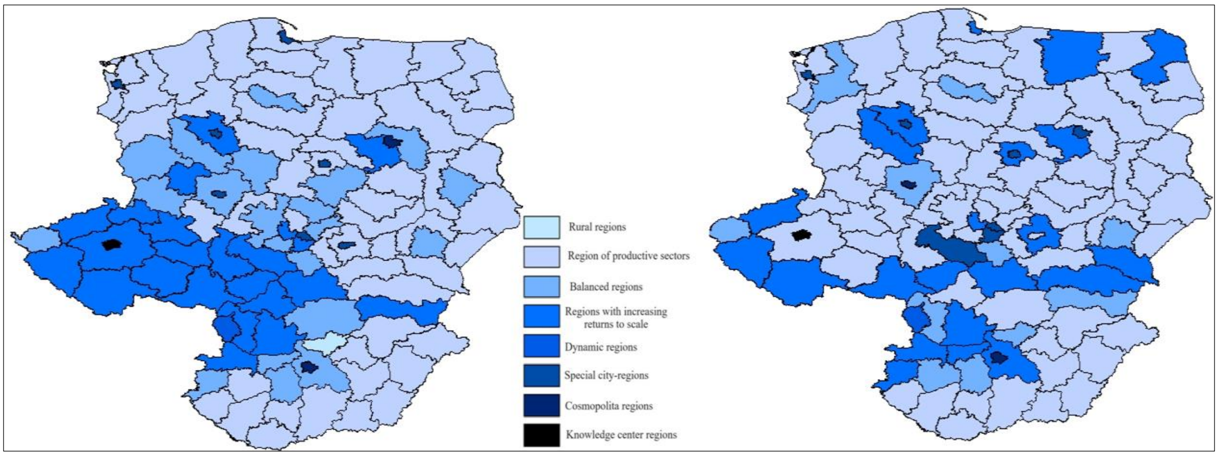
**Table 1.** Statistical summary table of the relationship between GDP per capita (euro) and population density (km²) indicators

| | Regression line equation | Significance | $R^2$ |
|---|---|---|---|
| **2014** | y = 4.8067x + 8767.5 | 0,000 | 0.668* |
| **2019** | y = 6.8665x + 11384 | 0,000 | 0.720* |

**Source:** own editing

Figure 5 illustrates the territorial distribution of the Visegrad countries based on the region type model. In both periods, Prague was classified as a knowledge centre region, while Budapest and Warsaw were in 2014; in 2019, Miasto Wroclaw was classified as a cosmopolitan region besides Budapest. In the special city-region group, the regions of the major cities in Poland, such as Katowicki, Miasto Krakow, Miasto Lodz, Miasto Poznan, Miasto Szczecin and Miasto Warszawa, are the most important ones in both time periods considered. In both 2014 and 2019, the Bratislavsky kraj region can be classified as a dynamic region. The classification of Bratislavsky kraj as a dynamic region is presumably due to the automotive sector in the region.

**Figure 5.** Territorial distribution of the Visegrad countries based on the region type model; NUTS3; 2014, 2019




**Source:** own editing based on eurostat data

There are larger differences in the spatial distribution of regions of increasing scale at the two points in time. In 2014, this category includes almost all of the Czech Republic, while Poland includes areas next to larger urban regions. However, in 2019, a smaller part of the Czech Republic was included in this category. In Hungary, the Pest, Győr-Moson-Sopron and Vas regions are still included in this category. Areas close to central urban areas can be classified as balanced regions, while regions in semi-peripheral or peripheral areas can be classified as productive sectors. The position of the Nógrád region is outstanding, as in 2014 it was a rural region, but in 2019 it is in a balanced category.

**Conclusion**

The development of spatial disparities has brought to the fore different social and economic factors, whose characteristics mean that no two points in space have the same characteristics. The spatial structure is constantly changing because of different economic processes, which means that studies of spatial inequality are constantly relevant. Today, competitiveness is a key issue not only for companies, but also for regions and countries. The competitiveness approach at regional level aims to raise living standards. The importance of regional competitiveness is supported by the literature and models presented.

The European Region model includes two dimensions - population density and GDP growth rate. They can be classified into theoretical types: regions of productive sectors, regions with increasing returns to scale and knowledge centre regions; and basic types: cosmopolitan regions, special urban regions, dynamic regions, balanced regions, resting regions and rural regions.

Each basic type can be connected to an economic theory. Regions of productive sectors are associated with classical, neoclassical and Keynesian theories; regions of increasing size are associated with evolutionary and Keynesian theories; while regions of knowledge centres are associated with evolutionary and Jacobsian urban growth theories.

In summary, the negative impact of the 2008 crisis was still felt in 2014, which can be explained by the homogeneous representation of the Czech Republic in the region type model.

In general, it can be stated that the European Region Model focuses on those areas that are more competitive. However, competitiveness cannot be explained only by factors such as GDP per capita and population density, but other factors (employment rate, education level, innovation presence, research and development expenditure, etc.) also need to be examined.

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# Econometrics of Risk: Theoretical and Methodological Foundations of Econometric Analysis of Risks

**Abstract**

Econometrics is the integration of economic theory, mathematical statistics, and empirical data, and in the insurance sector it is often regarded as the science of forecasting future outcomes based on historical information. In insurance, econometric methods are used to analyze and predict risks, losses, and financial indicators through mathematical and statistical models. This field lies at the intersection of econometrics and insurance practice, providing analytical tools for managing uncertainty and supporting evidence-based decision-making. Since insurance operations are inherently based on uncertainty, econometric analysis enables insurers to estimate future losses, calculate appropriate premium levels, and maintain financial solvency. Risk refers to the deviation of actual outcomes from expected results and, unlike uncertainty, can be measured and quantified. The insurance sector is a fundamental component of the modern digital economy, contributing to economic stability through risk distribution and financial protection mechanisms. This study examines the nature of risk factors affecting the insurance sector and explores their evaluation through econometric methods. The research analyzes the influence of macroeconomic and microeconomic indicators on insurance market performance using multivariate regression models. The findings indicate that inflation, gross domestic product, interest rates, and loss frequency significantly affect risk levels and the financial stability of insurance institutions.

**Keywords:** econometrics of risk, econometric model, correlation-regression analysis, risk forecasting, insurance sector.

**Introduction**

Econometrics of risk is a specialized branch of econometrics based on the quantitative modeling and statistical analysis of risk in various economic and financial contexts. This field incorporates multidisciplinary problems such as mathematical modeling, probability theory, and statistical inference for the evaluation of uncertainty, the measurement of risk exposure, and the forecasting of potential financial losses. This approach is widely applied in financial markets, insurance, macroeconomic policy, and corporate risk management. The main objective of econometrics of risk is the quantification of risk factors and the assessment of their impact on economic outcomes.

Econometrics of risk has emerged as a result of centuries of multidisciplinary research in mathematics, economics, and decision theory. According to Sakai's concept, its development is divided into six stages, and each stage is based on significant historical events that occurred.

*1. Early Period (before 1700): This period is associated with the development of the foundations of probability theory.* During this time, Blaise Pascal and Pierre de Fermat, in their 1654 correspondence concerning gambling games (the "problem of points"), formalized the concept of probability theory and laid the foundation for a new scientific discipline. In these studies, Pascal's work consisted of providing a scientific explanation for philosophical discussions related to early ideas of utility. Therefore, this research is known in science as Pascal's Wager Theory.

*It was precisely during this period that mechanisms for risk distribution were established:* Lloyd's Coffee House (1688), marine insurance, and stock exchanges such as the London Stock Exchange (whose predecessors existed from 1571, formally established in 1801) addressed practical risk problems related to trade and exploration, although the absence of formal economic foundations created limitations.

*2. 1700–1880: This period is called the era of Bernoulli and Adam Smith.* Daniel Bernoulli, in 1738, proposed the theory of expected utility to explain the St. Petersburg Paradox, replacing the expected monetary value with a logarithmic utility function. Adam Smith, in his 1776 work An Inquiry into the Nature and Causes of the Wealth of Nations, analyzed risky investments in markets and noted behavioral biases (tendencies). These cognitive and behavioral biases observed in decision-making under risk include individuals' inability to properly assess risk, making erroneous or irrational decisions under risky conditions, and systematic errors arising during information processing.

Major events of this period, such as the United States Declaration of Independence in 1776, the French Revolution in 1789, and the development of insurance institutions such as Tokio Marine Nichido (1879), increased the need for systematic risk assessment.

*3. 1880–1940: This period is referred to as the era of Keynes and Knight.* John Maynard Keynes, in his 1921 work A Treatise on Probability, distinguished between measurable risk and immeasurable uncertainty, and introduced the concept of "animal spirits." Frank Knight, in his 1921 book Risk, Uncertainty, and Profit, emphasized that profit arises from uninsured uncertainty. Additionally, World War I, the Great Depression, and the 1923 Great Kantō earthquake influenced the study of economic risks.

*4.* 1940–1970: This period is called the era of John von Neumann and Morgenstern. It is characterized as the period when game theory emerged. John von Neumann and Oskar Morgenstern, in their 1944 work Theory of Games and Economic Behavior, developed the expected utility approach. The second theory belonging to this period is Portfolio Theory. In this theory, Harry Markowitz introduced mean-variance analysis in 1952 to optimize the balance between risk and return (Markowitz, 1952). During the post-war development period, computational techniques and the Monte Carlo method accelerated risk modeling operations in the economy of the Cold War.

*5.* 1970–2000: This period in risk research is considered the era of Arrow, Akerlof, Spence, and Stiglitz. A characteristic feature of this era was information asymmetry, a situation in economic relations where one party possesses more and better-quality information than the other. According to this theory, in the insurance market, since the customer has more information about their health than the insurance company, high-risk individuals tend to purchase more insurance. In this context, George Akerlof's 1970 work The Market for Lemons introduced a new understanding of adverse selection and information asymmetry in markets (Akerlof, 1970). Consequently, volatility models were developed: Robert Engle created the ARCH model in 1982 (Engle, 1982), and Tim Bollerslev developed the GARCH model in 1986, enabling the measurement of time-varying volatility (Bollerslev, 1986). The 1973 oil crisis, the Chernobyl disaster in 1986, and the Dissolution of the Soviet Union exposed weaknesses in these models.

*6.* From 2000 to the Present Day: This period is considered the modern era in the development of risk studies. During this time, systemic risks emerged. For example, the 2008 financial crisis revealed the limitations of traditional risk measurement approaches and increased attention to systemic risk within financial and insurance markets (Cummins & Weiss, 2014). New instruments for econometric analysis of risks in insurance were developed: machine learning, extreme value theory, and Bayesian networks began to be widely used in modeling extreme risks. During this period, regulatory mechanisms were also developed, with special attention given to stress testing and liquidity risk in Basel III and Basel IV standards.

**Methodological Foundations of Econometric Risk Analysis**

Econometric risk analysis is one of the important scientific approaches for assessing risks in the insurance sector. Through econometric models, this approach enables the identification of functional relationships existing between risk factors and their outcomes. The application of econometric techniques contributes significantly to the efficiency and performance of insurance firms through improved risk management and financial intermediation activities (Cummins et al., 2009). The main objective of econometric risk analysis is to move away from subjective and intuitive assessments and ensure that risks are expressed through more precise quantitative indicators. This makes it possible to account for the multidimensional and complex nature of risks. Modern financial risk assessment methods are also closely linked to portfolio diversification principles (Markowitz, 1952) and asset valuation techniques developed in financial economics (Black & Scholes, 1973).

Furthermore, studies indicate that insurance sector development contributes positively to economic growth and financial stability (Outreville, 2013). Research on European insurance markets has also demonstrated that regulatory conditions, market competition, and business environments significantly influence the productivity and efficiency of insurance companies (Eling & Schaper, 2017). The following models are used in econometric risk analysis:

*Linear Regression Models*

These models allow the studied relationship to be expressed in the form of an analytical equation. In such models, dependent and independent (explanatory) variables are determined in advance, and a linear relationship is established between the risk indicator and the factors affecting it. This is expressed in the following form:

$$Y=\beta_0+\beta_1X_1+\cdots+\beta_nX_n+\varepsilon.$$

In the insurance context, the fundamental econometric equation describing insurance loss (Y) through the simplest linear model is represented as:

$$Y_i=\beta_0+\beta_1X_{1i}+\beta_2X_{2i}\cdots+\beta_kX_{ki}+\varepsilon_i\,.$$

Where:

- $Y_i$ – Expected amount of loss;
- $X$ – Risk factors (for example, age, engine capacity);
- $B_i$ – The impact strength of each factor;
- $\varepsilon_i$ – Error term. In insurance, this term is often very large because a significant part of risk is inherently random. The econometrician's task is to identify regularities hidden within this error component.

*Generalized Linear Models (GLM)*

GLM is considered the most powerful econometric tool in calculating insurance premiums because insurance losses do not follow a normal distribution.

GLM consists of three main components:

1. Random Component: The distribution of the dependent variable (Y), such as Poisson, Gamma, or Pareto.
2. Systematic Component: Formed from the linear combination of explanatory variables (Xi).
3. Link Function: A function that mathematically connects the expected value with the linear predictor (for example, log, logit).

For example, when applying a log-link function for automobile insurance, the model becomes:

$$ln(E[Y]) = \beta_0 + \beta_1 Yaş + \beta_2 Region,$$

Here, $\beta 0, \beta 1, \beta 2$ represent the impact strength of the factors.

*Logistic Regression Models*

These models account for the complexity and multidimensionality of risks and are particularly used in evaluating the probability of an event occurring. For example, this model is applied to determine the probability of an insurance event taking place. This method enables the transition from experts' subjective assessments to formal probability indicators and helps forecast the probability of project failure.

*Integration of Econometric Risk Analysis and Time Series Models*

Time series analysis and risk econometrics are among the main analytical approaches used in modern econometrics and financial economics for measuring, modeling, and forecasting risks. This field particularly serves to establish scientifically grounded decision-making processes under uncertainty.

A time series is a set of observations recorded sequentially over specific time intervals.

Economic and financial indicators (prices, revenues, interest rates) are usually presented in time-series form. Main components of time series include:

- *Trend* – Long-term tendency of growth or decline;
- *Seasonal component* – Periodically repeating changes;
- *Cyclical component* – Fluctuations related to economic cycles;
- *Random component* – Unexplained stochastic variability.

*In risk econometrics, time series are used for:*

- Analyzing changes in risks over time;
- Forecasting future risk levels;
- Evaluating financial stability;
- Studying the dynamics of insurance payments.

For example, insurance companies can analyze annual changes in claim payments to forecast future risks.

The following classical and modern time series models are widely used for risk analysis:

*AR (Autoregressive) Model*

$$Y_t=\alpha+\beta Y_{t-1}+\varepsilon_t$$

In this model, the current value depends on the previous period's value.

Where:

- $Y_t$ – Dependent variable showing the outcome at time *t* during analysis. In insurance examples, this may represent the number of insurance claims, the volume of insurance premiums, or the amount of loss as a risk indicator;

- *α (intercept)* – Constant term representing the expected value of $Y_t$ when $Y_t -1 = 0$. In insurance, α reflects the model's baseline level, meaning the expected minimum risk/premium value without considering historical observations. The expression risk/premium is mainly used in insurance and financial contexts: *Risk* – The probability of a certain event occurring or the potential loss caused by that event. For example, the risk of being involved in a car accident in automobile insurance, or illness/death risk in life insurance. *Premium* – The amount paid by the insured party to the insurance company under the insurance contract. This amount is determined according to the level of risk, coverage scope, and insurance duration. Thus, in insurance theory, the concept of risk/premium usually refers to "a premium corresponding to the insurance risk": the higher the risk, the higher the premium is likely to be.

- *β* – Autocorrelation/effect parameter measuring the influence of changes in $Y_t -1$ on $Y_t$.

- If β > 0, a high risk/premium in the previous period indicates a higher probability of remaining high in the current period.

- If β < 0, high risk in the previous period may lead to a lower level in the current period. In insurance, β is important for measuring the persistence or trend of risks.

- $\varepsilon_t$ – Residual (error) term representing random changes that the model cannot explain. In insurance, this includes impacts arising from unexpected events such as accidents, natural disasters, and similar occurrences.

This is an *AR(1) model***,** in other words, a first-order autoregressive model. In more complex insurance analysis, **εt** may exhibit a heavy-tailed distribution because rare but severe risks exist. The parameters of these risks are estimated using OLS (Ordinary Least Squares) or MLE (Maximum Likelihood Estimation) methods.

*OLS (Ordinary Least Squares)* is the most commonly used method in statistics and econometric modeling for estimating parameters related to the error term. Its objective is to minimize the sum of squared differences between observed quantities and the quantities predicted by the model. Suppose we have a simple linear regression model:

$$Y_i=\alpha+\beta X_i+\varepsilon_i .$$

Where: $Y_i$ – Dependent variable; $X_i$ – Independent variable; $\varepsilon_i$ – Errors; $\alpha, \beta$ – Parameters we want to estimate.

In the OLS method, we need to minimize the following objective function for α and β:

$$\min \sum_{i=1}^{n} \left(Y_i - \alpha - \beta X_i\right)^2 .$$

Characteristics of OLS: Simple and fast to apply; Under the assumption of normally distributed errors, it is considered the BLUE (Best Linear Unbiased Estimator)**.**

MLE (Maximum Likelihood Estimation) is a parameter estimation method based on probability theory. Its purpose is to identify the parameter values that maximize the likelihood of observing the given data. Suppose our observations $Y_i$ follow a certain probability distribution:

$$\theta_{MLE} = \arg\max_{\theta} \prod_{i=1}^{n} f(Y_i \mid \theta) .$$

Where:

-$(X_1, \ldots, X_n)$ are observations drawn from the same distribution. This distribution is characterized by parameter $\theta$***;***

**-** $f(Y_i \mid \theta)$ is the density function, or in the discrete case, the probability function;

-θ is the parameter we aim to estimate. That is, we seek the value of θ that maximizes the probability of the observed data.

Characteristics: It is highly flexible and can be applied to any distribution; for large samples, the MLE estimator is consistent (as the number of observations increases, its value approaches the true parameter, and the estimation error decreases), asymptotically normal, and efficient. The OLS method, when errors are normally distributed, can be considered a special case of MLE. A simple comparison table and graph are shown below (Table 1, Figure 1):

**Table 1.**

| **Characteristic** | **OLS** | **MLE** |
|---|---|---|
| Objective | Minimize the sum of squared errors | Maximize the likelihood (probability) |
| Main Assumption | Errors have zero mean and are homoscedastic | The distribution form must be known |
| Advantage | Simple and fast | More flexible, suitable for various distributions |

*MA (Moving Average) Model (Moving Average Calculation Method).* This model is a statistical method used in time series analysis to smooth short-term fluctuations in indicators and to observe the overall trend more clearly. In other words, MA means that the average of a certain number of consecutive observations is calculated, and in the next period this window "moves forward." A simple moving average is calculated as:

$$MA_t = \frac{Y_t + Y_{t-1} + \ldots + Y_{t-n-1}}{n}$$

In more complex situations, the MA(q) model is also written as:

$$Y_t = \mu + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \ldots + \theta_q\varepsilon_{t-q}$$

**OLS** **MLE**

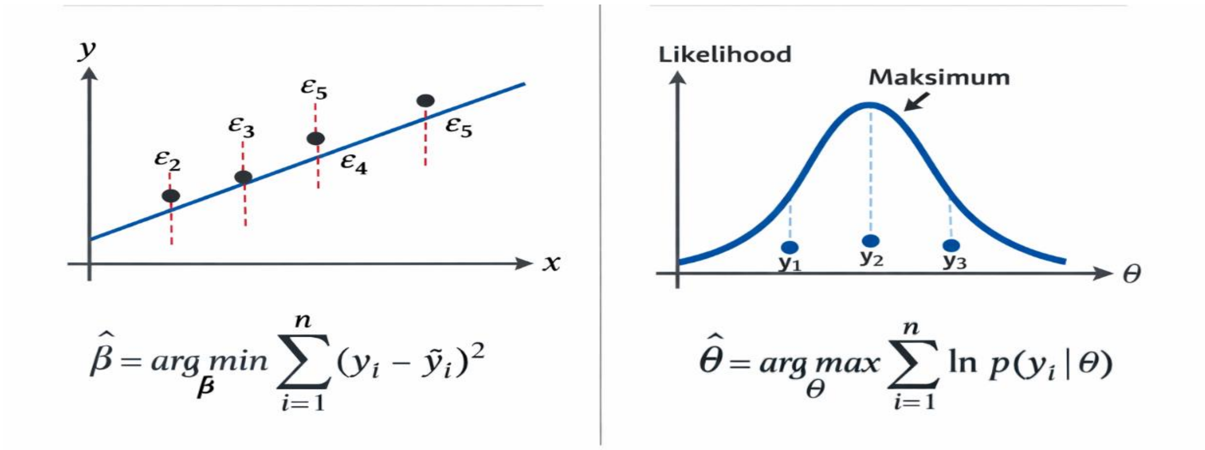


**Figure 1. Graphical representation of OLS versus MLE.**

Where:

- $Y_t$ – Time series variable (parameter) at time $t$;
- $\mu$ – Mean or constant value;
- $\varepsilon_t$ – White noise or random errors;
- $\theta_1, \theta_2, \ldots, \theta_q$ – Parameters of the MA model;
- $q$ – Order of the MA model (how many lagged error effects are considered).

In the simple case, the MA(1) model is expressed as:

$$Y_t = \mu + \varepsilon_t + \theta\varepsilon_{t-1}.$$

Here, $Y_t$ is the value of the current period, and $n$ is the number of periods over which the average is taken. Previous errors are considered in this process. For example, let us calculate a 3-day moving average (Table 2): Example data:

**Table 2**

| | |
|---|---|
| 1 | 10 |
| 2 | 12 |
| 3 | 14 |

For Day 3: MA=(10+12+14)/3=12, then (12 + 14 + new value) / 3.

In applications within the insurance sector, MA reduces random fluctuations, helps identify trends, and is used in forecasting risks.

*ARMA Model*

This is a combination of AR and MA models and is used for evaluating stationary time series. Stationarity of time series is an important condition in econometric analysis. Non-stationary series are transformed into another form through certain mathematical operations, such as differencing, in order to build the model more accurately and improve data properties.

*ARIMA Model (Autoregressive Integrated Moving Average).* The ARIMA model is widely used in the insurance sector to analyze time series of risks and revenues. This model is applied to non-stationary series and is generally represented as:

$$ARIMA(p,d,q),$$

Where:

p – Order of autoregression; d – Level of differencing; q – Order of moving average.

This model combines autoregressive (AR), integrated (I), and moving average (MA) components to explain time series dynamics. It is effective in short-term forecasting.

*Structure of the ARIMA Model.* The components of the ARIMA(p,d,q) model can be expressed in formula form as follows:

*1. AR(p) – Autoregressive Component: Shows the effect of past observations on the current value.*

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon_t \, .$$

*2. I(d) – Integration Component:* If a time series is non-stationary, a differencing operation ($\Delta^d Y_t$) is applied to make it stationary.

*3. MA(q) – Moving Average Component:* Shows the effect of past random errors (residuals) on the current value.

$$Y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \, .$$

When all components are combined, the ARIMA(p,d,q) model is formed.

*Application of the ARIMA Model in the Insurance Sector*

*1. Claims Forecasting:* Analyzes the time series of monthly or annual claims for a specific type of insurance. For example, in automobile insurance claims: The AR component reflects the impact of past claims; The MA component reflects unexpected events.

*2. Risk Management:* The ARIMA model helps insurance companies forecast the magnitude of future risks and allocate capital for those risks. It is particularly useful in modeling heavy-tailed and non-stationary risks.

*3. Premium Setting:* Forecasting future payments based on past claims is used in determining premiums. For example, annual insurance premiums can be optimized using the ARIMA model.

*4. Comparison of Different Insurance Portfolios:* By modeling time series for different types of insurance, it is possible to analyze the distribution of risks across portfolios.

*Simple Practical Example* (Zolkin A. L., 2025)

$$\Delta Y_t = \phi_1 \Delta Y_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} \, .$$

Where

- $\Delta Y_t = Y_t - Y_{t-1}$, $\phi_1$ – Effect of past monthly changes;
- $\theta_1$ – Past effect of random changes.

Based on this model, a company can forecast the number of insurance claims for the next month.

Now let us write Python program code for an ARIMA model built on simple insurance claims time series data and construct the forecast graph.

```
# Required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.arima.model import ARIMA

# 1. Sample insurance claims data (monthly)
np.random.seed(42)
months = pd.date_range(start='2022-01', periods=36, freq='M')

# Base trend + random noise
claims = 50 + np.cumsum(np.random.randint(-5, 6, size=36))
data = pd.Series(claims, index=months)

# 2. Plot of the time series
plt.figure(figsize=(10,4))
plt.plot(data, marker='o')
plt.title('Monthly Insurance Claims')
plt.xlabel('Month')
plt.ylabel('Number of Claims')
plt.grid(True)
plt.show()

# 3. Building the ARIMA model (p=1, d=1, q=1)
model = ARIMA(data, order=(1,1,1))
model_fit = model.fit()

# 4. Forecast (next 12 months)
forecast = model_fit.forecast(steps=12)
forecast_index = pd.date_range(
    start=data.index[-1] + pd.offsets.MonthEnd(1),
    periods=12,
    freq='M'
)
forecast_series = pd.Series(forecast, index=forecast_index)

# 5. Main graph + forecast
plt.figure(figsize=(10,4))
plt.plot(data, label='Observed Claims', marker='o')
plt.plot(
    forecast_series,
    label='ARIMA Forecast',
    marker='x',
    color='red'
)
plt.title('ARIMA(1,1,1) Forecast of Insurance Claims')
plt.xlabel('Month')
plt.ylabel('Number of Claims')
plt.legend()
plt.grid(True)
```

```
plt.show()
```

Explanation of the code:

1. `data` – In our example, this represents a 3-year (36-month) sample of insurance claims.
2. `ARIMA(data, order=(1,1,1))` – ARIMA(1,1,1) model:
   - p = 1 → AR(1);
   - d = 1 → first differencing;
   - q = 1 → MA(1).
3. `forecast(steps=12)` – Produces a forecast for the next 12 months (Figure 2).
4. `plt.show()` – Used to display the graph on the screen.

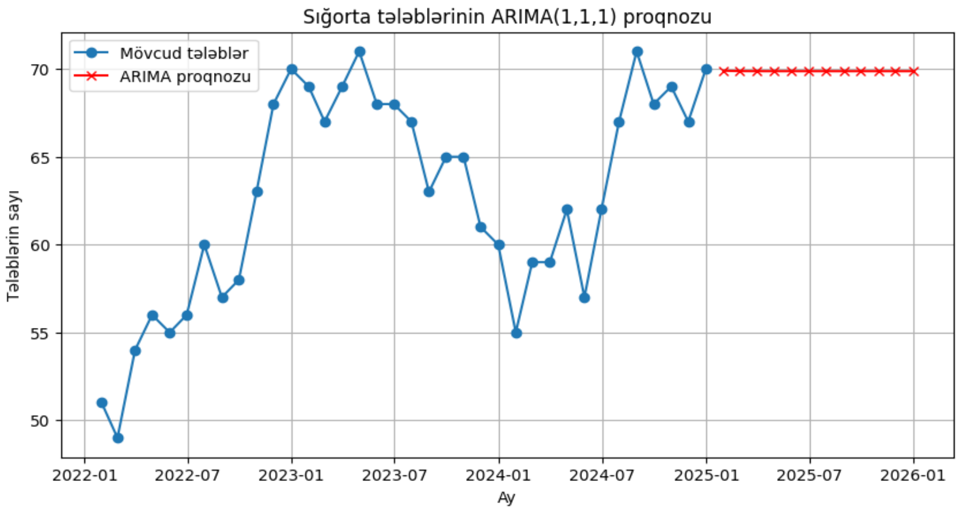


**Figure 2. Forecast of insurance claims based on the ARIMA (1,1,1) model built in Python.**

In the graph, the blue line represents the current monthly claims, while the red line shows the ARIMA forecast for the next 12 months. The graph demonstrates that the model follows the existing trend and predicts increases and decreases in claims for the future.

For real insurance data and heavy-tailed risks, a more advanced ARIMAX/non-normal model can also be built, which would provide a more realistic forecast (Figure 3).

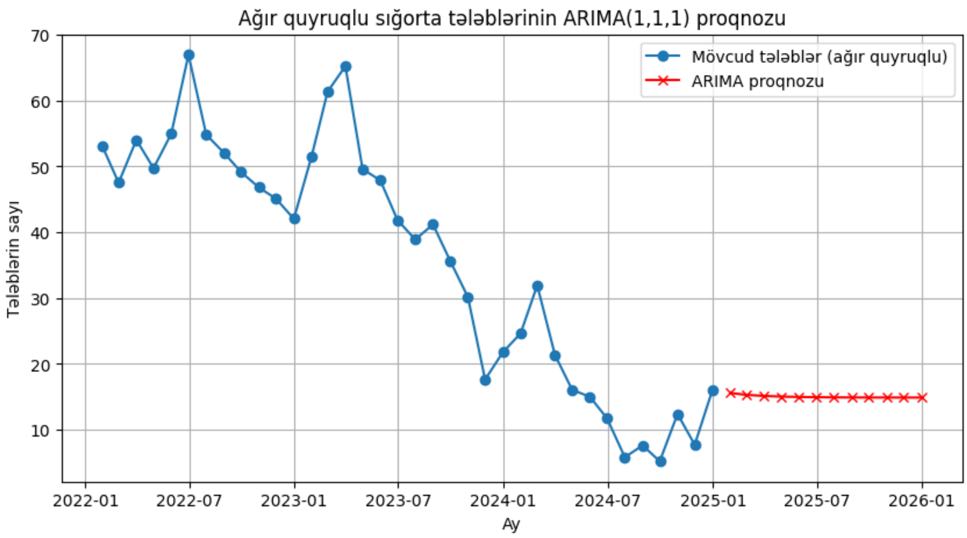


**Figure 3. A more realistic scenario: ARIMA(1,1,1) forecast for heavy-tailed insurance claims**.

The blue line shows the actual monthly claims with a heavy-tailed distribution, and the red line shows the ARIMA forecast for the next 12 months. The graph clearly shows that there are large jumps (heavy tails) in the claims, and the model takes them into account in the forecast.

*Volatility models (fluctuation models, such as GARCH) and multivariate volatility models*

1. These models are used to measure the time-varying nature of financial risks and are widely applied in assessing the risk level of insurance portfolios. In stochastic volatility (SV) models, volatility is treated as a separate latent stochastic process. These models play a crucial role in forecasting time-varying risks, measuring financial risks, and pricing derivative instruments (Babicheva I.V., "Lan," 2024).

In econometric analysis of insurance risks, volatility models are highly effective because they allow measurement and forecasting of risk variability (variance) over time. Volatility is the change in variance over time:

$$Var(Y_t) = \sigma_t^2 .$$

If $\sigma_t^2$ is non-stationary, heteroskedasticity arises, and classical models such as OLS are insufficient for risk analysis.

As a primary example of volatility models, the ARCH model developed by Engle in 1982 can be cited. Mathematically, the model can be expressed as follows:

$$\varepsilon_t \sim N(0, \sigma_t^2), \quad \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 .$$

This formula shows that current risk is directly proportional to past squared errors, meaning a large shock will cause higher future risk.

Volatility models in insurance econometrics check risk levels, measure variability, and are especially important for heavy-tailed and unstable risks. They are most effective when used together with ARIMA.

In 1986, Bollerslev developed the GARCH model, which is more realistic and "memory-aware." If the volatility depends on its past values, the model is called a "memory" volatility model.

In other words, if there is a large fluctuation (shock) in the market or insurance claims, its effect does not disappear immediately but persists for a period. If risk is high today, it is likely to remain high tomorrow, and if low today, it tends to stay low tomorrow. This phenomenon is called volatility clustering.

ARCH(1,1) model. In risk econometrics, this model is particularly important:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 .$$

Here, $\sigma_t^2$ is the current volatility, $\sigma_{t-1}^2$ is the effect of past shocks, and $\varepsilon_{t-1}^2$ is the coefficient of past volatility. The larger $\beta_1$ is, the longer the memory of volatility—i.e., past risk influences future risk for a longer period. The GARCH model shows risk peaks.

This model captures the time-varying nature of volatility and is particularly used in assessing insurance and financial risks. ARCH models account for conditional variance based on past shocks and help detect volatility clustering. GARCH extends this approach by including lagged variances. Models like EGARCH consider asymmetry (e.g., leverage effect).

In general, when natural disasters—such as strong earthquakes or floods—occur, the risks they create do not disappear immediately, and risk "retains memory." That is, during a severe flood or inundation, consecutive accidents or aftershocks can happen over several days, and the likelihood of such events occurring in subsequent periods remains high. For example, on October 22 and 29, 2024 (5,021 insurance claims) and March 27 and 28, 2026 (4,586 insurance claims), heavy rains in Baku and other regions of Azerbaijan caused floods and damage that resulted in substantial consecutive losses for people. According to statistical data, during these rainy periods, the number of car accidents increased 3.4 times. To address these issues, the insurance sector had to allocate substantial funds. This created prolonged instability characteristic of a crisis period in the financial and insurance markets. Such situations can be represented using ARIMA models for mean memory and GARCH models for volatility memory. The econometric formula is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 .$$

Here, $\sigma_{t-1}^2$ is a quantity that characterizes past risk, essentially representing "memory."

If a model has volatility memory, then risks cluster—that is, they occur in groups; classical models with constant variance give misleading results; more capital reserves are required, and in such cases, models like GARCH should be used.

Thus, we conclude that *"volatility has memory"* means that the variability of risk is not random: past risks inevitably influence future risks, and this effect gradually diminishes over time. In other words, if risk has memory:

1. Risks will cluster—consecutive periods will be either high or low;
2. Prediction becomes possible; and
3. The insurance company will be able to calculate reserves and premiums more accurately.

Another example of such a model is the EGARCH model.

$$\ln\left(\sigma_t^2\right) = \omega + \beta \ln\left(\sigma_{t-1}^2\right) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \alpha \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| .$$

The main feature is that it accounts for asymmetric effects, meaning positive and negative shocks have different impacts. This additional parameter creates a more realistic model (Sharapov Yu.V., Stovba E.V., Sharapova N.V., 2025).

*TGARCH / GJR-GARCH model*

This model treats bad and good shocks differently (bad news creates higher risk, while good news has a weaker effect).

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma D_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 .$$

Its application in insurance risk: when calculating reserves for future claims, if volatility is high, more capital is required.

The application of this model in insurance risk lies in the fact that, when calculating insurance reserves, the company sets aside funds for future claims, and if volatility is high, it is taken into account that more capital is required.

Risk measures, such as Value at Risk (VaR) and Expected Shortfall (ES), are calculated using volatility models and are especially important for heavy-tailed distributions.

If risk is highly variable, reinsurance is used. Reinsurance is a process in which an insurance company transfers a portion of the risk it has assumed to another insurance company.

The calculation of insurance premiums depends on the insurance system (mandatory state social insurance, voluntary insurance, etc.) and the applicable legislation. The general principle is the same: the insured income or risk is multiplied by a certain rate. Insurance premiums are usually calculated as:

*Insurance premium = Insurance base × Rate (percentage)*

For mandatory state social insurance in Azerbaijan:

*a) For the employee* – a certain percentage is deducted from the employee's salary, e.g., 3% (or it may vary according to legislation);

*b) For the employer* – the employer pays an additional percentage, e.g., 22% (or differential rates may apply).

*Example:* If the salary is 1500 AZN:

- Employee: 1500 × 3% = 45 AZN
- Employer: 1500 × 22% = 330 AZN
- Total amount: 375 AZN

For voluntary insurance (e.g., life insurance, car insurance), the calculation is more complex and depends on factors such as risk level (age, health, driving experience, etc.), insured amount, duration, statistics, and probability calculations.

A simple approach is:

*Premium = Probability of risk × Insurance amount + additional costs.*

Additional factors include minimum and maximum insurance base, discounts or additional charges, and sector-specific rates (construction, public sector, etc.).

*Use of ARIMA + GARCH models together.*

The combined use of ARIMA and GARCH models is widely applied to model both the mean dynamics and volatility of time series. This approach is particularly effective for financial data (e.g., income formation). The ARIMA model captures the mean level of the time series, while the GARCH model captures the variance (volatility) of the residuals. In other words, the forecast is first made with ARIMA, and then GARCH is applied to the ARIMA residuals.

For the ARIMA model (mean equation), we can use the following form:

$$y_t = \mu + \sum \phi_i y_{t-1} + \sum \theta_j \varepsilon_{t-j} + \varepsilon_t ,$$

Here, $\varepsilon_t$ are the residuals.

For the GARCH model (variance equation):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 .$$

Here, $\sigma_t^2$ is the conditional variance, and

$$\varepsilon_t \sim N(0, \sigma_t^2)$$

are the residuals.

Step-by-step implementation consists of the following sequential stages:

1. Checking for stationarity;
2. Selecting the ARIMA model;
3. Examining the residuals;
4. Building the GARCH model;
5. Making the forecast.

For example, in the case of financial returns: the ARIMA model is applied to estimate the expected value of returns, the GARCH model is used to assess risk, and volatility shows the variability over time. As a result, a model is constructed that determines both the return forecast and the risk measure.

Advantages: It is important in financial risk analysis because it allows constructing a model more consistent with real data. Disadvantages: Model selection is complex, parameters are sensitive, and computation can be intensive.

*VAR (Value-at-Risk) models*

This model measures the maximum possible loss with a certain probability, allows the simultaneous analysis of interactions among several variables, and is important for assessing systemic risks. The Expected Shortfall (ES) model takes a more conservative approach than VaR and accounts for extreme losses.

*Risk indicators (VaR, expected loss) and quantile methods are widely used.*

Econometricians evaluate risk measures in insurance value at risk (VaR) and expected shortfall (ES) using both parametric and non-parametric methods.

Extreme value theory is used to model "tail" risks and allows the assessment of potential losses at high quantiles.

Quantile regression, in turn, directly models the conditional quantiles of returns, enabling the calculation of the maximum expected loss at a specified confidence level.

**Conclusion**

The theoretical and methodological foundations of econometric analysis of risks provide scientifically grounded tools for better understanding, measuring, and managing risks. Using econometric models, the level of risk—for example, the probability of losses is quantified, variability (volatility) and uncertainty are expressed numerically, meaning that risk is no longer "approximate" but becomes a measurable indicator. Econometric analysis with models such as ARIMA, GARCH, and others allows the forecasting of future losses, claim counts, and financial damages, thereby strengthening decision-making.

Econometric models applied to identify risk factors reveal which factors increase risk during economic crises, interest rate calculations, and market volatility, as well as which variables have stronger impacts. Based on the results obtained, risks are managed: insurance tariffs are set correctly, reserve funds are calculated, and risk mitigation strategies are developed. Companies can make more informed decisions, minimize losses, increase profitability, and thus optimize the decision-making process. In conducting econometric risk analysis, we are able to measure, explain, forecast, and manage risks.

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## Section FINANCE

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# Dynamics and Short-Term Forecasting of the U.S. Consumer Price Index: An Empirical Analysis

**Abstract**
This article presents an empirical analysis of the dynamics and short-term forecasting of the U.S. Consumer Price Index (CPI) using econometric time-series modeling techniques. Official macroeconomic data from the Federal Reserve Bank of St. Louis (FRED) serve as the empirical basis for the study. Preliminary analysis reveals the non-stationary nature of the original time series, which necessitates the application of ARIMA-class models incorporating differencing. The optimal model specification is selected based on the Akaike and Bayesian information criteria, while model adequacy is confirmed through residual diagnostics. Based on the selected specification, short-term forecasts are generated over a 12-period horizon with corresponding confidence intervals. The forecasting results indicate the persistence of a moderately upward trend in the Consumer Price Index over the projected period. Forecast accuracy is further assessed using the Mincer–Zarnowitz test, which detects no statistically significant bias and confirms both the unbiasedness and informational efficiency of the forecasts. Overall, the findings demonstrate the high predictive performance of ARIMA models in analyzing CPI dynamics and their practical relevance for assessing short-term monetary conditions.
**Keywords:** consumer price index; time series; ARIMA; short-term forecasting; U.S. economy.

**Introduction**
Consumer Price Indices (CPI) constitute a key macroeconomic indicator reflecting the dynamics of inflationary processes and forming the basis for decision-making in monetary policy, macroeconomic forecasting, and the assessment of real economic conditions. For the U.S. economy, which plays a systemic role at the global level, CPI behavior is of particular analytical and practical importance, as inflationary trends directly affect interest rates, financial markets, and international capital flows (Stock & Watson, 2019; Faust & Wright, 2013).
In an environment of heightened macroeconomic uncertainty amplified by structural shifts, changes in

monetary policy regimes, and external shocks the demand for reliable short-term inflation forecasting tools has increased substantially. Accurate assessments of CPI dynamics are essential not only for monitoring inflation risks but also for analyzing real interest rates and evaluating current monetary conditions. Recent studies emphasize that, at short forecasting horizons, inflation processes exhibit pronounced inertia, which makes statistical time-series models especially relevant (Faust & Wright, 2013; Argiri et al., 2024).

Despite the rapid development of structural models and machine learning methods, the empirical literature demonstrates that simple univariate models often remain highly competitive benchmarks. Stock and Watson (2019) show that even extended inflation models frequently fail to outperform forecasts generated by autoregressive and ARIMA-based approaches, particularly in pseudo out-of-sample evaluations. Other studies confirm that the relative advantages of alternative models depend on the inflation regime and forecasting horizon, while their predictive performance may vary significantly over time (Dotsey et al., 2018).

A separate strand of the literature examines the role of structural factors and the Phillips curve in inflation forecasting. The results point to the conditional nature of their predictive usefulness: the relationship between inflation and real economic activity may weaken or strengthen depending on the macroeconomic regime and the stage of the business cycle (Dotsey et al., 2018). In parallel, a growing body of research focuses on real-time forecasting and nowcasting of CPI using high-frequency price data and machine learning techniques, which demonstrate potential gains in short-term accuracy but also underscore the necessity of benchmarking against strong statistical models (Beck et al., 2023; Barkan et al., 2023). An essential component of empirical forecasting analysis is the evaluation of forecast quality. In applied macroeconomics, the Mincer–Zarnowitz test remains a standard tool for assessing the unbiasedness and informational efficiency of forecasts (Hendry & Clements, 2001). Recent studies on central bank inflation forecasts indicate that even when average forecast errors are acceptable, forecasts may exhibit bias or efficiency losses over specific periods, making formal verification of their statistical properties critically important (Argiri et al., 2024).

The objective of this study is to conduct an empirical analysis of the dynamics of the U.S. Consumer Price Index and to construct short-term forecasts using ARIMA-class models based on official macroeconomic data from the Federal Reserve Bank of St. Louis (FRED). The analysis includes stationarity testing of the time series, selection of the optimal model specification using the Akaike and Bayesian information criteria, and comprehensive residual diagnostics. Forecasts are generated over a 12-period horizon and complemented with confidence intervals, while their quality is evaluated using the Mincer–Zarnowitz test.

The scientific novelty of the study lies in the systematic application of classical econometric techniques to short-term CPI forecasting with an explicit emphasis on the statistical validation of forecasts. The practical significance of the research is determined by the applicability of the results to analytical work, macroeconomic monitoring, and the assessment of short-term monetary conditions.

**Literature review**

The task of forecasting inflation, and CPI dynamics in particular, is among the most extensively studied problems in applied macroeconometrics. Nevertheless, a broad consensus in the literature holds that simple statistical benchmarks often remain highly competitive (Barkan et al., 2023). In their seminal contribution, Stock and Watson (2019) demonstrate that Phillips curve–based models and specifications incorporating alternative macroeconomic predictors frequently yield only limited accuracy gains relative to simple time-series models at a 12-month horizon, especially in pseudo out-of-sample comparisons.

More recent surveys emphasize that robust improvements in forecasting performance are typically achieved either through combinations of models and expert expectations or through carefully selected benchmarks and explicit consideration of regime changes in inflation dynamics. A key implication of this strand of research is that univariate models from the AR/ARIMA class often serve as a benchmark that is difficult to systematically outperform, thereby justifying their use in short-term CPI forecasting as a transparent and reproducible tool.

A separate branch of the literature investigates the conditions under which structural Phillips curve–based models improve inflation forecasts. The evidence suggests that their predictive usefulness is conditional: the contribution of real activity and economic slack to inflation forecasting varies over time and may depend on the prevailing regime (e.g., stable inflation versus post-shock periods). In parallel, a growing literature on nowcasting and real-time inflation forecasting employs high-frequency price data and machine learning techniques to produce timely CPI estimates prior to the release of official statistics. While these approaches demonstrate potential improvements in short-term accuracy under conditions of heightened volatility, they also underscore the importance of benchmarking against strong statistical baselines. Within this framework, ARIMA models remain a rational baseline choice, as they provide an interpretable representation of inflation dynamics and allow for a robust construction of confidence intervals when appropriately specified and diagnosed.

A rigorous evaluation of forecast quality constitutes a central standard in empirical macroeconomics. The traditional approach relies on regression-based tests of forecast unbiasedness and informational efficiency, most notably the Mincer–Zarnowitz test. Contemporary applied studies of central bank inflation forecasts similarly focus on bias and efficiency properties at short horizons, showing that even when average forecast accuracy is satisfactory, forecast quality may deteriorate as the horizon increases. In the present study, these evaluation techniques are employed to provide a comprehensive verification of short-term CPI forecasts based on official FRED data, thereby ensuring reproducibility and comparability with established macroeconomic monitoring practices.

Methodologically, macroeconomic time-series analysis faces the fundamental challenge of non-stationarity. The classic result of Nelson and Plosser shows that many U.S. macroeconomic indicators can be characterized as unit-root processes, implying the presence of stochastic trends and the necessity of properly accounting for integration in modeling and forecasting (Nelson & Plosser, 1982). A key practical implication of this literature is that unit-root testing must precede ARIMA estimation, and differencing should be applied when necessary; otherwise, the parameters of the autoregressive component may fall outside the stationarity region, rendering statistical inference invalid (Garcia et al., 2023).

In applied econometrics, unit-root tests from the Dickey–Fuller family represent the standard approach to assessing stationarity. Dickey and Fuller (1979) formalize the asymptotic properties of estimators and test statistics in the presence of a unit root, providing the foundation for subsequent developments. The augmented Dickey–Fuller (ADF) test extends this framework to account for more complex error dynamics; in particular, Said and Dickey (1984) justify approximating ARMA processes with higher-order autoregressions when the underlying lag structure is unknown. For short-term CPI forecasting, this literature establishes a clear empirical workflow: (i) testing for integration, (ii) transforming the series to stationarity if required, (iii) model estimation, and (iv) post-estimation diagnostic checking.

Forecasting within the ARIMA framework traditionally relies on systematic identification and diagnostic procedures, with particular emphasis on residual analysis and the absence of serial correlation, i.e., the white-noise condition (Hassani et al., 2025). The most widely used statistical tool in this context is the Ljung–Box test, a modification of the general Q-statistic that provides improved distributional approximations and more reliable inference regarding misspecification in ARMA/ARIMA models (Ljung & Box, 1978). In empirical applications, this allows researchers to formally verify that the model has adequately captured the systematic component of the dynamics and that the residuals do not contain predictable structure.

An important practical step in applied forecasting is the selection of model parameters and comparison criteria across alternative specifications. Automatic ARIMA selection based on information criteria (AIC, AICc, BIC) and stepwise search procedures is widely used (Escudero et al., 2021). A canonical reference in this area is Hyndman and Khandakar (2008), who describe automated forecasting algorithms for large collections of univariate time series and discuss practical aspects of estimation and model selection in the R environment. This approach is methodologically well-suited to macroeconomic data, where manual identification may be sensitive to sample choice, shock structures, and data revisions.

Finally, the applied relevance of statistical forecasting models is supported by large-scale comparative studies of forecast accuracy. The findings of the M3-Competition indicate that relatively "simple" statistical methods, including time-series models, often achieve competitive accuracy, particularly at short horizons. This evidence further supports the use of ARIMA models as a justified baseline tool for practical forecasting of economic indicators (Makridakis & Hibon, 2000).

According to data from the Federal Reserve and the ECB, following the global financial crisis the effective real interest rate (ERIR) in advanced economies remained structurally low, reinforcing the hypothesis that long-run forces related to capital accumulation, demographics, and innovation diffusion dominate its behavior (Del Negro et al., 2019; Rachel & Summers, 2019). Del Negro et al. (2019) document that the decline in ERIR is internationally synchronized, while Rachel and Summers (2019) link this phenomenon to secular stagnation. In the post-pandemic period, renewed debate has emerged regarding a potential increase in ERIR driven by inflationary shocks and accelerated investment in decarbonization, infrastructure, and digitalization (Holston et al., 2023; Jordà & Nechio, 2023). Nevertheless, assessments by the Federal Reserve Bank of New York and the ECB suggest that the structural drivers of low ERIR remain in place, making a return to 1990s levels unlikely (Wellink, 2023).

## Materials and methods

The empirical analysis is based on official macroeconomic data obtained from the Federal Reserve Bank of St. Louis database (FRED, 2026). The primary object of analysis is the Consumer Price Index (CPI), which represents a time series reflecting the dynamics of inflationary processes in the U.S. economy. The choice of the sample period is determined by data availability and ensures a sufficient sample length for reliable econometric modeling and forecasting.

At the first stage, a preliminary analysis of CPI dynamics is conducted, including graphical visualization and formal testing of its stochastic properties. The analysis indicates that the original time series exhibits pronounced non-stationarity, which is a characteristic feature of macroeconomic price indicators. To formally assess the presence of a unit root, standard stationarity tests are applied. The results indicate that the CPI series is integrated of order one, which necessitates first differencing to transform the series into a stationary form.

Given the non-stationary nature of the original series, subsequent analysis is carried out using ARIMA $(p, d, q)$models, with the order of differencing $d$fixed at one. Various combinations of the autoregressive $(p)$and moving average $(q)$orders are considered to determine the optimal model structure.

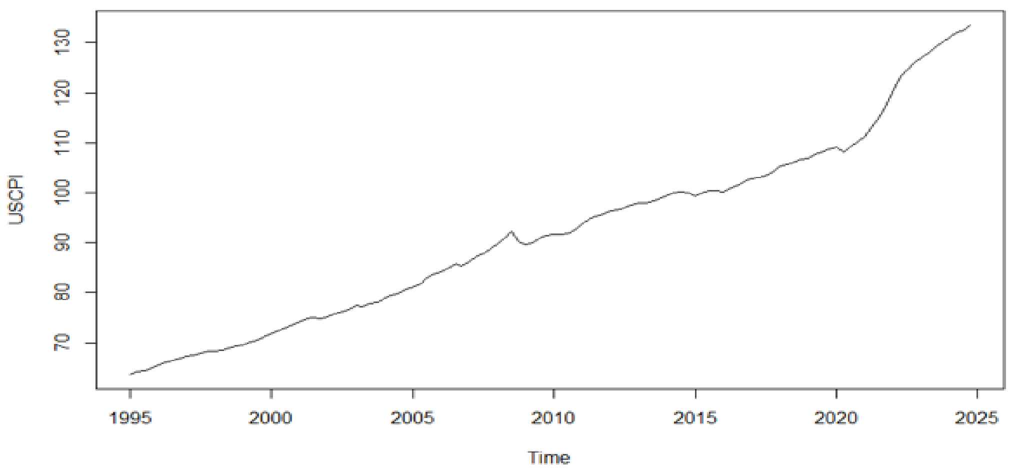
The selection of the optimal model specification is based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The final model is chosen as a compromise solution that minimizes these criteria while maintaining the statistical significance of the estimated parameters and the overall econometric consistency of the specification. To assess the adequacy of the selected ARIMA model, a comprehensive residual diagnostics procedure is conducted. The residuals are examined for the presence of autocorrelation, deviations from normality, and heteroskedasticity. The absence of statistically significant autocorrelation and the stability of residual variance confirm the correctness of the model specification and its suitability for subsequent forecasting. Based on the selected ARIMA model, short-term forecasts of the U.S. Consumer Price Index are generated over a 12-period horizon. In addition to point forecasts, confidence intervals are constructed to reflect forecast uncertainty and to allow for a probabilistic interpretation of expected CPI dynamics in the short run.

The quality of the resulting forecasts is evaluated using the Mincer–Zarnowitz test, which is applied to assess the unbiasedness and informational efficiency of the forecast estimates. Within this framework, the presence of systematic forecast bias and the ability of forecasts to adequately reflect available information are examined. The test results indicate no statistically significant bias and confirm the high quality of the short-term forecasts obtained from the ARIMA model.

**Results**

The analysis of the dynamics of the original data constitutes a necessary stage of the empirical investigation, as it allows for the identification of general trends in the time series and the formulation of preliminary hypotheses regarding its statistical properties. Figure 1 illustrates the dynamics of the U.S. Consumer Price Index (CPI) over the period 1995–2025, which is subsequently used to compute the real interest rate. The CPI serves as a deflator that adjusts the nominal interest rate for the inflation component, which is critically important for determining its real level (figure 1).

**Figure 1.** US CPI dynamics from 1995 to 2025.




As can be seen from the graph, the time series is characterized by a pronounced upward trend throughout the entire observation period. In the first half of the sample (1995–2008), the growth of the U.S. CPI was relatively smooth, reflecting moderate inflationary pressures and a stable macroeconomic environment. Following the 2008 financial crisis, a short-term deceleration is observed; however, from 2010 onward, growth resumes and remains persistent.

The most significant changes occur in the post-2020 period, when the rate of increase in the U.S. CPI accelerates markedly. This surge is associated with a combination of factors, including pandemic-related shocks, disruptions in global supply chains, the expansion of fiscal stimulus measures, and shifts in monetary policy. As a result, by 2025 the index reaches historically high levels, indicating a substantial intensification of inflationary processes in the U.S. economy.

The graphical behavior of the series suggests non-stationarity, the presence of a deterministic trend component, and the potential necessity of differencing when constructing econometric models. Based on this preliminary analysis, subsequent sections focus on modeling the real interest rate using time-series methods and generating short-term forecasts.

The stationarity of the series is formally examined using the Augmented Dickey–Fuller (ADF) test (table 1).

**Table 1.** Augmented Dickey-Fuller (ADF) Test

| **Data** | **USCPI** |
|---|---|
| Dickey-Fuller | -0.53715 |
| Lag order | 4 |
| p-value | 0.9788 |
| alternative hypothesis | stationary |

The results of the Augmented Dickey–Fuller (ADF) test indicate no statistical grounds for rejecting the null hypothesis of a unit root ($p$-value=0.9788), confirming the non-stationarity of the original U.S. CPI series. Consequently, transformation of the series through differencing is required to achieve stationarity prior to further modeling.

After differencing the U.S. CPI time series, four econometric models are estimated.

**Table 2.** Model 1-4 Arima

| | **Model 1 Arima (1,1,1)** | **Model 2 Arima (2,1,0)** | **Model 3 Arima (0,1,1)** | **Model 4 Arima (2,1,2)** |
|---|---|---|---|---|
| ar1 | 0.9398 | 0.5815 | - | 0.4195 |
| s.e. | 0.0408 | 0.0892 | - | 0.2268 |
| ar2 | - | 0.2225 | - | 0.5216 |
| s.e. | - | 0.0893 | - | 0.2007 |
| ma1 | -0.5209 | - | 0.6325 | 0.0833 |
| s.e. | 0.1225 | - | 0.0654 | 0.2271 |
| ma2 | - | - | - | -0.4936 |
| s.e. | - | - | - | 0.1124 |
| $sigma^2$ | 0.2838 | 0.2989 | 0.4301 | 0.2761 |
| log likelihood | -93.46 | -96.44 | -118.39 | -90.9 |
| AIC | 192.92 | 198.88 | 240.79 | 191.8 |
| BIC | 201.25 | 207.22 | 246.35 | 205.7 |

We proceed by comparing the models in order to identify the specification with the highest forecasting performance. Within the empirical analysis, several alternative time-series model specifications for the U.S. CPI are estimated. Model selection is based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which allow for the comparison of competing models while accounting for both goodness of fit and model complexity (Table 3).

**Table 3.** Comparison of models using penalty criteria

| | Model | AIC | BIC |
|---|---|---|---|
| 1 | ARIMA (1,1,1) | 192.9158 | 201.2532 |
| 2 | ARIMA (2,1,0) | 198.8790 | 207.2163 |
| 3 | ARIMA (0,1,1) | 240.7880 | 246.3463 |
| 4 | Auto | 191.8009 | 205.6965 |

Table 3 reports the AIC and BIC values for the following specifications: the automatic model selected by the *auto.arima* algorithm, as well as the ARIMA (1,1,1), ARIMA (2,1,0), and ARIMA (0,1,1) models. The lowest values of both information criteria are obtained for the automatically selected model (AIC = 191.8009; BIC = 205.6965), indicating the most favorable balance between goodness of fit and the number of estimated parameters.

Among the manually specified models, ARIMA (1,1,1) exhibits the lowest AIC and BIC values (AIC = 192.9158; BIC = 201.2532), although its performance is slightly inferior to that of the automatic specification. The ARIMA (2,1,0) model is associated with higher information criterion values, suggesting weaker performance relative to the preceding models. The least preferred specification is ARIMA (0,1,1), which yields substantially higher AIC and BIC values, indicating inadequate representation of the time-series dynamics.

To assess the presence of autocorrelation in the residuals of the selected ARIMA (2,1,2) model, the Ljung–Box test is applied, which is a standard diagnostic tool for evaluating the adequacy of time-series models.

**Table 4.** Ljung-Box test

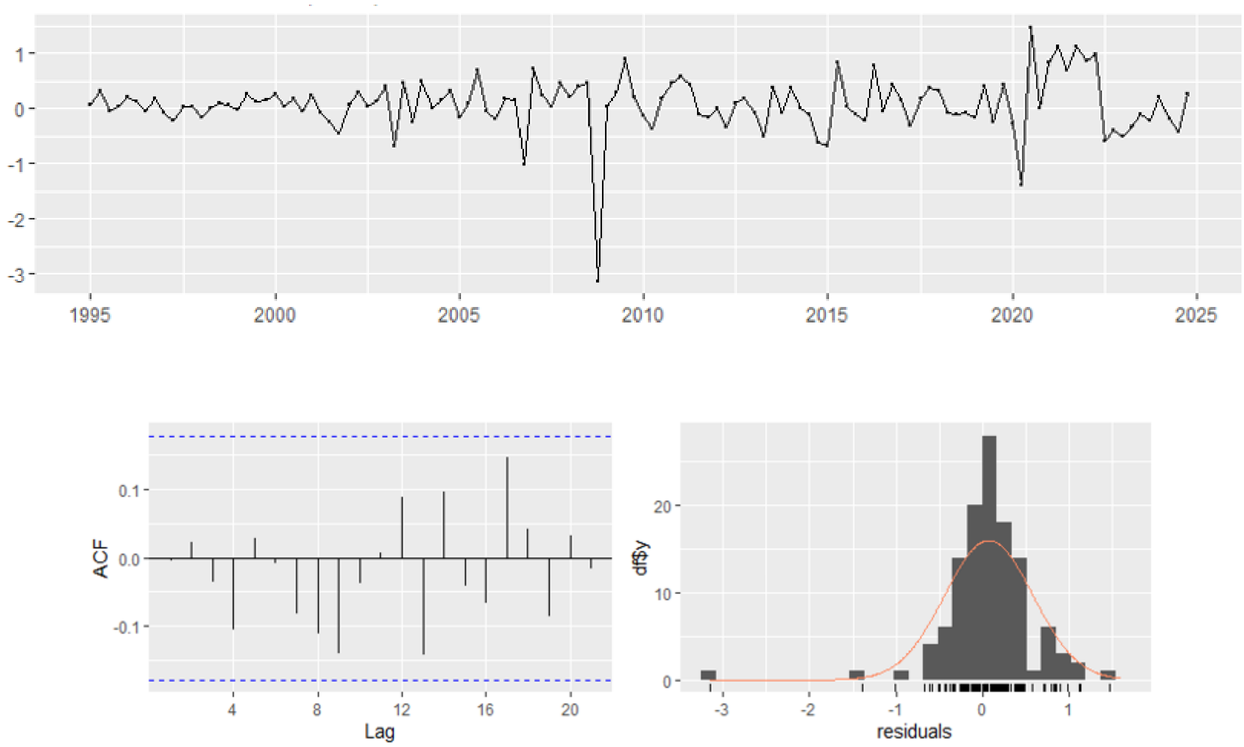
| data | Residuals from ARIMA (2,1,2) |
|---|---|
| Q* | 4.1947 |
| df | 4 |
| p-value | 0.3803 |
| Model df | 4 |
| Total lags used | 8 |

The test results indicate that the Ljung–Box statistic equals $Q^* = 4.1947$ with $df = 4$ degrees of freedom and a corresponding $p$-value $= 0.3803$. The obtained $p$-value substantially exceeds conventional significance levels (0.10, 0.05, and 0.01), implying that there is no statistical evidence to reject the null hypothesis of no residual autocorrelation.

Accordingly, it can be concluded that the residuals do not exhibit statistically significant autocorrelation and possess the properties of white noise. This finding indicates a correct specification of the ARIMA (2,1,2) model and confirms that it effectively captures the temporal dependence present in the original series. The results of the Ljung–Box test therefore support the suitability of the selected model for further analysis and short-term forecasting of the Consumer Price Index.

To further assess the adequacy of the ARIMA (2,1,2) model, a residual diagnostics analysis is conducted, including visual inspection of residual dynamics over time, examination of the autocorrelation function, and evaluation of the residual distribution (Figure 2).

**Figure 2.** Residual diagnostics of the ARIMA (2,1,2) model.




The time-series plot of the residuals (Figure 2) shows no pronounced trend or systematic pattern, indicating that the model satisfactorily captures the main dynamics of the original series. The residuals fluctuate around a zero mean, which suggests a correct specification of the conditional mean component of the model. At the same time, short-lived outliers are observed in certain subperiods, most notably during episodes of heightened macroeconomic turbulence. These deviations may reflect the influence of exogenous shocks that are not fully captured by the model.

The autocorrelation function (ACF) of the residuals indicates that the majority of autocorrelation coefficients lie within the 95% confidence bounds, supporting the conclusion that no statistically significant residual autocorrelation is present. This result implies that the model effectively removes linear dependence in the time series and satisfies the assumption of uncorrelated errors.

The residual histogram exhibits a distribution close to normal, with a concentration of observations around zero. Minor departures from normality and the presence of a limited number of extreme observations are consistent with the nature of macroeconomic data and do not materially affect the quality of parameter estimation or forecasting performance.

We now turn to short-term forecasting based on the selected model (Table 5). Using the optimal time-series specification, a short-term forecast of the indicator is generated over a 12-period (quarterly) horizon.

**Table 5.** Short-term forecasting results for the next 12 quarters.

| Period | Point Forecast | Lo 80 | Hi 80 | Lo 95 | Hi 95 |
|---|---|---|---|---|---|
| 2025 Q1 | 134.4365 | 133.7631 | 135.1100 | 133.4066 | 135.4665 |
| 2025 Q2 | 135.1917 | 133.9761 | 136.4073 | 133.3326 | 137.0508 |
| 2025 Q3 | 135.9704 | 134.2811 | 137.6596 | 133.3869 | 138.5538 |
| 2025 Q4 | 136.6909 | 134.4860 | 138.8958 | 133.3188 | 140.0630 |
| 2026 Q1 | 137.3993 | 134.6731 | 140.1255 | 133.2299 | 141.5687 |
| 2026 Q2 | 138.0723 | 134.8005 | 141.3441 | 133.0686 | 143.0761 |
| 2026 Q3 | 138.7241 | 134.8935 | 142.5548 | 132.8657 | 144.5826 |
| 2026 Q4 | 139.3486 | 134.9429 | 143.7544 | 132.6106 | 146.0866 |
| 2027 Q1 | 139.9506 | 134.9576 | 144.9436 | 132.3145 | 147.5867 |
| 2027 Q2 | 140.5288 | 134.9369 | 146.1208 | 131.9767 | 149.0810 |
| 2027 Q3 | 141.0854 | 134.8849 | 147.2859 | 131.6026 | 150.5682 |
| 2027 Q4 | 141.6205 | 134.8030 | 148.4380 | 131.1940 | 152.0470 |

Table 5 reports the point forecasts along with the corresponding 80% and 95% confidence intervals, which makes it possible to assess not only the expected trajectory of the indicator but also the degree of forecast uncertainty.

The point forecasts exhibit a moderately upward trajectory over the entire forecasting horizon. According to the results, the forecasted values increase steadily from early 2025 through the end of 2027, indicating the persistence of a gradual upward trend in the Consumer Price Index in the short run.

The confidence intervals widen as the forecasting horizon increases, which is a typical feature of time-series models and reflects the accumulation of uncertainty over time. Nevertheless, even at the maximum forecast horizon, the intervals remain relatively narrow, suggesting stability of the model estimates and an acceptable level of forecast accuracy. The 80% confidence intervals are substantially narrower than the 95% intervals, further illustrating the range of plausible scenarios for the evolution of the indicator under different probability assumptions.

To evaluate the quality of the forecasts generated by the ARIMA(2,1,2) model (fit_best), the Mincer–Zarnowitz test is applied. This test is based on a regression of the realized values of the indicator on the corresponding forecast values and allows for an assessment of forecast unbiasedness and informational efficiency. The regression model is specified as follows:

$$y_t = \alpha + \beta \hat{y}_t + \varepsilon_t, \qquad (1)$$

where $y_t$ denotes the actual value of the indicator, $\hat{y}_t$ represents the forecasted value, and $\alpha$ and $\beta$ are parameters to be estimated.

An ideal forecast—one that is both unbiased and informationally efficient—corresponds to the fulfillment of the following null hypothesis:

$$H_0: \alpha = 0, \beta = 1. \qquad (2)$$

The evaluation of forecast quality involves testing the following hypotheses:

(1) Test of the hypothesis

$$H_0: \beta = 1 \quad (3)$$

The results of the linear hypothesis test yield an $F$-statistic of 1.855 with a corresponding, p-value = 0.187.

Since the $p$-valueexceeds conventional significance levels (0.10, 0.05, and 0.01), there is no statistical basis for rejecting the null hypothesis that the coefficient on the forecast equals unity. This result indicates that the forecasts do not exhibit systematic scale bias and adequately capture the amplitude of fluctuations in the realized series.

(2) Joint test of the hypotheses $H_0: \alpha = 0$ и $\beta = 1$

The results of the joint test yield an $F$-statistic of 1.5415 with a corresponding, p-value = 0.2363.

The obtained $p$-valuealso substantially exceeds conventional significance levels, implying that the joint null hypothesis cannot be rejected. Consequently, the model's forecasts can be regarded as unbiased and statistically consistent with the observed data.

To enhance the robustness of the conclusions, coefficient estimates are additionally obtained using Newey–West robust standard errors, which are consistent in the presence of heteroskedasticity and weak autocorrelation. The results indicate that the coefficient on the forecasted value is highly statistically significant, with $\hat{\beta} = 0.9807 (p < 0.001)$, confirming the strong explanatory power of the forecast component. The intercept term is statistically insignificant ($p$-value $= 0.1234$), which further supports the absence of systematic forecast bias. Importantly, these conclusions remain robust when the robust covariance matrix is employed.

To assess out-of-sample forecasting accuracy, additional forecast performance measures are reported in Table 6:

**Table 6.** Model quality diagnostics

| Indicators | Value in percent |
|---|---|
| RMSE | 0.6857 |
| MAE | 0.5522 |
| MAPE | 0.474 |

Low error values, particularly a MAPE below 1%, indicate high short-term forecasting accuracy and confirm the practical applicability of the model.

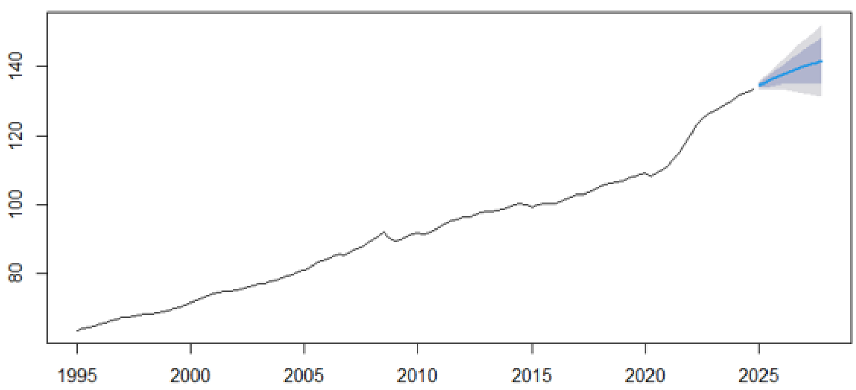


Figure 3. Forecast dynamics based on the selected ARIMA model.

Figure 3 presents the forecast of the analyzed indicator generated using the optimally selected ARIMA model. As shown, the observed time series exhibits a persistent upward trend over the period 1995–2024, with the most pronounced increase occurring during the post-pandemic period of 2020–2023. This pattern indicates strong inertia and a gradual upward shift in the level of the indicator over time.

**Discussion**

Based on the minimum values of the Akaike and Bayesian information criteria, the model selected by the *auto.arima* algorithm is identified as the optimal specification for subsequent analysis and forecasting of Consumer Price Index dynamics. This result confirms the appropriateness of automated model selection procedures when modeling non-stationary macroeconomic time series.

Diagnostic results confirm the adequacy of the ARIMA (2,1,2) model: the residuals can be treated as approximately white noise, exhibiting neither pronounced autocorrelation nor systematic patterns. This finding indicates correct model specification and supports its suitability for short-term forecasting of the U.S. Consumer Price Index. The obtained forecasts suggest the persistence of relatively tight monetary conditions in the short run. The projected increase in the Consumer Price Index may exert a restraining effect on investment and consumer activity, while simultaneously supporting financial stability through higher real returns on savings. Overall, the forecasting results confirm the applicability of the selected model for short-term analysis of CPI dynamics. The combination of point forecasts and confidence intervals allows the estimates to be effectively used in analytical and applied studies related to the assessment of monetary conditions and macroeconomic expectations.

The results of the Mincer–Zarnowitz test reveal no statistically significant forecast bias for the ARIMA(2,1,2) model. The null hypothesis of forecast unbiasedness and informational efficiency $(\alpha = 0, \beta = 1)$ cannot be rejected under both standard estimation and when using Newey–West robust standard errors. This provides strong evidence of the model's high predictive performance and supports its use for short-term forecasting of U.S. CPI dynamics.

The constructed forecast indicates the continuation of a moderately upward trajectory over the short-term horizon through 2027, consistent with the historical patterns identified in the data. The forecast confidence intervals are symmetric around the point forecast and widen as the forecast horizon increases, reflecting growing uncertainty at longer horizons—a typical characteristic of ARIMA models. The relatively narrow confidence intervals at the beginning of the forecast horizon indicate strong predictive ability and satisfactory stability of the model estimates. Taken together, the results confirm the adequacy of the selected ARIMA model and its suitability for short-term forecasting of the analyzed indicator.

**Conclusion**

Within this study, an empirical assessment of the dynamics and short-term forecasting of the U.S. Consumer Price Index was conducted using time-series analysis techniques. The main findings can be summarized as follows.

(1) Analysis of the original time series reveals pronounced non-stationarity, as confirmed by the

Augmented Dickey–Fuller test. This result justifies the use of differencing and the application of ARIMA-class models, which are appropriate for modeling integrated macroeconomic indicators.

(2) Based on a comparison of alternative specifications using the Akaike and Bayesian information criteria, an optimal ARIMA model is selected that provides the best balance between goodness of fit and model parsimony. Residual diagnostics indicate the absence of statistically significant autocorrelation and systematic patterns, confirming correct model specification and the validity of the white-noise error assumption.

(3) Short-term forecasting over a 12-period horizon reveals a moderately upward trajectory of the Consumer Price Index in the forecast interval. The 80% and 95% confidence intervals exhibit an acceptable degree of uncertainty and confirm the stability of the forecast estimates, even as the forecast horizon increases.

(4) Forecast quality is further evaluated using the Mincer–Zarnowitz test. The results of both individual and joint hypothesis tests reveal no statistically significant forecast bias: the null hypothesis that the intercept equals zero and the slope coefficient equals unity cannot be rejected. This finding indicates that the forecasts are unbiased and informationally efficient.

(5) Out-of-sample forecast accuracy measures (RMSE, MAE, and MAPE) display low error levels, confirming the high short-term predictive performance of the model and its practical applicability for analytical purposes.

Overall, the results demonstrate that ARIMA models, when combined with proper stationarity testing and residual diagnostics, constitute an effective tool for short-term forecasting of the U.S. Consumer Price Index. The obtained estimates can be applied in applied macroeconomic and financial research for assessing monetary conditions and constructing forecast scenarios, and they may also serve as a foundation for future extensions incorporating exogenous variables and alternative forecasting methods.

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# EU Digital Paradox: GDPR as a Barrier for the Digitalization of Polish SMEs

**Abstract**
Poland's transition to a digital knowledge economy is still slow, especially in the predominant micro-enterprise sector, despite the country's steady economic convergence with Western standards. This study explores the "EU Digital Paradox," in which Polish small and medium-sized enterprises (SMEs) face a structural obstacle due to the simultaneous pursuit of digital acceleration and strict data restrictions under the General Data Protection Regulation (GDPR). Using secondary quantitative data from the Polish Agency for Enterprise Development (PARP, 2025) and the Digital Economy and Society Index (DESI, 2022–2024), this study adopts the Resource-Based View (RBV) of the firm and uses a descriptive analytical design. The analysis reveals that companies are forced into "defensive digitalization" and data avoidance due to prohibitive compliance expenses, which are expected to be between 40,000 and 100,000 PLN per year. The study emphasizes that although making up the great majority of the economic landscape, micro-enterprises are subject to the same compliance obligations as larger businesses due to the current legal framework's failure to separate them. The article recommends introducing GDPR regulatory sandboxes for micro-enterprises and transitioning to a vendor-based compliance model to remove these structural barriers and accelerate digital growth.

**Keywords:** GDPR, digitalization, SMEs, Poland, compliance costs, Resource-Based View

## Introduction

Over the past decade, Poland's economic development has been characterized by consistent convergence with Western European standards. In 2004, at the time of Poland's accession to the European Union, the country's GDP per capita was 3.9 times lower than the EU average. By 2024, this disparity had decreased, with Poland's GDP per capita only 1.7 times lower than the EU average. Over this twenty-year period, the EU's average GDP per capita increased by a factor of 1.6 to 43,145 USD, while Poland's GDP per capita grew by a factor of 3.7, reaching 25,023 USD (World Bank, 2004-2024). Macroeconomic growth has been primarily driven by a dynamic sector of Small and Medium-sized Enterprises (SMEs), which serve as the foundation of the national economy. SMEs employ 6.7 million individuals, representing 65.5% of the workforce, and contribute 52.5% of the total value added, amounting to 223.8 billion euros (European Commission, 2025). Although Poland has demonstrated strong performance in traditional industrial sectors, its progress toward a digital knowledge economy remains inconsistent. According to the Digital Economy and Society Index (DESI), Poland consistently ranks below the European Union average in the integration of digital technology by businesses (European Commission, 2022). A significant challenge in the digital transition arises from the structural composition of the Polish private sector. The sector consists predominantly of micro-enterprises rather than mid-sized firms with the capacity to employ compliance teams (MAGDZIARCZYK & WIDERA, 2024). This fragmentation creates a regulatory challenge. Under the Resource-Based View (RBV), micro-entities face pronounced resource asymmetry, as the GDPR imposes fixed compliance costs nearly identical to those of 200-employee organizations, yet micro-enterprises lack legal departments or dedicated IT security personnel. Consequently, the GDPR functions less as a trust framework and more as a "compliance trap," diverting limited budgets from digital innovation toward legal defensibility. (Chmielarz, 2024). Existing literature often treats SMEs as a homogeneous group, failing to account for the specific resource constraints of the micro-enterprises that define the Polish market (GDPR TEXT, 2018). This article addresses the gap in existing research by analysing the General Data Protection Regulation (GDPR) as a structural barrier to the digitalization of Polish small and medium-sized enterprises (SMEs). This study is limited by its reliance on secondary data sources, which do not permit firm-level causal inference, and by the absence of primary survey data from Polish micro-entrepreneurs regarding their subjective compliance experiences.

**Literature Review**

This study uses the Resource-Based View (RBV) of the firm to analyse the impact of GDPR. RBV posits that a firm's competitive advantage relies on tangible and intangible resources (Mazzei, 2024). Small and Medium Enterprises (SMEs) make up 99.8% of all enterprises. While SMEs are legally defined by EU Recommendation 2003/361/EC, this study focuses on the resource asymmetry inherent in these definitions rather than the administrative thresholds (PragmaGo, 2021). The General Data Protection Regulation (GDPR), formally known as Regulation (EU) 2016/679, is a European Union law governing the handling of personal data belonging to EU residents. Adopted on 14 April 2016 and effective from 25 May 2018, the GDPR regulates data processing and transfer, requires the protection of personal data both at rest and in transit, and establishes specific rights for EU residents regarding their personal information (IBM, 2023).

Recent economic literature presents a dichotomy regarding the impact of privacy regulation on firm performance. Ullagaddi (2024) argues that the GDPR has shifted the paradigm from 'data hoarding' to 'data governance,' suggesting that compliance acts as a mechanism for building consumer trust and securing long-term competitive advantage. Under this view, regulation is a value-creating asset. Conversely, Johnson (2022) identifies a fundamental tension between privacy requirements and the data economy, noting that increased data observability for business intelligence directly conflicts with data minimization principles (Johnson, 2022). Empirical evidence supports this 'regulatory burden' perspective; Blind, Niebel, and Rammer (2022) found that compliance costs actively divert capital from innovation budgets, particularly in knowledge-intensive sectors (Blind, Niebel, & Rammer, 2024). This study posits that both perspectives are correct but structurally isolated: Ullagaddi's 'Trust Capital' is accessible primarily to large enterprises with resource redundancy, whereas Johnson's 'Innovation Drain' disproportionately characterizes the micro-enterprise experience. This divergence creates the 'EU Digital Paradox' observed in the Polish market

(Ullagaddi, 2024). Ashraf (2021) emphasizes that GDPR frameworks are frequently tailored to large organizations, which results in small and medium-sized enterprises (SMEs) facing challenges in interpreting "appropriate technical measures" as outlined in Article 32 (Article 32) (Ashraf, 2021). Magdziarczyk and Widera (2024) offer empirical evidence from Poland, highlighting that 96.43% of Polish enterprises are micro-entrepreneurs. Their findings indicate that GDPR implementation is closely linked to enterprise size. Medium-sized organizations may employ dedicated IT staff, whereas micro-enterprises often require the business owner to fulfill the roles of CEO, Data Protection Officer (DPO), and IT security manager simultaneously (MAGDZIARCZYK & WIDERA, 2024). Kobis and Chmielarz further demonstrate that the awareness level of information security managers in Polish small enterprises remains insufficient and is frequently reactive instead of proactive. These findings indicate that, for Polish SMEs, the General Data Protection Regulation (GDPR) has not yet served as a catalyst for security by design. Instead, it functions primarily as a bureaucratic checklist and has not fundamentally changed risky behaviours (Kobis & Chmielarz, 2023). Omowole (2024) and Cahyono (2025) examine strategies for small and medium-sized enterprises (SMEs) to utilize Big Data, highlighting that although Big Data facilitates market analysis and customer insight, the stringent consent requirements outlined in GDPR (Article 6) hinder adoption. Among Polish SMEs, which are generally risk-averse, the complexity associated with anonymizing large datasets often results in data avoidance (Omowole, Olufemi-Phillips, Ofodile, Eyo-Udo, & Ewim, 2024) (Cahyono, Sijabat, Panjaitan, Julianingsih, & Lorenzo, 2025). Zanker and colleagues, in a comparative study of eight European countries including Poland, found that the administrative burden associated with documenting data processing activities frequently discourages SMEs from collecting data that could provide valuable business insights (Zanker, Bureš, Cierniak-Emerych, & Nehéz, 2021). VinciWorks reports on fines, such as the McDonald's Poland case, indicate that regulatory enforcement in Poland is becoming increasingly stringent. The threat of financial penalties, which may reach up to 4% of turnover, has led to a trend of 'defensive digitalization,' in which organizations prioritize investment in legal disclaimers over enhancements to firewall infrastructure or intrusion detection systems (VINVIWORKS, 2025).

**Methodology**

A descriptive analytical design grounded in the Resource-Based View (RBV) is employed to assess the GDPR's structural impact on the digitalization of Polish SMEs. The RBV explains how fixed regulatory compliance costs disproportionately diminish the resources micro-enterprises need for competitive digital advantage. The analysis draws on secondary quantitative data from three institutional sources: the European Commission's Digital Economy and Society Index (DESI), benchmarking Poland against the EU average across indicators such as cloud computing, big data, and AI adoption; the Polish Agency for Enterprise Development (PARP) reports, detailing adoption trends and barriers across enterprise sizes; and Statistics Poland (GUS) data on ICT infrastructure, including broadband access and 5G coverage. The research compares infrastructure availability with business utilization rates, categorizes compliance challenges into technical, legal, organizational, and regulatory domains, and estimates direct and indirect compliance costs to quantify the "compliance tax" redirecting capital from innovation.

**Digitalization Analysis of Polish SMEs**

A 2023 study reported that Polish companies exhibit a moderate level of engagement in technological advancement. Approximately 67% of surveyed entrepreneurs identified specific Industry 4.0 solutions. However, only about 6% of these businesses were classified as highly digitalized, having implemented partial digitization of their operational processes. The data further indicate that 30% of businesses, regardless of size, lack the fundamental understanding required to participate actively in the fourth industrial revolution (Jankowska, Mińska-Struzik, Bartosik-Purgat, Götz, & Olejnik, 2023). Poland ranks as the fifth country in the European Union (EU) by total number of small and medium-sized enterprises (SMEs), with 2.2 million such businesses (Statista, 2024). Since 2014, the European Commission has monitored the digital progress of Member States through annual Digital Economy and Society Index (DESI) reports. Member States with larger economies or populations are expected to demonstrate strong performance to support Europe in achieving the 2030 targets (European Commission, 2022). Three primary sources provide data on Polish SMEs, particularly regarding digitalization: the Digital Economy and Society Index (DESI), the Polish Agency for Enterprise Development (PARP), and Statistics Poland (GUS). DESI offers the most detailed information, covering both general digitalization and SME-specific data, and includes comparisons with other EU countries and the EU average. PARP focuses on annual reports that present comprehensive data. GUS supplies limited data, and for 2024, 10 out of 15 indicators on enterprise ICT usage are unavailable. Table 1 presents detailed data on the digitalization status of Poland, distinguishing between the private and public sectors as reported by DESI.

**Table 1.** DESI: digital transformation of business indicators and digitalization of public services, comparing Poland and the European Union (EU) average

| Indicator | Unit of measure | Poland | European Union (EU) | Difference |
|---|---|---|---|---|
| **Digital Transformation of Businesses** | | | | |
| SMEs with at least a basic level of digital intensity | % of enterprises | 69.95 % | 72.91 % | - 2.96 % |
| Electronic information sharing | % of enterprises | 33.94 % | 42.09 % | - 8.15 % |
| Social media | % of enterprises | 19.32 % | 30.64 % | - 11.32 % |
| Big data | % of enterprises | 7.74 % | 13.64 % | - 5.9 % |
| Data analytics | % of enterprises | 17.62 % | 32.09 % | - 14.47 % |
| Cloud | % of enterprises | 45.44 % | 38.09 % | 7.35 % |
| AI | % of enterprises | 4.92 % | 12.64 % | - 7.72 % |
| e-Invoices | % of enterprises | 13.98 % | 38.04 % | - 24.06 % |
| AI or Cloud or Data Analytics | % of enterprises | 50.43 % | 53.74 % | - 3.31 % |
| e-Commerce turnover | % of turnover | 8.46 % | 12.44 % | - 3.98 % |
| SMEs selling online | % of enterprises | 13.88 | 20.13 % | - 6.25 % |

| | | | | |
|---|---|---|---|---|
| | | % | | |
| SMEs selling online cross-border | % of enterprises | 5.43 % | 8.74 % | - 3.31 % |
| **Digitalization of Public Services** | | | | |
| e-Government users | % of internet users (last 12 months) | 67.94 % | 74.71 % | 6.77 % |
| Digital public services for citizens | Score (0 to 100) | 70.69 | 82.32 | - 11.63 |
| Digital public services for businesses | Score (0 to 100) | 85 | 86.23 | - 1.23 |
| Pre-filled Forms | Score (0 to 100) | 86.80 | 70.98 | 15.82 |
| Transparency of service delivery, design and personal data | Score (0 to 100) | 73.33 | 69.46 | 3.87 |
| User support | Score (0 to 100) | 81.48 | 88.75 | - 7.27 |
| Mobile friendliness | Score (0 to 100) | 92.72 | 96.13 | - 3.41 |
| Access to e-health records | Score (0 to 100 | 91.82 | 82.70 | 9.12 |

Source: (European Commission, 2022)

Poland ranks below the EU average in 11 of 12 business digitalization indicators, yet exceeds the EU in cloud adoption (45% vs. 38%) and nearly matches the EU in basic digital intensity. Infrastructure is strong: VHCN coverage (83%) surpasses the EU average (82%), broadband access reached 98.7% in 2024 (GUS, 2025), and 5G coverage stands at 89%. However, the public sector outperforms the private sector, with higher adoption of e-government, pre-filled forms, and e-health solutions relative to the EU. The core finding is a digital divide based on utilization rather than access, with Polish SMEs focusing on operational continuity rather than transformative innovation.

**Ошибка! Неверная ссылка закладки.** presents a recent snapshot of digitalization among Polish small and medium-sized enterprises (SMEs)

**Table 2.** PARP: state of the small and medium-sized enterprise (SME) sector in Poland

| Technology / Metric | Enterprise Type | Adoption Rate (%) | Year | Growth / Change Trend (pp = percentage points) | Primary Barrier or Motivation |
|---|---|---|---|---|---|
| Paid Cloud Computing Services (Płatne usługi w chmurze) | Small | 51.00% | 2024 | Data not specified | Motivation: Increasing operational efficiency, improving communication / collaboration, and flexibility. |
| | Medium | 73.20% | 2024 | Data not specified | |
| | Large | 88.40% | 2024 | Data not specified | |
| Artificial Intelligence (AI) (Sztuczna inteligencja) | Small | 4.00% | 2024 | +1.8 pp (vs 2023) | Barrier: Lack of human resources and knowledge (1.9%), high implementation costs (1.7%). |
| | Medium | 10.40% | 2024 | +3.9 pp (vs 2023) | |
| | Large | 33.00% | 2024 | +8.6 pp (vs 2023) | |
| E-commerce Sales (Sprzedaż przez sieci komputerowe) | Small | 15.90% | 2023 | -0.4 pp (vs 2022) | Motivation: Better adjustment of the offer to customer needs. |
| | Medium | 22.30% | 2023 | +1.0 pp (vs 2022) | |
| | Large | 42.70% | 2023 | -0.8 pp (vs 2022) | |
| Open Public Data Usage (Otwarte dane publiczne) | Small | 16.40% | 2023 | +5.1 pp (vs 2022) | Motivation: Supporting planning processes and business decision-making. |
| | Medium | 28.90% | 2023 | +5.7 pp (vs 2022) | |
| | Large | 53.70% | 2023 | +2.2 pp (vs 2022) | |
| ICT Specialists Employed | Small | 19.40% | 2024 | Data not specified | Constraint: Small firms rely more on |

| | | | | | |
|---|---|---|---|---|---|
| (Specjaliści ICT) | Medium | 47.80% | 2024 | Data not specified | external providers (outsourcing). |
| | Large | 88.10% | 2024 | Data not specified | |

**Source:** Zakrzewski, Robert; Tarnawa, Anna; Orłowska, Joanna; Nieć, Melania; Skowrońska, Anna; Chaber, Paweł; Zadura, Paulina, Raport o stanie sektora małych i średnich przedsiębiorstw w Polsce (2025), PARP, Warszawa, 2025, https://www.parp.gov.pl/

PARP report also clearly shows that small businesses see lower adoption in the critical tools than medium and large business such as cloud with 51% (-22% than medium, -37% than large), AI with 4%(-6% than medium, -29% than large), e-commerce with 16% (-6% than medium, -27% than large), open public data usage with 16% (-13% than medium, -37% than large) and ICT specialists employed with 19% (-19% than medium, -69% than large). The main reasons why small businesses perform worse than large ones are: human resources and knowledge, and high implementation costs. Without targeted intervention to lower the cost of entry and boost technical literacy, the sector risks long-term digital exclusion (PARP, 2025).

## Analysis of GDPR as a Barrier

### *Barriers companies face in implementation GDPR*

The GDPR provides only two exemptions for small companies: Article 30(5) on record-keeping and Article 37 on appointing a DPO. Article 30(5) exempts businesses with fewer than 250 employees from maintaining processing records, but only if processing is "occasional." Since virtually no digitalizing business processes data occasionally, whether e-commerce, SaaS, or digital marketing, this exemption is effectively negated for Polish SMEs (European Parliament; Council of the European Union, 2016). Similarly, DPO appointment is required only for high-risk data processing, yet SMEs adopting AI or Big Data invariably trigger this threshold, requiring costly outsourced DPOs or consultants (Pansy, 2024). Article 35 further mandates Data Protection Impact Assessments for high-risk technologies, creating additional pre-launch expenses. The financial burden is disproportionate. When measured by turnover, SME compliance costs are thousands of times higher per unit than those of global technology companies (Bieliauskaite, 2018). Article 83 fines, up to 10 million EUR (2% turnover) for administrative breaches or 20 million EUR (4% turnover) for fundamental breaches, represent existential threats for micro-enterprises. This creates a chilling effect: firms avoid data collection to minimize exposure. Empirical evidence confirms this pattern. EU firms decreased data storage by 26% post-GDPR, with manufacturing firms reducing by 40% (Walsh, 2024). European data-intensive SMEs were the most disadvantaged group in post-GDPR profit developments compared to US counterparts (Koski & Valmari, 2020), and GDPR implementation resulted in an 8.1% profit decline across affected businesses (Swabey, 2022). For Polish micro-enterprises, annual compliance maintenance costs of 40,000–100,000 PLN represent capital diverted from R&D, marketing, and hiring. This "compliance tax" renders digitalization ROI prohibitive, forcing firms toward either non-compliance or non-digitalization (Harmeling, 2025). Approximately one-third of Polish micro-entrepreneurs earn no more than the national average income after mandatory levies, with only 10% exceeding PLN 15,000 monthly.

**Table 3.** GDPR compliance costs and total amounts adjusted for Poland

| Compliance Category | Cost Item | Estimated Annual Cost | Currency | Impact on Business Operations |
|---|---|---|---|---|
| Personnel | Data Protection Officer (DPO) salary | 240,000 (annually) (Dpo Data Protection Officer Salaries, 2025) | PLN | High fixed cost burden for small companies |
| Personnel | Employee training | 50 - 1,000 per employee (annually) | USD | Diversion of capital from R&D and marketing |
| Cybersecurity | Cybersecurity measures (Average data breach cost) | 4,400,000 (one-time total) | USD | High financial risk from non-compliance |
| Regulatory Risk | Fines and penalties (Average) | 69,119 (one-time total) | EUR | Risk of prohibitive costs for micro-enterprises |
| Operational Management | Managing Data Subject Access Requests (DSARs) | 3,000 - 7,000 (annually) | EUR | Ongoing administrative burden |
| Technology | Compliance software Cookies (Usercentric tool per 1500 sessions) | 7 (ongoing) | EUR | Direct operational expense; diversion of capital from growth areas |
| Legal & Consultancy | Legal and consultancy fees | 2,500 - 6,000 (daily) | PLN | Reduction in ROI of digitalization projects |
| **Total Compliance Cost Estimation** | Overall compliance maintenance for SMEs | 40,000 - 100,000 (annually) | PLN | Massive diversion of capital from R&D, marketing, or hiring; may lead to non-digitalization |

**Source:** Harmeling, Tilman, How much does GDPR compliance really cost? Guide for 2025, Usercentric, 05.10.2025, https://usercentrics.com/knowledge-hub/cost-of-gdpr-compliance/

Cybersecurity and regulatory risks are excluded from the total estimation, as they marked as fines in the event of legal breaches. These risks impose not only financial costs but also divert managerial time and attention from core business functions such as sales, marketing, product development, and other primary growth activities.

**Table 4.** Scenario analysis: GDPR compliance burden by enterprise size

| Scenario Profile | Annual Revenue (Est.) | Compliance Cost (Low/High) | Ratio | Resource Impact |
|---|---|---|---|---|
| **Low-performing Micro** | 180,000 PLN | 40,000 PLN (Low est.) | 22.2% | Critical Resource Depletion: Compliance consumes ~1/4 of revenue. Innovation is financially impossible. |
| **High-Performing Micro** | 1,000,000 PLN | 40,000 PLN (Low est.) | 4.0% | Significant Constraint: equivalent to a major tax levy; reduces net profit margins significantly. |
| **Medium Enterprise** | ~43,000,000 PLN *(~€10M EU Threshold)* | 100,000 PLN (High est.) | 0.2% | Negligible Cost: Compliance is a minor operational expense (<1%). |

**Source:** Author's own calculation

The scenario analysis indicates a severe resource drain for most participants in the Polish market. For 90% of micro-enterprises, the General Data Protection Regulation (GDPR) operates less as a regulatory framework and more as a prohibitive market entry fee, amounting to 22.2% of total revenue. In contrast, medium-sized enterprises experience a compliance burden of only 0.2%, even when higher absolute compliance costs (100,000 PLN) are assumed. The findings suggest that 'Defensive Digitalization' constitutes a rational survival strategy; when compliance costs exceed 20% of revenue, firms are compelled to avoid data-intensive activities to mitigate the risk of bankruptcy.

**Discussion**

Poland's digital divide is rooted in utilization, not access. Despite VHCN coverage surpassing the EU average, SME adoption of advanced tools remains low. This "implementation gap" represents a rational economic response to uniform GDPR enforcement rather than technical illiteracy. The RBV framework reveals three distinct strategic behaviours. Naive Non-Compliance characterizes low-resource, low-awareness micro-enterprises that disregard mandates until penalized. Strategic Compliance describes large enterprises that leverage compliance costs as competitive barriers and convert privacy into "trust capital." Between these lies Defensive Digitalization, the dominant response among Polish micro-enterprises possessing low resources but high regulatory fear, who actively avoid data-intensive technologies. This explains why 67% of entrepreneurs recognize Industry 4.0 solutions but only 6% implement them. The chilling effect is starkest in AI adoption: 4% among small firms versus 33% in large enterprises, driven by Article 35 DPIA requirements and Article 22 restrictions on automated decision-making that function as non-tariff barriers excluding micro-enterprises from the AI economy.

**Conclusion**

The GDPR, while effective as a global privacy benchmark, acts as a regressive tax on the Polish micro-enterprise sector, with compliance costs consuming up to 22.2% of revenue for the most vulnerable firms. The market exhibits Defensive Digitalization, where compliance fear surpasses the perceived benefits of technology adoption. Two policy interventions are recommended. First, GDPR Regulatory Sandboxes for micro-enterprises, drawing on Fintech models, would permit experimentation with AI and Big Data within simplified compliance frameworks, mitigating Article 83 penalties while safeguarding data subject rights. Second, a transition to SaaS-Based Compliance Inheritance would shift primary regulatory responsibility from individual micro-enterprises to certified cloud service providers, allowing small firms to inherit compliant status. Absent such reforms, Poland's Digital Decade 2030 objectives remain unreachable, as the regulatory environment continues to promote data avoidance over data-driven value creation.

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# An Investigation into the Relationship Between Service Quality and Customer Satisfaction in Cargo Companies in Azerbaijan

**Abstract**
This study examines the relationship between service quality and customer satisfaction in cargo companies operating in Azerbaijan. The research is based on the SERVQUAL model, which is widely used in the service management literature to evaluate service quality across diverse sectors. SERVQUAL conceptualizes service quality through five fundamental dimensions tangibles, reliability, responsiveness, assurance, and empathy and posits that these dimensions collectively shape customers' perceptions and evaluations of service performance. Within the scope of the present study, each of these dimensions was assessed to determine its relative influence on customer satisfaction in the cargo industry, where timely delivery, transparency, and operational efficiency are of critical importance. The empirical component of the research is grounded in data gathered from 114 participants who regularly use cargo and delivery services. The dataset was analyzed to evaluate how customers perceive service quality and to identify which dimensions most strongly predict their satisfaction levels. Overall, this study contributes theoretically to the service quality literature while offering practical implications for the strategic development of cargo service providers in Azerbaijan.

**Keywords:** Customer Loyalty, Service Quality, Customer Satisfaction, Cargo Companies

**Introduction**
The rapid transformation of global markets and the digitalization of the logistics sector have significantly altered customer expectations regarding cargo services. In an increasingly competitive environment, service quality has become a strategic determinant for businesses seeking to achieve

sustainable competitive advantage and maintain customer loyalty. Within the service management literature, service quality is defined as the extent to which the delivered service meets or exceeds customer expectations (Parasuraman et al., 1988; Sureshchandar et al., 2002). In the cargo and logistics sector, delivery reliability, responsiveness to customer inquiries, transparency in communication, shipment security, and technological competence are widely recognized as the key determinants of customer satisfaction.

Advancements in digital technologies particularly real-time tracking systems, automated status notifications, and user-friendly digital interfaces have transformed the nature of interaction between cargo companies and their customers (Wang et al., 2018). However, the literature emphasizes that technology-driven improvements alone are insufficient; human centered service elements such as empathy, problem-solving ability, and effective complaint management continue to play a decisive role in shaping customer satisfaction and behavioral intentions. This highlights the need to examine service quality components based on both technological efficiency and human interaction within the cargo sector.

In Azerbaijan, the rapid expansion of e-commerce and the growing demand for cargo services have further increased the importance of measuring service quality and analyzing the determinants of customer satisfaction. Despite the sector's growth, academic studies investigating the relationship between service quality and customer satisfaction within the Azerbaijani context remain limited.

Accordingly, the present study aims to systematically evaluate the perceptions of cargo service users in Azerbaijan regarding service quality and to examine the impact of these perceptions on overall customer satisfaction. The primary objectives of the study are as follows:

1. To determine the importance customers, assign to various dimensions of service quality;
2. To analyze the effect of service quality dimensions on customer satisfaction;
3. To identify the service attributes considered most critical by customers within the Azerbaijan context.

This research contributes to the logistics service quality literature from a theoretical perspective and provides practical insights for cargo companies seeking to enhance service performance, strengthen customer trust, and improve competitive positioning.

**Literature Review**

Quality of service is the most important factor driving customer satisfaction in cargo shipping and logistics. There are several models to measure service quality, among them being Parasuraman, Zeithaml, and Berry's (1988) SERVQUAL model. It calculates service quality based on five dimensions: tangibles, reliability, responsiveness, assurance, and empathy. Several authors have applied SERVQUAL for measuring logistics services effectiveness in customer satisfaction (Bienstock et al., 1997).

Studies of cargo companies emphasize the importance of delivery speed, reliability, and security as dimensions of service quality (Mentzer et al., 2001). Stank et al. (2003) established through a study that logistics service quality influences customer loyalty. Customer expectations in cargo transport have also evolved with digitalization, requiring real-time tracking and seamless communication (Wang et al., 2018).

Thai (2013) examined service quality in the maritime transport sector and demonstrated that service quality has a direct impact on customer satisfaction and loyalty. Feng et al. (2020) also examined the impact of logistics service quality on e-commerce and concluded that reliability and responsiveness

are key factors in sustaining customer retention.
Cargo firms tend to use the SERVPERF model, which is performance-based measurement instead of expectation-based measurement. Cronin and Taylor (1992) state that the model offers a better measure of customer satisfaction through the measurement of perceived service performance.
Literature further indicates that newer technologies such as AI-based logistics, blockchain tracing, and IoT-based monitoring have enhanced the quality of cargo services (Ding et al., 2021). Companies implementing these emerging technologies have enhanced customer satisfaction due to greater transparency and efficiency (Zhao et al., 2022). Others argue that despite technology advancement, human touch and personalized services still remain crucial for customer satisfaction (Ladhari et al., 2017).

**Population and Sample**

The population of this study consists of customers who regularly use the services of cargo companies operating in Azerbaijan. The research employed a convenience sampling method. This method is frequently preferred in-service quality studies due to its accessibility and ease of participation. Data were collected through online survey platforms and social media channels. Valid responses were obtained from a total of 114 participants. Participants were selected from individuals who had used cargo and delivery services at least once in the past year. The demographic distribution of the sample exhibits diversity in a manner that represents cargo users in Azerbaijan's urbanized regions (particularly Baku and its surroundings). This approach enhances the generalizability of the research and aims to reflect customer perceptions in the cargo sector.

**Materials and Methods**

As presented in Table 1, the majority of respondents participating in the study fall within the 27–35 age category (45.6%). This indicates that this age group constitutes the predominant users of cargo services.Participants aged 26 and below also represent a substantial proportion of the sample (42.1%), suggesting that the findings largely reflect the perspectives of a younger population. In contrast, the number of respondents aged 36 and above is considerably lower, implying that the survey primarily reached younger individuals.
In terms of gender distribution, female respondents (67.5%) outnumber male respondents by nearly a two-to-one ratio. This disparity may suggest that women engage with cargo services more frequently than men. Analysis of cargo service usage frequency demonstrates that more than half of the respondents (51.8%) report using such services occasionally. This suggests that cargo services hold a significant role in daily life, although they have not yet become a fully regularized practice for many users. The proportion of respondents who use cargo services frequently (32.5%), combined with the relatively small share of those who use them rarely(15.8%), indicates a generally elevated level of demand for these services. Overall, both the demographic profile and usage frequency data suggest that courier services are predominantly utilized by a young and largely female population, with usage occurring at a moderate yet increasing rate.

| Age | n | % |
|---|---|---|
| Under 26 | 48 | 42.1 |
| 27-35 | 52 | 45.6 |
| 36-44 | 12 | 10.5 |

| | | |
|---|---|---|
| 44 and above | 2 | 1.8 |
| **Total** | 114 | 100.0 |
| **Gender** | **n** | **%** |
| Female | 77 | 67.5 |
| Male | 37 | 32.5 |
| Total | 114 | 100.0 |
| **How often do you use courier services?** | n | % |
| rarely | 18 | 15.8 |
| sometimes | 59 | 51.8 |
| often | 37 | 32.5 |
| **Total** | 114 | 100.0 |

**Table 1.** Demographic Characteristics of the Respondents

**Source:** Prepared by the author based on the conducted research

## Research Hypothesis

This study aims to examine the relationship between service quality and customer satisfaction in cargo companies operating in Azerbaijan. In line with the purpose of the research, the following hypothesis has been formulated:

**H1:** Perceived service quality in cargo companies operating in Azerbaijan has a positive and statistically significant effect on customer satisfaction.

**H1.1**. There is a positive and statistically significant relationship between the *perceived service quality dimensions tangibles, reliability, assurance, empathy, and responsiveness and customer satisfaction* in cargo companies operating in Azerbaijan.

## Research findings

The reliability analysis demonstrates that both scales used in the study exhibit excellent internal consistency. The Service Quality scale achieved a Cronbach's Alpha of 0.947 across 15 items, indicating a very high level of reliability and suggesting that the items consistently measure the same underlying construct. Similarly, the Customer Satisfaction scale yielded a Cronbach's Alpha of 0.925 for 6 items, which also reflects excellent internal consistency. According to widely accepted reliability thresholds, Cronbach's Alpha values above 0.90 are considered excellent, confirming that both measurement instruments are highly dependable for empirical analysis.

**Table 2.** Results of Reliability Analysis

| Scale | Cronbach's Alpha | N of Items |
|---|---|---|
| Service Quality | 0.947 | 15 |
| Customer Satisfaction | 0.925 | 6 |

**Source:** Prepared by the author based on the conducted research

Upon examining the correlation analysis in Table 3, it is evident that there are positive and statistically significant correlations between Customer Satisfaction (7) and all other variables, with values ranging from 0.711 to 0.920. The correlation coefficients of 0.7 and above indicate a strong relationship, suggesting that there is a robust correlation between the two variables. Service Quality has a significant and strong effect on customer satisfaction, with a direct or indirect relationship with all other sub-dimensions. The dimensions of Tangibles, Reliability, Assurance, Empathy, and Responsiveness play crucial roles in enhancing customer satisfaction. Moreover, a strong relationship exists between Empathy and Responsiveness, where an empathetic approach toward customers

increases responsiveness, thereby improving customer satisfaction. Service Quality and Reliability exhibit the highest correlations, highlighting the importance of service reliability and quality in influencing customer satisfaction.
The results of the correlation analysis indicate that each dimension of service quality significantly contributes to enhancing customer satisfaction in cargo companies. These findings are consistent with Hypotheses H1 and H1.1, both of which propose that service quality positively and significantly impacts customer satisfaction.

**Table 3.** Correlation Analysis

| Size | Mean | Std. Deviatio | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|---|
| **Service Quality (1)** | 3.6450 | .71365 | 1 | | | | | | |
| **Tangibles (2)** | 3.7544 | .75915 | .816** | 1 | | | | | |
| **Reliability (3)** | 3.7456 | .73980 | .861** | .674** | 1 | | | | |
| **Assurance (4)** | 3.7398 | .76907 | .905** | .664** | .785** | 1 | | | |
| **Empathy (5)** | 3.6082 | .91448 | .909** | .626** | .671** | .817* | 1 | | |
| **Responsiveness (6)** | 3.3772 | .87858 | .893** | .647** | .686** | 717* | .829** | 1 | |
| **Customer Satisfaction (7)** | 3.7032 | .74363 | .920** | .711** | .808** | .859** | .849** | .805** | **1** |

****. Correlation is significant at the 0.01 level (2-tailed).**

**Source:** Prepared by the author based on the conducted research

## Results and Discussion

The findings of this study indicate that all dimensions of perceived service quality tangibles, reliability, assurance, empathy, and responsiveness are positively and statistically significantly related to customer satisfaction in cargo companies operating in Azerbaijan. Correlation coefficients ranging from 0.711 to 0.920 demonstrate strong relationships, confirming that service quality is closely associated with customer satisfaction. These results support Hypotheses **H1** and **H1.1**, which propose a positive and significant relationship between service quality and customer satisfaction.

Among the service quality dimensions, reliability and overall service quality show the highest correlations, highlighting the critical role of dependable and consistent service delivery in shaping customer satisfaction. Additionally, the strong relationship between empathy and responsiveness suggests that customer-oriented and empathetic approaches improve responsiveness, further enhancing satisfaction. This aligns with the SERVQUAL framework, where reliability and responsiveness are considered core elements of perceived service quality (Parasuraman, Zeithaml, & Berry, 1988).

The study confirms that delivery reliability is a key determinant of customer satisfaction**.** Variability in delivery times can lead to dissatisfaction, while real-time tracking, transparent communication, and guaranteed delivery schedules are highly valued by customers (Mentzer et al., 2001; Wang et al., 2018). Positive service experiences directly contribute to repeat business and long-term customer relationships (Stank et al., 2003). Cargo companies that invest in technology, employee development, and customer care are more likely to achieve higher customer satisfaction and retention.

Technological tools, such as real-time shipment tracking and automated notifications**,** enhance perceived service quality (Wang et al., 2021). However, human interaction, especially in complaint handling and problem resolution, remains crucial (Ladhari et al., 2017). Furthermore, this study highlights regional and market-specific expectations, as local customers in Azerbaijan prioritize transparency, communication, and reliability over speed and cost efficiency, supporting the notion that cultural and contextual factors shape perceptions of service quality (Zeithaml et al., 1990).

In conclusion, the study provides strong evidence that improving service quality across all dimensions significantly contributes to higher customer satisfaction in cargo companies. Managers should focus on maintaining reliability, responsiveness, and empathetic customer service while leveraging technology to meet evolving customer expectations in the local market.

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# Artificial Intelligence and Digital Transformation in Labor Market: Implications for Sustainable Development

**Abstract**

In the context of the modern economy, AI and digital transformation are fundamentally reshaping the structural and functional characteristics of the labor market. Technological advancements do not merely optimize production processes; they also fundamentally transform workers' skill requirements, occupational structures, and the availability of jobs. As a result, certain job functions are automated, routine and standardized tasks are replaced by technological systems, and simultaneously, new occupations requiring high-level skills emerge. The objective of this study is to analyze the impact of artificial intelligence technologies and digital transformation on the labor market within the framework of sustainable development, evaluating structural changes and socio-economic outcomes. The analysis indicates that AI enhances labor productivity while generating polarization in the skill structure of the workforce. However, managing the risks associated with this technological transformation requires appropriate institutional and educational policies. Lifelong learning programs, reskilling initiatives, and skill development-oriented state policies can help maintain workforce competitiveness and promote labor market inclusiveness. In this regard, AI and digital transformation are not only technological processes that enhance economic efficiency but also strategic instruments for achieving sustainable and balanced socio-economic development. The study also proposes policy recommendations and strategic approaches to help labor markets adapt to evolving demands.

**Keywords**: Artificial intelligence, digital transformation, labor market, sustainable development, technological unemployment, skills transformation

**Introduction**

The rapid development of artificial intelligence and digital technologies has become a major transformative force in the global economy of the 21st century. These technologies not only enhance efficiency in production and service sectors but also have profound effects on workforce structures, occupational requirements, and labor market dynamics. Automation, machine learning, big data, and other digital technologies are reshaping traditional work models, giving rise to new forms of labor relations. As a result, some job functions are replaced by technology, while others require new skills and competencies, leading to a fundamental transformation of the labor market's structural and functional characteristics.

The labor market is among the sectors most affected by artificial intelligence and digital transformation. Technological changes result in a decline in low- and medium-skilled jobs, the creation of high-skilled positions, and the emergence of new occupations. This leads to labor market polarization, structural imbalances, and increasing disparities in income and skills. Simultaneously, digital transformation stimulates innovative economic activities and contributes significantly to productivity growth. The main scientific challenge is that while artificial intelligence enhances economic efficiency, it also generates social risks and structural changes in the labor market. This complicates the balance between the economic, social, and institutional dimensions of sustainable development. Automation can marginalize certain groups of workers, while the emergence of new occupations creates opportunities for highly skilled employees. Therefore, technological transformation strengthens the labor market but requires appropriate policies and institutional mechanisms to manage its social and structural impacts effectively.

The objective of this study is to analyze the impact of artificial intelligence and digital transformation on the labor market within the framework of sustainable development, evaluating structural changes and socio-economic outcomes. The research considers both global experiences and country-level statistical data to assess current and prospective effects of artificial intelligence and digital transformation on the workforce. In addition, the study examines skill transformation, potential implications for income inequality, and the role of technology in balancing economic efficiency with social inclusiveness.

Consequently, this paper provides policy and strategic recommendations to adapt to evolving labor market demands and evaluates the potential of artificial intelligence and digital transformation for promoting sustainable and inclusive development. The study is significant both theoretically and practically, as it contributes to forecasting future labor market transformations and informing strategic decision-making processes.

## The impact of artificial intelligence on the labor market

Artificial intelligence and digital technologies have become some of the most transformative forces in the 21st-century economy. These technologies not only enhance efficiency in production and service sectors but also fundamentally reshape the structural and functional characteristics of the labor market. Automation, machine learning, big data analytics, robotics, and other advanced digital technologies are redefining traditional work models. As a result, some job functions are being replaced by technology, while others require new skills and competencies, leading to both structural and functional transformation in the labor market.

On one hand, Artificial intelligence enables the automation of routine and repetitive tasks. This process increases labor productivity, reduces operational costs, enhances organizational efficiency, and minimizes errors. Automation is widely applied in manufacturing, logistics, financial services, retail, and administrative functions. For instance, automated warehouse systems and robotics accelerate workflows, improving both quality and productivity. In banking and finance, Artificial intelligence algorithms support credit risk assessment, fraud detection, and customer service optimization. (Azərbaycan-2030: sosial-iqtisadi inkişafa dair Milli Prioritetlər, 2021 AR Prezidentinin Sərəncamı)

On the other hand, the application of such technologies can create structural imbalances in the labor market, highlighting the risk of technological unemployment. Medium-skilled workers, in particular, face a higher risk as repetitive and standardized tasks are increasingly automated. This contributes to skill polarization: low-skilled jobs decline while high-skilled positions expand. Consequently, socio-economic disparities in the labor market increase, income inequality rises, and unemployment risks grow for specific worker groups.

Digital transformation also drives the emergence of new occupations. Roles such as data analysts, Artificial intelligence engineers, cybersecurity experts, robotics specialists, cloud technology professionals, and digital marketing experts reflect growing labor demand in these areas. For example, a McKinsey study estimates that by 2030, approximately 375 million workers worldwide will need to adapt their job functions to new technologies, acquiring new skills accordingly. This underscores the necessity of adapting education and vocational training systems, as well as engaging workers in lifelong learning and skill development programs. The impact of AI extends beyond technological and economic domains; it also drives social and institutional change. Modernizing education systems, expanding vocational training, and implementing lifelong learning initiatives are essential for workforce adaptation. These measures are crucial for maintaining workers' competitiveness, ensuring alignment with new technologies, and promoting inclusivity in the labor market.

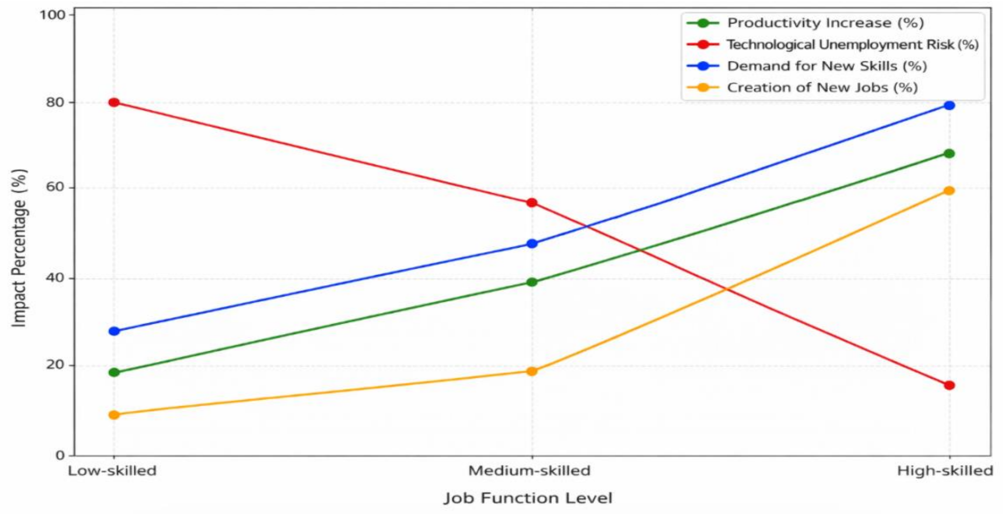
Moreover, Artificial intelligence adoption provides strategic advantages for organizations. By optimizing work processes, technology enhances innovation opportunities and supports the development of new products and services. This transformation influences not only job structures but also workers' professional behaviors and skill development. Strengthening employees' analytical and technological competencies enables them to perform existing tasks more efficiently while contributing to creative and innovative sectors. (Azərbaycan Respublikasında sosial xidmətin inkişafına dair 2023-2026-cı illər üçün Dövlət Proqramı.AR Prezidentinin Sərəncamı.

Overall, these trends indicate that Artificial intelligence is transforming the labor market economically, socially, and institutionally. Its impacts are multifaceted:

- Positive effects: increased productivity, enhanced efficiency, expanded innovation opportunities, and the creation of high-skilled jobs;
- Challenges and risks: reduction of medium- and low-skilled positions, skill polarization, technological unemployment, and rising income inequality.

Maintaining a balance requires adaptive labor market policies, integration of education and skill development programs, and strengthened social protection mechanisms. In this way, Artificial intelligence can be considered not only a technological enabler but also a strategic tool supporting sustainable and inclusive labor market development. (A. Hashimova,2023)

**Diagram 1.** The mechanism of artificial intelligence's impact on the labor market




**Source:** Data prepared by the author

## Skills and transformation and emerging professions

Artificial intelligence and digital transformation not only induce structural changes in the labor market but also fundamentally alter the skill requirements of the workforce. These changes create new challenges and opportunities in both technological and socio-economic domains, the systematic study of which is crucial for research analyzing the sustainable development of labor markets. Statistical data from international organizations clearly illustrate the impact of artificial intelligence on the labor market. For instance, according to the World Economic Forum "Future of Jobs Report", over the next decade, more than 50% of the global labor market will experience structural changes, and approximately 40% of employees will need to participate in reskilling and upskilling programs to adapt to evolving job functions.

According to the OECD, technology-driven automation risk is estimated at around 60% for medium-skilled jobs, while for high-skilled jobs, this risk remains below 10%. These statistics confirm the ongoing process of skill polarization in the labor market: high-skilled positions are preserved and even expanded, whereas low- and medium-skilled functions face a significantly higher risk of automation. (Hashimova, 2022)

Furthermore, the McKinsey Global Institute projects that by 2030, approximately 375 million workers worldwide will need to adapt their current occupational functions to new technologies, reskill, and transition to emerging professions. Simultaneously, the creation of new job categories is expected to generate an additional 50–60 million positions, providing a more precise reflection of the total impact of labor market transformation.

**Table 1.** Key indicators of artificial intelligence and digital transformation in the labor market

| Indicator | Value |
|---|---|
| Need for worker re-/up-skilling | ~40% |
| Automation risk in medium-skill jobs | ~60% |
| Automation risk in high-skill jobs | <10% |
| Number of workers needing adaptation in perspective | ~375 million |
| Expected new jobs to be created | ~50-60 million |

**Source:** World Economic Forum (2024), Future of Jobs Report; OECD (2023), Employment Outlook; McKinsey Global Institute (2023), Future of Work.

Under digital transformation, the skill portfolio required from employees undergoes profound changes. The adoption of artificial intelligence increases demand for the following key skill categories:

- Technical skills: Data analytics, machine learning, programming, cloud computing.
- Analytical and decision-making skills: Strategic decision-making based on data, optimization of business processes.
- Creative and social skills: Complex problem-solving, innovation, collaboration, and communication.

For example, the LinkedIn Professional Learning Report indicates that demand for skills in data analytics and programming has grown by 35–45% over the past two years. This demonstrates that skill reconfiguration in the labor market requires not only technological competencies but also growth in social-emotional abilities. (Rəhmanov,2021)

Thus, adaptation in the labor market entails not only technical adaptation but also soft skill-oriented adaptation.

Digital transformation accelerates the emergence of new professions. Among the most in-demand emerging roles are:

- Data specialists: Data science, data engineering, statistical analytics.
- Artificial intelligence engineers and researchers.
- Cybersecurity specialists.
- Technology product managers and strategists.
- Robotics and automation systems engineers.

According to the WEF, high-tech sectors are projected to maintain an average growth rate of 22–28% in new professions by 2025. This indicates that labor market transformation is not merely structural but also involves qualitative improvement.

The skills transformation in the labor market necessitates the renewal of existing education and vocational training systems. Lifelong learning, online and modular educational programs, as well as corporate reskilling and upskilling initiatives, are strategically crucial for the sustainable development of the labor market.

Statistically, the OECD reports that in developed countries, only approximately 25–30% of employees participate in formal lifelong learning programs. This highlights the still limited adaptation in the context of digital transformation and underscores the urgent need for reforms in education systems.

Skills transformation in the labor market extends beyond occupational shifts and has significant social and economic implications. Workers acquiring new skills earn higher wages, build careers in innovative sectors, and enhance labor market competitiveness. Conversely, employees unable to acquire new skills or lacking sufficient resources face increased risks of social marginalization, unemployment, and income loss. For instance, the World Bank reports that workers without digital skills earn on average 30–40% less than those with digital competencies, clearly highlighting the social inequality risks associated with digital transformation. (Rahmanov, et al.,2023)

Skills transformation and the emergence of new professions are central to the sustainable development of the labor market. Changes in skill requirements due to artificial intelligence and digital transformation, the formation of new occupations, and the adaptation of education systems will determine the future dynamics of the labor market. For sustainable development, it is essential to expand reskilling and upskilling opportunities, ensure flexibility in education systems, and implement social inclusiveness strategies.

**Productivity and economic outcomes**

Artificial intelligence and digital transformation serve as key transformative factors aimed at enhancing productivity and efficiency in both the labor market and the broader economic system. The dynamics of the modern economy demonstrate that the adoption of these technologies not only increases production volumes but also reshapes business models, updates workforce skill requirements, and generates socio-economic impacts.

The application of artificial intelligence optimizes operational and production processes within enterprises. The widespread implementation of robotics and automated systems reduces the time employees spend on repetitive and routine tasks. This, in turn, increases labor productivity and enables more efficient utilization of resources.

For instance, in manufacturing sectors, artificial intelligence technologies optimize the use of raw materials, minimize production errors, and contribute to process sustainability. According to the McKinsey Global Institute, enterprises implementing artificial intelligence and automation technologies have experienced an average 20–25% increase in labor productivity, accompanied by a 15–18% reduction in operational costs. These results indicate that technologies not only enhance economic efficiency but also strengthen the revenue-generating potential of enterprises.

Digital transformation affects not only workforce activities but also promotes economic efficiency. Algorithmic decision-making, big data analytics, and predictive systems enable enterprises to plan production more accurately, leading to more effective utilization of both financial and material resources. (Qasımlı, et al.,2023)

According to the World Bank, enterprises adopting digital technologies have achieved a 15–20% improvement in resource efficiency. Concurrently, optimization of energy and material expenditures reduces operational costs, creating a synergy between ecological sustainability and economic efficiency.

Digital transformation reshapes not only production functions but also business models. Artificial intelligence and big data technologies allow enterprises to personalize products and services, analyze consumer behavior with greater precision, and generate new revenue streams.

For example, the adoption of the Software as a Service (SaaS) model enables companies to offer subscription-based services, while data monetization serves as an additional revenue source. The World Economic Forum reports that enterprises implementing digital transformation have improved competitiveness by 30–35% and increased the speed of bringing new products and services to market by 25%. This enhances economic efficiency while generating added value for both regional and national economies.

The economic impact of artificial intelligence is observed not only at the micro level but also at the macroeconomic level. According to the IMF, countries implementing digital transformation have experienced annual GDP growth rates approximately 1.5–2% higher than those without such technologies. This results in the creation of new jobs, increased demand for technological skills, and strengthened overall economic dynamics.

On the other hand, technology adoption alters the role of certain workers. The functional scope of medium- and low-skilled employees becomes limited, highlighting the importance of reskilling and upskilling strategies. These strategies are crucial for labor market adaptation and ensuring social inclusiveness.

While productivity growth strengthens economic efficiency, maintaining socio-economic balance is essential. The additional value generated by artificial intelligence and digital transformation should be directed not only from a technological perspective but also from a socio-economic standpoint.

- Education and skills development programs should be implemented to ensure broad access to new economic opportunities.
- Social policies and institutional support mechanisms are essential to prevent productivity gains from exacerbating social inequalities.

Sustainable development requires a synchronized balance between economic efficiency and social inclusiveness. (Acemoglu & Restrepo, 2019)

In conclusion, artificial intelligence and digital transformation not only increase labor productivity but also enhance economic efficiency and create new business opportunities. These processes provide enterprises with revenue growth, faster market introduction of new products and services, efficient resource utilization, and competitive advantages. However, this transformation should not be limited to technology adoption alone but must also be supported by socio-economic and institutional adaptation measures to ensure that productivity gains are inclusive and sustainable.

**Table 2.** Economic impact of new business models

| Business Model | Revenue growth (%) | Time-to-market (%) | Competitiveness (%) |
|---|---|---|---|
| SaaS (Software as a Service) | 30 | 25 | 35 |
| Data Monetization | 20 | 20 | 30 |
| Personalized Services | 20 | 15 | 20 |
| Innovative Products | 35 | 30 | 40 |

**Source:** World Economic Forum (2024), Future of Jobs Report; McKinsey Global Institute (2023), Future of Work.

## Comparative assessment of labor market structural transformation in Azerbaijan and Germany

Artificial intelligence and digital transformation are driving fundamental changes in the structure of the modern labor market. These changes are characterized by shifts in job content, the emergence of new professions, and the reconfiguration of existing occupations. Labor market transformation is directly dependent on a country's technological potential, institutional development level, and government policies. In this context, a comparative assessment based on the cases of Azerbaijan and Germany clearly demonstrates the stages, speed, and future prospects of structural labor market transformation.

Germany is among the countries at the forefront of the "Industry 4.0" strategy. Here, the application of artificial intelligence technologies is implemented intensively across industry, logistics, healthcare, and service sectors. According to 2023 statistics, the share of industrial enterprises utilizing robots in Germany is 32%, while approximately 28–30% of enterprises benefit from artificial intelligence -based applications. In high-tech sectors, around 60% of employees possess digital skills. These figures indicate that labor market transformation in Germany is both rapid and systematic. (Aghion, Jones, & Jones,2017)

In Azerbaijan, digital transformation is still in a developmental phase. Based on 2023 data, the share of the digital economy in GDP is approximately 4–5%, and artificial intelligence implementation is mainly limited to the public and service sectors. The proportion of the workforce with digital skills is about 15–18%. This situation indicates that labor market transformation in Azerbaijan is relatively gradual and uneven.

In Germany, the industrial sector demonstrates high productivity due to automation and robotics. Routine tasks are decreasing, while demand for highly skilled engineers and technology specialists is increasing. Productivity growth in the industrial sector is around 20–25%.

In the service sector, artificial intelligence -based decision support systems and automated processes optimize workloads and create new employment opportunities. The IT and startup sector is developing rapidly, giving rise to new professions, such as data analysts, AI engineers, and digital service specialists, who are entering the labor market.

In Azerbaijan, automation in the industrial sector is mainly implemented in large enterprises. Productivity growth is approximately 5–10%, and structural transformation is largely confined to internal processes within large companies. (Bessen, 2019)

Digitalization is observed in the service sector, particularly in banking and government services, but artificial intelligence applications remain limited. New professions are emerging, but their scale is relatively small. While the IT and startup sectors are developing, there is a shortage of highly skilled personnel, which limits labor market transformation. Germany’s dual education system and vocational training programs are closely aligned with labor market demands. Collaboration between educational institutions and industrial enterprises ensures the development of a workforce with advanced technological skills.

In Azerbaijan, although reforms have been initiated to enhance digital skills within the education system, full alignment between educational programs and labor market requirements has not yet been achieved. This limits the pace of structural transformation and reduces workforce competitiveness.

AI and digital transformation are priority areas in Germany, supported by government funding, infrastructure, and regulatory measures. This support increases the effectiveness of transformation in both industrial and service sectors.

In Azerbaijan, the government has identified digital economy development as a priority; however, the role of the private sector and the innovation ecosystem remains limited. Government initiatives primarily support the digitalization of large enterprises, but additional measures are needed to promote the development of startups and small businesses. (Dauth, et al.,2017)

**Table 3.** Statistical indicators and comparative analysis of labor market structural transformation in Azerbaijan and Germany

| Indicator | Azerbaijan | Germany |
|---|---|---|
| Share of digital economy in GDP (%) | 4–5% | 10–12% |
| Level of AI implementation (% of enterprises) | 12–15% | 28–30% |
| High-tech employment (%) | 15–18% | 60% |
| Automation risk (%) | 8–10% | 14–18% |
| Alignment of vocational education with labor market | Partially aligned | Highly aligned |
| Innovation index | Medium | High |

**Source:** State Statistical Committee of Azerbaijan (2024); OECD (2023); Federal Employment Agency Germany (Bundesagentur für Arbeit) (2023)

Comparative analysis indicates that Germany possesses a more developed and resilient model of labor market structural transformation. The country's high-tech industrial sector, dual education system, and public-private partnerships enable rapid labor market adaptation. This model ensures labor market flexibility, the development of a highly skilled workforce, and a sustainable contribution to economic growth.

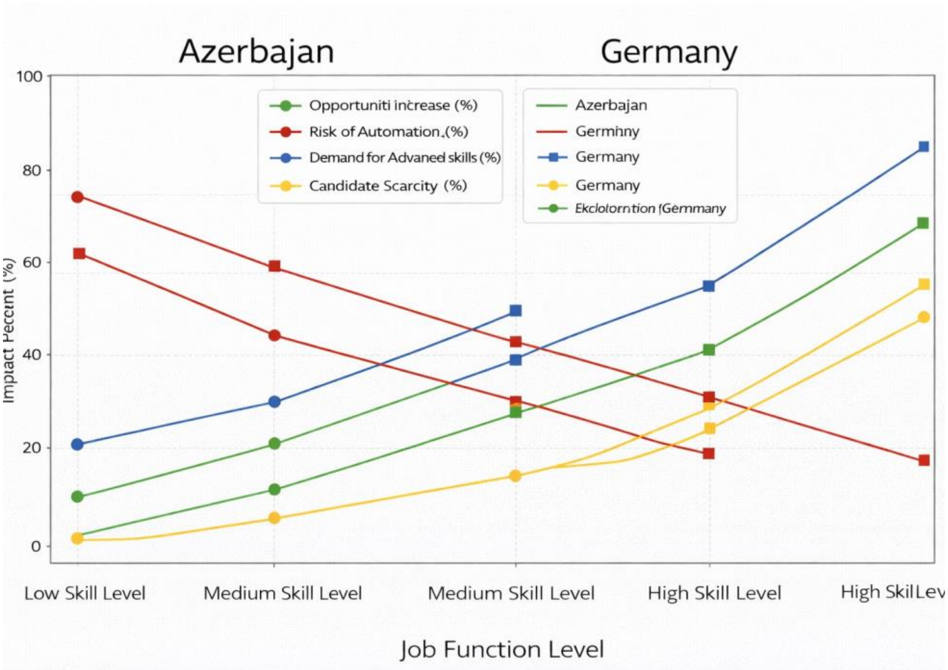
In Azerbaijan, the potential for structural labor market transformation is high, but its full realization requires systematic measures. One of the main challenges is the misalignment of education and vocational training programs with the rapidly evolving labor market demands. Another challenge is the insufficient development of collaboration between government initiatives and the private sector. Nevertheless, recent advancements in the digital economy, the strengthening of the startup ecosystem, and technology-oriented government policies provide a foundation for realizing this potential.

To accelerate structural transformation and ensure sustainable development, the following measures are necessary:

| **Strategic Area** | **Recommended Actions** |
|---|---|
| 1. Modernization of Education and Vocational Training Programs | • Align higher education and vocational training curricula with evolving labor market requirements.<br>• Integrate digital skills, artificial intelligence, data analytics, and IT competencies as core subjects.<br>• Expand practical training programs and internships through cooperation between educational institutions and industry. |
| 2. Strengthening Public–Private Sector Collaboration | • Prioritize government support for innovation, startups, business incubators, and technology parks.<br>• Provide financial and technical assistance for AI and digital transformation projects in SMEs and large enterprises (McKinsey Global Institute, 2023). |
| 3. Mass Development of Digital Skills | • Enhance workforce digital and technological competencies through training and certification programs.<br>• Implement targeted upskilling initiatives for young workers and unemployed individuals to meet changing labor market demands. |
| 4. Creation of New Professions and | • Expand educational pathways for emerging occupations |

| | |
|---|---|
| Career Opportunities | such as AI engineers, data analysts, and digital marketing specialists.<br>• Support existing employees through reskilling and upskilling programs to facilitate adaptation to new technologies. |
| 5. Ensuring Sustainable Development and Social Impact | • Promote socially inclusive and equitable digital transformation policies.<br>• Strengthen social protection mechanisms to mitigate technological unemployment and reduce inequality risks.<br>• Develop long-term strategies and agile regulatory frameworks to maintain labor market flexibility and resilience (OECD, 2023). |

**Diagram 2.** Labor market structural transformation in Azerbaijan and Germany




**Source:** Data prepared by the author

**Social and sustainable development aspects**

Artificial intelligence and digital transformation not only fundamentally reshape the structure and functional capabilities of the labor market but also exert significant impacts on socio-economic systems. While technological advancement enhances labor productivity, it may simultaneously deepen social and regional inequalities and lead to the exclusion of certain occupational groups from the labor market. Therefore, the implementation of policies aligned with the principles of sustainable and inclusive development should be among the strategic priorities of every country.

Technological innovations primarily increase the efficiency of highly skilled workers and raise their income levels, whereas low- and medium-skilled workers tend to occupy weaker positions in the labor market. As a result, income inequality increases, and the potential for social discontent rises. (World Bank, 2024)

According to the OECD, the incomes of highly skilled workers possessing digital competencies are approximately 40–50% higher than those of medium- and low-skilled workers. Statistical analyses conducted across the European Union indicate that the average annual income of workers utilizing digital technologies is around €55,000, whereas workers with limited technological skills earn approximately €35,000. In the United States, 10% of employees in the technology sector belong to the highest income group, while 30% of low- and medium-skilled workers remain below the average income level. (World Economic Forum, 2024)

To mitigate income inequality, it is essential to promote reskilling and upskilling programs, regulate taxation policies, and strengthen social protection mechanisms.

The benefits of digital transformation are predominantly concentrated in urban and industrial centers with advanced technological infrastructure and a highly skilled workforce. In contrast, rural and remote regions are often deprived of these benefits due to insufficient technological infrastructure and limited access to knowledge.

According to the World Bank, labor productivity has increased by 15–20% in regions with a high level of digital technology adoption, whereas only a 5–7% increase has been observed in remote areas. In Europe, the implementation of digital transformation in urban areas has increased workers' incomes by approximately 30–35% compared to rural and remote regions.

To ensure regional balance, it is crucial to develop digital infrastructure through government programs, ensure the equitable distribution of technological knowledge, and provide equal access to education across all regions. (Tarafdar, Beath & Ross, 2019)

Artificial intelligence and automation are replacing many low- and medium-skilled job functions, leading to significant structural changes in the workforce. According to the McKinsey Global Institute, approximately 20–25% of medium-skilled workers may be displaced over the next decade due to technological change if they fail to acquire new skills.

In the United States, projections suggest that by 2025, the roles of approximately 15 million workers will be significantly transformed due to technology and automation. In Europe, the working hours of low- and medium-skilled employees in enterprises adopting digital transformation have decreased by an average of 10–15%.

Therefore, reskilling and upskilling programs, vocational training, and lifelong learning initiatives are essential to maintain workers' positions in the labor market and ensure its flexibility. (Zeynep Tüfekci, 2020)

Policies implemented alongside technological transformation play a crucial role in ensuring social inclusiveness and sustainable development in the labor market. These policies should encompass the following areas:

1. Education and skills development programs – facilitating workers' adaptation to new technologies.
2. Reskilling and upskilling initiatives – reducing technological unemployment and reintegrating displaced groups into the workforce.
3. Social protection mechanisms – minimizing income inequality and social discontent.
4. Regional balance strategies – ensuring the equitable distribution of technological and educational opportunities across all regions.
5. Innovation and inclusive technology strategies – directing the benefits of technology toward all social and economic groups.

When effectively implemented, these measures ensure that artificial intelligence and digital transformation not only enhance economic efficiency but also contribute to the formation of an inclusive and sustainable labor market. (Zuboff S, 2019)

## Conclusion

In the context of the accelerating transformation of the global economic system, artificial intelligence and digital technologies have emerged as fundamental drivers of structural and functional reconfiguration within the labor market. The empirical findings of this study reveal that the integration of digital technologies substantially enhances labor productivity and operational efficiency, with observed productivity gains ranging between 15–25% in technology-adopting enterprises. Concurrently, this transformation induces a profound restructuring of workforce composition, characterized by the displacement of routine and low-skilled occupations and the increasing demand for highly qualified human capital, particularly in data-intensive and technology-oriented domains.

Notwithstanding these advancements, the analysis underscores the emergence of critical socio-economic challenges associated with technological diffusion. In particular, the asymmetric distribution of technological capabilities across regions exacerbates income inequality and reinforces spatial disparities, as productivity growth in rural and peripheral areas remains comparatively limited. This divergence highlights the systemic risk of uneven development and underscores the necessity of embedding technological progress within a comprehensive sustainable development framework.

From a theoretical and empirical standpoint, this research contributes to the existing literature by advancing a multidimensional approach to labor market analysis, integrating economic, social, and regional perspectives. Furthermore, the study provides a statistically grounded assessment of skills transformation and occupational shifts, while formulating evidence-based policy recommendations aimed at mitigating the adverse implications of technological change.

The findings emphasize that the long-term sustainability and inclusiveness of labor market development are contingent upon the implementation of coherent and adaptive policy measures. These include the alignment of education systems with evolving skill requirements through continuous reskilling and upskilling initiatives, the reinforcement of social protection mechanisms to address structural inequalities, the promotion of balanced regional development via equitable access to digital infrastructure, and the stimulation of innovation through targeted institutional and economic incentives.

In conclusion, while artificial intelligence and digital transformation serve as catalysts for enhanced productivity and structural flexibility, their broader socio-economic benefits can only be fully realized through strategically coordinated, inclusive, and sustainability-oriented policy frameworks that effectively address emerging disparities and ensure equitable labor market outcomes.

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