STATISTICS IN TRANSITION new series, March 2025
Vol. 26, No. 1, pp. 1–XX, https://doi.org/10.59139/stattrans-2025-xxxx
Received – xx.xx.xxxx; accepted – xx.xx.xxxx

Impact of human capital on the innovation performance of EU economies

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Abstract

The purpose of the paper is to empirically determine the impact of human capital on the innovation performance of EU economies. Currently, most researchers consider human capital a significant factor of economic growth based on knowledge and innovation. Depending on the amount and quality of the available resources, human capital can play various parts in an economy, e.g. that of a user of existing knowledge and technology (general human capital), an implementer of new solutions, or a creator of previously undiscovered knowledge (specialised human capital). However, there is a gap in the literature regarding empirical research into the influence of human capital on the innovativeness of economies. This is related to the difficulties associated with the measurement of the two categories, as well as the limited number of methods to study the relationships between unobservable variables. The research described in the paper fills this gap. In order to study the relationship between human capital (general and specialised) and the innovation performance of economies, the partial least squares structural equation modelling (PLS-SEM) was used. The research spanned the years 2014-2020. Four PLS-SEM models were estimated based on cross-sectional data for the EU economies. The results showed that human capital significantly boosts the innovation performance of EU economies. Both general human capital and specific human capital had a significant positive impact on the innovation performance of these countries in the analysed years. The results can have a practical application and serve as an instrument of innovation policies or as a tool helpful in creating conditions for innovation systems.

Key words: human capital, innovativeness, innovation performance, structural equation modeling, PLS-SEM.

1. Introduction

Human capital, understood as the knowledge, skills, competences and other attributes embodied in individuals that are relevant to economic activity (OECD, 1998), has nowadays become a crucial factor behind knowledge- and innovation-based

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growth. The significance of human capital is corroborated by numerous studies (see Azariadis and Drazen, 1990; Mankiw et al., 1992; Benhabib and Spiegel, 1994; Barro, 2001). Many of them emphasize direct relationships between human capital and economic growth. There are, however, reasons to believe that these relationships are more complex than is often assumed (Aleknavičiūtė et al., 2016). Depending on the size and quality of resources, human capital can play various parts in an economy, e.g. that of a user of existing knowledge and technology, an implementer of new solutions, or a creator of previously undiscovered knowledge.

The article analyses the problem of human capital in terms of its impact on the innovativeness of EU countries. Innovativeness is defined as the ability to create and implement innovations. Moreover, two categories to describe innovation are distinguished:

– innovation capacity, i.e. the extent to which an economy is capable of creating and commercialize new ideas,
– innovation performance, i.e. the outcome stemming from a combination of society's creativity and the financial assets of a given economic and institutional environment.

The purpose of the paper is to empirically identify the impact of human capital on the innovation performance of EU economies. Two kinds of human capital are distinguished: general human capital, i.e. overall base of knowledge, skills, competences, and qualifications indispensable in processes associated with diffusion of knowledge and innovation; and specialized human capital, i.e. specialized knowledge, skills, competences and qualifications used for creating new knowledge and developing innovative solutions.

The paper consists of five parts. Section 2 presents selected empirical studies featuring analyses of the relationships between human capital and the innovativeness of European economies. Section 3 describes the research method – partial least squares structural equation modelling. Section 4 discusses the results of modeling. Section 5 sums up the conducted research.

2. Literature review

Empirical verification of the hypothesis that human capital significantly influences the innovativeness of economies presents numerous difficulties. First, the definitions of both of these categories vary in the literature. Second, neither of them is directly observable. Third, there is no universally accepted method to measure them. Fourth, few econometric methods make it possible to examine the influence of one unobservable variable on another. Below presented are examples of empirical research regarding European economies.

R. Aleknavičiūtė, V. Skvarciany and S. Survilaitė (2016) analyzed the impact of human capital on innovation in 26 EU countries. The study covered the years 2002-2012. Ten indicators were used to measure human capital and one indicator to measure innovation.

The studied countries were divided into two clusters: highly innovative economies (Austria, Belgium, Czechia, Cyprus, Dania, Estonia, Finland, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Sweden, United Kingdom) and economies with low innovation levels (Bulgaria, France, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, Slovenia, Spain). Correlation analysis was the research method used. The following conclusions were reached (Aleknavičiūtė et al., 2016):

1. Among the countries with low innovation, 9 human capital indicators were found to have significant correlations with the level of innovativeness, whereas one – participation of young people in education – was insignificantly correlated. Lifelong learning and high level of computer skills were the most strongly correlated indicators.
2. In the group of highly innovative countries, 6 indicators proved to be significantly correlated with innovation, while 4 (lifelong learning, secondary and higher education, high level of computer skills, and the level of satisfaction with one's education) had insignificant correlations. 'Results achieved by school students in Mathematics' was the indicator which was the most closely correlated with innovation performance.
3. In all the analyzed countries, 8 human capital indicators showed significant correlations with the level of innovation in the economies, with one of them (population with secondary or higher education) being negatively correlated. Two indicators (participation of young people in education and high level of computer skills) were insignificantly correlated. Indicators of the quality of human capital were the most strongly associated with the level of innovation.

One of the advantages of the above-discussed research is the fact that it takes into consideration the qualitative aspect of human capital. As far as its limitations are concerned, innovation is addressed one-dimensionally. Apart from this, analysis of dependencies on the basis of correlation coefficients poses interpretation problems, because it is difficult to unequivocally determine the direction of each dependency.

The influence of human capital and social capital on the innovation activity of economies was investigated by A. Kaas, E. Parts and H. Kaldaru (2012). The statistical sample consisted of 30 European countries. Data on human and social capital were derived from the year 1999, while data on innovation activity from the period of 2002-2004. Innovation was measured with 4 indicators, human capital with 2 indicators, and social capital with 10 indicators.

The countries were divided into 4 groups:

- large, developed Western European economies: Austria, Belgium, France, Germany, Greece, Italy, Netherlands, Portugal, Switzerland, Spain, Sweden, Turkey, United Kingdom,
- small, developed Western European economies: Denmark, Finland, Ireland, Island, Luxembourg, Malta,
- large, catching-up post-communist economies: Bulgaria, Czechia, Hungary, Poland, Romania,
- small, catching-up post-communist economies: Estonia, Latvia, Lithuania, Slovakia, Slovenia.

The values of variables 'human capital' and 'social capital' were estimated by means of the confirmatory factor analysis. The conclusions of the study were as follows (Kaasa et al., 2012):

1. Small, developed Western European economies were found to be the most innovating, followed by large, developed Western European economies. Western economies were relatively far ahead of small, catching-up economies, whereas large, catching-up economies were in the most difficult situation.
2. An analogous pattern applied to the levels of human capital and social capital.
3. Catching-up economies were characterized by less innovation activity and, at the same time, lower levels of human and social capital.

Among the merits of the study is that it accounts for several different indicators of innovation and that it measures human and social capital using the confirmatory factor analysis. What raises doubts, however, is the large disproportion between the numbers of indicators ascribed to the categories under analysis. Besides, the conclusions regarding dependencies were drawn merely on the basis of comparison between the values of latent constructs and the mean values of innovation indicators.

Different statistical and econometric methods were applied by M. Dakhli and D. Clercq (2004) in their research into the impact of human and social capital on the country’s level of innovation. The statistical sample comprised 59 countries: 30 from Europe, 13 from Asia and Australia, and 3 from Africa. Data related to human and social capital were from 1995, while data on innovation from 1998.

Innovation was measured with 3 indicators, human capital with 4, while social capital with 31 indicators deriving from surveys. The first stage involved construction of synthetic measures of human capital and social capital, and their dimensions. Next, a correlation analysis was conducted, which revealed that (Dakhli and Clercq, 2004):

1. Human capital was positively correlated with each of the indicators of the level of innovation in an economy.
2. 'Level of overall confidence' and 'trust in institutions' were positively correlated with at least one indicator of innovation.

3. 'Activity in associations' and 'norms of civic behavior' did not have any correlation with the level of innovation in an economy.

In the next step, three regression models were estimated. The innovation indicators were used as dependent variables, while human capital and selected dimensions of social capital were independent variables. Moreover, each country's population size was taken into consideration. In order to ascertain whether social polarization had an impact on the relationship between social capital and innovation, a control variable – 'income gap' – was included into the models. The analysis yielded the following conclusions (Dakhli and Clercq, 2004):

1. Human capital had a positive impact on each of the specified indicators of the level of innovation in an economy.
2. Level of overall confidence and trust in institutions had a positive impact on at least one of the three indicators of innovativeness, i.e. a high level of overall confidence leads to an increase in the number of patents and amount of expenditure on R&D, while trust in institutions had a positive influence on the volume of high-tech exports.
3. 'Activity in associations' had a positive impact on only one indicator of innovativeness, and namely 'R&D expenditure index'.
4. 'Norms of civic behavior' had a negative influence on the level of high-tech exports.
5. Inclusion of 'income gap' as a control variable resulted in higher parameter estimates. Nevertheless, the control variable proved significant only in the model where 'R&D expenditure' was the dependent variable.

Application of various methods of statistical analysis should be regarded as an asset of the study. However, the paper also seems to have several weaknesses. The level of innovation in an economy was approached in a one-dimensional way in each of the regression models. What is more, no full statistical verification of the estimated models was performed. The authors failed to include information as to, e.g. whether the estimated models met the rigorous standards of the least squares method. There is also an evident disproportion between the number of indicators used for measuring the analyzed types of capital.

3. Research method

3.1. Fundamentals of PLS-SEM modelling

Structural equation models (SEM) include a number of statistical methodologies meant to estimate a network of causal relationships, defined according to a theoretical model, linking two or more latent complex concepts, each measured through a number of observable indicators. Among the methods of estimating SEM models, the covariance-based method (CB), invented by K. G. Jöreskog, enjoyed the greatest popularity for a long time. Its recognition was so universal that in social sciences the phrases: structural equation modeling (SEM) and covariance-based structural equation modeling (CB-SEM) used to be synonymous for many years (Chin, 1998). Meanwhile, H. Wold developed an alternative approach – the partial least square method (PLS).

An SEM model consists of two submodels: a structural one and a measurement one. A structural model describes the relationships among latent variables, whereas a measurement model – the relationships among the latent variables and the indicators by which they are identified (Wold, 1980). Definition of latent variables by means of indicators can be done either deductively or inductively (Rogowski, 1990). Under the former approach, indicators reflect the defined latent variable. In the case of inductive definition, it is assumed that indicators make up the latent variables, hence the expressions formative indicators.

Estimation of a PLS-SEM model is performed using the PLS method. The algorithm simultaneously estimates inner model parameters – path coefficients – and outer model parameters – outer weights and outer loadings. The procedure also yields estimations of the values of all the latent variables included in the model (see Hair et al., 2022). Verification of a PLS-SEM model is a two-stage process. First, the structural model is assessed. Second, if the validity of the structural model has been confirmed, the structural model is tested. Table 1 lists the properties of the model which should undergo evaluation.

Table 1: Evaluation of PLS-SEM model

<table>
<tr><th colspan="6">Evaluation of the measurement models</th></tr>
<tr><th colspan="3">Reflective measurement model</th><th colspan="3">Formative measurement model</th></tr>
<tr><td rowspan="2">Internal consistency</td><td>Cronbach’s alpha</td><td>0.60-0.95</td><td rowspan="2">Convergent validity</td><td rowspan="2">Redundancy analysis</td><td rowspan="2">≥ 0.7 correlation</td></tr>
<tr><td>Composite reliability</td><td>0.60-0.95</td></tr>
<tr><td rowspan="2">Convergent validity</td><td>Loadings</td><td>≥ 0.7</td><td rowspan="2">Collinearity between indicators</td><td rowspan="2">Variance Inflation factor (VIF)</td><td rowspan="2">≥ 0.5</td></tr>
<tr><td>Average variance extracted (AVE)</td><td>≥ 0.5</td></tr>
<tr><td rowspan="3">Discriminant validity</td><td>Cross-loadings</td><td>-</td><td rowspan="3">Significance of outer weights</td><td rowspan="3">p-value</td><td rowspan="3">< 0.05</td></tr>
<tr><td>Fornell-Larcker criterion</td><td>-</td></tr>
<tr><td>Heterotrait-monotrait ratio (HTMT)</td><td>< 0.9</td></tr>
</table>

Table 1: Evaluation of PLS-SEM model (cont.)

Evaluation of the structural model		
Collinearity	Variance Inflation factor (VIF)	≥ 0.5
Predictive power	Coefficients of determinations (R^2)	values of 0.75, 0.50 and 0.25 are considered substantial, moderate and weak
Predictive relevance	Stone-Geisser's Q^2 value	≥ 0
Significance of path coefficients	p-value	< 0.05

Source: own work on the basis of (Hair et al., 2017, p. 106).

3.2. PLS-SEM models with higher order latent variables

Introducing a higher-order latent variable to an SEM model has numerous advantages associated, among other things, with the theoretical usefulness of the model, the level of abstraction, or the integrity and accuracy of the measurement model. Nevertheless, using higher-order latent variables also involves several challenges, e.g. the decision to choose the type of higher-order latent variable measurement model, selection of estimation method, or the more complex process of statistical verification of the model (Wetzels et al., 2009).

The literature offers a variety of approaches to identification and estimation of models with higher-order latent variables. The most frequently cited is the approach proposed by Wold, now known as the repeated indicators approach. In this approach, higher-order latent variables are defined by means of the indicators of all the lower-order latent variables which define them (Sarstedt et al., 2019).

Statistical verification of a PLS-SEM model with higher-order latent variables is relatively complicated. Admittedly, the evaluation criteria used are analogous to those applied in standard PLS-SEM models, but particular attention must be paid to distinguishing the relationships which are part of the measurement model from those which belong to the structural model. The measurement model of a higher-order latent variable is a complex one, which should be taken into consideration at the evaluation stage. It consists of a measurement model of lower-order latent variables and a measurement model of higher-order latent variables (as a whole), represented by the relationships among the higher-order variable and the lower-order variables (Hair et al., 2022).

The PLS-SEM method is not without its limitations. Some researchers note that the non-parametric nature of this modelling technique is a serious flaw. Also, collection of samples of insufficient size and application of PLS-SEM instead of CB-SEM is subject to criticism in the case of studies based on sample sets. Another disadvantage of PLS-

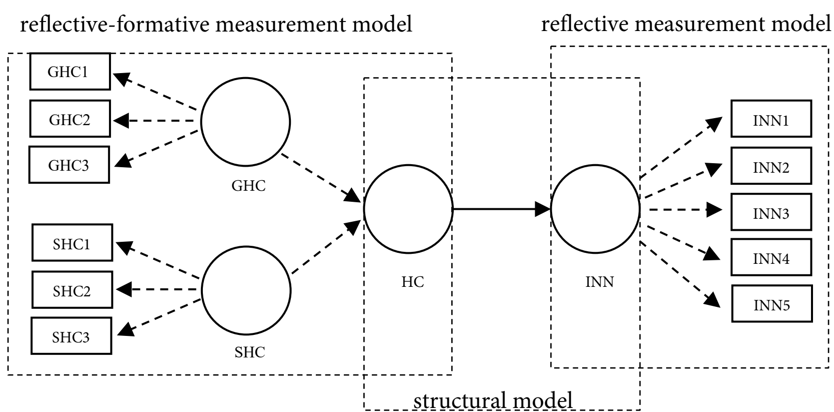
SEM models is that they are linear, whereas the relationships between many economic variables are of non-linear nature.

3.3. PLS-SEM model specification

In line with the stated research objective, the following main hypothesis was adopted: Human capital has a positive influence on the innovation performance of EU economies. Apart from this, two specific hypotheses were verified:

1. General human capital has a positive impact on the innovation performance of EU economies.
2. Specialized human capital has a positive impact on the innovation performance of EU economies.

The PLS-SEM model (a diagram of which is shown in Figure 1) was used to verify the above hypotheses. Latent variable HC was defined by means of two unobservable indicators comprising: general human capital (GHC) and specialized human capital (SHC). The model contained, therefore, a second-order latent variable (HC). In the next step, latent variables GHC and SHC were defined by means of reflective indicators. A deductive approach and reflective indicators were also applied to define latent variable INN. The indicators which defined the latent variables are presented in Table 1.



HC – 2nd order latent variable,
GHC, SHC, INN – 1st order latent variables,
GHC*i*, SHC*i*, INN*j* – indicators, $i = 1, 2, 3,\ j = 1,\ldots, 5$.

Figure 1: Specification of PLS-SEM model.

Source: own work.

Table 2: Indicators of latent variables

Latent variable	Indicator	Description	Source
GHC	GHC1	Population aged 25-64 having completed tertiary education (%).	Eurostat
	GHC2	Employees aged 20-64 having completed tertiary education (%).	Eurostat
	GHC3	Population aged 25-64 participating in education and training (%).	Eurostat
SHC	SHC1	Population aged 25-64 employed in science and technology (%).	Eurostat
	SHC2	Researchers (% of total employment).	Eurostat
	SHC3	Employment in technology and knowledge-intensive sectors (% of total employment).	Eurostat
INN	INN1	SMEs introducing product innovations (%).	EIS
	INN2	SMEs introducing business process innovations (%).	EIS
	INN3	PCT patent applications per billion GDP (PPS).	EIS
	INN4	Scientific publications among the top-10% most cited publications worldwide (% of total scientific publications of the country).	EIS
	INN5	Knowledge-intensive services exports (% of total services exports).	EIS

Source: own work.

The database, constructed with the use of data from the Eurostat, the World Bank and the European Innovation Scoreboard (EIS), consisted of 42 indicators. Seventeen of them regarded the innovation performance of economies, while 25 – human capital. As a result of statistical verification, at various stages of the modelling process, the indicators were removed from the base, e.g. due to gaps in data, insufficient variation, of negative verification of the measurement model. Eventually, 11 indicators were selected for estimation (Table 1). The model was estimated using the SmartPLS software, on the basis of cross-sectional data for four years: 2014, 2016, 2018, and 2020.

4. Results and discussion

The results of the estimation of the models are depicted in Figures 2–5. The estimated models underwent multi-stage statistical verification. First, the properties of the measurement models of the first-order latent variables (GHC, SHC, INN) were tested. Tables 3–6 present the results of these analyses. The indicators fulfilled the criteria of convergent validity, internal consistency reliability, and discriminant validity, and thus were approved.

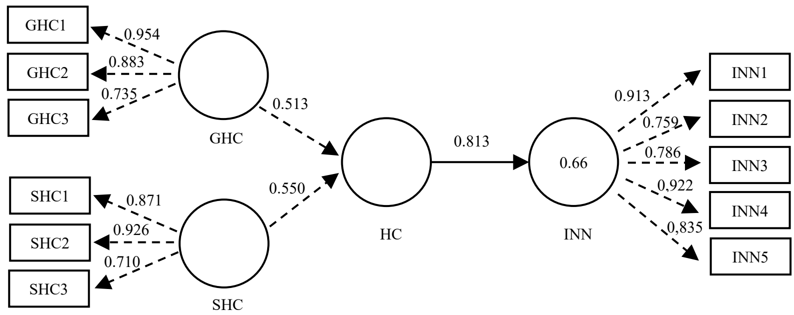


Figure 2: PLS-SEM$_{2014}$ results of estimation

Source: own work.

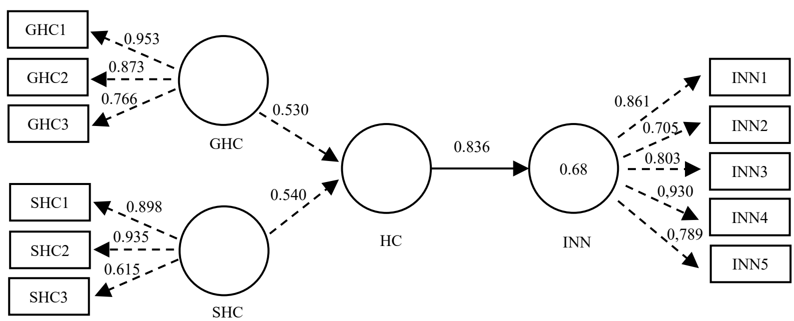


Figure 3: PLS-SEM$_{2016}$ results of estimation

Source: own work.

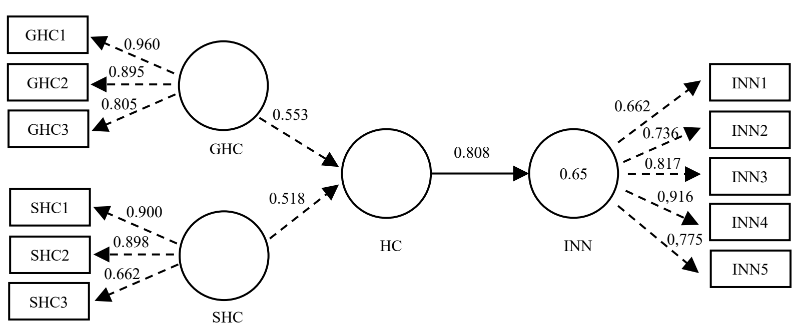


Figure 4: PLS-SEM$_{2018}$ results of estimation

Source: own work.

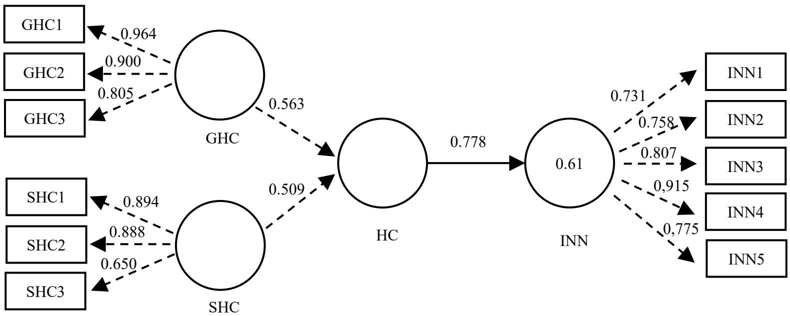


Figure 5: PLS-SEM$_{2020}$ results of estimation

Source: own work.

Table 3: Assessment of reflective measurement model in PLS-SEM$_{2014}$

Latent variable	Indicator	Convergent validity		Internal consistency reliability		Discriminant validity
		Loading	AVE	Composite reliability	Cronbach's alpha	Cross loadings criteria
		>0.7	>0.5	0.6-0.95	0.6-0.95	
GHC	GHC1	0.954	0.74	0.82	0.82	Yes
	GHC2	0.883				
	GHC3	0.735				
SHC	SHC1	0.871	0.71	0.83	0.79	Yes
	SHC2	0.926				
	SHC3	0.710				
INN	INN1	0.913	0.72	0.91	0.90	Yes
	INN2	0.759				
	INN3	0.786				
	INN4	0.922				
	INN5	0.835				

Source: own work.

Table 4: Assessment of reflective measurement model in PLS-SEM$_{2016}$

Latent variable	Indicator	Convergent validity		Internal consistency reliability		Discriminant validity
		Loading	AVE	Composite reliability	Cronbach's alpha	Cross loadings criteria
		>0.7	>0.5	0.6-0.95	0.6-0.95	
GHC	GHC1 GHC2 GHC3	0.953 0.873 0.766	0.75	0.84	0.83	Yes
SHC	SHC1 SHC2 SHC3	0.898 0.935 0.615	0.69	0.84	0.76	Yes
INN	INN1 INN2 INN3 INN4 INN5	0.861 0.705 0.803 0.930 0.789	0.67	0.90	0.88	Yes

Source: own work.

Table 5: Assessment of reflective measurement model in PLS-SEM$_{2018}$

Latent variable	Indicator	Convergent validity		Internal consistency reliability		Discriminant validity
		Loading	AVE	Composite reliability	Cronbach's alpha	Cross loadings criteria
		>0.7	>0.5	0.6-0.95	0.6-0.95	
GHC	GHC1 GHC2 GHC3	0.960 0.895 0.805	0.79	0.87	0.87	Yes
SHC	SHC1 SHC2 SHC3	0.900 0.898 0.662	0.69	0.81	0.76	Yes
INN	INN1 INN2 INN3 INN4 INN5	0.662 0.736 0.817 0.916 0.775	0.62	0.88	0.85	Yes

Source: own work.

Table 6: Assessment of reflective measurement model in PLS-SEM$_{2020}$

Latent variable	Indicator	Convergent validity		Internal consistency reliability		Discriminant validity
		Loading	AVE	Composite reliability	Cronbach's alpha	Cross loadings criteria
		>0.7	>0.5	0.6-0.95	0.6-0.95	
GHC	GHC1 GHC2 GHC3	0.964 0.900 0.805	0.80	0.87	0.87	Yes
SHC	SHC1 SHC2 SHC3	0.894 0.888 0.650	0.67	0.81	0.75	Yes
INN	INN1 INN2 INN3 INN4 INN5	0.731 0.758 0.807 0.915 0.775	0.64	0.89	0.86	Yes

Source: own work.

Next, the second part of the measurement models of the second-order latent variable (HC) was verified. The unobservable indicators of HC were not colinear, whereas the estimates of weights proved to be statistically significant (Table 7). Therefore, the models were approved.

Table 7: Significance testing results of the formative model weights

Relation	Weight	*t* value	*p* value	95% confidence interval	Significance (p<0.05)?
			PLS-SEM$_{2014}$		
GHC→HC	0.513	13.79	0.000	(0.43, 0.58)	Yes
SHC→HC	0.550	13.14	0.000	(0.48, 0.65)	Yes
			PLS-SEM$_{2016}$		
GHC→HC	0.530	14.01	0.000	(0.44, 0.59)	Yes
SHC→HC	0.540	11.76	0.000	(0.47, 0.65)	Yes
			PLS-SEM$_{2018}$		
GHC→HC	0.553	13.29	0.000	(0.48, 0.64)	Yes
SHC→HC	0.518	11.65	0.000	(0.44, 0.62)	Yes
			PLS-SEM$_{2020}$		
GHC→HC	0.563	12.75	0.000	(0.48, 0.65)	Yes
SHC→HC	0.509	11.00	0.000	(0.43, 0.61)	Yes

Source: own work.

In the last step, statistical verification of the structural models was conducted. In every case, variable HC showed a statistically significant effect on variable INN (Table 8). The statistical hypothesis that HC did not have significant effect on INN was, therefore, rejected in favor of the alternative hypothesis.

Table 8: Significance testing results of the structural model path coefficients

Model	Path coefficient	*t* value	*p* value	95% confidence interval	Significance ($p<0.05$)?
PLS-SEM_{2014}	0.813	16.86	0.000	(0.72, 0.91)	Yes
PLS-SEM_{2016}	0.825	17.45	0.000	(0.74, 0.92)	Yes
PLS-SEM_{2018}	0.808	14.50	0.000	(0.70, 0.92)	Yes
PLS-SEM_{2020}	0.778	11.85	0.000	(0.65, 0.91)	Yes

Source: own work.

The coefficients of determination had values ranging from 0.61–0.68 (Figures 2–5), which means that the variability of INN was explained by the models to a satisfactory degree. The Q^2 values of the Stone-Geisser test were positive (Table 9), and thus the models proved to have high prognostic accuracy. The structural models were positively assessed. The next stage of the modelling process involved analysis of the obtained results.

Table 9: Q^2 values

Indicators	Q^2			
	PLS-SEM_{2014}	PLS-SEM_{2016}	PLS-SEM_{2018}	PLS-SEM_{2020}
INN1	0.37	0.24	0.11	0.14
INN2	0.22	0.13	0.11	0.13
INN3	0.48	0.54	0.54	0.49
INN4	0.48	0.57	0.54	0.51
INN5	0.53	0.46	0.40	0.34
General	0.63	0.64	0.62	0.57

Source: own work.

The estimates of the parameters of structural models demonstrated that general human capital had a strong, positive influence on the innovation performance of EU economies in each of the four analyzed years. The path coefficients assumed values within the range 0.778–0.836. Moreover, both general human capital and specialized human capital had a positive impact on the innovation performance of the economies under study. This is evidenced by the parameters of substitution relationships, which can be derived by substituting latent variable HC with the relationships of its measurement model (Table 10). The strength of the influence exerted by both kinds of capital on innovation performance was comparable, although it should be noted that in the years 2014 and 2016, specialized human capital had a slightly stronger impact, while in 2018 and 2020 the influence of general human capital was more pronounced.

Table 10: Significance testing results of the substitution relation parameters

Relation	Parameter	*t* value	*p* value	95% confidence interval	Significance ($p<0.05$)?
			PLS-SEM$_{2014}$		
GHC→INN	0.417	9.66	0.000	(0.33, 0.48)	Yes
SHC→INN	0.447	13.33	0.000	(0.39, 0.52)	Yes
			PLS-SEM$_{2016}$		
GHC→INN	0.437	9.42	0.000	(0.34, 0.52)	Yes
SHC→INN	0.445	12.95	0.000	(0.39, 0.53)	Yes
			PLS-SEM$_{2018}$		
GHC→INN	0.447	9.06	0.000	(0.35, 0.54)	Yes
SHC→INN	0.418	11.77	0.000	(0.36, 0.50)	Yes
			PLS-SEM$_{2020}$		
GHC→INN	0.438	8.80	0.000	(0.35, 0.54)	Yes
SHC→INN	0.396	9.11	0.000	(0.31, 0.49)	Yes

Source: own work.

PLS-SEM modelling also yielded estimates of the values of the latent variables included in the model. They were treated as values of synthetic measures and used for ranking and classification of the studied countries. Four typological groups were created: Group I – very high level of analyzed category; Group II – high/medium level; Group III – low level; and Group IV – very low level. Interval boundaries were calculated using the mean and standard deviation of the synthetic measures.

The classification of EU countries according to the level of human capital in 2014 was as follows (the order of countries within groups corresponds to the ranking status):

- Group I: Finland, Denmark, Sweden, Luxembourg, Ireland,
- Group II: Netherlands, Belgium, France, Austria, Estonia, Slovenia,
- Group III: Germany, Spain, Lithuania, Cyprus, Czechia, Latvia, Malta, Portugal, Hungary, Poland, Greece, Bulgaria,
- Group IV: Slovakia, Italy, Croatia, Romania.

The division of the studied countries into typological groups in terms of their innovation performance in 2014 is presented below:

- Group I: Finland, Sweden, Netherlands, Ireland, Germany, Belgium, Denmark,
- Group II: Luxembourg, Austria, France, Cyprus, Portugal, Italy,

- Group III: Greece, Slovenia, Czechia, Spain, Estonia, Malta, Hungary, Lithuania, Croatia,
- Group IV: Slovakia, Latvia, Bulgaria, Poland, Romania

In 2020 several changes occurred in both classifications, as compared to 2014. In the human capital clustering, Lithuania rose from group III to group II, whereas Slovakia moved up from group IV to group II. Bulgaria, meanwhile, dropped from group III to group IV. In the innovation performance clustering, Ireland fell from group I to group II, Portugal – from group II to group III, whereas Greece advanced from group III to group II.

The present empirical study confirmed that human capital is an important factor behind enhancing the innovation performance of EU economies. Similar conclusions can be drawn from theoretical and empirical research by other authors. In particular, selected endogenous models emphasize the indirect effect of human capital on increased productivity due to improvement of capacity for creating domestic innovations and absorption of new technologies (see Nelson and Phelps; 1966, Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992; Jones, 2003). Empirical investigations performed for various groups of countries indicate that human capital exerts a positive influence on the level of innovation in economies and increases their capacity to transfer knowledge and technology (see Benhabib and Spiegel, 2005; Vandenbussche et al., 2006, Ang et al., 2011; Danquah and Ouattara, 2014, Balcerzak and Pietrzak, 2016).

5. Conclusions

Empirical research on the relationship between human capital and innovativeness of economies is a very complex issue. This is related to the difficulties associated with measurement of the two categories, as well as the limited number of methods to study the relationships between unobservable variables. Nevertheless, various authors have attempted to identify the strength and direction of the impact of human capital on different aspects of innovativeness. This paper also makes such an attempt.

The research focused on EU economies during the years 2014–2020. PLS-SEM models were developed and estimated, containing the variables: human capital, general human capital, specialized human capital, and the innovation performance of the economy. The results of the modeling revealed a positive impact of human capital on the innovation performance of the analyzed economies. This indicates that economies with higher levels of human capital are also more innovative. Moreover, the model showed that the impact of general human capital and specialized human capital on innovation performance was comparable.

Based on the obtained results, the following conclusions can be drawn. The diversification of human capital is crucial for the innovativeness of an economy. General human capital provides flexibility and broad adaptability to new technologies and market changes, while specialized human capital enables the creation of advanced technological innovations. Optimal conditions for innovation arise when both types of human capital are well-developed and complement each other. Although both types of human capital have their specific functions, their combination is crucial for maximizing the innovativeness of an economy. General human capital creates the foundation on which specialized human capital can develop, meaning that countries must invest in both forms simultaneously.

The results of the conducted study can have a practical application and serve as an instrument of innovation policies or as a tool helpful in creating conditions for innovation systems.

Future research can be improved by considering other factors of innovation, e.g. financial factors. Then, it would be possible to verify which type of factors, tangible or intangible, have a stronger impact on innovation. Models accounting for relationships between various aspects of an economy's innovation capacity and its innovation performance provide an interesting direction for future research.

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