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# Factors impacting university–industry collaboration in European countries

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## Abstract

This paper aims to examine the links between university–industry collaboration (UIC) predictors (inputs) and the results of UIC cooperation (outputs). The focus of the research is UIC within the European Union member states and the Western Balkan countries. The analysis was conducted using the partial least squares structural equation modeling (PLS–SEM). This method enabled examining the links between variables that are not directly observable. The authors used data for the period of three years, 2015–2018. The results prove that countries investing in UIC predictors (inputs) have better UIC performance (outputs). Based on the statistical analysis, the authors identified the investments in knowledge, networking, and research and development (R&D), in general, as the most significant that impact UIC performance.

**Keywords:** University–industry collaboration, Europe, knowledge, Networking, R&D, PLS–SEM

## Introduction

In recent decades, researchers have been intrigued by the ever-increasing importance of university–industry collaboration (UIC), in particular by the factors of its success (Hillebrand & Biemans, 2003; Parkhe, 1993). UIC is emerging as a critical component of the innovation process. It is a vital component of the regional innovation policy-mix for regional policymakers as the successful exploitation of R&D results is fundamental for regional competitiveness (Morisson & Pattinson, 2020).

A noticeable shift towards regionalization in innovation policy and technology is evident. One of its consequences is the expectation for universities to draft networks and establish regional ties (Koschatzky & Stahlecker, 2010). Also of considerable importance is the construction of broad collaborative cluster networks, although most clusters focus on loosely defined local level networks. Notwithstanding, network members are responsible for more patent applications than others. What is more, there seems to be no loss of patent quality when collaborating with same cluster region universities (Nishimura & Okamuro, 2010).

The authors emphasize the impact of co-patenting and co-publishing on the UIC and the importance of technological specialization. The analysis of co-patent data enhances the understanding of transnational knowledge flows, especially when used in

combination with the interpretation of co-patent statistics. The share of co-published research has increased since the 1990s, especially in European countries. As a result, smaller countries tend to collaborate more often, and the new European Union (EU) member states make up a larger portion of co-publishing activities. Lata et al. (2018) find that knowledge distance plays by far a larger role than technological distance for co-publication activities. Links between distant regions in Europe are less likely than in the United States of America (USA). However, being neighbors matters more in the USA than in Europe. This counterbalances the geographical effect for regions that are not too far away from each other. When examining patents, authors notice that the USA, Japan, Canada and Western Europe (G4) countries host the large majority of international teams, almost 80%, followed by the combination G4—the rest of the world. But the two groups follow different trends, and G4—the rest of the world collaborations almost catch up with intra-G4 ones by the turn of the century (Miguelez et al., 2019).

UIC is mostly based on knowledge and technology transfer. Philbin (2010) notes that there is much evidence for a strong correlation between technology transfer and practical knowledge on the one side, and successful collaboration on the other. An intense transfer can improve the technology novelty (Guan et al., 2005), encourage innovation performance (Mingji & Ping, 2014), and/or boost product development (Fernandes & Ferreira, 2013). Nevertheless, many barriers impact knowledge and technology transfer, and this is a topic of many pieces of research (see de Medeiros et al., 2012; Hong et al., 2010; Schofield, 2013). In their study from 2009, Flores et al. state that technology transfer and knowledge are influenced by strategy and motivation (Flores et al., 2009), where utilization of adequate policies and incentives can enhance transfer activities in UIC (Schofield, 2013). Knowledge transfers might be impacted differently by universities and companies. While the former initiate knowledge transfer through research, the latter take on more managerial positions afterward (Goel et al., 2017).

There are multiple motives for UIC, which often meet many barriers. In their study, Muscio and Vallanti (2014) identified the following obstacles in the UIC: Misalignment of incentives between researchers and firms (conflicts with companies); Lack of academic procedures or intermediaries to ease the interaction with businesses (academic networking problems); Misalignment between academic goals and technological transfer activity (conflicts with academic goals), and distance between academic research and business needs (nature of research). Financial obstacles are shown to be strongly related to the propensity of knowledge-intensive business services to collaborate with universities and research institutes (URIs). Knowledge obstacles are moderately related to the propensity of high-tech manufacturing SMEs to collaborate with URIs. Silva et al. (2019) conclude that while URIs have other important roles in the techno-economic system, their perceived contribution to alleviating internal innovation barriers for technology-based SMEs may be less prominent than policy decision-makers in emerging economies may expect.

To investigate factors that impact UIC, the authors used data provided by the Global Innovation Index (GII). The Innovation Input Sub-Index and the Innovation Output Sub-Index—each constructed around pillars, are two sub-indices the GII relies on. In the Innovation Input Sub-Index, elements of the national economy that enable innovative activities are captured by five input pillars. The five input pillars are business

sophistication, market sophistication, infrastructure, human capital and research, and institutions. The Innovation Output Sub-Index encompasses innovation outputs, which stem from innovative activities within the economy. The output pillars are creative outputs, and knowledge and technology outputs. The average of the Input and Output sub-indices marks the overall GII score (Cornell University, INSEAD, & WIPO, 2010–2020).

Based on the defined elements, the authors created groups of factors that influence UIC (impact factors). On the other hand, the UIC performance level in a specific country is measured by the set of output factors. The differences in approach to the support of UIC also lead to companies achieving different results. This motivated the authors to explore the main factors that impact UIC in European countries. Thus, this research intends to answer the following question: “What are the vital factors that influence UIC”?

### **Literature review**

Many articles deal with the factors that make UIC successful. Rybnicek and Königsgruber (2019) conducted a thorough, in-depth review of the published scholarly literature on industry-university collaboration. They performed an extensive analysis of UIC projects’ research to distil factors that influence such partnerships’ success. Given the comprehensiveness of this research, as the authors of this paper used it as a base for identifying factors that determine UIC. Many other authors also deal with this topic, and the most recent and relevant articles are presented in this part of the research.

Based on the review of the existing literature, the authors could organize the factors that determine UIC. They are marked as “input factors” in the research and deployed into four categories. Firstly, there are institutional factors, which refer to business environment and government effectiveness. Secondly, there are human factors, which refer to human capital and research. Thirdly, there are linkage factors, which refer to relationships between universities and companies. Fourthly, there are framework factors, which refer to the business infrastructure. Finally, the authors define “output factors” that presents the level of UIC in a specific country.

### **Institutional factors**

Institutional factors include the business environment, legal restrictions, and/or governmental support. Kozlinska (2012) defines the government as an influential power with the ability to either facilitate or harm collaboration. On the one hand, the governmental network (Rampersad, 2015), public funding (e.g., Flores et al., 2009; Piva & Rossilamastra, 2013), or tax incentives (Bodas Freitas et al., 2013) can facilitate UIC. On the other hand, the absence of regional bracing structures (Șerbănică, 2011), and/or regulations and legal restrictions (Arvanitis et al., 2008; Attia, 2015; Hadjimanolis, 2006) can have a negative impact on collaboration. As a rule, industry-university partnerships rely heavily on governmental support (e.g., Collier et al., 2011; de Medeiros et al., 2012; Hemmert et al., 2014; Muscio & Vallanti, 2014; Myoken, 2013; Newberg & Dunn, 2002; Schofield, 2013; Sohal, 2013). Additional factors of business environmental success correspond to the market potential of research results (Ankrah & AL-Tabbaa, 2015; Barnes et al., 2002; Guan et al., 2005; Hadjimanolis, 2006) or market uncertainties (Hemmert et al., 2014).

### Human factors

Human resources play a vital role in the successful implementation of university-industry projects (Albats et al., 2020). Normally, there exists a strong dependence of the utility and quality of collaboration on the partner's available resources. The need for specific resources further limits the scope of potential partners (Ferru, 2010). For successful collaboration, highly qualified human resources (Myoken, 2013) are paramount. Also, of significance are unrestricted access to libraries, lab space, and similar infrastructure (Boardman & Bozeman, 2015); and/or technical equipment (Arvanitis et al., 2008). Companies with better-educated and/or more knowledgeable managers/supervisors tend to innovate more (Marotta et al., 2007). In his analysis of a survey of 39,336 enterprises, Merrit (2015) argues that larger enterprises due to a higher level of human capital can harness university-driven and generated knowledge more efficiently than smaller enterprises. The latter are less capable of absorbing said knowledge since they generally lack qualified technicians and engineers who are invaluable for innovation endeavors.

### Linkage factors

In the research, linkage factors refer to gross domestic expenditure on R&D (GERD) performed by an enterprise, GERD financed by a business enterprise, university-industry research collaboration, the state of cluster development, GERD financed from abroad, and by joint venture/strategic alliance deals. Working together and implementing each other's experience and feedback in the pursuit of improvements has been proven beneficial for both universities and companies (Ryan, 2009). Albats et al. (2020) argue that the preeminent aspect of a company's strategy in the shaping of their innovation performance is the creation of strategic partnerships, in particular university partnerships. The impact of communication is thoroughly examined in the addressed literature. The authors ought to emphasize that to establish a shared understanding, communication frequency is paramount (Hong et al., 2010; Lee, 2011). Close personal relationships also enable crucial links between universities and companies (Barnes et al., 2002; Collier et al., 2011). Contacts and actions ought to be on the operational level (regular interaction, mutual exchange of information with continuous feedback, and updating partners on new activities or incidents) and encompass the management level (Wu, 2017). Guan et al. regard the absence of communication channels as the primary barrier in partnerships (Guan et al., 2005). Also beneficial for the establishment of positive expectations about the partner's future behavior (especially when the partnership is still fresh) is reciprocal communication (accurate, adequate, timely, and regular) (Bstieler et al., 2017). Finally, The authors considered the role of culture in UICs. The latter is defined as the mutual understanding within a company on how employees ought to view, feel and think about issues and challenges (Schein, 2004).

### Framework factors

In the research, the framework factors refer to ICT access, ICT use, electricity output, logistics performance, gross capital formation, environmental performance, and the rule of law. Nishimura and Okamuro (2010) explained that UIC's legal aspects and intellectual property rights (IPRs) are significant. The IPR policy of governments and universities has a positive and significant impact on UIC project performances, controlling

for firm and project characteristics and considering potential selection bias from UIC participation. Betz et al. (2010) state that a favorable business environment does not, by default, affect the university's technology transfer activities positively. It is the implemented strategy of each university that is much more important than the environmental factors. Nevertheless, with an overall improvement in R&D capability, R&D collaboration, and technology, commercialization will also be enhanced (Vea, 2014).

The results demonstrate that increased attention to technology R&D and the protection of patents by governments and companies has led to immense improvements in the ICT sector. What is more, companies have now become the main body of technological innovation (Xia et al., 2014). Yarmouk University has developed dynamic programs of ICT enrichment and adopted an innovative partnership model, which in the form of an on-campus facility seeks to bridge the academia-industry gap. The facility offers a productive, internal collaborative environment for technical and business faculties, which together pursue projects to cultivate collaboration with industrial and business partners. Moreover, it facilitates the alignment of skills and knowledge of university staff and students to contemporary real industry needs, and updates the university's knowledge base with the latest industry developments (Al-Agtash & Al-Fahoum, 2008).

### Output factors

In the literature, there are many performance indicators of UIC. The number of patents (Xia et al., 2014), scientific and technical articles (Salimi & Rezaei, 2016), high-tech manufactures and exports (Aiello et al., 2019), intellectual property receipts (Valentin & Jensen, 2007), ICT services exports (D'Costa, 2006; Hwang, 2020), cultural and creative services exports (Draghici et al., 2016), creative goods exports (Banal-Estañol et al., 2011), are frequently mentioned. In general, the output indicators can be divided into two groups: tangible and intangible.

As Rybnicek and Königgruber (2019) stated, the compatibility of partner-to-partner goals is among the most discussed subjects in UICI literature. Failure to achieve the desired outcome is often the result of incompatibility (Henderson et al., 2006). For example, companies strive towards withholding the groundbreaking findings from universities from competitors, while the universities desire to publish them (Newberg & Dunn, 2002). Lai and Lu provide similar results Lai and Lu (2016). They state that companies and universities strive towards different goals. Consequently, it is paramount to seek a win-win situation with balanced benefits for both partners. This can be achieved only if both partners understand the other's interests. Also essential is for partners to agree upon achievable goals through a shared understanding of the objectives, and to materialize a precise strategy throughout the collaboration (Hong et al., 2010). It should also be added that partners more often than not hold unrealistic expectations about the outcome of cooperation, and/or have a different sense of urgency (Attia, 2015).

For the purpose of finding the appropriate partner, a correct partner selection process is advised prior to collaboration. In this sense, confidence in one's own needs and requirements is also a prerequisite. Only then can the search for an adequate partner with concordant interests and goals begin (Arvanitis et al., 2008). Adequate search strategies can facilitate the search for a matching partner. Barnes et al. (2002) recommend a partner evaluation method with specific criteria.

## Methodology

### Construct measures

The authors have grounded the theoretical framework of this research in a systematic review of relevant scholarly literature while also considering the availability of the variables' data. At the outset, the authors elicited 36 measures. These were grouped into six constructs, four of which focus on input factors, the remaining two on output factors (Table 1). The authors depicted the research model in Fig. 1.

Figure 1 depicts the model' schematic diagram. Both the internal and external relationships were considered.<sup>1</sup> The estimation was conducted with the help of SmartPLS software.

### Research method

This research uses the structural equation modeling method (SEM). SEM encompasses a plethora of statistical methodologies by which a causal relationship's network can be approximated. A theoretical model defines such a network as one which links at least two latent complex concepts. Several observable indicators measure each of these concepts. In essence, it can study the complexity within a system by considering a causality network among latent concepts—"latent variables". Many observed indicators usually defined as "manifest variables" are used to measure each of these latent variables. According to this, structural equation models represent a joint-point between path analysis and confirmatory factor analysis (Esposito Vinzi et al., 2010). Among the methods of estimating SEM models, the covariance-based (CB) method,<sup>2</sup> invented by K. G. Jöreskog, enjoyed the greatest popularity for a long time. So universal was its recognition that in social sciences the phrases: SEM and covariance-based structural equation modeling (CB-SEM) were synonymous for many years (Chin et al., 1996). Meanwhile, H. Wold developed an alternative approach—the partial least square method (PLS). Its description and application for estimating models with latent variables were presented by Wold in, among others: (Wold, 1980a, 1980b, 1982). Because the PLS method was an alternative to K. G. Jöreskog's 'hard' modelling, i.e. one based on strong assumptions regarding the normality of distributions and requiring large samples, Wold referred to his PLS approach as 'soft' modelling (Wold, 1980b, 1982). After a time, the term 'PLS-path modelling.'<sup>3</sup> Came into use, and then—in order to emphasize that PLS was an alternative to CB, it began to be called 'PLS Structural Equation Modeling' (PLS-SEM).

PLS-SEM and CB-SEM were developed as distinct, though complementary, methods with specific purposes and requirements. This was clearly stressed by the authors of both approaches at the beginning of the 1980s (Jöreskog & Wold, 1982). At present, the varying properties of PLS-SEM and CB-SEM are also noticed, with emphasis on the complementarity of the two methods instead of the competition between them. The advantages of the non-parameter, variance-based PLS-SEM modelling are, at the

<sup>1</sup> Internal model relationships are represented by the solid line, while the broken line was used for the external model relationships.

<sup>2</sup> In the CB-SEM method, a theoretical covariance matrix is estimated on the basis of a structural equations model. The estimation of model parameters is performed in such a way as to minimize the difference between the theoretical covariance matrix and the estimated covariance matrix.

<sup>3</sup> Among other things, in order to distinguish models containing latent variables estimated by means of the PLS method from PLS-based regression. Even now, in many publications, authors confuse the work of H. Wold and that of S. Wold.

**Table 1** Factor measures and data source

Construct	Measure	Code	Data source
Institutional factors	Political and operational stability	IIF1	World Intellectual Property Organization (WIPO), 2015–2018
	Government effectiveness	IIF2	
	Regulatory quality	IIF3	
	Ease of starting a business	IIF4	
	Gross expenditure on R&D (GERD)	IIF5	
	Expenditure on education	IIF6	
Human factors		IHF	
	PISA scales in reading, math, & science	IHF1	
	Graduates in science & engineering	IHF2	
	Tertiary level inbound mobility	IHF3	
	Researchers, full-time equivalent / Million population	IHF4	
	Employment in knowledge-intensive services	IHF5	
Linkage factors	Research talent in business enterprise	IHF6	
		ILF	
	GERD performed by business enterprise	ILF1	
	GERD financed by business enterprise	ILF2	
	University–industry research collaboration	ILF3	
Framework factors	State of cluster development	ILF4	
	Joint venture/strategic alliance deals	ILF5	
		IFF	
	ICT access	IFF1	
	ICT use	IFF2	
	Electricity output, kWh/mn pop	IFF3	
	Logistics performance	IFF4	
Output intangible indicators	Gross capital formation	IFF5	
	Environmental performance	IFF6	
	The rule of law	IFF7	
		OII	
	Patent applications by origin	OII1	
	Patent Cooperation Treaty (PCT) international applications by origin	OII2	
	Scientific and technical publications	OII3	
Output tangible indicators	Trademark application class count by origin	OII4	
	Industrial designs by origin	OII5	
	ICTs and business model creation	OII6	
		OTI	
	Cultural and creative services exports	OTI1	
	Creative goods exports	OTI2	
	The growth rate of Gross domestic product (GDP) per person engaged	OTI3	
	High-tech and medium high-tech output	OTI4	
	New business density	OTI5	

same time, the disadvantages of the parameter, covariance-based CB-SEM—and the other way around. Therefore, the choice of method should depend on the empirical context and research purposes (Hair et al., 2019).

An SEM model consists of two sub-models: a structural one and a measurement one. In PLS-SEM terminology, the phrases ‘inner model’ and ‘outer model’,

respectively, are also used. 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, also known as manifested variables (Wold, 1980a).

When constructing a structural model, one must pay particular attention to two aspects: the nature of the analyzed latent variables and the associations which occur among them. It is important to distinguish between exogenous variables and endogenous ones. Furthermore, all the formulated elements of the conceptual framework should be derived from theory and logic. If a theoretical basis is lacking, or if the theory is inconsistent, one should rely on one's own judgment, experience, and intuition (Hair et al., 2017).

Specification of the measurement model is an equally important stage of the modeling process. Verification of the hypotheses reflected in the structural model's equations can be reliable when, and only when, the latent variables are correctly defined by means of indicators. And the choice of indicators is as crucial as the choice of the way in which they are defined (Hair et al., 2017). 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 and are then referred to as reflective indicators, while the measurement model is called a reflective measurement model. In the case of inductive definition, it is assumed that indicators make up the latent variables, hence the expressions formative indicators and formative measurement model. The type of definition (inductive or deductive) should follow from the assumed theoretical description (Rogowski, 1990). Also, the choice of observable indicators should be preceded by an in-depth and thorough literature review, including the theory and empirical studies in measuring the latent variables present in the model.

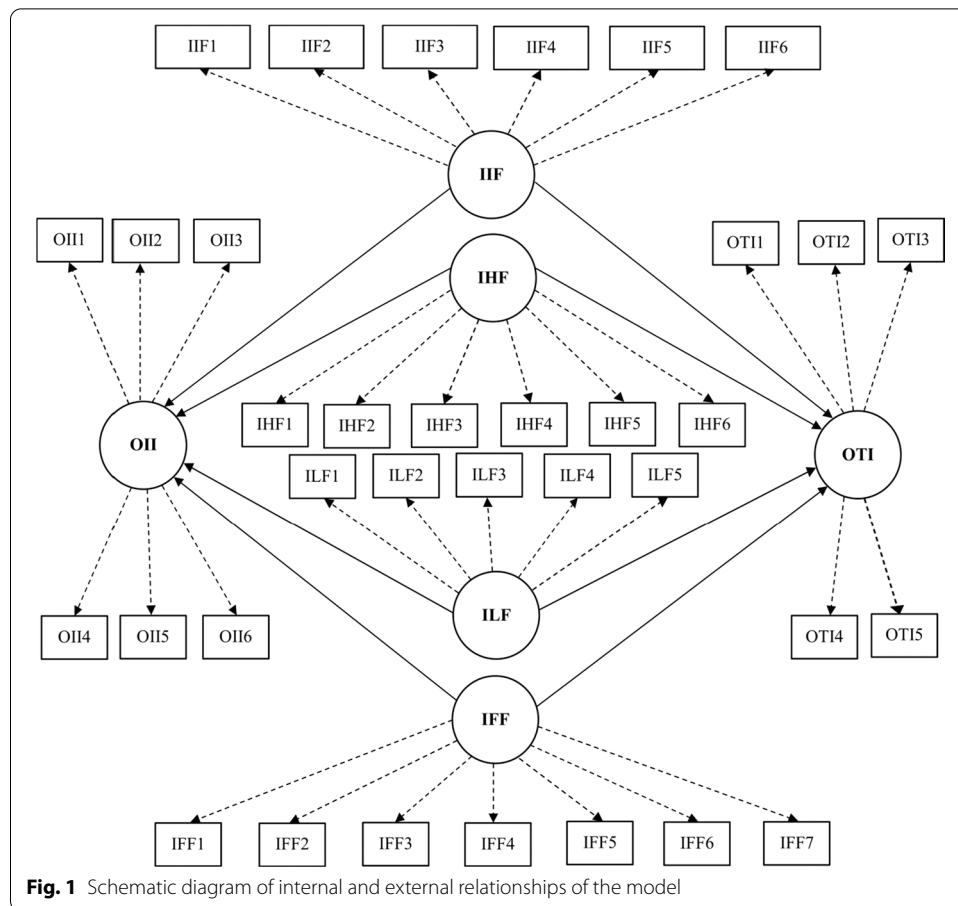
Alongside examining latent variables' correlations, PLS-SEM modeling also helps approximate the values of said variables (weighted sums of indicators). For that reason, a synthetic measurement, with which we can obtain a linear ordering of the studied objects, is calculated for each of the model's latent variables.

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. The estimation aims to maximize the explained variance of the latent dependent variables. The first stage involves the iterative estimation of measurement model weights and the values of latent variables. At the second stage, the loadings and path coefficients of the structural model are estimated. A detailed description of the PLS algorithm can be found, e.g., in Henseler et al. (2012) and Wold (1982), and its generalization in (Rogowski, 1990).

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 2 lists the properties of the model, which should undergo evaluation.

SEM using the PLS procedure used to be difficult due to the unavailability of software. Now the situation has greatly improved thanks to the wide range of user-friendly





programs, which enable estimation and statistical verification of PLS-SEM models, e.g. WarpPLS (Kock, 2020), ADANCO (Henseler & Dijkstra, 2015), SmartPLS (Ringle et al., 2015). This study will use the SmartPLS software.

**Specification of the model**

The model used for the realization of the research objective, i.e., proving the influence of UIC predictors on UIC performance, contains Eqs. 1a and 1b.

$$OTI_t = \alpha_1 IIF_t + \alpha_1 IHF_t + \alpha_1 ILF_t + \alpha_1 IFF_t + \alpha_0 + \nu_t, \tag{1a}$$

$$OII_t = \alpha_1 IIF_t + \alpha_1 IHF_t + \alpha_1 ILF_t + \alpha_1 IFF_t + \alpha_0 + \nu_t, \tag{1b}$$

where:

- OTI<sub>t</sub>—output tangible indicators in period *t*,
- OII<sub>t</sub>—output intangible indicators in period *t*,
- IIF<sub>t</sub>—institutional factors in period *t*.
- IHF<sub>t</sub>—human factors in period *t*.
- ILF<sub>t</sub>—linkage factors in period *t*.
- IFF<sub>t</sub>—framework factors in period *t*.
- α<sub>0</sub>, α<sub>1</sub>—structural parameters of the model,

$v_t$ —random component,  
 $t$ —Period of three years 2015–2018.<sup>4</sup>

The authors used the deductive approach to defining latent variables in the model, i.e., each latent variable as a theoretical notion is a starting point for the search for empirical data. The indicators were selected based on substantive and statistical criteria. The following things were accounted for from the statistical perspective: indicator values' diversity, measured by the coefficient of variation<sup>5</sup> (the coefficient's critical value was calculated at 10%), and the quality of the estimated model (model evaluation measures—ex-post analysis). Table 3 presents the indicators that passed substantive and statistical verification. The indicators of the input latent variables point to the most frequent and significant predictors of the UIC. Meanwhile, the OTI and OII measures reflect the outputs of UIC.

### Estimation results and statistical verification of the model

Figure 2 shows the PLS-SEM estimation results obtained in the SmartPLS software (Ringle et al., 2015). The results are interpreted in section “Results and Discussion”.

Table 4 contains the results of the estimation of the outer sub model.

Individual indicator reliability values significantly larger than the lowest acceptable level of 0.4 can be observed (Hulland, 1999).

Cronbach's alpha and composite reliability are shown to be larger than 0.6, which means that high levels of internal consistency reliability have been demonstrated among the latent variables.

In order to confirm convergent validity, the average variance extracted (AVE) is evaluated for each latent variable. Table 4 also shows that the AVE values are greater than the acceptable threshold of 0.5, which confirms convergent validity.

As suggested by Fornell and Larcker (1981), if this value exceeds other latent variables' correlation values, it can be used the square root of AVE in each latent variable to establish discriminant validity.

The latent variable OII's AVE is found to be 0.944 (from Table 4) hence its square root becomes 0.920 (Table 5). The result indicates that discriminant validity is well established.

Using a two-tailed t-test with a significance level of 5%, the path coefficient will be significant if the T-statistics is larger than 1.96. As presented in Table 6 all path coefficients in the inner model are statistically significant.

The values of the Stone–Geisser test statistic, which verifies the model in terms of its predictive usefulness (see Table 7), are positive, which proves the model's high predictive quality.

Both the measurement models and the structural models were positively assessed, therefore, in the next stage of modeling, the results can be interpreted.

<sup>4</sup> The Program for International Student Assessment (PISA) results is one of the significant indicators in the model. The PISA test was conducted across OECD countries in 2015 and 2018, and that is the reason why the authors chose these two years to examine changes in variables.

<sup>5</sup> This is calculated as a ratio of the standard deviation to the arithmetic mean, expressed in percentage.

**Table 2** Evaluation of PLS-SEM models

Evaluation of the measurement models					
Reflective measurement models			Formative measurement models		
Internal consistency	Cronbach's alpha Composite reliability	0.60–0.95 0.60–0.95	Convergent validity	Redundancy analysis	≥ 0.7 correlation
Convergent validity	Loadings The average variance extracted (AVE)	≥ 0.7 ≥ 0.5	Collinearity between indicators	Variance Inflation Factor (VIF)	≥ 0.5
Discriminant validity	Cross-loadings Fornell-Larcker criterion Heterotrait-monotrait ratio (HTMT)	< 0.9	Significance of outer weights	p-value	< 0.05
Evaluation of the structural models					
Collinearity		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: authors' work based on Hair et al. (2017)

### Results

Figure 3a–e present the ordering of the indicators of each of the latent variables in terms of values of outer loadings, i.e., in terms of the strength of the relationship between the values of the latent variable and the values of the indicators.

The following interpretation of the  $\pi_{ij}$  outer loading is assumed:

- $|\pi_{ij}| < 0.2$ —no correlation,
- $0.2 \leq |\pi_{ij}| < 0.4$ —weak correlation,
- $0.4 \leq |\pi_{ij}| < 0.7$ —moderate correlation,
- $0.7 \leq |\pi_{ij}| < 0.9$ —strong correlation,
- $|\pi_{ij}| \geq 0.9$ —very strong correlation.

The latent variable IIF is very strongly reflected by two indicators: “Gross expenditure on R&D” (IIF5) and “Political and operational stability” (IIF1).

The latent variable IHF is very strongly reflected by one indicator—“Researchers in R&D (per million people)” (IHF4)—and strongly reflected by three indicators: “Employment in knowledge-intensive services” (IHF5); “PISA scales in reading, math, and science” (IHF1); and “Research talent in business enterprise” (IHF6).

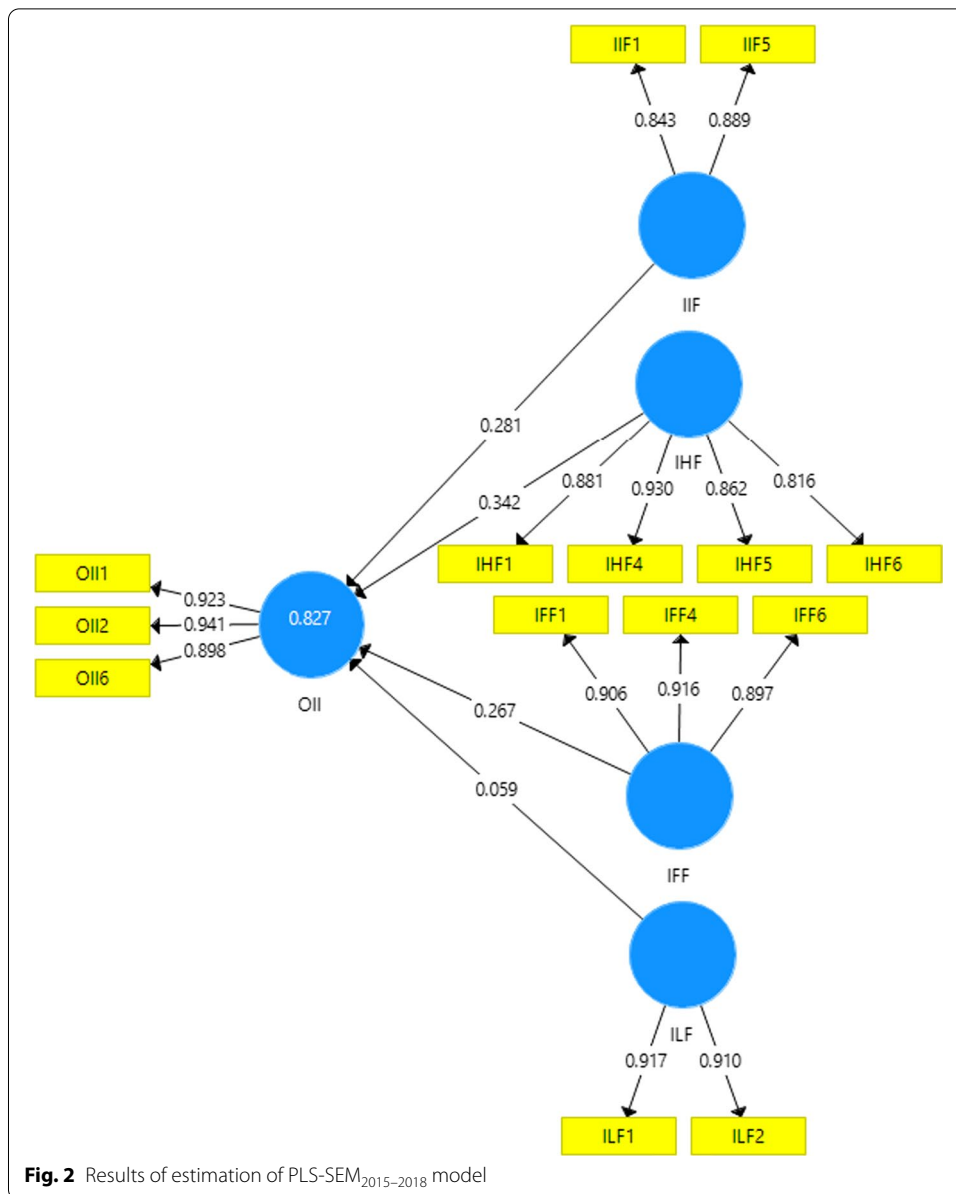
Two indicators very strongly reflect the latent variable ILF: “GERD performed by business enterprise” (ILF1), and “GERD financed by business enterprise” (ILF2).

**Table 3** Indicators of latent variables qualified for the model

Latent variables	Description of indicator	Code	Loadings
Institutional factors		IIF	
	Political and operational stability	IIF1	0.843
	Government effectiveness	IIF2	0.975 (Omitted)*
	Regulatory quality	IIF3	0.945 (Omitted)*
	Ease of starting a business	IIF4	0.479 (Omitted)
	Gross expenditure on R&D (GERD)	IIF5	0.889
Human factors		IHF	
	PISA scales in reading, math, & science	IHF1	0.881
	Graduates in science & engineering	IHF2	0.107 (Omitted)
	Tertiary level inbound mobility	IHF3	0.536 (Omitted)
	Researchers, full time equivalent/million people	IHF4	0.930
	Employment in knowledge-intensive services	IHF5	0.862
Linkage factors		ILF	
	GERD performed by business enterprise	ILF1	0.917
	GERD financed by business enterprise	ILF2	0.910
	University–industry research collaboration	ILF3	0.920 (Omitted)*
	State of cluster development	ILF4	0.918 (Omitted)*
Framework factors		IFF	
	ICT access	IFF1	0.906
	ICT use	IFF2	0.951 (Omitted)*
	Electricity output, kWh/mn pop	IFF3	0.525 (Omitted)
	Logistics performance	IFF4	0.916
	Gross capital formation	IFF5	0.055 (Omitted)
	Environmental performance	IFF6	0.897
Output intangible indicators		OII	
	Patent applications by origin	OII1	0.923
	PCT international applications by origin	OII2	0.941
	Scientific and technical publications	OII3	0.478 (Omitted)
	Trademark application class count by origin	OII4	0.357 (Omitted)
	Industrial designs by origin	OII5	0.533 (Omitted)
Output tangible indicators		OTI	
	ICTs and business model creation	OII6	0.898
	Cultural and creative services exports	OTI1	0.668 (Omitted)
	Creative goods exports	OTI2	0.446 (Omitted)
	The growth rate of GDP per person engaged	OTI3	0.517 (Omitted)
	High-tech and medium high-tech output	OTI4	0.468 (Omitted)
	New business density	OTI5	0.484 (Omitted)

\*The indicators that do not meet collinearity criteria

The latent variable IFF is very strongly reflected by two indicators: “Logistics performance” (IFF4) and “ICT access” (IFF1). Also, the latent variable ILF is strongly reflected by one indicator, “Environmental performance” (IFF6).



The latent variable OII is very strongly reflected by two indicators: “PCT international applications by origin” (OII2) and “Patent applications by origin” (OII1). Moreover, the latent variable OII is strongly reflected by one indicator— “ICTs and business model creation” (OII6).

The estimation of the internal model parameters indicates a significant positive correlation between UIC predictors and the level of UIC performance in the studied group of 33 European countries in the period 2015–2018. This means that those countries that reported a higher level of development of input factors also had a better UIC performance in the observed period.<sup>6</sup>

$$OII_t = 0.488 * ILF_{2015-2018} + 3.7695 \tag{2}$$

<sup>6</sup> Parameter  $\alpha_0$  was estimated in the PLS program (Rogowski, 1990).

**Table 4** Assessing the results of outer models

Latent variables	Indicators	rho_A	Average Variance Extracted (AVE)	Composite Reliability	Cronbach's Alpha
IIF	IIF1	0.681	0.750	0.857	0.669
	IIF5				
IHF	IHF1	0.902	0.763	0.928	0.896
	IHF4				
	IHF5				
	IHF6				
ILF	ILF1	0.803	0.834	0.910	0.802
	ILF2				
IFF	IFF1	0.895	0.821		
	IFF4				
	IFF6				
OII	OII1	0.916	0.848	0.944	0.911
	OII2				
	OII6				

\*Average Variance Extracted (AVE)

**Table 5** Fornell–Larcker criterion analysis for checking discriminant validity

	IIF	IHF	IIF	ILF	OII
IIF	0.915				
IHF	0.920	0.863			
IIF	0.940	0.942	0.900		
ILF	0.863	0.929	0.879	0.879	
OII	0.886	0.893	0.904	0.905	0.919

**Table 6** Assessing the results of inner models

	Path coefficients	Standard deviation (STDEV)	T-statistics ( O/STDEV )	P values	R <sup>2</sup>
IIF → OII	0.191	0.256	0.749	0.454	0.827
IHF → OII	− 0.156	0.238	0.657	0.512	
IIF → OII	0.407	0.224	1.818	0.070	
ILF → OII	0.488	0.163	2.992	0.003	

Aside from investigating latent variables correlations, this way of modelling also helps estimate these variables' values (weighted sums of indicators). For that reason, a synthetic measurement, with which we can obtain a linear ordering of the studied objects, is calculated for each of the model's latent variables.

Based on estimated values of the input and output variables, rankings of the studied countries have been compiled: a ranking of input and output variables. The results are shown in Table 8.

The countries are also divided into typological groups, according to similar volumes of UIC inputs and outputs. The results of the grouping are presented in Fig. 4a–e. The

**Table 7** Stone–Geisser test  $Q^2$  values

Indicator	2015–2018
OII1	0.516
OII2	0.482
OII6	0.798
General	0.827

Source: authors’ own work

boundaries between the groups have been established based on the arithmetic means and standard deviations of the synthetic measure  $z_i$  (equal to 0 and 1, respectively, for each of the latent variables). The groups are as follows:

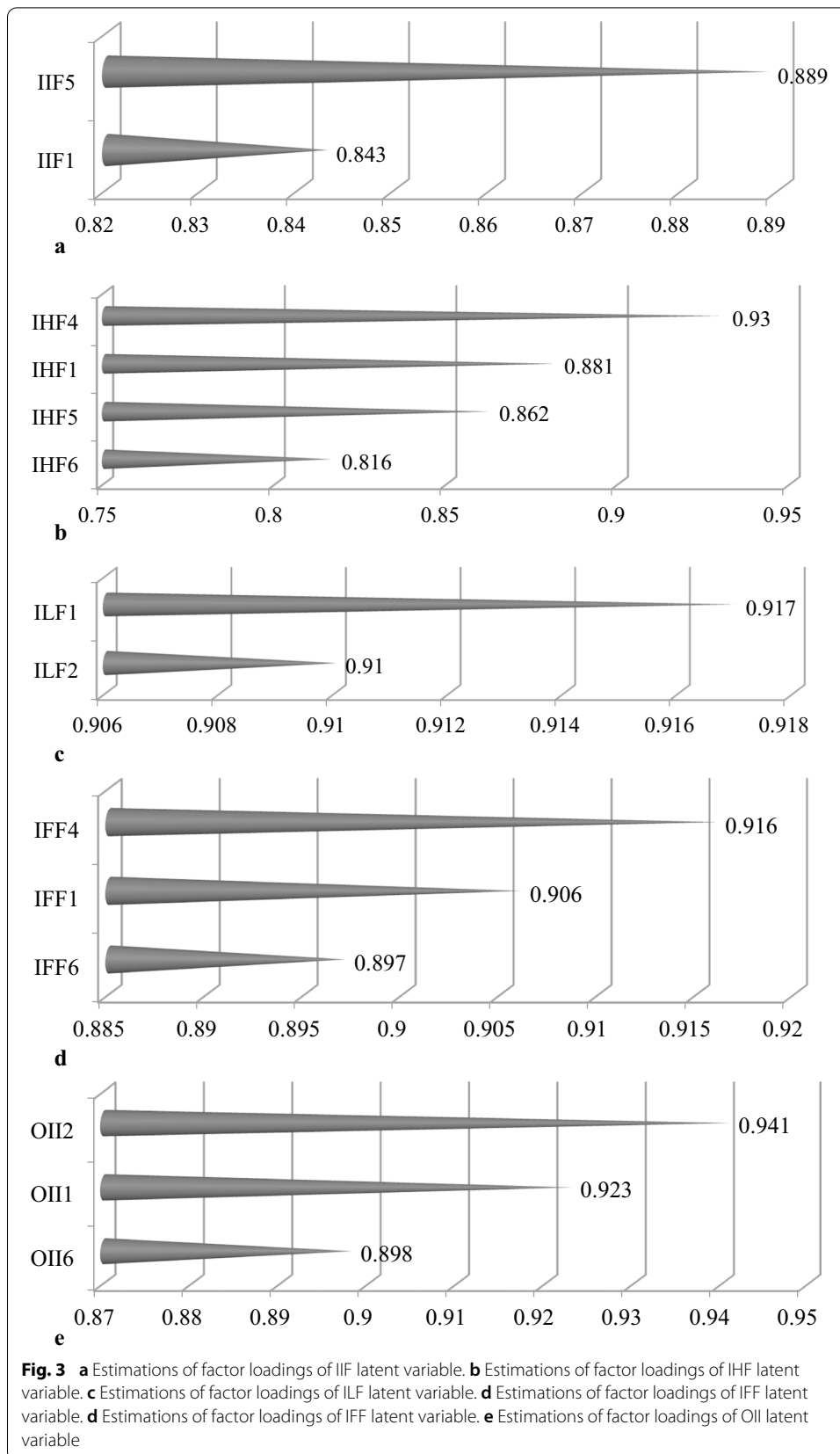
- Group I (very high level of latent variable):  $z_i \geq 1$ ,
- Group II (high level of latent variable):  $0 < z_i \leq 1$ ,
- Group III (medium and low level of latent variable):  $-1 < z_i \leq 0$ ,
- Group IV (very low level of latent variable):  $z_i \leq -1$ .

**Discussion**

A very high level of institutional factor development was observed in the following six countries: Finland, Denmark, Germany, the Netherlands, Austria, and Luxemburg. The group of the countries with a high level of institutional factors development comprised eleven countries: Ireland, United Kingdom, Belgium, Sweden, Spain, Estonia, Czech Republic, France, Lithuania, Malta, and Slovenia. Nine countries were qualified for the group of economies with a medium level of institutional factors development: Slovakia, Poland, Portugal, Cyprus, Latvia, Hungary, Italy, Croatia, and Serbia. Six countries were characterized by low levels of institutional factors development: North Macedonia, Bulgaria, Greece, Romania, Montenegro, and Albania. Finally, Bosnia and Herzegovina is in the bottom place as the country with the lowest level of institutional factors development.

When one considers the human factors, the classification looks somewhat different. Here, the top ranks are occupied by EU member states based on highly developed human capital, focusing on functional literacy, knowledge, and the R&D sector (Denmark, Finland, the Netherlands, Germany, Belgium, Luxemburg, and Austria). The group with a high level of human capital development comprised 11 countries: France, Ireland, United Kingdom, Sweden, Slovenia, Estonia, Spain, Czech Republic, Hungary, Malta, and Poland. Eight countries were qualified for the group of economies with a medium level of human capital development: Lithuania, Italy, Slovakia, Latvia, Portugal, Croatia, Bulgaria, and Greece.

Countries with weak indicators of functional literacy and of knowledge, and a small percentage of spending on R&D sectors (Cyprus, Serbia, Montenegro, North Macedonia, Romania, Bosnia and Herzegovina, Albania) are ranked at the bottom.



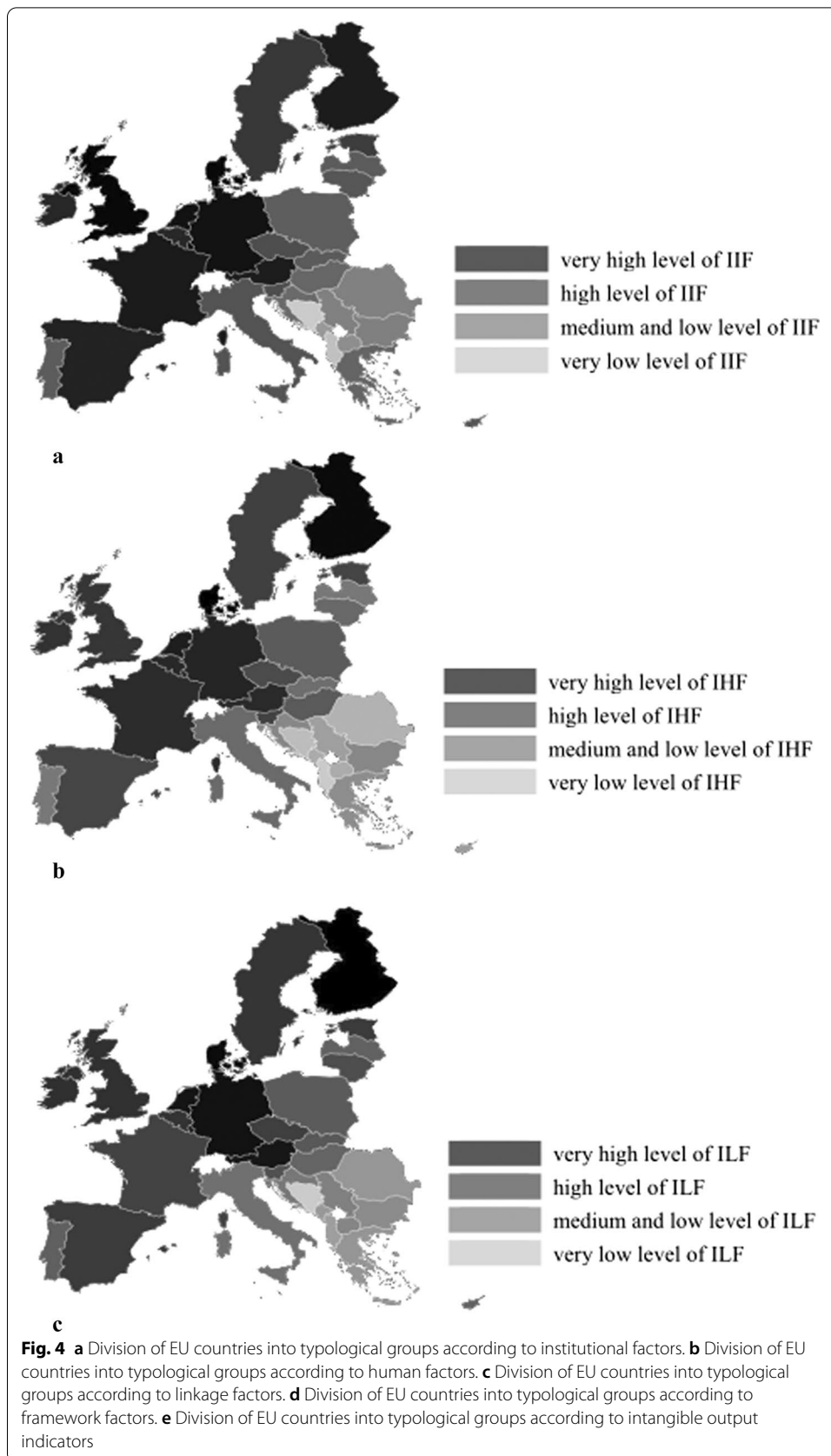


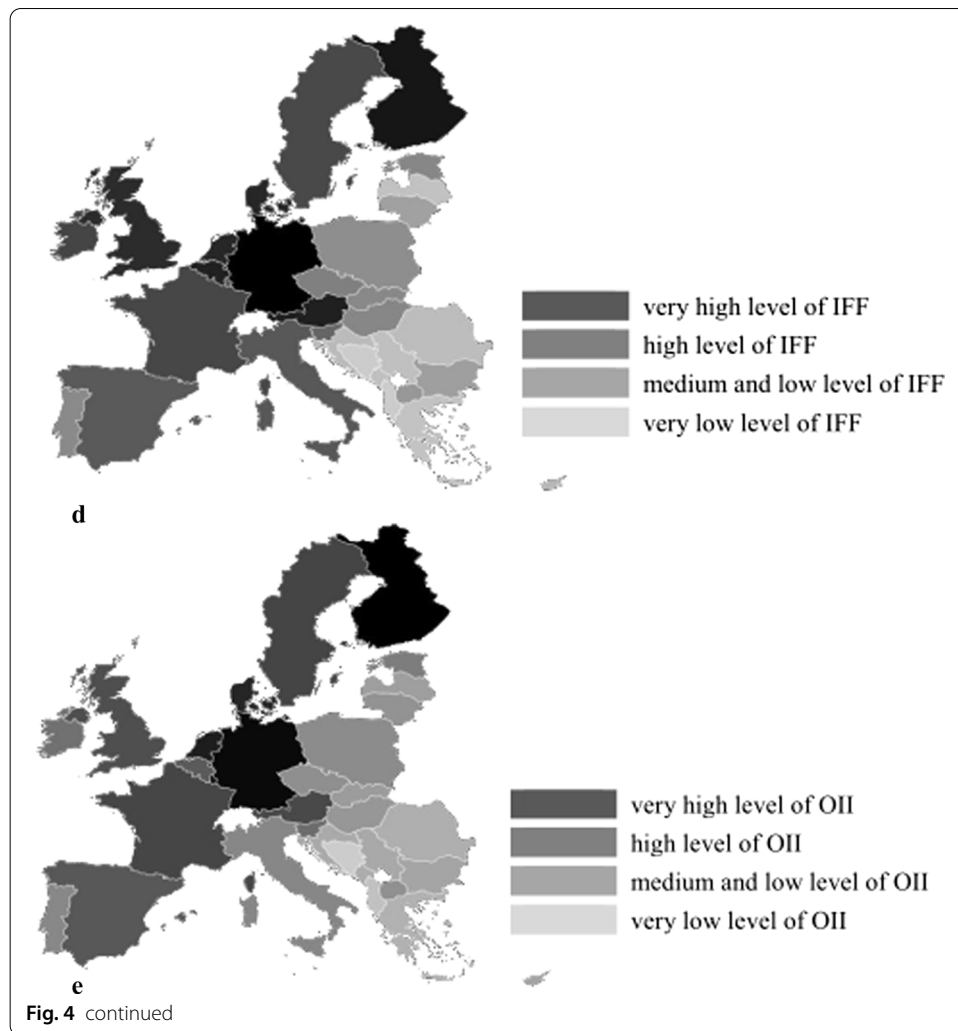
**Table 8** Rankings of UIC input and output indicators over the period of three years (2015–2018)

Country	IFF	IHF	IIF	ILF	OII
Albania	32	33	32	33	32
Austria	8	7	5	3	8
Belgium	11	5	9	4	12
Bosnia and Herzegovina	33	32	33	32	33
Bulgaria	27	25	28	23	26
Croatia	26	24	25	26	28
Cyprus	19	27	21	25	25
Czech Republic	15	15	13	16	19
Denmark	2	1	2	6	5
Estonia	14	13	12	17	15
Finland	7	2	1	2	1
France	6	8	14	9	7
Germany	5	4	3	1	2
Greece	24	26	29	31	31
Hungary	25	16	23	18	22
Ireland	10	9	7	8	14
Italy	17	20	24	11	16
Latvia	22	22	22	30	24
Lithuania	18	19	15	24	21
Luxemburg	1	6	6	12	3
Malta	12	17	16	15	10
Montenegro	31	29	31	28	29
The Netherlands	4	3	4	5	4
North Macedonia	30	30	27	22	20
Poland	23	18	19	21	18
Portugal	21	23	20	20	17
Romania	28	31	30	27	30
Serbia	29	28	26	29	27
Slovakia	20	21	18	19	23
Slovenia	16	12	17	14	13
Spain	9	14	11	13	11
Sweden	13	11	10	10	6
United Kingdom	3	10	8	7	9

According to institutional factors, the ranking of countries demonstrates a dominance of North and Western European economies and those “catch-up” economies from Central Europe. Economies of Southeastern Europe occupy the lower ranks.

A very high level of developed linkage factors was observed in the following six countries: Finland, Denmark, Germany, the Netherlands, Austria, and Luxemburg. The group with a high level of developed linkage factors comprised 11 countries: Ireland, United Kingdom, Belgium, Sweden, Spain, Estonia, Czech Republic, France, Lithuania, Malta, and Slovenia. Nine countries qualified for the group of economies with a medium level of developed linkage factors: Slovakia, Poland, Portugal, Cyprus, Latvia, Hungary, Italy, Croatia, and Serbia. Six countries were characterized by low levels of developed linkage





factors: North Macedonia, Bulgaria, Greece, Romania, Montenegro, and Albania. Bosnia and Herzegovina were characterized as the country with very low levels of developed linkage factors.

A very high level of developed framework factors was observed in the following eight countries: Luxemburg, Denmark, United Kingdom, the Netherlands, Germany, France, Finland, and Austria. The group with a high level of developed framework factors comprised six countries: Spain, Ireland, Belgium, Malta, Sweden, and Estonia. Thirteen countries were qualified for the group of economies with a medium level of developed framework factors: Czech Republic, Slovenia, Italy, Lithuania, Cyprus, Slovakia, Portugal, Latvia, Poland, Greece, Hungary, Croatia, and Bulgaria. Four countries were characterized by low levels of developed framework factors: Romania, Serbia, North Macedonia, and Montenegro. Finally, two Balkan countries were characterized by very low levels of developed framework factors: Albania and Bosnia and Herzegovina.

According to framework factors, the countries' ranking demonstrates a dominance of North and Western European economies and those "catch-up" economies from Central Europe. Economies of Southeastern Europe occupy the lower ranks.

As presented in the analysis of intangible output indicators, the top ranks are occupied by five EU member states based on highly developed human capital, focusing on functional literacy, innovation, ICT use, and the R&D sector (Finland, Germany, Luxembourg, the Netherlands and Denmark.). The group with a high level of intangible output indicators comprised nine countries: Sweden, France, Austria, United Kingdom, Malta, Spain, Belgium, Slovenia, and Ireland. Fifteen countries qualified for the group of economies with medium and low levels of intangible output indicators: Estonia, Italy, Portugal, Poland, Czech Republic, North Macedonia, Lithuania, Hungary, Slovakia, Latvia, Cyprus, Bulgaria, Serbia, Croatia, and Montenegro. Countries with weak indicators of patent applications by origin, PCT international applications by origin, and ICTs and business model creation (Romania, Greece, Albania and Bosnia and Herzegovina) were ranked at the bottom.

Within the EU-28, most countries treat UIC as a vital source of increasing the performance of companies. Nevertheless, the Balkan countries still lack cooperation between the universities and companies.

## Conclusions

This research presents empirical studies' results of the relationship between UIC predictors and performances in selected European countries. The research involved developing a PLS-SEM model, measurement of the latent variables based on sets of observable variables, and the estimation and verification of the PLS-SME model. The modeling outcomes reveal a significant favorable influence of impact factors on the UIC performance in the analyzed European countries. Based on the literature review, the authors identified four main groups of factors that impact UIC performance. Firstly, there are institutional factors, which refer to the business environment and expenditures on R&D; secondly, there are human factors, which refer to functional literacy and research; thirdly, there is a linkage factor, which refers to relationships between universities and firms; and fourthly, there are framework factors, which refer to the business infrastructure. Finally, the authors defined the "output factors" that present the level of UIC in a specific country.

On average, predictors of successful UIC are led by EU-15 member states. A very high-level input indicator was observed in the following seven countries: Denmark, Finland, Germany, the Netherlands, Austria, Luxembourg, and the United Kingdom. The group with a high level of developed input factors comprised nine countries: Belgium, Ireland, France, Sweden, Spain, Estonia, Slovenia, Czech Republic, and Malta. Eleven countries qualified for the group of economies with a medium level of developed input factors: Italy, Poland, Lithuania, Slovakia, Hungary, Portugal, Latvia, Cyprus, Croatia, Bulgaria, and Greece. Six Balkan countries are ranked bottom in Europe, and these are countries with a low level of institutional factors development: North Macedonia, Serbia, Romania, Montenegro, Albania, and Bosnia and Herzegovina.

To improve the economic situation in the region, the Balkan countries should, in the long term, revise their education systems and invest more money in knowledge, networking, and R&D in general. Based on both public and private initiatives, this investment will have a long-term positive impact on companies' productivity, as well as their profit. Furthermore, they should follow successful examples from the EU member states

and launch specialized programs for supporting innovation in the short term. The authors suggest Austria and Slovenia as the best model countries for the Balkan region since these two countries have been the best example for the Balkan economies in many fields throughout history. Moreover, universities must be more focused on the companies' real needs in the future if they want to justify their role in society.

This research provides new knowledge on how different factors accelerate UIC in Europe. To the best of the authors' knowledge, it is the first research to investigate links between institutional factors, human capital, linkage factors, and framework factors on the one side, and output factors of UIC on the other by using the PLS-SEM method. Based on the described indicators, the authors improved a UIC model driven by investments in linkage factors.

#### Abbreviations

AVE: Average variance extracted; CB: Covariance-based; CB-SEM: Covariance-based structural equation modeling; EU: The European Union; G4: USA, Japan, Canada and Western Europe; GDP: Gross domestic product; GERD: Gross domestic expenditure on R&D; GI: Global innovation index; HTMT: Heterotrait-monotrait ratio; PCT: Patent cooperation treaty; PLS: Partial least square method; PLS-SEM: Partial least squares structural equation modeling; R&D: Research and development; SEM: Structural equation modeling method; STDEV: Standard deviation; UIC: Between university–industry collaboration; URS: Universities and research institutes; USA: The United States of America; VIF: Variance inflation factor; WIPO: World Intellectual Property Organization.

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#### Authors' contributions

BC investigated links between institutional factors, human capital, linkage factors, and framework factors on the one side, and output factors of UIC on the other by using the PLS-SEM method. PA provided literature review about the factors impacting university–industry collaboration. DH provided dataset, and worked on technical issues in the paper (copy editing, creation of tables and figures, etc.). All authors read and approved the final manuscript.

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#### Availability of data and materials

Public data, provided by WIPO, 2015–2018: [https://www.wipo.int/edocs/pubdocs/en/wipo\\_pub\\_gii\\_2020.pdf](https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2020.pdf).

#### Declarations

##### Competing interests

Not applicable.

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