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Are We Ready for Artificial Intelligence? Comparative Causal Relationship of Origins Variables and Local Policy Implications

Yapay Zekâya Hazır mıyız? Köken Değişkenlerin Karşılaştırmalı Nedensel İlişkisi ve Yerel Politik Öneriler

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ÖZ

Bu çalışma, 174 ülkenin yapay zekaya hazır olmasına yönelik belirtilen değerin, köken değişkenleri ile nedensel ilişkisini ortaya koymayı, asimetrik sonuçlar elde etmeyi ve buna yönelik olarak yerel bağlama özgü sonuçlar belirlemeyi amaçlamaktadır. Araştırmanın yöntemi fsQCA (fuzzy-set Qualitative Comparative Analysis) olarak seçilmiştir. Elde edilen genel bulgulara göre yapay zekaya hazırlık için koşul değişkenlerin tamamının varlığının/yüksek seviyede olmasının küme-teorik bağlamda mutlak gerekli ve yeterli olduğu belirlenmiştir. Öte yandan asimetrik bulguların avantajını kullanarak yapay zekaya hazır olmama durumlarına yönelik ortaya çıkarılan sonuca göre DI'nın ve RE'nin olmamasının teorik anlamda mutlak gerekli olduğu diğer koşulların ise yeterli olduğu belirlenmiştir. Konfigürasyon bulgularına göre ise yapay zekaya hazırlığın tek bir değişkene bağlı olmadığı ülkeler için yerel bağlama göre çeşitli etkenlerin bir kombinasyonu tarafından belirlendiği tespit edilmiştir.

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A B S T R A C T

This study aims to reveal the causal relationship between the stated value of 174 countries' readiness for artificial intelligence and its origin variables, to obtain asymmetric results and to identify local context-specific results. The method of the research is fsQCA (fuzzy-set Qualitative Comparative Analysis). According to the general findings, it has been determined that the presence/high level of all the condition variables for preparation for artificial intelligence is absolutely necessary and sufficient in the set-theoretical context. On the other hand, using the advantage of asymmetric findings, it was determined that the absence of DI and RE is absolutely necessary in the theoretical sense, while the other conditions are sufficient. According to the configuration findings, it has been determined that AI readiness is not dependent on a single variable but is determined by a combination of various factors according to the local context for countries.

1. Introduction

The concept of AI was first defined as an academic research field in 1956 at the Dartmouth Conference organized by John McCarthy, Marvin Minsky, Nathaniel Rochester and Claude Shannon (McCarthy et al., 2006). At this conference, it was claimed that the basic features of human intelligence could be modeled by machines and that these machines could solve problems on their own. In the 1960s and 1970s, the symbolic AI approach became dominant; logical rule-based systems and expert systems were developed (Newell & Simon, 1976). However, when the limitations of knowledge-based systems became apparent in the 1980s, AI research entered a period of stagnation. The fact that instant

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communication has been made possible with internet networks since the 1990s to the present day has led to a significant increase in added value in the instant realization of virtual interactions with cyber physical systems (Huynh-The et al., 2023). Since the 2000s, great progress has been made in the fields of machine learning and deep learning thanks to the increase in the amount of data, improvements in computing power and the development of new algorithms (LeCun, Bengio, & Hinton, 2015). The concept of artificial intelligence (AI) is known as one of the most important requirements for adapting online networks to the current socio-economic structure. For more than sixty-five years, AI research has been carried out by all scientists, especially engineers, and has been integrated into many daily routines in industry, health, transportation, education, labor market and economic context (Jiang et al., 2022). The fact that artificial intelligence has a massive data processing size is effective in gaining a place in our daily lives, and it is seen that AI-supported systems provide a great advantage for competitive advantage and have become a critical tool (Minh et al., 2022). The development of application-oriented AI technologies has been possible with the allocation of the theoretical infrastructure. It is known that studies on the scope of AI in the literature generally focus on conditions such as digitalization levels, impact on socio-economic developments, etc. (Brynjolfsson and McAfee, 2014; Acemoglu and Restrepo, 2018). Today, artificial intelligence is at the center of decision support mechanisms in many sectors from healthcare to financial technologies, from education to public administration, and is the subject of intense debates with its ethical, social and legal dimensions (Floridi et al., 2018). This situation shows that AI is not only a technical field, but also a multidimensional research field whose social impacts should be taken into consideration. The rapid development of AI technologies has been considered as one of the most important factors in the socio-economic development of countries, and the preparation and development of AI infrastructure for this is considered necessary (WEF, 2024). In this context, the "Artificial Intelligence Preparedness Index" (AIP) data was introduced by the International Monetary Fund (IMF), which focuses on the vital role of AI, and was deemed valuable for setting a benchmark for countries' readiness for artificial intelligence (IMF, 2024). It was shared that the factors that are fundamentally effective in determining artificial intelligence readiness include factors such as digital infrastructure, innovation, human capital, labor market regulations, ethical regulations. With the inclusion of the index for AI readiness in the literature quite recently, although artificial intelligence is a major factor in providing competitive advantage among countries, the causal relationship of the origin variables has been addressed in the literature in a very limited way by including asymmetric findings of local context-specific results. For these reasons, the importance of this research is considered high. In this context, comparative asymmetric analysis offers a valuable approach for understanding the effects of different variables in multi-combination causal analysis methods. This study adopts the fsQCA technique to reveal country-specific results with asymmetric findings by examining the causal relationships of key factors determining the level of AI readiness of countries. Unlike traditional linear statistical methods, fsQCA offers the possibility of revealing the causal effect for a dichotomous outcome with multiple condition combinations (Ragin, 2009). Thus, this research is considered important as it is effective in revealing the asymmetric relationships between the countries' level of preparedness for artificial intelligence and the origin variable defined by the IMF, which is not only dependent on a single variable. In addition, the study has the potential to make a significant contribution to both theory and practice with its conditional variable combinations. The findings aim to fill an important literature gap in theoretical developments since the studies on the adoption of artificial intelligence technologies are still in their infancy and to improve the current literature on the subject. Moreover, with country-specific results, it goes beyond a uniform approach and reveals the need to take into account local conditions in policy development processes. In this context, by revealing the necessary findings for both academic circles and policy makers, it will be useful for the development of effective strategies in our age where artificial intelligence is at the center.

2. Literature Review and Hypothesis Development

Industry 4.0 and Society 5.0, which are the current final stages of industrial development processes, have enabled instant socio-economic integration through information technologies in the global context. Especially after the 2000s, the instant communication of information, money, labor, capital, etc. has been effective in the spread of global networks within global integration. The concept of artificial intelligence, which is stated to be the most important and central in the future, is also in the central position in the process of Industry 4.0 and beyond. Artificial intelligence is at the point of instant transformation of different concepts such as economic, social, cultural, etc. on a global scale and an important tool in communication. Today, artificial intelligence is an indispensable strategic power, especially for countries to make their economic growth and social development sustainable and to gain international competitive advantage. It is accepted that artificial intelligence has the capacity to create significant added value in the global development goals of economies through mass data analysis (Russel and Norvig, 2022). In fact, Raikov and Abrosimov (2018) propose econometric models based on artificial intelligence to predict the import priority of countries and provide competitive advantage due to low confidence in weak formalized data for the formulation of import-export policies. In addition to economic factors, artificial intelligence is a highly successful system in the process of data collection, resource management and customization to predict trends with data patterns by analyzing usage behavior in social, cultural, etc. developments (Okoroma, 2024). At the same time, Pençe et al. (2019), which covers environmental factors, uses artificial intelligence effectively in a predictive sense by making comparative analysis with systems such as artificial neural networks with economic growth, industrial development and energy consumption in Turkey. Therefore, in the theoretical and practical context, artificial intelligence technologies have gained popularity after the 2000s and it is predicted that they will continue to take center stage in order to create added value. However, in addition to the fact that artificial intelligence is gaining importance day by day, it is a curious situation whether countries are ready for this factor and whether the infrastructure has been allocated. As a matter of fact, when the literature is evaluated, there are very few studies on the readiness of countries for artificial intelligence. Artificial intelligence technologies are not only composed of digital infrastructure, but are also affected by many factors such as political implications, management and organization, human capital, labor markets, ethics, etc. Among these factors, IMF acknowledged the importance of artificial intelligence readiness and created an artificial intelligence readiness index with data from 174 countries by stating that there are four separate root factors for this factor (IMF, 2024). These factors consist of digital infrastructure, labor market regulations and human capital, ethical regulations, innovation and economic integration data and stand out as a comprehensive tool to measure the effects on countries' readiness for artificial intelligence. Although there is no direct research in the literature on conducting comparative analysis across countries based on these factors, it has been emphasized that these variables and their derivatives play a guiding role for policymakers (Athey, 2018). However, local analyses that include multi-conditional structures for the preparation of countries for artificial intelligence are not sufficiently covered in the literature and contain an important current and future-oriented gap.

First of all, one of the basic conditions for the formation of artificial intelligence is the establishment of a digital infrastructure. Digital infrastructure is considered to be the most important tool for increasing innovation and scalability with tools such as 5G, cloud platforms and artificial intelligence technologies (Borges, 2024). As digital infrastructure reveals the capacity of countries to adopt artificial intelligence, it is also thought that integration is more effective in developed economies through fiber internet, cloud computing, mobile networks (Verhoef et al., 2021). The onset of commerce-based internet technologies in the 1990s brought about a deep restructuring in the digital infrastructure, revealing the potential to have a direct impact on the GDP of countries (Greenstein, 2021). Artificial intelligence, which has established itself through digital infrastructure, has also been an important tool for small businesses and developing countries to gain a competitive advantage through mass data processing by restricting the monopoly of large companies in the gaps of digitalization (Kraus et al., 2022). However, despite this, according to the OECD (2024) digital report, digital infrastructure is one of the most effective conditions in the formation of artificial intelligence, as well as the idea that the possible lack of infrastructure may constitute an obstacle in the technological competition of countries. Although it has been shared in the literature that digital infrastructure is a definitive element for AI technologies, empirical research on the readiness among countries remains quite lacking. The hypothesis is developed by considering this situation in the literature.

H1: Digital infrastructure is one of the effective factors in the formation of AI readiness and is in a causal relationship with different country-specific combinations.

On the other hand, one of the most critical roles in preparing for AI technologies is the development of innovation and economic integration systems. The innovation capacity of countries and the possibility of economic integration in return is an important tool in increasing the readiness of countries for artificial intelligence. Integration into international innovation is known to increase the prevalence of AI-based solutions by making the transfer of information, money, and capital instantly possible (Furman and Seamans, 2019). Especially in the global context, the importance of technology-centered policies in shaping economic integration with online networks is an accepted situation (Strusani and Houngbonon, 2019). In fact, Huy et al. (2024), who analyzed the economic effects of artificial intelligence using a data set covering 141 countries between 2010 and 2023, found that innovation technologies and technological strategies through artificial intelligence significantly increased the surplus value output in the country's economy. In another study, Adigwe et al. (2024) used 642 survey data to try to specify the economic landscape of AI and found that innovation and economic integration through AI has a wide range of findings such as corporate competitive advantage, societal development, socio-economic dynamics enhancement, especially the surplus value advantage in the labor market. Ultimately, AI enhances competitiveness by promoting innovation management, standardization of routine work tasks, appropriate decision-making, and economic efficiency (Yi and Ayangbah, 2024). These results lead to the conclusion that innovation and economic integration is an effective factor for AI. According to the hypothesis formed within the framework of the findings in the literature;

H2: Innovation and economic integration is one of the effective factors in the formation of AI readiness and is causally related in different country-specific combinations.

One of the additional factors for the formation of the readiness of artificial intelligence is the development of human capital and labor policies. Human capital is an important concept for the adoption and implementation of all conditions that can create added value for employees in the current sense. As A. Smith first stated the human capital factor as a condition that creates added value in the country's economy, the concept has taken on a more institutionalized structure with Schultz, and it has been evaluated as one of the only factors that will increase the wealth of the country with the dominance of the flexible employee structure in the current sense (Navruz-Zoda & Shomiev, 2017). It has been revealed that the increase in expertise in human capital, especially in STEM (science, technology, engineering, mathematics) fields, increases initiatives in digital technologies, artificial intelligence and global networks (Acemoglu and Restrepo, 2018). By increasing investment in sustainable human capital, STEM expertise, and labor mobility, AI is made possible (IMF, 2024). The reflection of up-to-date inclusive labor policies on education services has made it necessary for artificial intelligence to take place in the coordination position, as it is the driving force of learning society structures, sustainable development, socio-economic development (Goldin, 2024). Especially in recent years, artificial intelligence models within the human resources theory, which is important in the value-added increase of human capital, have an incentive role for labor market policies in the economic development process (Wang & Li, 2019). At the same time, this role has a bidirectional effect. Artificial intelligence, platform economies, and digital networks have a transformative role in labor markets in terms of policy and are one of the important tools in the expansion of heterogeneous job types where human capital acquisition is required (Carbonero et al., 2023). Finally, it is assessed that human capital and labor markets are deeply related to artificial intelligence within the framework of the literature and a hypothesis is developed accordingly.

H3: Human capital and labor market policies are one of the effective factors in the formation of artificial intelligence readiness and are in a causal relationship with different country-specific combinations.

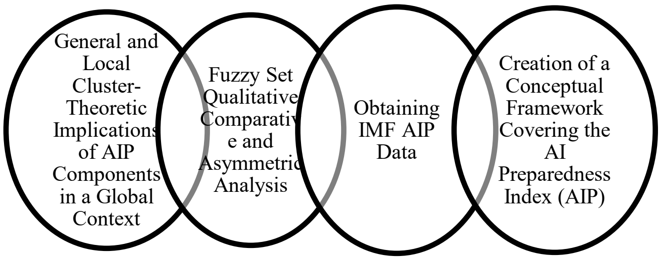
Finally, one of the indicators of countries' readiness for artificial intelligence is ethical and legal regulations. The fact that ethical and legal regulations are in a structure that supports artificial intelligence contains valuable phenomena that support each other in terms of technological development. Although artificial intelligence reflects a situation where there is concern in the ethical and legal dimension, artificial intelligence activities are carried out based on theoretical and practical examination of the legal system, governance models and regulatory foundations (Carrillo, 2020). The continuous development of smart computing technologies based on artificial intelligence brings technological regulations based on law and modern ethical infrastructure as a result of the increasing interconnectedness between humans and intelligent machines in daily life (Magrani, 2019). Recognizing the importance of this scope, the European Union has developed ethical guidelines and legal principles for artificial intelligence (Smuha, 2019). Larsson (2020), who examines the EU Commission's guidelines on artificial intelligence, shares that the need for in-depth research based on absolute ethics and regulations on the basis of artificial intelligence technologies continues. Almeida et al. (2021), who conducted a systematic literature review for scientific research on artificial intelligence between 2010-2020, stated that factors such as justice, freedom, social values, ethics from an integrative framework accelerated the literature on technological developments. Considering the theoretical developments, it is accepted that the use of artificial intelligence according to sectoral and regional differences has the potential to increase social trust (Roberts, 2021). Finally, according to the framework in the literature, it is thought that ethical and legal regulations are important for artificial intelligence and will become more important as it is included in sensitive tasks in the future. In this context, the research hypothesis is shared.

H4: Legal regulations and ethics are one of the factors in the formation of AI readiness and are causally related in different country-specific combinations.

3. Research Methodology

In social sciences, it is important to determine the philosophical source of the research in order to determine the research method. In the research, qualitative interpretation of quantitative data is made in order to obtain set-theoretical results. The philosophical view that will form the basis for this is pragmatism, which is effective in using both quantitative and qualitative research techniques together (Günbayı & Sorm, 2018). In the research, a mixed research framework is used for axiological, ontological, epistemological and methodological sub-dimensions based on the philosophy of pragmatism (Creswell & Clark, 2017). This research is based on an approach to understanding the multidimensional, context-sensitive and causally complex nature of social and organizational phenomena. The basic philosophical stance adopted in the study is not limited to positivist and post-positivist paradigms, but is rather informed by cultural realism and pragmatic ontology. It is accepted that reality cannot be reduced to a single objective interpretation; on the contrary, multiple paths can lead to the same result under different conditions. In this context, the concept of causal complexity is central to the research. Within the framework of this philosophical perspective, mixed research methods, in which qualitative evaluation of quantitative data is used together, constitute the source of the study. Mixed research methods are considered important for appropriate analysis of data and high levels of validity and reliability. Mixed research methods are very important in terms of exploring theoretical foundations and causal relationships in social sciences (Johnson & Onwuegbuzie, 2004). The results targeted in the research are to obtain cluster-theoretical findings in the local context of causal relationships in the mixed model. The research design was developed for this purpose. First of all, an effective literature review process was carried out through the R package program, bibliometrix application and the studies deemed important in the literature. Then, the process of analyzing the data and obtaining asymmetric results was carried out.

Figure 1: Research Design



3.1. Research Data and Analysis

All data for the study is derived from secondary data including the year 2023, which includes the AI Preparedness Index (AIP) and its components shared by the International Monetary Fund (IMF). The purpose of sharing the data by the IMF is based on the fact that it identifies areas for improvement for the policy makers of the countries and includes practical and theoretical contributions. The AIP is based on the index results of 174 countries within the macro-structural data set for digital infrastructure, human capital and labor market policies, economic integration and regulation, and innovation. The AIP data source includes perception surveys conducted by major international organizations such as the International Labor Organization, the United Nations, International Telecommunications, the Universal Postal Union, the World Bank, the World Economic Forum, and the Fraser Institute. Important statements and descriptive statistics for recognizing the research data within the framework of Cazzaniga et al. (2024) and IMF data are shared in table 1.

Table 1: Descriptive Statistics

Variable (n=174)	Origin Description	Abb.	Std. Dev.	Mean (0.50)	Min. (0.05)	Max. (0.95)
AI Preparedness Index	Digital infrastructure is the sum of sub-components such as human capital and labor market policies, innovation and economic integration, and regulation and ethics	AIP	0.156	0.467	0.105	0.800
Regulation and Ethics	Identifies strong legal framework and implementation mechanisms.	RE	0.050	0.121	0.007	0.230
Human Capital and Labor Market Policies	Includes education and digital skills and labor market flexibility policies	HCLM	0.035	0.122	0.001	0.195
Innovation and Economic Integration	R&D spending per GDP represents technological readiness and incentives for AI businesses	IEI	0.037	0.113	0	0.190
Digital Infrastructure	Affordable and secure internet access and e-commerce infrastructure	DI	0.048	0.109	0.015	0.208

In the research, the Fuzzy Set Qualitative Comparative Analysis (fsQCA) technique was adopted in order to reveal the adequacy and necessity of the variables including the data obtained for the AI Preparedness Index and its components in the IMF for AIP and to reflect country-specific results in the local context. FsQCA technique is effective in revealing a meaningful result in the local context for the result of the condition variables with its set-theoretical approach to reveal the causal relationships of sociological events and phenomena (Ragin, 2014). This unit of analysis appears as a technique that contains a trendy policy recommendation in the field of social sciences in order to obtain mixed results, make exploratory inferences and interpret causal relationships by constructing quantitative and qualitative paradigms together (Schneider & Wagemann, 2010). The main reason for choosing the fuzzy-set Qualitative Comparative Analysis (fsQCA) method in determining the factors affecting the readiness levels for artificial intelligence is that the research object contains complex structural relationships such as multiple causality and equivalent solutions. fsQCA provides a powerful methodological framework for heterogeneous samples and the non-linear nature of cause-and-effect relationships encountered especially in social sciences (Ragin, 2008). This method recognizes that more than one combination of conditions may be sufficient to achieve a particular outcome and thus provides the possibility to analyze different path structures (Schneider & Wagemann, 2012). fsQCA has significant advantages over traditional regression analyses or symmetric statistical methods such as structural equation modeling (SEM). While regression-based approaches assume that the effects on the dependent variable are linear and unidirectional, fsQCA allows analyzing non-symmetric relationships, i.e. combinations of outcomes that change both in the presence and absence of conditions (Fiss, 2011). In this respect, fsQCA contributes to a deeper understanding of multidimensional and context-sensitive concepts such as AI preparation. In addition, fsQCA offers a flexible research approach as it allows working with small and medium-sized samples, considers combinations of conditions, and does not necessarily look for average effects (Misangyi et al., 2017). In this context, the choice of fsQCA method in this study was a more appropriate and meaningful methodological choice to explain the diversity of factors affecting AI readiness levels and how these factors interact together to create different readiness profiles. Within the framework of many reasons such as these, fsQCA has been determined as an appropriate technique for determining causal relationships between AI preparedness and condition variables and for determining local configuration findings as well as generating a general competence and necessity findings in the global context. Moreover, this technique was deemed necessary for obtaining bidirectional results in both symmetric and asymmetric dimensions, as well as techniques involving many linear findings.

Before obtaining the research findings, it is important to calibrate the data sets to bring them into a stable format. Since the data reflect a wide variety of types and values, all data were calibrated and index values were created (Duşa, 2018). The calibration process was carried out using various threshold values. Using the thresholds suggested by Cangialosi (2023), the threshold for full membership in the cluster was 0.95, the average threshold was 0.50, and the minimum threshold was 0.05, as shown in Table 1. Thus, the data reached a fixed value unit to be subject to analysis.

4. Findings

4.1. Necessity and Adequacy Findings

The first unit of analysis in fsQCA for the calibrated data is the necessity-adequacy analysis. With the findings of this analysis, it is discussed whether the presence/absence of condition variables is necessary and/or sufficient for the presence/absence of the outcome variable by covering 174 countries. The study first discusses whether regulation and ethics (RE), human capital and labor market policies (HCLM), innovation and economic integration (IEI), digital infrastructure (DI) variables are necessary and/or sufficient for AI preparedness (AIP) in both directions. According to the necessity analysis, the condition variables should have a consistency value of 0.90 and above for the outcome variable, while according to the adequacy analysis, the coverage value should be 0.50 and above (Ragin, 2006).

According to the necessity and sufficiency findings shared in Table 2, the presence of DI, IEI, HCLM and REI are the variables that are absolutely necessary for the existence of AIP in the cluster theoretical context. The presence of all variables proved to be absolutely necessary for the existence of AIP in the theoretical sense. However, among them, HCLM stood out as the more necessary condition for AIP by a small margin compared to the others. On the other hand, the absolute necessary conditions for ~AIP are ~DI and ~REI. Among the conditional variables, the variable with the most effective necessity value is ~DI. All other conditions are found to be not absolutely necessary for ~AIP. Therefore, the advantage of asymmetric findings was used and presence and absence did not produce the same results for AIP. As another result, according to the sufficiency findings, both values of the condition variables for both values of AIP were determined to be sufficient and suitable for configuration analysis. DI was prioritized in terms of adequacy for AIP compared to other variables. For ~AIP, ~HCLM was found to have a higher coverage value. Finally, the consistency and coverage values indicate that the designed model is highly reliable for both aspects of AIP.

Table 2: Necessity and Sufficiency Findings

Cond.	Outcome Variable: AIP		Result Variable: ~AIP	
	Con.	Cov.	Con.	Cov.
DI	0.925	0.948	0.508	0.521
~DI	0.532	0.519	0.949	0.927
IEI	0.931	0.878	0.628	0.593
~IEI	0.569	0.604	0.871	0.926
HCLM	0.958	0.885	0.633	0.586
~HCLM	0.552	0.601	0.876	0.954
REI	0.936	0.934	0.563	0.563
~REI	0.562	0.562	0.934	0.936

4.2. Truth Table Findings and Logical Minimization

Before the configuration findings are revealed, all potential condition combinations are revealed by truth table analysis and the consistency-scope value of the combinations in relation to the outcome variable is determined (Cangialosi, 2023). However, accessing the truth table is not a suitable situation for obtaining configuration findings. Simplification-logical minimization of the findings of a bulk configuration is a must. All of the conditional configurations reveal all combinations in the subset and the simplification process evolves the data into a form suitable for configuration analysis. Accordingly, in fsQCA, n= represents the number of conditions and all possible combinations are included in a subset of 2n. In our research, since there are 4 condition variables in total for the presence of AIP, 24=16, and 24=16 for the absence of AIP, there are 32 causal condition combinations in total in the subset, as the first five rows are shared in table 3 Considering that these combinations are difficult to define, logical minimization was applied. In the truth table, the number of rows was cut to 0.80 within a consistency value of 1 (main cluster), taking into account the recommendations of Sedita et al. (2022). For the presence of AIP, 4 of the 16 possible configurations were obtained as suitable for interpretation as a result of simplification. On the other hand, for the absence of AIP, 4 configuration equations worthy of interpretation were obtained.

Table 3: Truth Table Top Five Rankings

DI	IEI	HCLMI	REI	AIP	Count.	Raw Con.	PRI Con.	SYM Con.
Outcome Variable: AIP								
1	1	1	1	1	58	0.999	0.999	0.999
1	1	0	1	1	1	0.999	0.992	0.992
1	1	1	0	1	2	0.994	0.918	0.918
1	0	1	1	1	7	0.993	0.922	0.925
1	1	0	0	1	1	0.993	0.785	0.785
Outcome Variable: ~AIP								
0	0	0	0	1	52	1	1	1
0	1	0	0	1	10	0.998	0.991	0.991
0	0	1	0	1	8	0.997	0.984	0.984
1	0	0	0	1	3	0.996	0.888	0.888
0	0	0	1	1	8	0.994	0.937	0.937

4.3. Configuration Results

Configurations represent the function of causal conditions in the formation of the outcome variable in a wide variety of combinations and are effective in generating results in the local context (Fiss, 2011). Each configuration provides a unique path for the outcome variable and reveals causal relationships based on the presence/absence of conditions (Ragin, 2009). After the simplification process in the logical minimization process, the configuration above the threshold value represents the local results of the causal relationship between the condition and outcome variables of the research. Accordingly, as presented in Table 4, four configurations on the path to the presence of AIP and four configurations on the path to the absence of AIP are worthy of interpretation. All countries were included in these evaluations and some of them had to be deleted because they were below the threshold value due to the nature of the application. For the countries above the threshold, causal relationships that should be considered on the path to AIP were identified.

Table 4: Configuration Findings

Outcome Variable: AIP				
	1	2	3	4
DI	●			
IEI			●	⊗
HC LM			⊗	●
RE		●		
	Singapore, Estonia, Denmark, HongKong, Austria, NewZealand, Luxemburg, Switzerland, China, Netherlands, UnitedStates, Germany, Finland, Korea, Australia, UnitedKingdom, France, Sweden, Lithuania, Belgium	Finland, NewZealand, Netherlands, Luxembourg, Estonia, UnitedStates, UnitedKingdom, Denmark, Singapore, Australia, Sweden, Iceland, Norway, Japan, Canada, Switzerland, Germany, Austria, Korea, Ireland	Haiti, Niger, Liberia, Somalia, Timor-Leste, Djibouti, Guinea-Bissau, Yemen, NorthMacedonia, Guatemala, Lebanon, Dominican Republic, Kuwait	Algeria, PuertoRico, Tajikistan, Mongolia, Azerbaijan, Ukraine, Uzbekistan, Colombia, Tunisia, Jamaica, Moldova, Indonesia, Belize, SriLanka, BruneiDarussalam, Kazakhstan, Serbia, Montenegro, Fiji
solution coverage: 0.995628				
solution consistency: 0.808918				
Outcome Variable: ~AIP				
	1	**2**	**3**	**4**
DI			●	⊗
IEI		⊗		
HC LM	⊗			
RE			⊗	●
	Somalia, CentralAfricanRepublic, SouthSudan, Guinea-Bissau, Afghanistan, PapuaNewGuinea, Haiti, Ethiopia, Niger, Mauritania, Comoros, Angola, Mozambique, Sudan, Congo, SãoTooméandPríncipe, Chad, Yemen, Maldives, BurkinaFaso	Afghanistan, Uzbekistan, MacaoSAR, PuertoRico, SaintVincentandtheGrenadines Maldives, SãoToméandPríncipe Iraq, SouthSudan.Republic of SaintLucia, Libya, Venezuela, Ethiopia, Burundi, Mauritania, Algeria, Congo, Mozambique, Madagascar, Chad	Belarus, Vietnam, Bahrain, Iran, RussianFederation, BosniaandHerzegovina, Kuwait, SriLanka, Azerbaijan, Mongolia	Bhutan, SaintVincentandtheGrenadines, PuertoRico, Rwanda, SaintLucia, Ghana, Barbados, Ecuador, Kenya, India, Jordan, Panama, Dominican Republic, Philippines, Senegal
solution coverage: 0.959352				
solution consistency: 0.88883				

"●" means that the condition is present, "⊗" means that the condition is not present, and spaces left blank mean that its presence or absence is not important.

First of all, according to the results in Table 4, there is no absolute variable for the presence of AIP in each configuration and the presence or absence varied according to the countries. The rate of explanation of the AI readiness index (solution coverage: 0.995) of the configuration included in the first configuration is 99.5%, which is almost an absolute value in the theoretical context. In the first configuration, the provision of digital infrastructure is important for the existence of the AI readiness index in the majority of developed countries. The presence or absence of other factors for AI readiness in the context of these countries is determined to be of no importance (neutral). For the developed countries in the second configuration, it was found that the effective factor in the formation of AI readiness emerged as a result of the importance they attach to regulations and ethical concepts. The presence or absence of other factors does not matter for AI readiness. For developing countries in the third configuration, it is found that the factor in the formation of AI readiness is provided by innovation and economic integration, although the impact of human capital and labor market policies is low. Other factors were found to be insignificant and neutral.

Finally, for developing countries in the fourth configuration, although innovation and economic integration are at a low level, the impact on human capital and labor market policies is effective in the formation of AI readiness. On the other hand, in table 4, local context-specific causal conditions for the absence of AIP are revealed. It was determined that the rate of these 4 configurations explaining the absence of AIP is at a very high level of 95.9%. It is observed that the countries in the absence of AIP have relatively lower levels of development compared to the countries in the presence of AIP. For example, it is determined that the causal condition for the absence of AIP is the absence of human capital and labor market policies for the majority of low-development countries in the first configuration. Other conditions are found to be neutral for the same countries. For the regions in the second configuration, which are categorized as undeveloped or developing countries, the lack of innovation and economic integration is found to be the causal factor for the non-formation of AIP. In the third configuration, it was determined that the reason why the majority of the countries in the Sub-Saharan Africa region did not form AIP was due to the low level of legal regulations and ethical systems despite the presence of digital infrastructure. Finally, for the countries in the fourth configuration, where the middle-income level is in the majority, it is seen that the factor in the non-formation of AIP is due to the low level of digital infrastructure despite the existence of legal and ethical regulations. Finally, according to all the results, country-specific results of high or low level of readiness for artificial intelligence have been revealed.

5. Conclusion and Discussion

The phenomenon of artificial intelligence has become vital in the process of data analysis and application against the huge accumulation of internet technologies, especially after the 2000s. Today, companies, regions and countries that keep artificial intelligence at the center have the opportunity to gain competitive advantage. In response to this situation, the IMF has shared the indicators of countries' readiness for artificial intelligence. This research contributes to the production of artificial intelligence policies with country-specific local results by revealing the causal relationships of the origin variables for the readiness of 174 countries for artificial intelligence. For this purpose, cluster-theoretic qualitative comparative analysis is used, which allows to bring together both the necessity-competence of the variables in a singular sense and the countries with similar characteristics in an asymmetric context. First of all, according to the consistency ratios of the condition variables with both values (presence/high level-absence/low level) on the outcome variable; digital infrastructure, innovation and economic integration, human capital and labor market policies, regulations and ethics variables were among the absolute necessary factors for AI readiness in the cluster-theoretical sense. In the absence/low level of AI readiness, it was determined that the absence of digital infrastructure and regulations-ethics is absolutely necessary. Other variables were determined to be sufficient for the analysis even if they were not necessary for the cases of having/not having artificial intelligence readiness. These results indicate that similar findings are confirmed when the literature is evaluated.

Artificial intelligence has become one of the main indicators that determine competitiveness as a necessity of the digital age. In our research, the bidirectional causal effects of relevant variables on readiness for artificial intelligence beyond the singular necessity-competence were determined. The findings are largely consistent with the existing literature and emphasize that practical outcomes play a critical role in the transition to AI. These results confirm all the hypotheses predicted in the research. For example, one of the sole drivers of AI readiness is digital infrastructure. Digital infrastructure is a prerequisite for the realization and sustainability of AI. In Frey and Osborne's (2017) study, it was determined that the adoption rate of artificial intelligence is high in countries with developed digital infrastructure. Similarly, in Bhowmick and Seetharaman's (2024) study, the effective stage of artificial intelligence in product development was evaluated; it was determined that there are origin dimensions such as digital infrastructure, data integration and ethics. In Serrano's (2018) research, the role of developments in urbanization and infrastructure in creating smart societies through artificial intelligence using the basis of digitalization is accepted. Deshmukh and Pasumarti (2018) shared the importance of artificial intelligence based on a digital predictor in shaping human behavior and lifestyles through an innovative system. However, there are also different finding in the literature that the effect of digital infrastructure on AI readiness is not decisive in every case. The McKinsey Global Institute report prepared by Bughin et al. (2018) showed that the existence of digital infrastructure alone is not sufficient for AI adaptation, and human capital, regulatory framework and cultural acceptances also affect the process in a decisive way. Therefore, this study confirms that digital infrastructure is an important determinant of AI readiness, but also shows that this relationship is not absolute and varies according to country conditions. It is concluded that AI readiness should be evaluated together with other factors such as not only technical infrastructure but also human resources, digital skill level and regulatory environment. These findings show that the study provides not only a confirmatory but also a deepening and explanatory contribution to the literature. On the other hand, human capital and the impact of labor markets constitute one of the component factors of AI. Acemoglu and Restrepo (2020) believe that analyzing the effects of artificial intelligence on the labor market and policies to increase labor competencies will accelerate transformation in both individual and country contexts. M'hamed et al. (2024) conducted a literature review on the scope of significant developments in artificial intelligence technologies and the role of job roles, skill requirements and thus human capital in increasing operational efficiency is critical. Analyzing 2021

EUROSTAT data, Brey and van der Marel (2024) found that differences in human capital are a driving force in sectoral development with the adoption of artificial intelligence. According to Brey and Van der Marel (2023), the impact of artificial intelligence and human capital in science, technology, engineering and mathematics constitute policy requirements that have the potential to strengthen Europe's growth and productivity trajectory. The research confirms the hypothesis and provides country-specific results by considering policy imperatives. However, there are also studies in the literature indicating that the effect of human capital on AI adaptation is not unconditional and direct. Mishel and Bivens (2017) emphasized that high human capital does not always lead to rapid integration of AI technologies; institutional infrastructure deficiencies, resistance to technology, and policy gaps are also decisive in this process. In addition, Susskind (2020) stated that AI has shown rapid adaptation in some sectors independently of human capital, and that the human capital factor remains limited, especially in jobs that require low skills. Therefore, this study confirms that human capital is an important element in the AI readiness process, but also shows that this relationship may vary depending on contextual factors. It is understood that in order for AI technologies to be successfully adopted, not only individual skill development but also institutional support mechanisms, educational reforms, and holistic policies for technology should be evaluated together. These findings show that the study provides not only a confirmatory but also an explanatory contribution to the literature that takes into account different contextual conditions. In the study, innovation capacity and the possibility of economic integration were found to be among the factors considered important for generating added value in the global competitive market. Similarly, in Jiang's (2022) research on economic integration, stock market price data was collected using the Shanghai Composite Index, and a neural network model was created to determine the probability of accurate prediction of pricing through artificial intelligence. Komninos (2006), conducting research on smart cities, argues that by encouraging knowledge-intensive activities, advanced communication infrastructure and innovative cooperation, AI-mediated sustainable cities can be established. Ultimately, it is thought that rapid advances in the field of artificial intelligence will continuously promote economic integration and provide a great advantage to increase productivity, employment, and competition (Cockburn et al., 2019). Finally, as one of the AI readiness factors, regulations and ethics were found to be an important component. Although the development of AI and its integration into the socio-economic structure is of strategic importance, regulatory and ethical issues are of vital importance. For example, according to Wong (2021), it is stated that in recent years, the principles of legal regulations and ethics have been reinterpreted within the framework of artificial intelligence and the integration of standard truths into the system is important. In Carter's (2020) study, it is discussed that possible risks can be eliminated by determining the framework of ethical and legal regulations for these concepts, considering that the potential of technologies such as artificial intelligence and machine learning to do good and help in daily life is increasing day by day. According to Iphofen and Kritikos (2021), it is especially important to establish moral structures within autonomous systems for processes such as ownership, management, control and supervision among the most discussed issues. On the other hand, Floridi and Cowls (2022) shared that the lack of ethical codes and legal framework will negatively affect the integration of AI technologies in the socio-economic structure.

Finally, it is assumed that all of the functions specified for AI readiness are included among the origin variables in line with the literature. However, as a result of the configuration, additional findings are included that different conditions are effective in the readiness of each country for artificial intelligence. In the results of the configuration, it was determined that the majority of the countries preparing for artificial intelligence are developing or developed countries. These countries also yielded results in the AI readiness dimension, each of which is associated with different causal conditions. On the other hand, it was determined that the countries in the configuration related to the lack of readiness for artificial intelligence were clustered in the category of undeveloped or developing countries. This situation converges on the point that country-specific results emerge in the literature. In Dağlı's (2022) study, the most successful countries were evaluated with factors such as R&D expenditures, scientific publications, and the number of researchers for artificial intelligence, and it was seen that they were similar to the countries that are ready for artificial intelligence. Similarly, according to the report of the International Science Council (2024), the readiness of each country for artificial intelligence is at different levels in different causal relationships, and it is stated that the level of development of countries that are mostly adapted is higher. Therefore, each country's access to and readiness for artificial intelligence is possible through combinations of different indicators. As a result of the research simplification, the readiness or lack of readiness for artificial intelligence has political implications for countries. Considering this, in future research, there is a need to deepen the country-specific results by reducing our research result in different contexts. The findings clearly indicate the need for strategic differentiation between developed and developing countries. For developed countries, policymakers are advised to focus on further strengthening the existing digital infrastructure as well as increasing the global harmonization of ethical standards and regulatory mechanisms for AI applications. Expanding innovation ecosystems through international collaborations, especially in the case of European countries and the Asia-Pacific region, will help them maintain their leadership position in AI (Bughin et al., 2018; OECD, 2021). For developing countries, the priority should be to expand basic digital infrastructure, support the use of accessible internet and increase investments in human capital. Focusing on digital skills in education systems and increasing labor market flexibility can significantly improve their capacity to adapt to AI technologies (UNCTAD, 2021). Moreover, the study results indicate that international cooperation can play a decisive role in preparing for AI. It is especially important for developing countries to cooperate with international organizations and developed economies in sharing technical knowledge, infrastructure investments and developing regulatory capacities in digital transformation processes (World Bank, 2022). In order for AI technologies to develop in a fair and inclusive manner at the global level, there is a critical need to establish common standards on multilateral platforms. With all this in mind, in future research, there is a need to deepen country-specific results by reducing our research result to different contexts.

The datasets provided by the IMF and other international organizations used in this study provide an important basis for global comparisons and systematic analysis. However, it should be noted that such international databases have certain limitations and potential biases. Especially in developing countries, incomplete data collection processes, measurement errors and methodological inconsistencies may affect the reliability and generalizability of the results (Jerven, 2013). In developing economies, high levels of informal activities, insufficient statistical capacity and political interventions are among the important factors that limit the accuracy of macroeconomic indicators (Deaton, 2010). This raises the possibility that some of the patterns observed in the findings of the study may be affected by data-related deviations. Therefore, openly discussing the limitations of the data sets used would both contribute to the methodological transparency of the research and enable a more cautious approach to the interpretation of the findings (Sandefur & Glassman, 2015). In conclusion, while data from the IMF and similar institutions provide a strong starting point, future research should be designed accordingly, taking into account the impact of data quality issues, especially in developing countries, on the analysis.

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