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Structural equation modeling (SEM) in Jamovi: An example of analyzing the impact of factors on enterprise innovation activity

Abstract

The aim of this study is to demonstrate the capabilities of the Jamovi software in analyzing complex economic models, using the case of examining the impact of various factors on enterprise innovation activity. Structural Equation Modeling (SEM) was employed to identify both direct and mediated relationships among economic and digital infrastructure, factors related to research and development (R&D), and innovation activity. The analysis results confirmed the positive impact of economic infrastructure on the level of R&D and the innovation activity of enterprises, as well as the mediating role of R&D factors in transmitting the effects of infrastructure. Meanwhile, the influence of digital infrastructure was found to be weak, highlighting the need for further development of digital technologies and their integration into economic activities. The findings and methodology of the study can be utilized to enhance the competitiveness of enterprises and to develop effective measures for state support of innovation activities in various regions.

1. INTRODUCTION

Modern economic research requires the analysis of complex interrelationships among numerous socio-economic indicators (Ratner at al., 2024; Mansoor et al., 2022; Relich et al., 2022). One of the key methods capable of addressing dependencies between multiple independent and dependent variables is Structural Equation Modeling (SEM). This method enables researchers to test theoretical models that include latent variables measured through observed indicators.

SEM emerged in the 1960s, integrating elements of factor analysis and regression (Kaplan, 2000). Initially applied in psychology and sociology, SEM has become an indispensable tool in economic research due to advances in computer technologies and statistical approaches (Shahzad et al., 2024). Modern SEM techniques enable the analysis of large datasets and the consideration of complex structures, making the method valuable for both theoretical and applied analyses.

Among the software supporting SEM, Mplus, SPSS, Stata, Statistica, and Jamovi stand out, each offering unique analytical capabilities. Mplus and SPSS are widely used for analyzing latent variables in a broad spectrum of economic studies, including innovation management and corporate sustainability (Dewantara et al., 2024; Jiang & Papi, 2024). However, the complexity of their interfaces, the requirement for specialized programming skills, and the high cost of these programs limit their accessibility for novice researchers.

Jamovi, in contrast, stands out for its accessibility, ease of use, and free open access, making it available across various operating systems. Its intuitive interface and integration with R enable efficient application to complex economic models. For instance, Ahmed and Muhammad (2021) demonstrated how Jamovi can be utilized to analyze the economic activity of enterprises, highlighting its convenience for researchers. Eser (2022) showcased the advantages of Jamovi in testing data heterogeneity and model fit indices, emphasizing its superiority over Meta-Essentials. Caldwell (2022) noted the utility of the SimplyAgree module, integrated with Jamovi, for assessing data consistency and reliability—critical aspects of quantitative research.

Recent studies further confirm the versatility of Jamovi. Yangailo et al. (2024) illustrated how Jamovi's integration with R enhances its capabilities for testing complex econometric models. Alqahtani et al. (2024) employed Jamovi to analyze social and economic factors influencing sustainable safety in the construction sector. Moreover, Jamovi is increasingly used for SEM analysis across various disciplines. Recent studies have utilized the software to model relationships in behavioral economics, marketing, and human resource management, highlighting its flexibility and extensive analytical capabilities (Adiguzel et al., 2025; Kim & Jeong, 2024; Sardohan Yildirim et al., 2025). These examples underscore Jamovi's cost-effectiveness, versatility, and growing relevance in economic research.

A review of studies has confirmed that SEM is a key tool for analyzing complex interrelationships in economics. This method enables the consideration of both exogenous and endogenous variables that jointly influence multifaceted phenomena such as the innovation activity of enterprises. Due to its capacity to analyze latent variables, SEM remains an indispensable tool for studying processes that require a comprehensive approach.

With the growing volume of data and the increasing complexity of research tasks, modern studies demonstrate a rising demand for tools that combine accessibility, robust analytical capabilities, and an intuitive interface. Jamovi, with its free accessibility and integration with the R programming language, offers unique solutions for analyzing complex economic models. However, its practical application in the context of SEM, particularly for economic research, remains relatively underexplored. This study aims to address this research gap.

Innovation activity, as a key factor in enterprise competitiveness, depends on numerous interrelated factors, including organizational culture, investment levels, and the adoption of modern technologies. Analyzing these determinants requires methods capable of identifying both direct and mediated effects. SEM effectively addresses this task, providing researchers with the ability to analyze complex interrelationships and test hypotheses about the influence of various factors. Similar conclusions were drawn in studies investigating the impact of organizational culture (Shahzad et al., 2024), investment levels (Forés & Fernández-Yáñez, 2024), and technological infrastructure (Chen et al., 2024) on enterprise competitiveness.

The choice of Jamovi for this study is justified by its unique advantages, including an intuitive interface, ease of use, and integration with powerful statistical tools. Unlike paid alternatives such as SPSS or Mplus, Jamovi provides free access to a wide range of functions, including model testing, fit indices evaluation, and data heterogeneity analysis. These features make it an optimal choice for implementing SEM analysis.

The purpose of this study is to demonstrate the capabilities of Jamovi through an example of analyzing the impact of various factors on enterprise innovation activity. This research not only illustrates the program's potential for analyzing complex models but also provides valuable insights for developing innovation management strategies that enhance the competitiveness of modern organizations.

2. METHODOLOGY

2.1. The data

To analyze the relationships between factors influencing enterprise innovation activity, data were collected from 20 regions of Kazakhstan over the period from 2014 to 2023, resulting in a panel dataset of 200 observations. The selection of these regions was based on their relevance to the study of innovation activity, ensuring a diverse representation of economic conditions. The dataset includes both highly industrialized regions, such as Almaty, Astana, and Karaganda, as well as regions with varying levels of innovation potential. This approach allows for a more comprehensive analysis of the factors driving enterprise innovation across different economic contexts. The data sources include official statistical reports from the Committee on Statistics of the Republic of Kazakhstan, industry-specific studies, and regional economic reviews. All variables were carefully selected based on their theoretical significance for studying enterprise innovation activity.

Preliminary data normalization using the Z-score method in Excel was performed to eliminate significant differences in variable scales, bringing them to a common scale with a mean of zero and a standard deviation of one. However, normalization is not always mandatory. If the variables are measured on the same scale and have a similar order of magnitude, normalization can be omitted without compromising the accuracy of the model.

To enhance the reliability of the analysis, multicollinearity checks were performed. Two methods were employed: constructing a correlation matrix and calculating Variance Inflation Factor (VIF) values in Jamovi. The correlation matrix identified variables with high correlations (values exceeding 0.7), indicating potential multicollinearity issues. Variables with strong correlations were either excluded or combined into latent factors to account for their joint effects. Additionally, VIF values exceeding the threshold of 10 served as criteria for revising the data structure.

As a result of data preprocessing, groups of variables were formed to minimize mutual influence, thereby improving the stability and interpretability of the model. After normalization and verification, the data were deemed suitable for conducting SEM analysis in Jamovi.

2.2. Preparing variables before analysis

Jamovi supports data import in various formats, including .csv (a text format for transferring data from Excel and other programs), .xlsx (Microsoft Excel format for direct import without prior conversion), .sav (SPSS format for working with data from this software), .ods (OpenDocument Spreadsheet format for LibreOffice and OpenOffice), and .jmv (Jamovi's internal format that preserves data and variable settings). To upload data into Jamovi, navigate to the File → Open menu, select the appropriate file, and ensure that the data structure is displayed correctly (Jamovi Project, 2023).

After importing the data into Jamovi, it is essential to verify that each variable is assigned the correct measurement type and data format. For SEM, all variables must be set as "Continuous" with a data type of "Decimal." This can be checked in the variable section, where each variable should display an icon resembling a ruler. If the icon is missing, the parameters can be manually adjusted through the variable editing menu (Figure 1).

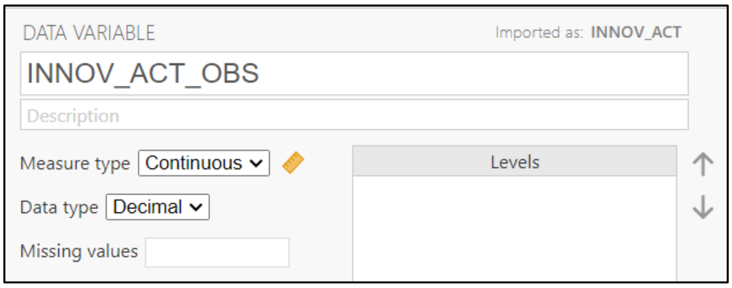

Fig. 1. Setting up variable parameters in the Jamovi program

It should be noted that to conduct SEM in Jamovi, the "semlj – SEM" module (version 1.2.4) was installed. This module, based on the lavaan library, provides functionality for SEM analysis, including the calculation of latent variables, hypothesis testing, and evaluation of model fit indices. The module can be installed through the Modules → Available tab, where it is available for download and installation (Figure 2).

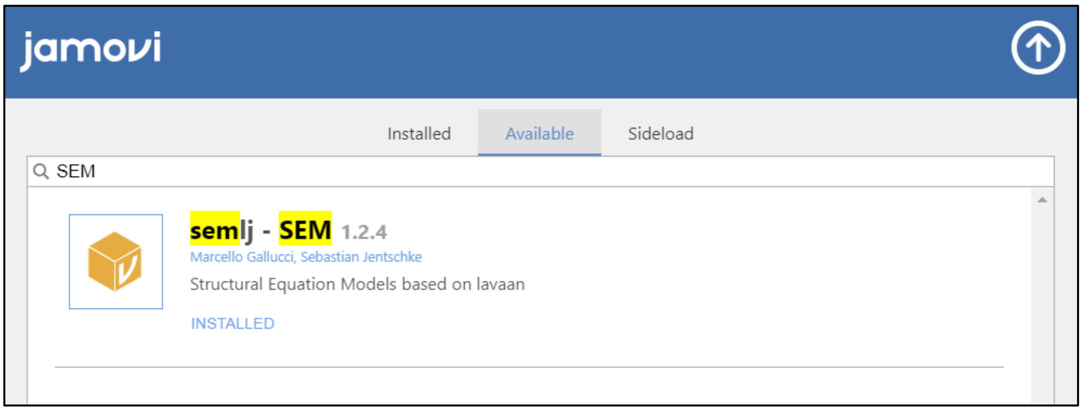

Fig. 2. Window for installing the semj module - SEM in the Jamovi program

The use of this module provides a convenient and intuitive solution for implementing SEM analysis, leveraging the graphical interface of Jamovi. This interface allows users to visually define the model, add latent variables, establish relationships between variables, and configure analysis parameters. This tool not only reduces the time required for preparing the analysis but also ensures the representativeness and transparency of the results, which is particularly important in the context of economic research.

2.3. Model structure

In SEM, variables are divided into exogenous and endogenous variables, which helps structure the model and clearly highlight the relationships between factors.

Exogenous variables (EXO) represent independent factors that influence other variables in the model but are not influenced by other factors. In this study, exogenous variables are grouped into two latent categories: economic infrastructure (EXO_ECON) and digital infrastructure (EXO_DIGITAL).

Endogenous variables (ENDO) are dependent variables explained by exogenous variables and/or other endogenous variables. In this study, endogenous variables include R&D factors (ENDO_RND) and innovation activity of enterprises (ENDO_INNOV), which serves as the final outcome of the model.

This approach is based on the classical concept of causal modeling, as described in Bollen (1989), which views exogenous variables as independent inputs into the system and endogenous variables as outputs or results shaped by the interaction of factors. The application of this concept allows for the correct interpretation of causal relationships within the model.

A detailed structure of latent and observed variables is provided in the following table.

Tab. 1. Structure of latent and observed variables used in the model

Latent variables	Observed variables		Description of variables
EXO_ECON	GRP_PC	Gross Regional Product (GRP) of the region divided by the population, tenge/person	Describes the level of economic development of regions
	INV_CAP	Capital investments as a share of total GRP, %	
	EMP_RATE	Number of employed individuals in the working-age population, %	
EXO_DIGITAL	CLOUD_USE	Number of enterprises using cloud technologies as a share of total enterprises in the region, %	Reflects the level of digitalization of enterprises
	BIGDATA_USE	Number of enterprises using big data analytics as a share of total enterprises in the region, %	
ENDO_RND	RND_EXP	Share of R&D expenditures in GRP, %	Characterizes the intensity of research and development processes in regions
	RND_EMP	Number of employees working in R&D, persons	
ENDO_INNOV	INNOV_ACT_OBS	Number of enterprises implementing innovations as a share of total enterprises in the region, %	Represents an observed variable that assesses the share of innovation-active enterprises

Thus, based on the presented data and the formed latent variables, the model structure was built in Jamovi. The variables were grouped according to the research hypothesis using the previously mentioned "semlj – SEM" module (described in detail in Section 2.2).

The following hypotheses were tested within this model:

H1: Economic infrastructure has a positive impact on R&D factors.

H2: R&D factors act as significant mediators between economic infrastructure and innovation activity.

H3: Digital infrastructure has a significant impact on R&D and innovation activity.

Figure 3 illustrates how the model structure was implemented in the Jamovi interface. The visualization includes latent variables, their indicators, and the key relationships corresponding to the research hypotheses.

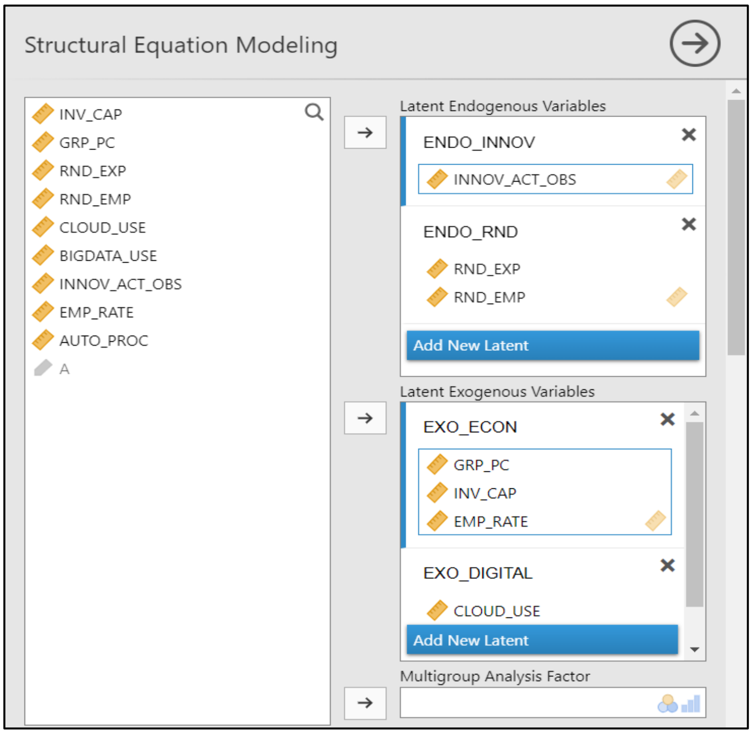

Fig. 3. The structure of latent variables and their indicators in the Jamovi program interface

The next step in implementing the model structure in Jamovi involves establishing relationships between the latent variables. This process was based on the theoretical justifications and research hypotheses outlined above.

2.4. Establishing relationships between variables

The relationships between variables in SEM can be direct, indirect (mediating), or covariance-based. These relationships form the foundation of the model, allowing the researcher to test hypotheses regarding the influence of various factors on target variables.

Direct effects describe the immediate influence of one variable on another. In this study, it is hypothesized that economic infrastructure (EXO_ECON) has a direct impact on the level of R&D (ENDO_RND) and innovation activity of enterprises (ENDO_INNOV). The impact of digital infrastructure (EXO_DIGITAL) on R&D and innovation activity is also examined.

Indirect effects occur when one variable affects another through intermediate factors. In this model, it is assumed that R&D factors (ENDO_RND) act as mediators between economic infrastructure (EXO_ECON) and innovation activity (ENDO_INNOV). Additionally, the potential influence of digital infrastructure on innovation activity through R&D is evaluated, which helps identify the mechanisms of interaction between exogenous and endogenous variables.

Covariance relationships describe the correlation between exogenous variables, which may be driven by common external factors or data-specific characteristics. In this model, the covariance between economic infrastructure (EXO_ECON) and digital infrastructure (EXO_DIGITAL) is assumed, allowing for the consideration of the interconnectedness of these factors.

Based on SEM, a model was developed that reflects the relationships between economic and digital infrastructures, R&D factors, and the innovation activity of enterprises. The figure illustrates the main relationships and covariances used in the model.

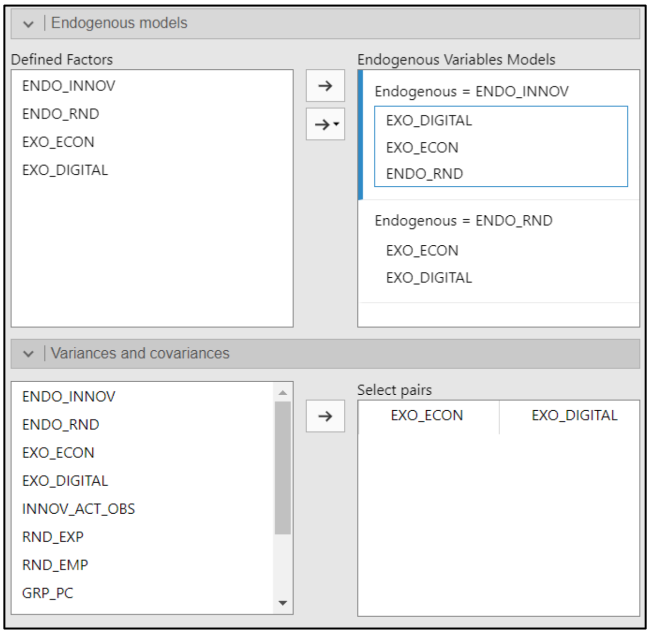

Fig. 4. Structural model settings: Relationships and covariances in SEM

The theoretical foundation of the model is based on the approach by Kenny and Kashy (1992), which describes three levels of causal relationships: descriptive (describing relationships), predictive (identifying likely effects), and causal (testing causal links). This approach enables the connection of research hypotheses with existing theoretical and empirical frameworks.

In this study, economic and digital infrastructures are considered as factors that exert both direct and indirect (through R&D factors) influence on innovation activity. The model settings were developed according to these hypotheses and are illustrated in Figure 4. For a more detailed analysis, Table 2 presents the types of relationships, their model representation, and theoretical interpretation. This approach allows for reflecting both direct and mediated effects of variables, as well as their interrelationships.

Tab. 2. The structure of latent and observed variables used in the model

Type of connection	Model connection	Interpretation
Direct connection	ENDO_INNOV ~ EXO_DIGITAL	Influence of digital infrastructure on the innovation activity of enterprises
Direct connection	ENDO_INNOV ~ EXO_ECON	Influence of economic infrastructure on the innovation activity of enterprises
Direct connection	ENDO_INNOV ~ ENDO_RND	Impact of R&D factors (expenditures and personnel) on the innovation activity of enterprises
Direct connection	ENDO_RND ~ EXO_ECON	Impact of economic infrastructure on R&D factors
Direct connection	ENDO_RND ~ EXO_DIGITAL	Impact of digital infrastructure on R&D factors
Covariance	EXO_ECON ~~ EXO_DIGITAL	Interrelation between economic and digital infrastructures caused by their complementary effects
Latent variables	EXO_ECON =~ GRP_PC + INV_CAP + EMP_RATE	A latent variable describing economic infrastructure through indicators such as Gross Domestic Product (GDP) per capita, the share of investments in GDP, and employment rat
Latent variables	EXO_DIGITAL =~ CLOUD_USE + BIGDATA_USE	A latent variable describing digital infrastructure through the use of cloud technologies and big data analytics
Latent variables	ENDO_RND =~ RND_EXP + RND_EMP	A latent variable describing R&D factors through expenditures and personnel involved in research and development
Latent variables	ENDO_INNOV =~ INNOV_ACT_OBS	A latent variable describing innovation activity through the observed indicator of activity.

The table provides the theoretical basis for interpreting the connections and covariances in the SEM model. Each connection and covariance is justified by relevant theoretical and empirical data, as well as reflecting the research hypotheses.

3. RESULTS AND DISCUSSION

After completing all the settings described in the "Methodology" section, the Jamovi software automatically performs SEM calculations and displays the results on the right side of the panel. Among the provided data are overall model fit indices, parameter estimates, information on the connections between latent variables and observed indicators, covariances between the model variables, and intercept values. These results require careful interpretation to determine whether the model aligns with theoretical assumptions and empirical data.

3.1. Overall model fit

The quality of the structural model is evaluated using fit indices, which indicate how well the model matches the empirical data. Contemporary studies (Cheung et al., 2024; Sarkar et al., 2021; Wongsansukcharoen & Thaweepaiboonwong, 2023) highlight the importance of using multiple metrics for a comprehensive assessment of the model, such as Chi-square test (χ^2), Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI). These indices provide unique insights into how well the model corresponds to real data, enabling researchers to draw well-founded conclusions.

The main metrics calculated to evaluate the model's fit are presented in Table 3. These metrics demonstrate that the constructed model meets adequacy criteria and can be used to test the research hypotheses.

Tab. 3. Key metrics of model fit quality

Metric	Standard	Result	Interpretation
Chi-square test (x^2)	Low value, $p > 0.05$	$x^2 = 8.26$ $p = 0.311$	Model fits data well
RMSEA	< 0.05 (good fit), < 0.08 (acceptable)	0.039	Good fit, CI interval CI (0.000–0.123)
SRMR	< 0.08	0.041	Excellent fit of model to data
CFI	> 0.95	0.993	High degree of agreement of model to data
TLI	> 0.95	0,979	Model demonstrates good fit
NNFI	> 0.90	0.979	Model meets quality criteria
IFI	> 0.90	0.994	Confirms high adequacy of model
PNFI	> 0.50	0.320	Low value due to complexity of model, but acceptable

The chi-square test (χ^2) evaluates the model's fit to empirical data, where a high p-value ($p > 0.05$) indicates a good fit. However, this criterion is sensitive to sample size and may detect statistically significant but practically insignificant deviations (Huang et al., 2024).

Residual fit indices, such as RMSEA and SRMR, measure the discrepancy between the model and the observed data. RMSEA assesses the degree of model approximation, where values below 0.05 indicate a good fit and values below 0.08 are considered acceptable (Codina et al., 2024). SRMR reflects the average discrepancy between predicted and observed covariances, with values below 0.08 confirming the model's adequacy. However, as noted by Nordhoff et al. (2021), fit indices such as RMSEA and SRMR can vary depending on the complexity of the model and its parameters, highlighting the importance of using multiple indices to ensure reliable conclusions.

To assess the model's fit to empirical data, comparative fit indices such as CFI and TLI are also used. CFI measures the degree of model improvement compared to a baseline model, while TLI adjusts CFI by accounting for model complexity. In both cases, values above 0.95 indicate a good fit to the data (Mai et al., 2021).

Additionally, NNFI (Non-Normed Fit Index), IFI (Incremental Fit Index), and PNFI (Parsimonious Normed Fit Index) were calculated. NNFI accounts for model complexity, while IFI compares the tested model against a null model. Both indices indicate an acceptable fit if their values exceed 0.90. PNFI, in turn, considers model complexity and is used as an additional measure of fit quality.

Using multiple fit indices provides a comprehensive model evaluation, as each captures different aspects of model-data correspondence. The calculated metrics confirm the adequacy of the constructed model and its suitability for further analysis.

Figure 5 presents a visualization of the model evaluation results automatically generated by the Jamovi software. This graph reflects the key model fit metrics and serves as a standard tool for interpreting the results of structural equation modeling.

Overall Tests

Model tests

Label	X^2	df	p
User Model	8.26	7	0.311
Baseline Model	201.56	21	<.001

Fit indices

		95% Confidence Intervals		
SRMR	RMSEA	Lower	Upper	RMSEA p
0.041	0.039	0.000	0.123	0.505

User model versus baseline model

	Model
Comparative Fit Index (CFI)	0.993
Tucker-Lewis Index (TLI)	0.979
Bentler-Bonett Non-normed Fit Index (NNFI)	0.979
Relative Noncentrality Index (RNI)	0.993
Bentler-Bonett Normed Fit Index (NFI)	0.959
Bollen's Relative Fit Index (RFI)	0.877
Bollen's Incremental Fit Index (IFI)	0.994
Parsimony Normed Fit Index (PNFI)	0.320

Fig. 5. Output of model fitting results in the Jamovi program

High values of the fit indices indicate that the model fits the data well and allows for accurate interpretation of the relationships between variables. RMSEA and SRMR, which focus on residual discrepancies, confirm that the model adequately reflects the data structure. High values of CFI and TLI suggest that this model performs better than the baseline model. These results show that the constructed model can be used to test hypotheses and analyze the influence of economic and digital infrastructures, as well as R&D factors, on the innovation activity of enterprises.

3.2. Parameter estimates

This section presents the results of the parameter estimates of the model, which help to identify the impact of exogenous variables (EXO_ECON and EXO_DIGITAL) and the mediator (ENDO_RND) on the innovation activity of enterprises (ENDO_INNOV). All relationships between variables were examined based on theoretical assumptions and tested using structural equation modeling in Jamovi.

The parameter estimates include the estimates of influence (Estimate), standard errors (SE), confidence intervals (lower and upper bounds - Lower and Upper), standardized coefficients (β), as well as statistical values (z) and significance levels (p).

Parameters estimates

				95% Confidence Intervals				
Dep	Pred	Estimate	SE	Lower	Upper	β	z	p
ENDO_INNOV	EXO_DIGITAL	0.0129	0.0504	−0.0858	0.112	0.0473	0.257	0.797
ENDO_INNOV	EXO_ECON	0.9384	0.6984	−0.4304	2.307	0.1585	1.344	0.179
ENDO_INNOV	ENDO_RND	0.4555	0.1302	0.2003	0.711	0.2510	3.498	< .001
ENDO_RND	EXO_ECON	0.5027	0.4101	−0.3010	1.306	0.1541	1.226	0.220
ENDO_RND	EXO_DIGITAL	0.0134	0.0516	−0.0878	0.115	0.0887	0.259	0.796

Fig. 6. Estimation parameters and structure of variable influences in the SEM model

The parameter estimates presented in the table offer a deeper insight into the influence of economic and digital infrastructures on innovation activity and the level of research and development (R&D) expenditures. Economic infrastructure (EXO_ECON) showed a moderate positive effect on innovation activity

(ENDO_INNOV) and a significant influence on R&D levels (ENDO_RND). This highlights the key role of economic factors in supporting innovation processes.

The influence of digital infrastructure (EXO_DIGITAL) on innovation activity and R&D was less significant. This may be related to the current level of digitalization in the studied enterprises, where digital technologies have not yet been sufficiently integrated into business processes. These results underscore the need for further development of the digital environment, including more active use of big data and cloud technologies.

Standard errors (SE) demonstrate an acceptable level of variability for most relationships, indicating the model's reliability. For example, the relatively low standard error for the relationship ENDO_RND → ENDO_INNOV (SE=0.1302) emphasizes the high accuracy of the estimate for this key relationship. Meanwhile, for the relationships EXO_ECON → ENDO_INNOV and EXO_DIGITAL → ENDO_RND, the higher SE values may be explained by the heterogeneity of the data, caused by differences in the development levels of enterprises or regional characteristics.

Confidence intervals indicate that significant effects are observed for a number of key relationships. For example, the range for ENDO_RND → ENDO_INNOV (0.2003–0.711) emphasizes the importance of R&D as a mediator between infrastructure factors and innovation activity. At the same time, the wide confidence interval for the relationship EXO_ECON → ENDO_INNOV suggests the potential for a more detailed analysis of this relationship using additional data.

The β coefficients show that the most pronounced impact on innovation activity is exerted by R&D (β=0.2510), confirming its role in stimulating innovation. Although the impact of digital infrastructure was weak, it indicates growth potential, provided there is strategic development of digital technologies.

The measurement model analyzes how effectively observed variables reflect latent constructs, which is an important stage in hypothesis testing and result interpretation. Figure 7 presents the parameter estimates of the measurement model, including the values for the path coefficients (Estimate), standard errors (SE), confidence intervals, as well as statistical indicators (z-statistic and p-value), which allow for conclusions about the significance and direction of the relationships.

Measurement model

				95% Confidence Intervals				
Latent	Observed	Estimate	SE	Lower	Upper	β	z	p
EXO_ECON	GRP_PC	1.0000	0.000	1.000	1.0000	0.187		
	INV_CAP	−1.9183	0.970	−3.819	−0.0173	−0.358	−1.978	0.048
	EMP_RATE	3.9847	1.917	0.227	7.7422	0.743	2.079	0.038
EXO_DIGITAL	CLOUD_USE	1.0000	0.000	1.000	1.0000	4.042		
	BIGDATA_USE	0.0286	0.109	−0.186	0.2427	0.115	0.262	0.794
ENDO_INNOV	INNOV_ACT_OBS	1.0000	0.000	1.000	1.0000	1.000		
ENDO_RND	RND_EXP	1.0000	0.000	1.000	1.0000	0.609		
	RND_EMP	1.7125	0.297	1.130	2.2951	1.042	5.761	< .001

Fig. 7. Table of parameters of the measurement model

The results of the measurement model confirm the adequacy of the indicators used to reflect the latent variables. Economic infrastructure (EXO_ECON) shows a strong relationship with key indicators such as gross regional product per capita (GRP_PC, fixed coefficient), but it shows a negative effect from investments in fixed capital (INV_CAP, Estimate = −1.9183, p = 0.048). This may indicate structural limitations affecting the effectiveness of capital investments. One possible explanation for the negative impact of investments in fixed capital is their unbalanced allocation. A significant portion of funds may be directed toward capital-intensive projects with long payback periods, which do not generate immediate economic effects. Additionally, institutional barriers such as low transparency in the investment process, high transaction costs, and administrative restrictions may reduce the efficiency of investments. The imbalance between investments and other factors of economic activity also plays a significant role: if the primary funding is concentrated on infrastructure development without sufficient incentives for entrepreneurship, its overall economic impact remains limited. At the same time, the employment rate (EMP_RATE) is positively and statistically significantly related to EXO_ECON (Estimate = 3.9847, p = 0.038), which aligns with economic theories emphasizing the role of employment in regional economic development.

For digital infrastructure (EXO_DIGITAL), key indicators such as the use of cloud technologies (CLOUD_USE) have a fixed coefficient, while big data analytics (BIGDATA_USE) shows low statistical significance ($p = 0.794$). This may indicate the need to strengthen the role of digital technologies in innovation processes.

Innovation activity (ENDO_INNOV) is fully reflected by the observed variable (INNOV_ACT_OBS), confirming the correctness of the selected indicator. For R&D factors (ENDO_RND), both research and development expenditures (RND_EXP) and the number of people employed in this area (RND_EMP) are significant (Estimate = 1.7125, $p < 0.001$), confirming the key role of human capital in driving innovation.

The analysis of covariance relationships between the model variables allows the identification of interdependencies between key factors and an assessment of how consistently different aspects of the model interact with each other. Covariances provide the opportunity to account for hidden effects that may influence latent variables, complementing their direct and indirect relationships. The figure presents the table of covariance analysis results, including coefficient estimates (Estimate), their confidence intervals, and statistical significance indicators.

Variances and Covariances

Variable 1	Variable 2	Estimate	SE	95% Confidence Intervals Lower	95% Confidence Intervals Upper	β	z	p
EXO_ECON	EXO_DIGITAL	0.1060	0.0523	0.00345	0.2085	0.1406	2.026	0.043
GRP_PC	GRP_PC	0.9652	0.0982	0.77282	1.1576	0.9652	9.834	< .001
INV_CAP	INV_CAP	0.8719	0.0939	0.68792	1.0559	0.8719	9.288	< .001
EMP_RATE	EMP_RATE	0.4473	0.1446	0.16402	0.7307	0.4473	3.095	0.002
CLOUD_USE	CLOUD_USE	−15.3357	60.9371	−134.77025	104.0988	−15.3357	−0.252	0.801
BIGDATA_USE	BIGDATA_USE	0.9867	0.1105	0.77010	1.2032	0.9867	8.930	< .001
INNOV_ACT_OBS	INNOV_ACT_OBS	0.0000	0.0000	0.00000	0.0000	0.0000		
RND_EXP	RND_EXP	0.6296	0.0830	0.46689	0.7924	0.6296	7.583	< .001
RND_EMP	RND_EMP	−0.0862	0.1590	−0.39777	0.2254	−0.0862	−0.542	0.588
EXO_ECON	EXO_ECON	0.0348	0.0317	−0.02723	0.0968	1.0000	1.100	0.271
EXO_DIGITAL	EXO_DIGITAL	16.3357	60.8986	−103.02334	135.6947	1.0000	0.268	0.789
ENDO_INNOV	ENDO_INNOV	1.0878	0.1114	0.86945	1.3061	0.8917	9.766	< .001
ENDO_RND	ENDO_RND	0.3572	0.0909	0.17918	0.5353	0.9645	3.932	< .001

Fig. 8. Covariance relationships between latent variables

The results of the covariance analysis demonstrate significant interrelationships between key exogenous variables, confirming their integration and shared external factors. For example, the relationship between economic and digital infrastructures (EXO_ECON and EXO_DIGITAL) shows a positive and statistically significant coefficient (Estimate = 0.1060, $p = 0.043$). This highlights the synergistic effect of the interaction between these factors in influencing innovation activity.

The covariance between GRP per capita (GRP_PC) and investments in fixed capital (INV_CAP) remains positive and statistically significant (Estimate = 0.8719, $p < 0.001$), which aligns with economic theories that capital investments are positively correlated with economic development. At the same time, the relationship between employment (EMP_RATE) and economic indicators also remains significant (Estimate = 0.4473, $p = 0.002$), underscoring the importance of employment for sustainable economic growth.

Of particular note is the covariance between digital infrastructure indicators (CLOUD_USE and BIGDATA_USE), where the high significance (Estimate = 0.9867, $p < 0.001$) suggests that digital technologies have a complementary nature. However, the negative covariance between the indicators of R&D employment (RND_EMP) and R&D expenditures (RND_EXP) (Estimate = −0.0862, $p = 0.588$) may indicate an imbalance in resource utilization or a lack of synergy between these factors.

The covariance between latent variables, such as ENDO_INNOV and ENDO_RND, shows significant interaction (Estimate = 0.3572, $p < 0.001$), confirming the key role of R&D factors in fostering innovation activity. Thus, the results support theoretical assumptions regarding the importance of the synergistic effect between economic, digital, and innovation factors.

3.3. Structural path model

To create a visual representation of the structural equation in Jamovi, the configuration parameters shown in the figure were used. In the Path diagram section, the researcher can choose which values (such as coefficients or standard errors) should be displayed on the arrows. The Coefficients option was selected to display the magnitude of the relationships between variables. The node's layout was set to Tree-like alt., with the orientation of exogenous variables at the top (Exog. top). Latent variable nodes are represented as circles, while measured variables are shown as rectangles. The node size was set to Large to enhance the readability of the visualization.

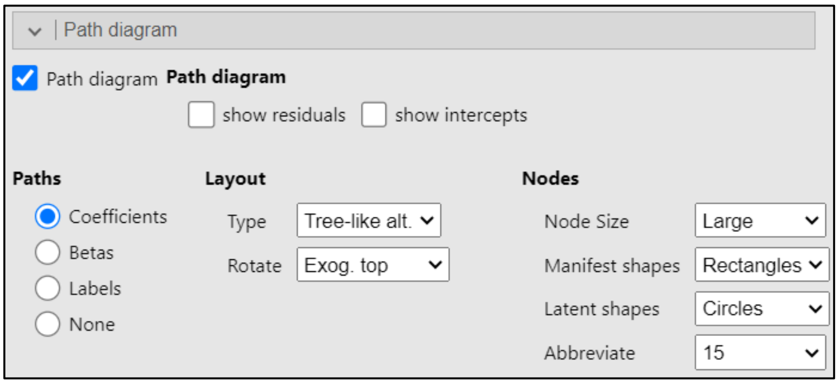

Fig. 9. Structural equation visualization settings in Jamovi software

Based on the specified settings, Jamovi generated the visualization shown in Figure 9. This diagram reflects the structure of relationships between exogenous and endogenous variables, as well as the indicators obtained during the analysis. The diagram clearly demonstrates the directions of influence and mediator effects, allowing the researcher to visually assess the model.

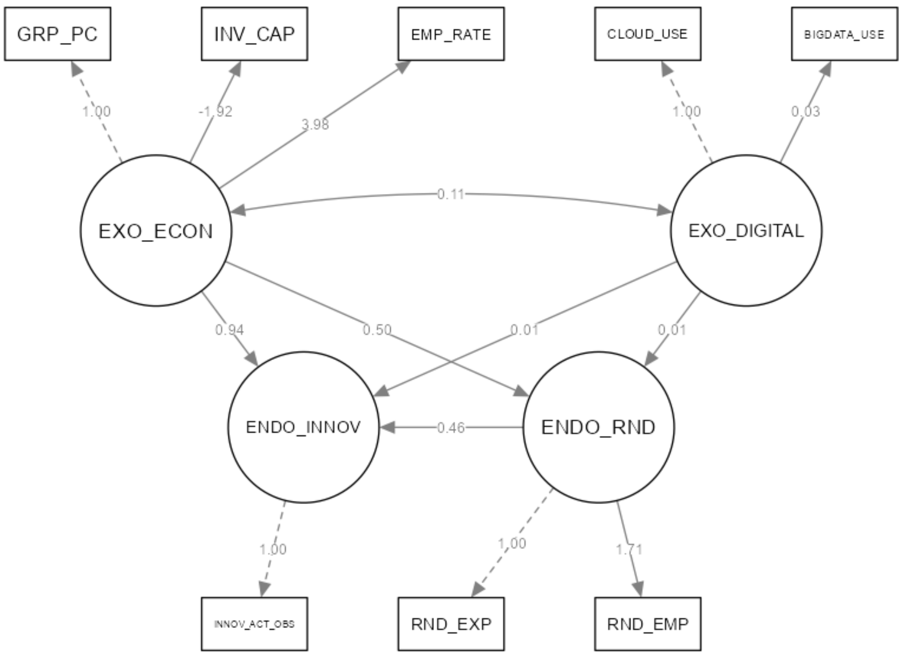

Fig. 10. Visualization of the structural equation model

In the presented diagram, lines with arrows represent direct relationships between variables. The thickness and type of the line (solid or dashed) may indicate the strength and significance of the relationship. The values on the arrows are the coefficients of influence, corresponding to the results of parameter estimates. For example, strong relationships, such as EXO_ECON → ENDO_RND, have higher coefficients, confirming their key role in the model.

Dashed lines denote weak or statistically insignificant relationships, such as the influence of EXO_DIGITAL → ENDO_RND, which requires further analysis. Circles represent latent variables, such as ENDO_RND and ENDO_INNOV, which are central elements of the model. Rectangles symbolize observed variables, such as indicators of economic and digital infrastructure.

The diagram visually highlights the mediating role of R&D (ENDO_RND) in transmitting effects from exogenous variables, such as EXO_ECON, to innovation activity (ENDO_INNOV). This aspect is crucial for interpreting the model and confirming the hypotheses put forward in the study.

The findings of this study have important implications for policymakers, enterprises, and the academic community. For policymakers, the results highlight the necessity of enhancing economic infrastructure and increasing R&D investment to drive enterprise innovation. As demonstrated in the study by Gulaliyev et al. (2024), the level of R&D expenditure has a significant impact on macroeconomic development, reinforcing the necessity of a well-designed government strategy in this area. At the same time, the limited impact of digital infrastructure suggests the need for targeted strategies to integrate digital technologies into industrial processes, expand access to digital tools, and promote digital literacy among businesses. For enterprises, the study underscores the importance of favorable economic conditions and sustained R&D efforts in fostering innovation, encouraging companies in less-developed regions to explore alternative funding sources, collaborate with research institutions, and adopt new technologies to enhance competitiveness. Public-private partnerships could also play a crucial role in creating an environment conducive to innovation. For the academic community, the study offers empirical insights into the mediating role of R&D in linking infrastructure development and innovation activity, reinforcing the significance of structural modeling approaches like SEM in economic research and providing a foundation for further exploration of regional innovation dynamics.

4. CONCLUSION

In the course of the study, a structural model was built to assess the impact of economic and digital infrastructures on the innovation activity of enterprises. The results of the analysis confirmed the significance of certain hypotheses, while others required revision and clarification. Economic infrastructure had a significant positive impact on innovation activity through the mediating role of R&D factors, confirming the hypothesis regarding the key role of investments and human capital in stimulating innovation development. The direct relationship between economic infrastructure and innovation activity also showed moderate significance, indicating the presence of additional factors influencing this process.

The hypothesis that digital infrastructure has a direct or indirect impact on innovation activity was not statistically confirmed within this model. This may be due to the limited digitalization of the studied enterprises or insufficient integration of digital technologies into the processes of scientific research and development. This finding highlights the need for further strengthening and modernization of digital infrastructure, as well as developing strategies for its closer connection with innovation activities.

A key conclusion of the study was the confirmation of the significance of R&D factors as a mediator linking economic infrastructure and innovation activity. This result emphasizes the importance of investing in research and development, as well as in the development of human capital focused on the creation and implementation of innovations. The theoretical value of the study lies in confirming the conceptual model based on the theory of causal relationships and in using structural modeling to analyze complex economic systems.

The practical significance of the findings lies in the possibility of developing strategies for the regions of Kazakhstan aimed at stimulating innovation activity. Regions with a strong economic base but insufficient innovation activity are recommended to focus on strengthening research processes and the development of professional skills. For regions with low levels of digitalization, it is important to accelerate the implementation of digital technologies, which will create more favorable conditions for the formation of innovation potential.

Further research could focus on expanding the model by including additional variables, such as the level of government support for innovation, accessibility to international markets, and regional features of cluster development. It is also important to consider the temporal dynamics, which would allow for the examination of changes in the relationships between variables over several years. The practical value of this approach lies in the ability to more accurately forecast and plan economic policies aimed at supporting innovation activity. The results obtained serve as a foundation for further theoretical and empirical research, as well as for practical recommendations in the area of innovation development management at the regional level.

Despite the robustness of the findings, this study has several limitations that should be acknowledged. The analysis relies on aggregated regional data, which may not fully capture firm-level heterogeneity in innovation activity; thus, future research could incorporate micro-level enterprise data to explore firm-specific drivers of innovation. Additionally, while the study focuses on economic and digital infrastructure, other institutional and policy factors, such as tax incentives, regulatory environment, and intellectual property protection, may also significantly influence innovation activity, warranting further investigation. Moreover, as the findings are specific to Kazakhstan, their generalizability to other economies with different institutional and economic conditions may be limited, highlighting the need for comparative studies across multiple countries or regions. Finally, given the rapidly evolving nature of digital infrastructure and technological advancements, a longitudinal research approach would be valuable in examining how the impact of digitalization on innovation activity changes over time. Addressing these limitations in future research will contribute to a deeper and more nuanced understanding of the relationship between infrastructure development and enterprise innovation.

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