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The role of R&D and innovation on income inequality: A study with discriminant analysis

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Abstract: This study examines the role of Research and Development (R&D) and innovation on income inequality using discriminant analysis, a multivariate statistical method. The main objective of the study is to assess how well R&D and innovation components can classify income inequality (or development) in different countries. The independent variables include 'Industrial Design Applications (IDAPPNR)', 'Patent Applications (PAPPNR)' and 'Trademark Applications (TRAPPR)', while the dependent variable is represented by the Gini index, which measures income inequality and serves as a proxy for a country's level of development. Using data from 2021 onwards, the study categorises countries into two groups according to their Gini index values: high inequality/underdeveloped and moderate inequality/developing countries. The analysis takes into account the statistical requirements of normal distribution, homogeneity of variance-covariance matrices, outliers and multicollinearity. The results obtained from the discriminant analysis show that the independent variables, especially patent applications and trademark applications, make a significant contribution in distinguishing between the two groups. The findings suggest that countries with higher levels of R&D and innovation tend to show lower income inequality, reflecting more developed economies. This study highlights the potential role of R&D and innovation as key drivers in reducing income inequality and promoting sustainable economic development.

Keywords: *Research and development (R&D), income inequality, innovation, discriminant analysis, gini index.*

Introduction

Income inequality constitutes one of the most important and controversial problems of today's economies and is a phenomenon that deeply affects economic and social structures worldwide (Alderson & Nielsen, 2002; Neckerman & Torche, 2007). High income inequality not only creates differences between individuals and families, but also triggers social unrest and strengthens the barriers to sustainable development (Roseland, 2000; Schneider et al., 2010). In this context, it is important to analyse the factors affecting the internal dynamics of societies in order to solve this major obstacle to economic development. In recent years, an expanding

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body of research has suggested that research and development (R&D) and innovation may influence income inequality, often indicating potential positive effects. However, further empirical studies are still needed to better clarify and substantiate the nature of this relationship. In this context, the present study aims to investigate the impact of R&D and innovation on income inequality by applying discriminant analysis.

R&D and innovation are recognised as one of the main drivers of economic growth and play an important role in increasing growth rates, especially in developed economies (Bilbao-Osorio & Rodríguez-Pose, 2004; Krammer, 2009; Hasan & Tucci, 2010). Innovative processes not only transform existing markets but also contribute to the development of societies (Hekkert et al., 2007; Schot & Steinmueller, 2018). R&D and innovation bring about many positive outcomes such as creating new jobs, increasing productivity and improving social welfare. However, analyses on how these processes affect income inequality are limited (Lee & Rodríguez-Pose, 2013; Schillo & Robinson, 2017; Skare et al., 2024).

Kuznets' (1955) famous theory describing the relationship between income inequality and economic growth suggested that inequality initially increases in developing economies, but decreases over time with growth. This theory helps us to understand how innovative processes and technological developments shape changes in income distribution. However, Kuznets' theory emphasises that income inequality does not only improve with economic growth, but that the role of social policies and innovation is also of great importance.

Baumol's (1990) entrepreneurship theory makes an important contribution to understanding the relationship between innovation and income inequality. Baumol stated that economic inequality can create an impetus for innovation up to a certain level, but emphasised that extreme inequality can block innovative ventures. Many studies reveal that countries with low income inequality have higher innovation rates and this situation positively affects economic growth.

In their analyses on this issue, Huan & Qamruzzaman (2022) emphasise that low inequality rates in developed economies result in more R&D investment and innovation-based growth. These findings suggest that innovative processes operate more efficiently in more egalitarian societies, which in turn increases overall economic growth.

In conclusion, this study reveals that R&D and innovation play an important role in reducing income inequality and promoting sustainable development. Innovative processes appear to be more effective in countries with low income inequality, accelerating economic development. These findings suggest that states and international organisations should take into account the goals of reducing income inequality while shaping their R&D and innovation strategies.

The Relationship Between Income Inequality and Innovation: A Literature Review

The relationship between income inequality and innovation is important for economic growth and social development. The literature analysing the effects of income inequality on economic growth and innovation presents different perspectives and theories on this issue. Aghion et al. (1999) argue that income inequality encourages innovation and economic growth up to a certain level, but very high inequality can reverse this effect. In this context, it is emphasised that income inequality may be an inhibiting factor against the creative stimulus necessary to increase the capacity to innovate.

Understanding the relationship between innovation and income inequality reveals the importance of the social structure and the forms of economic intervention of the state. In his theory, Kuznets (1955) argues that income inequality initially increases in the process of economic development, but then starts to decrease when it reaches a level. The Kuznets curve provides an important model for understanding the cyclical relationship between innovation and growth and inequality. High income inequality is often associated with low social mobility and unequal educational opportunities, which negatively affects the potential for innovation. However, in Kuznets' model, the decline in inequality with economic growth can help create an environment that favours innovation.

On the other hand, Piketty (2014), in his work on the effects of modern capitalism on income inequality, emphasises the negative effects of social inequality on economic growth due to the inability of low-income groups to participate in innovative initiatives. Piketty's study reveals that more unequal societies are less willing to invest in developing and innovative industries. Piketty's findings suggest that, especially in societies with high income inequality, a more capitalist-orientated production approach can channel innovation only to certain elite groups, which can increase social tensions rather than economic growth.

In discussing the impact of income inequality on innovation, Baumol's (1990) theory of entrepreneurship also gains importance. Baumol argues that economic inequalities can create a motivation for innovation because lower income groups seek innovative solutions to achieve economic mobility. However, this positive relationship is only valid when inequality is at a certain level. High levels of inequality can increase social unrest and social tensions, which can lead to innovation being replaced by less efficient and riskier business models. Thus, Baumol's view provides an approach that demarcates between inequality that favours innovation and negative effects on innovation.

Moreover, the theory of inclusive and incentivising institutions developed by Acemoglu & Robinson (2012) provides an important theoretical framework to explain the relationship between income inequality and innovation. Acemoglu & Robinson argue that inclusive institutions provide opportunities to all segments of the society, thus enabling the encouragement of innovative initiatives. On the other hand, the existence of exclusive institutions, by enabling only elites to participate in innovative activities, hinders overall economic growth and increases social inequality. In this framework, the relationship between income inequality and innovation is directly related to the inclusiveness of institutions.

However, studies making cross-country comparisons also point out that low income inequality in developed economies increases innovation rates. It has been found that innovation rates in countries with low income inequality are significantly higher than in countries with high inequality. Such studies show how income inequality affects social development and innovation processes, especially through experiences in developed regions such as Western Europe and North America (Pinheiro, 2022). Societies with low inequality result in higher levels of education and more R&D investments, which in turn encourage innovation (Arocena & Sutz, 2003).

Another important study on the relationship between innovation and income inequality is based on Schumpeter's (1942) concept of creative destruction. Schumpeter argues that innovations are destructive innovations that transform the economic structure and replace old structures over time. However, for this creative destruction to take place, there must be sufficient economic resources and opportunities. In this context, in societies with high income inequality, the creative destruction capacity of innovations may remain limited. Because high inequality may limit the innovative potential by unfairly distributing resources among social groups.

In addition, Arrow's (1994) studies on knowledge economy are also important in understanding this relationship. Arrow states that knowledge-based economies require equal access to knowledge and the ability to use this knowledge in innovative processes. However, income inequality may have an inhibiting effect on innovation by restricting access to knowledge. Arrow's perspective reveals that when income inequality increases in society, innovative processes begin to serve the interests of only a certain elite group, which limits the wider social benefit.

In conclusion, there are many different theories and models in the literature explaining the relationship between income inequality and innovation. Most of these theories suggest that inequality can stimulate innovation at a certain level, but high levels of inequality can reverse the positive effects on innovation. The results show that income inequality shapes the nature of innovation by interacting with institutions, education levels, entrepreneurial activities and social infrastructures. In this context, it can be argued that innovation-related strategies should be aligned with policies aimed at reducing income inequality.

Method

Analysis of Data

In this study, discriminant analysis, one of the multivariate statistical techniques, was employed. Discriminant analysis is commonly used to develop a model that predicts group membership based on observed variables. The method constructs discriminant functions through linear combinations of predictor variables in order to achieve the highest possible level of separation between predefined groups (Çokluk et al., 2010: 105).

For the application of discriminant analysis, each observation must have values for one or more quantitative variables as well as a categorical variable indicating the group to which the observation belongs. Within this technique, quantitative variables are generally referred to as independent variables, discriminant variables, or predictor variables, while the categorical variable that determines group membership is defined as the dependent or criterion variable (Çokluk et al., 2010: 105). In the present study, the variables representing research and development (R&D) and innovation include industrial design applications (IDAPPNR), patent applications (PAPPNR), and trademark applications (TRAPPR). The main objective of the study is to examine the extent to which these R&D and innovation indicators can classify income inequality levels, which are considered as a proxy for development.

The dependent variable in the analysis is represented by the GINI index, which is widely used as an indicator of income distribution. The GINI index measures the degree to which income or consumption distribution among individuals or households in an economy deviates from a perfectly equal distribution. A value of 0 indicates complete equality, whereas a value of 100 reflects maximum inequality. The World Bank Group also emphasizes the importance of the GINI coefficient as a key contextual indicator for monitoring shared prosperity, defined as the income growth of the bottom 40 percent of the population (WBG, 2025a). The index ranges between 0 and 100; values closer to 0 indicate lower income inequality (and thus higher levels of development), while values approaching 100 signify greater inequality (and consequently lower levels of development).

This is primarily because the GINI data for 2022 and 2023 covers a very limited number of countries and does not provide a sufficient sample size for statistical analysis. In particular, a sufficient number of observations are needed in each group to conduct a robust discriminant analysis. As of 2021, there are 69 countries with GINI data, and evaluating these countries together with their data on independent variables provides advantages in terms of timeliness and methodological consistency. Therefore, the analysis was based on 2021 data and excluded data from other years.

In order to use the GINI index as the dependent variable of the study and to classify countries (e.g. undeveloped / underdeveloped, developing, developed), the lowest and highest GINI values between 1960 and 2023 were first analysed. The lowest and highest values of the GINI index were 20.7 and 65.8. In the data for 2021 used in this study, the lowest value of 24.1 and the highest value of 55.1 were determined (WBG, 2025b). Since it was aimed to categorise countries in 3 classes, firstly, an equal interval classification was made as 0.00 - 33.333 / 33.334 - 66.666 / 66.667 - 100, and in this classification, it was determined that countries were classified in only 2 groups (0.00-33.333: High inequality - undeveloped and 33.334 - 66.666: Moderate inequality / developing), and the number of countries in the third group (4) was not

4-5 times the number of independent variables. The dependent variable (GINI) has 2 groups and the number of countries included in the research is determined as 65.

In discriminant analysis, sample size, normal distribution, homogeneity of variance-covariance matrices, extreme values and multiple linear connection assumptions were checked. In discriminant analysis, 4-5 times the number of group elements is considered sufficient (Çokluk et al., 2010: 105). In this study, since the number of independent variables is 6 and the sample numbers in the groups are 36 and 29, the sample size is sufficient. Another requirement in the discriminant analysis is the normal distribution of the independent variables, and a singular normal distribution was provided by logarithmic transformations of the variables, and according to the Jarque-Bera test results (J-B=0,382; p=0,825), it was determined that the combination of independent variables showed a normal distribution (Appendix-1).

In the discriminant analysis, homogeneity of variance-covariance matrices was examined by Box's M test and homogeneity of variance-covariance matrices was determined (Appendix-2). Outlier control, which is another requirement, was performed with Mahalonobis test and according to the test results, there is no outlier (Appendix-3). Before the discriminant analysis, the multicollinearity problem was examined and it was determined that the tolerance and VIF values were at appropriate levels (tolerance >0.20 and VIF<10), in other words, the multiple normal distribution condition was met (Appendix-4).

Methodological Rationale

The decision to apply discriminant analysis in this study stems not only from the categorical nature of the dependent variable (level of income inequality), but also from the need to examine how multiple innovation-related variables collectively contribute to group differentiation. Unlike logistic regression, which models the probability of an outcome, discriminant analysis provides a more direct interpretation of which independent variables are most effective in distinguishing the identified groups. In this context, discriminant analysis provides both predictive accuracy and explanatory depth, providing insight into the relative strength and direction of each R&D indicator in distinguishing between countries with different levels of inequality. This method provides a comprehensive understanding of how innovation operates across broader socioeconomic classifications and supports the hypothesis that countries with higher innovation indicators exhibit lower income inequality. Therefore, the chosen methodology aligns well with both the research purpose and the theoretical assumptions underlying the study.

Findings

Group statistics are given in Table 1.

Table 1: Group statistics.

GINI Levels	Independent Variable	Mean	Sd	Unweighted	Weighted
	IDAPPNR	5,804	1,723	23	23
1	PAPPNR	4,420	2,812	23	23
	TRAPPR	9,491	1,807	23	23
	IDAPPNR	6,239	2,169	20	20
2	PAPPNR	7,047	2,848	20	20
	TRAPPR	10,773	2,029	20	20
	IDAPPNR	6,006	1,932	43	43
Total	PAPPNR	5,642	3,093	43	43
	TRAPPR	10,087	1,998	43	43

IDAPPNR: Industrial Design Applications; PAPPNR: Patent Applications; TRAPPR: Trademark Applications; GINI 1: High inequality / underdevelopment; GINI 2: Intermediate inequality / developing

According to the group statistics in Table 1, the average IDAPPNR score of GINI Level 1 countries is 5.80; the average IDAPPNR score of GINI Level 2 countries is 6.24. The average PAPPNR score of GINI Level 1 countries is 4.42; the average PAPPNR score of GINI Level 2 countries is 7.05. The average TRAPPR score of GINI Level 1 countries is 9.49; the average TRAPPR score of GINI Level 2 countries is 10.77. For the three independent variables of the research, the scores of GINI Level 2 countries are higher than Level 1 countries.
Table 2 shows the eigenvalue and canonical correlation findings.
Table 2: Summary of canonical discriminant functions.

Function	Eigenvalue	Variance	Canonical Correlation
1	0,340	100,0	0,503

In discriminant analysis, the eigenvalue also referred to as the characteristic root indicates how much variance in the dependent variable is explained by the discriminant function. Each discriminant function is associated with its own eigenvalue (Çokluk et al., 2010: 122). Because the dependent variable in this study consists of two categories, the analysis generated only a single discriminant function. One limitation in interpreting eigenvalues is that they do not have a defined upper boundary, which can make direct evaluation less straightforward (Çokluk et al., 2010: 123). Canonical correlation, on the other hand, represents the strength of the relationship between the groups defined by the dependent variable and the discriminant function. A canonical correlation value of zero indicates no association between the groups and the function, whereas higher values reflect a stronger relationship. As presented in Table 2, the analysis yielded one discriminant function with an eigenvalue of 0.340 and a canonical correlation of 0.503.
Table 3 shows the Wilks' Lambda statistic, the chi-square value and the significance level.
Table 3: Wilks' Lambda.

Test of Function	Wilks' Lambda	Chi-Square	df	p
1	0,747	11,547	3	0,009

Wilks' Lambda statistic and chi-square significance test results for the model in Table 3 show that the discriminant power of the function is significant ($p<0.05$) and that the groups can be separated by a discriminant function (Çokluk et al., 2010: 127).
Table 4 shows the standardised discriminant function coefficients and Wilks' Lambda equality of group means.
Table 4: Standardized canonical discriminant function coefficients and tests of equality of group means.

Independent Variable	SCDC (Function 1)	Structure Matrix (Function 1)	Wilks' Lambda	F	df1	df2	p
IDAPPNR	-0,872	0,196	0,987	0,536	1	41	0,468
PAPPNR	1,278	0,814	0,816	9,229	1	41	0,004
TRAPPR	0,223	0,587	0,895	4,803	1	41	0,034

IDAPPNR: Industrial Design Applications; PAPPNR: Patent Applications; TRAPPR: Trademark Applications; SCD: Standardized canonical discriminant coefficient

Standardized discriminant function coefficients indicate the relative contribution of each independent variable to the discriminant function when predicting the dependent variable. In

other words, they reflect the unique effect of each predictor within the model while controlling for the influence of the other variables. In this respect, standardized discriminant coefficients are conceptually similar to beta coefficients used in regression analysis (Çokluk et al., 2010: 123). The structure matrix coefficients show the relationship of each variable with the discriminant function and are used to evaluate the importance of independent variables. These are Pearson correlation coefficients pooled within-group and are also called ‘correlations’ or ‘discriminant loadings’ (Çokluk et al., 2010: 124). According to the standardised canonical discriminant functions and structure matrix coefficients in Table 4, the most important independent variables in distinguishing the groups are PAPNR and TRAPPR. When the Wilks' Lambda statistics of the effects of these variables were analysed, it was found that similar to the structure matrix, the PAPPNR variable (λ=0,816; F=9,23; p=0,004) had the most significant effect, followed by TRAPPR ((λ=0,895; F=4,80; p=0,034), and the IDAPPNR coefficient was not statistically significant (did not have a significant effect) (p>0,05).
Table 5 shows the classification results.

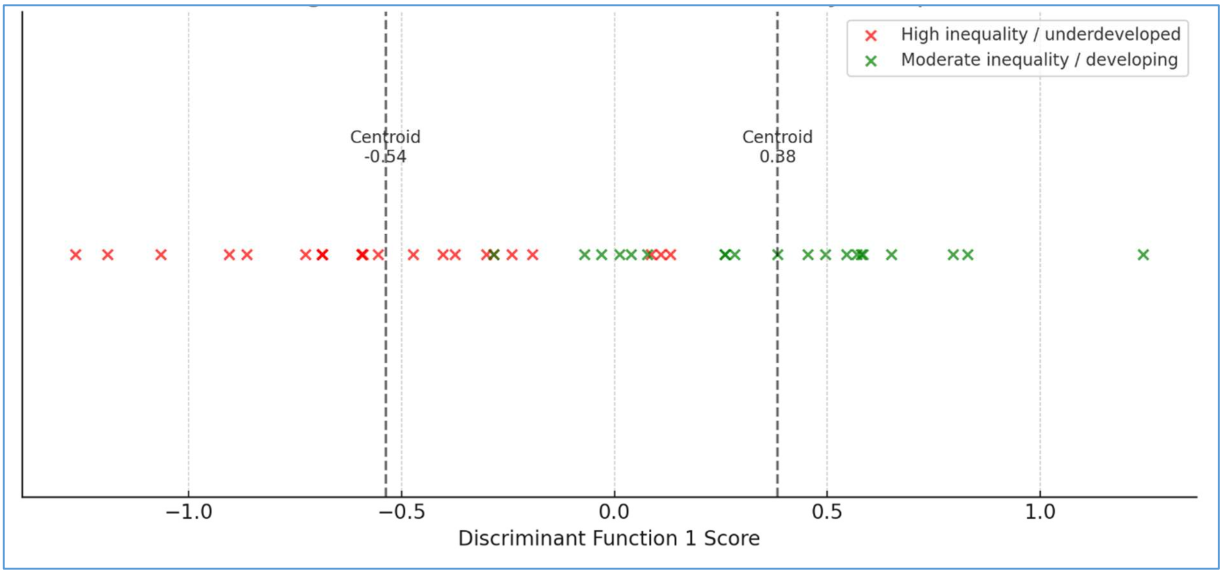
Table 5: Classification results.

	Level 1		Level 2		Total	
GINI Levels	f	%	f	%	f	%
1	17	73,9	6	26,1	23	100,0
2	4	20,0	16	80,0	20	100,0
Total correct classification			%76,7			

Level 1: High inequality / underdevelopment; Level 2: Intermediate inequality / developing

According to the classification results in Table 6, 73.9% of GINI Level 1 countries (high inequality / undeveloped) and 80% of GINI Level 2 countries (moderate inequality / developing) were correctly classified by the independent variables of the research. The total correct classification percentage of the discriminant function was determined as 76.7% and according to these results, ‘industrial design’, ‘patent’ and ‘trademark’ applications can classify countries with high accuracy in terms of development. In other words, it can be said that there is a high relationship between the development of a country and the importance it attaches to R&D and innovation.
In addition to the classification findings, relative chance criteria and maximum chance criteria were calculated to evaluate the classification accuracy. There are 43 samples in the classification table, 23 of which are in GINI Level 1 and 20 of which are in GINI Level 2. In this case, the chance ratio is between 46.5% and 53.5%. Considering that the 76.7% correct classification value obtained as a result of the analysis is greater than 53.5%, it is determined that the classification accuracy of the analysis is higher than the chance criterion. In other words, it is understood that the obtained discriminant function makes correct classification beyond the classification by chance.
To increase the clarity and interpretability of the discriminant analysis findings, a visual representation of the group separation based on the discriminant function is presented in Figure 1. As recommended in the methodological literature, visualizing the discriminant scores via a scatter plot or canonical plot improves the understanding of how well the model discriminates between predefined groups. The inclusion of this figure provides a more intuitive grasp of the underlying structure of the data and supports the interpretation of basic statistics such as canonical correlation, Wilks' Lambda, and classification accuracy.

Figure 1: Discriminant Function Plot of Group Segregation by R&D and Innovation Variables



This figure presents the distribution of countries along the discriminant function axis, clearly showing how R&D and innovation indicators differentiate countries with high and medium income inequality. The visual depiction of group separation not only supports statistical outputs such as canonical correlation and classification accuracy, but also provides an intuitive understanding of the discriminant power of the model.

Limitations

This study has some limitations. Firstly, the time span and geographical coverage of the data set used are limited. The study analyses cross-country income inequality and R&D data for a specific time period (e.g. the last 10 years). This may lead to an incomplete reflection of long-term effects or different period dynamics. Moreover, the fact that the dataset is mostly based on developed economies may lead to the underestimation of the effects of R&D and innovation levels in developing and low-income countries. Another limitation is that the study focuses only on the relationship between income inequality and R&D activities. However, R&D and innovation processes are influenced by many other factors, such as policy, cultural factors, education level and labour skills. Ignoring these factors may prevent the results of the study from having full general validity. Finally, the scope of the study is limited to address only the link between income inequality and innovation. A more comprehensive analysis of the social, environmental and cultural impacts of innovative processes has not been conducted. This means that the study only addresses the part of the study related to economic growth and development, while excluding other societal factors. In future studies, it is recommended to use larger data sets and more comprehensive methodologies to overcome these limitations.

Conclusion

In this study, how R&D and innovation components may affect income inequality is examined by discriminant analysis method. The findings show that R&D and innovation, especially patent and trademark applications, play an important role in classifying income inequality. The study revealed that countries with higher levels of R&D and innovation will show lower income inequality, reflecting more developed economies. This result is consistent with previous studies in the literature; in particular, researchers such as Aghion et al. (1999) suggest that inequality up to a certain level can stimulate innovation and economic growth, while extreme inequality can negatively affect this effect. In this study, the findings confirming the relationship between income inequality measured by the Gini index and R&D investments suggest that low inequality in developed economies has the potential to stimulate innovation.

In addition to supporting existing theories, this study contributes to the growing literature examining the intersection between income inequality and innovation, and suggesting that reducing inequality can stimulate innovation and enhance economic development.
In contrast, some studies argue that innovation is not always uniformly beneficial in reducing inequality. For example, Sun et al. (2024) argues that technological innovation can sometimes exacerbate income inequality by disproportionately benefiting those at the top of the economic ladder. According to Sun et al. (2024), innovation can create monopolies or lead to a 'winner-take-all' economy where the rich benefit the most from new technologies, widening the income gap. This nuanced view suggests that while R&D and innovation can contribute to economic growth, they may not always result in a more equitable income distribution without appropriate regulation or redistributive mechanisms. Therefore, the findings of this study should be considered in light of the broader debate in the literature on whether innovation necessarily reduces inequality or merely reinforces existing inequalities (Aghion et al., 2018).
Furthermore, the results are consistent with the work of Acemoglu & Robinson (2012) who argue that inclusive institutions that provide access to education, healthcare and innovation opportunities are important in reducing income inequality. Our findings support the idea that innovation can be a vehicle for economic and social mobility, but only when the benefits of innovation are widely shared across society. Acemoglu & Robinson emphasize the importance of inclusive institutions in shaping the distribution of technological benefits, arguing that R&D investments can reduce inequality when accompanied by policies that promote access to education and health care. This framework suggests that the relationship between R&D, innovation, and income inequality is a function not only of economic conditions but also of the institutional structures that shape how innovation benefits society.
Furthermore, the results support the findings of Law et al. (2020), who argue that the benefits of innovation are more pronounced in societies where income distribution is relatively equal. Law et al. (2020) argue that innovation not only drives economic growth but also contributes to greater social mobility, particularly in societies with lower levels of inequality. Our study's confirmation of this relationship between R&D investment and lower income inequality further underscores the importance of fostering environments where innovation can thrive in conjunction with a more equitable income distribution. Therefore, our results highlight the dual importance of innovation policies and inclusive economic institutions in reducing income inequality.
In conclusion, while the findings of this study support the view that R&D and innovation play an important role in reducing income inequality, they also highlight the complexities of this relationship. As shown by Tang et al. (2022), without appropriate institutional support, innovation can worsen rather than alleviate inequality. Therefore, for R&D and innovation to effectively reduce income inequality, policies must ensure that the benefits of innovation are widely distributed and that economic institutions are inclusive. Future research should examine the role of government intervention in ensuring that technological advances contribute to reducing rather than increasing inequality, particularly in developing economies where institutional frameworks are still developing.

Discussion

The findings of the study explain in detail how economies match their development levels. For example, it is seen that innovation rates are higher in countries with low income inequality, which supports economic growth. This finding supports Kuznets's (1955) theory, because according to Kuznets's model, income inequality may initially increase during the economic development process, but at a certain point it begins to decrease, creating an environment that encourages innovation. The results of our study show that this cyclical relationship is observable.

However, contributions from researchers such as Piketty (2014) and Schumpeter (1942) also have an important place in the study. Piketty's findings that income inequality limits participation in innovative initiatives are consistent with our findings. The possibility that in countries with high inequality, state interventions or elite-focused investments limit innovative processes, but certain local initiatives can flourish has been emphasized in some studies (Aghion et al., 1999). This situation indicates that innovation is not only driven by elites, but also that social participation plays an important role. Especially in countries with high income inequality, innovative initiatives may be limited as the capitalist-oriented production approach may direct innovation only to elite groups. Similarly, Schumpeter's concept of creative destruction shows that innovations have the power to transform the economic structure, but high inequality limits this power. In our study, it has been observed that high levels of inequality may limit the potential for innovation.

Another important finding is that in developed economies, low income inequality is associated with higher education levels and more R&D investment. In addition, studies by Tian & Xiang (2024) have also shown that income inequality is an important strategy not only for achieving social justice, but also for economic growth and innovation. The interactions of education levels, R&D investments, and government policies on innovation allow us to understand how these factors interact with each other.

In conclusion, the findings of this study reveal that reducing income inequality is a fundamental requirement for sustainable development and innovation. It is emphasised that R&D and innovation are important driving forces in the process of economic development and social development, but extreme income inequality can negatively affect these processes. In this context, the development of policies by governments and international organisations to reduce income inequality will ensure that both economic growth and innovation processes will be more sustainable. Moreover, in future studies, the use of larger data sets and cross-country comparisons may help to obtain more in-depth insights on this issue.

Theoretical Recommendations

This study provides important theoretical contributions to understanding the relationship between income inequality and R&D and innovation. First, the effect of income inequality on innovation can be addressed within the framework of Kuznets's theory of economic development and Schumpeter's concept of creative destruction. The finding that R&D investments can develop more efficiently in environments with low income inequality indicates that these relationships should be examined in more depth in theoretical terms. In addition, Piketty's findings on income inequality reveal that lower levels of inequality create an encouraging effect on innovation. In this context, the theoretical literature should focus more on the inequality-growth relationship and the practical validity of existing theories should be evaluated.

Practical Recommendations

From a practical perspective, it is important for policy makers to develop strategies to reduce income inequality in order to encourage R&D and innovation activities. Since countries with low levels of inequality generally have greater innovative success, it may be useful to take policy practices in these countries as examples. Policies to increase education levels and support innovative ecosystems will allow for increased R&D investments and a more equitable income distribution. In addition, increasing incentives for private sector R&D activities should be among the steps to reduce inequality. Incentives that provide more support for R&D investments and patent applications will increase innovative initiatives while also reducing income inequality.

Recommendations for Policy Makers

For policy makers, developing policies to reduce income inequality will ensure that economic growth and sustainable development goals are achieved more soundly. In particular, factors that directly affect income inequality - education, health services and labor market reforms - should be a priority in this context. Governments need to implement policies that support R&D activities and innovation ecosystems. R&D budgets need to be distributed more fairly so that low-income groups can also be included in innovation processes. In addition, strengthening R&D capacity in regions with low inequality will support regional development and sustainable economic growth. In addition, policy makers should focus on increasing entrepreneurship support in regions with high income inequality, thus increasing innovative initiatives and investments.

Strategic Recommendations for Entrepreneurs and Policymakers

Successful R&D and innovation policies from different countries provide guidance for the development of AI-enabled entrepreneurship. For example, South Korea has expanded R&D investments with a regional development focus by encouraging public-private partnerships under its "Creative Economy" strategy (Lee, 2020). Germany has supported the digitalization of industrial enterprises through its "Industrie 4.0" initiative, enabling the adoption of AI-based production models (Kinkel et al., 2022). Canada is supporting academic research through its "Pan-Canadian Artificial Intelligence Strategy" while also allocating direct public funds to AI initiatives (Attard-Frost et al., 2024). Finland has integrated human-centered leadership models into its digital transformation policies, focusing on education, ethics, and workforce transformation in its national AI roadmap (Salo-Pöntinen & Saariluoma, 2022). Israel is supporting the rapid growth of small enterprises with AI-enabled venture capital systems that combine entrepreneurship and defense Technologies (Schwarz, 2025). These examples show that entrepreneurship policies should be addressed holistically, not only in terms of financial support but also education, ethical governance, digital infrastructure and regional equality.

Recommendations for Future Research

Future research should address the relationship between R&D and innovation and income inequality with larger data sets. In particular, comparisons should be made between developed and developing countries, and the effects of innovation activities in different sectors on income inequality should be investigated. In addition, more comprehensive analyses should be conducted by considering not only the economic but also the social impacts of R&D investments. In addition, more case studies should be conducted on the impact of cross-country policies on reducing income inequality and encouraging innovation. Future studies should address in more detail how innovative policies can reduce income inequality and increase social benefits. In addition, studies in this area should be conducted to increase the methodological diversity and use more powerful data analysis techniques.

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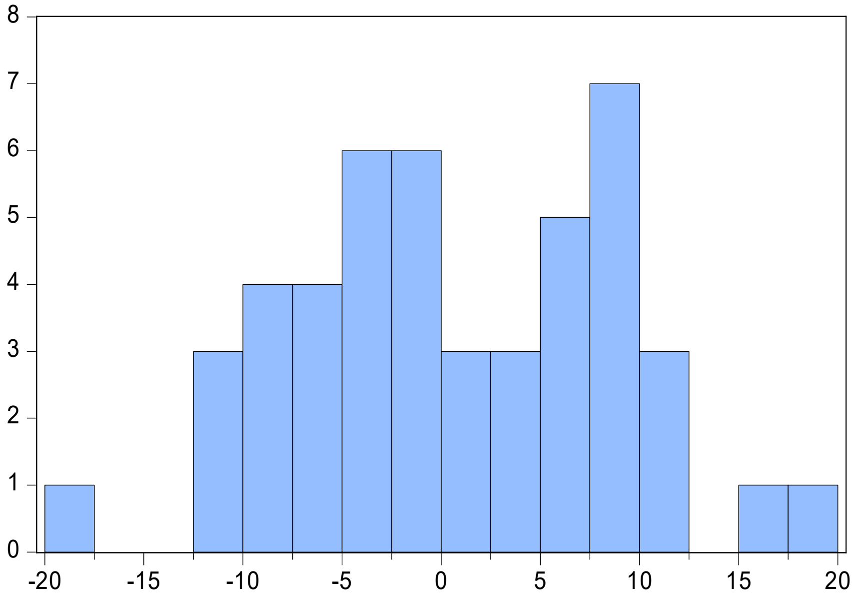
ANNEX-1 Normal distribution

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
IDAPPNR_nrm	102	,00	10,75	5,6848	2,11580	-,153	,239	,284	,474
PAPPNR_nrm	118	,00	12,70	5,2543	2,97074	,295	,223	-,707	,442
TRAPPR_nrm	119	1,10	16,03	8,5472	2,77651	-,463	,222	,404	,440
Valid N (listwise)	90								



Series: Residuals	
Sample 7 198	
Observations 47	
Mean	0.872494
Median	-0.265792
Maximum	19.69596
Minimum	-18.39058
Std. Dev.	8.158333
Skewness	0.032238
Kurtosis	2.562570
Jarque-Bera	0.382859
Probability	0.825778

ANNEX-2 Box's-M Equality of Covariance Matrices

Test Results

Box's M		9,637
F	Approx.	1,477
	df1	6
	df2	11512,798
	Sig.	,182

Tests null hypothesis of equal population covariance matrices.

ANNEX-3 Outliers

Descriptives

			Statistic	Std. Error
Mahalanobis Distance	Mean		2,9662921	,26107812
	95% Confidence Interval for Mean	Lower Bound	2,4474542	
		Upper Bound	3,4851300	
	5% Trimmed Mean		2,7266877	
	Median		2,3464084	
	Variance		6,066	
	Std. Deviation		2,46300605	
	Minimum		,19275	
	Maximum		10,48767	
	Range		10,29492	
	Interquartile Range		2,46433	
	Skewness		1,445	,255
	Kurtosis		1,616	,506

Extreme Values

			Case Number	Value
Mahalanobis Distance	Highest	1	46	10,48767
		2	52	10,46288
		3	37	9,92478
		4	74	9,37400

	5	92	8,92693
Lowest	1	56	,19275
	2	54	,26372
	3	58	,29688
	4	12	,38887
	5	42	,40810

ANNEX-4 Multicollinearity

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta	Tolerance	VIF	B	Std. Error
1	(Constant)	104,361	40,521		2,575	,012		
	IDAPPNR_nrm	-3,783	5,389	-,107	-,702	,485	,494	2,026
	PAPPNR_nrm	1,127	4,147	,044	,272	,787	,447	2,238
	TRAPPR_nrm	3,479	6,200	,097	,561	,576	,387	2,583

a Dependent Variable: no