Mapping Key Competencies for the Knowledge Society Era

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Abstract: The growing conceptual complexity and persistent ambiguity surrounding the definition and measurement of the Knowledge Society/Knowledge Economy (KS/KE) and its associated competencies point to an unresolved research gap, which may contribute to fragmented and insufficiently coordinated policy responses. While numerous frameworks describing 21st-century skills and competencies exist, their linkage to macro-level indicators capturing the performance of knowledge-based economies remains limited and methodologically underexplored. This paper addresses this gap by examining the methodological viability of systematically deriving key competencies for the KS/KE from Knowledge Economy Index (KEI) indicators and by assessing whether the resulting competency model demonstrates conceptual congruence with established 21st-century competency frameworks. The primary objective of the study is to develop and apply a novel and robust methodological framework for constructing a key competency model tailored to the contemporary socio-economic context of the KS/KE. The proposed approach is grounded in a systematic content analysis of existing KEIs and their constituent indicators. Specifically, the methodology is applied to a dataset comprising 301 indicators derived from four internationally recognised KEIs: the Global Knowledge Index (GKI), the Global Innovation Index (GII), the European Innovation Scoreboard – Summary Innovation Index (EIS- SII), and the Digital Economy and Society Index (DESI). A central methodological contribution of the study lies in the uniform semantic categorisation of all indicators and their systematic division into input indicators, capturing structural prerequisites and investments, and output indicators, reflecting achieved results and performance. This analytical structure enables the identification of key competencies that mediate the transformation of invested resources into measurable and socially desirable outcomes within KE. To assess the conceptual robustness of the proposed model, the resulting key competency model for KS/KE is validated against a reference database of competencies synthesised from authoritative policy and strategic documents issued by organisations such as the OECD, UNESCO, the European Commission, the Council of the European Union, the World Economic Forum, and the Partnership for 21st Century Learning. The validation confirms a high degree of conceptual alignment between the empirically derived competencies and established 21st-century competency frameworks. In addition, the study exploits an extensive longitudinal dataset of KEI indicators available since 2017 as the empirical basis for a model-based analysis of anticipated trends in key competency development over a forthcoming three-year horizon. Compared to traditional competency modelling approaches based on expert studies, job analyses, behavioural observations, Delphi methods, or surveys, the proposed model leverages dynamically updated KEI indicators, offering greater flexibility and responsiveness to rapid socio-economic change. At the societal level, the resulting KS/KE key competency model provides a foundation for preparing future knowledge workers, while at the organisational level it supports talent management practices and the development of organisation-specific competency models aimed at sustaining competitive advantage.

Keywords: Knowledge society, Knowledge economy, Knowledge index, Key competencies, Modelling methodology, Competency model, Prediction

1. Introduction

The major deployment of automation and scientific breakthroughs in the 1960s ended a long period of stability and marked the start of a phase of discontinuity that brought profound socio-economic changes—still ongoing today. Initially, the focus was on the growing role of computers and the increasing volumes of information, viewed positively as “energy for the work of the mind” (Drucker, 1992). This triggered prominent yet elusive socio-economic changes. Naming this phenomenon proved challenging. Early on, terms such as *information society, information revolution* (Robertson, 1990), *white collar revolution* (Gottmann, 1964), *post-industrial society* (Bell, 1973), *third wave society* (Toffler, 1980), etc. Later, the dark side—information overload—also became evident. Original expectations tied to the information society remained largely unfulfilled, likely due to a widespread failure to distinguish between information and knowledge. While an increase in knowledge and innovation was anticipated, digital information alone is only a prerequisite, not a sufficient condition, for such progress (Tsoukas, 1997; Cohen and Garasic, 2024). Competent individuals are needed to navigate this information and transform information into applicable knowledge and innovation (Sugiyama and Meyer, 2008; Nonaka and Takeuchi, 1995) at both the micro and macroeconomic levels. Among the required competencies,

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critical thinking is the most frequently emphasised, as it involves the analysis, evaluation, synthesis, and application of information to guide action (Scriven and Paul, 1987).

The issue of competencies is explored both at the general education level, aimed at identifying essential knowledge and skills, and at the organizational level, focusing on the specific competencies required within a company or field. Globalization and the specifics of the KE have shifted more attention from the organizational to the societal level, aiming to identify so-called *key competencies* (Rychen and Salganik, 2002).

The main *research question* guiding this paper is to what extent is it methodologically viable to systematically derive key competencies for the KS/KE from KEI indicators, and does the resulting key competency model for KS/KE demonstrate conceptual congruence with established 21st-century frameworks? The specific *objective* of this study is to devise a methodological framework for developing a key competency model tailored to the contemporary socio-economic context, grounded in an analysis of existing KEI and their constituent indicators. Subsequently, the study aims to apply this methodology to construct a pilot key competency model for the KS/KE, utilizing a dataset of 301 indicators derived from four identified KEIs. This model is then validated against a reference database of competencies synthesized from authoritative documents issued by organizations such as the OECD, UNESCO, the European Commission, the Council of the European Union, the World Economic Forum, and the Partnership for 21st Century Learning. A supplementary objective is to leverage the extensive longitudinal dataset of KEI indicators accumulated since 2017 to conduct a model-based analysis of anticipated trends in key competency development for the forthcoming three-year horizon.

2. Knowledge Economy

The fact that knowledge contributes in some way to economic growth has been discussed in professional circles for a long time. As early as 1776, Adam Smith pointed out in The Wealth of Nations that a man who all his life performs a few simple operations (division of labour) has no opportunity to make use of his invention in the search for solutions to eliminate (non-existent) difficulties. However, more analyses focused on the importance of knowledge in economics did not emerge until the twentieth century. The endogenous meaning of innovation was analysed as part of the concept of development, with an individual being merely the bearer of the mechanism of change (Schumpeter, 1934), and a little later the theory of knowledge was developed (Hayek, 1937; Hayek, 1945) which contributed significantly to economics and social science. Friedrich August von Hayek (1945) emphasised, among other things, that the most relevant knowledge for economic decisions is not general knowledge, but local, dispersed, fragmented, and often tacit knowledge of many individuals. Subjective or tacit knowledge also interested philosophers such as Gilbert Ryle (1949) who saw it as a disposition and a matter of competence, and Michael Polanyi (1962), who elaborated on the theory of inexpressible tacit knowledge. Polanyi described it as knowing more than we can tell, or knowing how to do something without thinking, like riding a bicycle (Polanyi, 1966). These are individual experiences, skills, ideas, values, intuition, emotions, etc., which are difficult to express and often integrated into complex competencies. Because of their intangible nature, this knowledge is rarely captured in socio-economic measurements, yet its importance continues to grow.

2.1 The Problem of a Uniform Definition

As soon as socio-economic changes began, experts writing about the "new" society and economy often failed to distinguish between information and knowledge. This was particularly visible in the early stages, but even today many still treat them as synonyms, creating semantic confusion. For instance, while Marc Porat (1977) measured the *information* economy and *information* work, Peter Drucker (1992) distinguished between the attributes of information (industry), as related to the times when first computers were made, and knowledge (industry), producing thoughts. In current terminology, new forms of economy are more often labelled in ways that highlight their essence. Alongside *knowledge* economy or *knowledge*-based economy scholars and institutions use related terms emphasizing specific pillars: *learning* economy (Lundvall, 1997; Lundvall and Johnson, 1994), *innovation* economy (Locke and Wellhausen, 2014; Tafti et al. 2012), or e-*economy* or *digital* economy (Fudenberg and Villas-Boas, 2012; Haltiwanger and Jarmin, 2000).

The main difficulty with defining the KE lies in the fluid nature of knowledge itself, which is semantically complex. The OECD report described knowledge as capricious: sometimes sticky, often slippery, rarely tangible, often silent, and extremely heterogeneous (OECD, 2000). Philosophically, epistemology approaches knowledge as universal and abstract, often as a normative reflection of reality or a method of valid inference, with truth as the central criterion. The classic definition of knowledge in philosophy is "justified true belief", or "true opinion combined with reason" (Hilpinen, 1970). Within economic and management literature, the complexity of knowledge has given rise to two main paradigms. The *objectivist* perspective on knowledge and *the practice-based* perspective (Hislop, 2013), sometimes referred to as knowledge as truth and knowledge as socially constructed (McAdam and McCreedy, 2002), or knowledge as asset and knowing as process (Empson, 2001). The second perspective emphasizes tacit and subjective knowledge, yet economic and sociological literature has focused primarily on explicit knowledge, as it is measurable and linked to innovation and science-based industries (Ducatel, 1998).

Because of these ambiguities, experts tend to analyse the pillars of KE rather than provide strict definitions. Commonly cited are information and communication technology (ICT), innovation, education, human resources, research and development (R&D), the economic incentive regime, and socio-economic sustainability. International organisations usually define KE in broad and abstract terms. For example, the Organisation for Economic Co-operation and Development (OECD, 1996) defined KE as an economy that is based directly on the production, distribution, and use of knowledge and information. The World Bank (Chen and Dahlman, 2006) views KE as one that utilises knowledge as the key engine of economic growth. It is an economy where knowledge is acquired, created, disseminated, and used effectively to enhance economic development. It is natural that the heterogeneous nature of the concept of knowledge, which must be aggregated and compared with caution, and consequently broad and abstract definitions of KE, also cause a problem with a uniform approach to measuring KE. We have discussed the development and current ways of measuring knowledge in detail in our paper on methods to measure KE (Katuščáková, Capková and Grečnár, 2023a).

2.2 The Problem of Measurement

As we mentioned in Katuščáková Capková and Grečnár (2023a), measurement may be understood as the assignment of scaled numbers to items in a way that reflects the relationships among the possible states of a variables (Andriessen, 2003). In the context of knowledge, measurement can be studied at two levels: the micro level, where firms assess stocks and flows of intellectual or knowledge capital (like Balanced Scorecards, Intangible Asset Monitor, Skandia Navigator, etc.), and the macroeconomic level, where measurement concerns national knowledge resources. Inevitably, such measurement is imperfect, as knowledge remains capricious and resistant to standardisation. The difficulty lies in comparing monetary inputs in research with intangible outcomes, such as professional networks disseminating tacit knowledge. As emphasised in the OECD report, less codified and personalised knowledge complicates quantification (OECD, 2000).

In early efforts to measure economic growth through technological progress, the 'growth accounting' method (Solow, 1957; Denison, 1962; Romer, 1986; Lucas, 1988) was used alongside 'national income accounting' (Kuznets, 1946), which relies on descriptive statistics and data on goods and services production. For example, Fritz Machlup used data from various sources in his calculations of knowledge production and distribution in the United States. He did not consider his work a statistically precise calculation, but rather a message that knowledge is a key economic entity (Godin, 2010). He included areas such as education, R&D, publishing, IT, personal and financial services, media, advertising, conventions, business services, and government. He focused on professional groups and distinguished white- and blue-collar workers (Machlup, 1962). Unlike Machlup, Marc Porat (1977) followed the national income accounting framework and preferred the concept of *information* over *knowledge*. He defined information activity as one primarily producing, processing, or transmitting economically valuable information. He further distinguished primary (market-oriented) and secondary (internally consumed) information sectors. Porat classified 422 occupations reported by the U.S. Census and the Bureau of Labor Statistics into information and non-information groups. His matrix showed that the information sector had grown from 15% of the workforce in 1901 to nearly 40% by 1970, with information workers earning over 53% of labour income in 1967, arguing that the U.S. had become an information-based economy (Porat, 1977).

As the KE's role grew, international organizations also joined the measurement efforts. The first major international initiatives came from the OECD and the World Bank. Since 1995, the OECD has developed indicators for the KE, largely adapted from the Industry and Technology Scoreboard. However, the search for relevant KE indicators and pillars changed frequently: five categories in 1999 (Knowledge-Based Economy, ICT, S&T Policies, Globalization, Output and Impact), four in 2001 (ICT, innovation and diffusion, human capital, entrepreneurship), and five again in 2003. In 2017, the OECD analysed six groups of indicators under a new structure, including digital transformation, skills, innovation, competitiveness, and society (OECD, 1999; OECD, 2001; OECD, 2003; OECD, 2017).

A major milestone was the World Bank's *Knowledge for Development* (K4D) programme launched in 1999, which introduced the *Knowledge Assessment Methodology* (KAM). KAM provides a cross-sectoral assessment of countries' readiness for the KE using 80 variables grouped under four pillars: education, innovation, ICT, and economic/institutional regime, including gender equality. All indicators are normalised on a 0–10 scale, and 128 countries were ranked (Chen and Dahlman, 2006). Today, KE is increasingly measured using international indices, KEI, as we discussed in detail in (Katuščáková, Capková and Grečnár, 2023a).

3. Competencies

Contemporary society is characterised by discontinuity, requiring individuals to assume diverse roles, adapt to shifting contexts, and face unpredictable challenges throughout their working lives. Already in the late 1960s, with the onset of automation, debates emerged on the changing nature of work and the implications for education (Schumann et al. 1985). The initial focus on competencies was at the organizational level, where their identification is typically rooted in internal process analysis, superior performer behaviour modelling, and alignment with strategic goals to establish a competitive advantage (Prahalad and Hamel, 1990). Recent research highlights that competency modelling has evolved through the integration of best practices in analysing, structuring, and applying competency information, thereby strengthening talent management and aligning HR practices with organisational objectives (Campion et al. 2011). Competency models further function as strategic mechanisms that translate organisational strategy into employee behaviour and support sustained alignment between managerial intent and workforce priorities (Campion et al. 2019). Conceptual advances also emphasise the multidimensional nature of competencies, framing them as an interplay of individual, organisational, and contextual dimensions within enterprise management (Szafrański, 2019).

Later, processes of globalisation (segmentation and specialisation), networking (system rationalisation), and the rise of the KE (innovation, knowledge workers) reframed the discussion and largely shifted the emphasis of preparing competent workers from organisational to societal levels (Rychen and Salganik, 2002).

At the macroeconomic level, individual competencies, including knowledge and skills have been recognised as key drivers of productivity, competitiveness, employment, and innovation. They also underpin democratic participation, social cohesion, and social justice (Rychen and Salganik, 2002). Education thus represents a cornerstone of the KE. Developing human resources capable of transforming growing volumes of information into knowledge and innovation is therefore essential (Sugiyama and Meyer, 2008). Yet the question of which competencies define the "knowledge worker" remains contested (Rychen and Salganik, 2002).

Literature shows that this debate mirrors the conceptual ambiguity surrounding "knowledge" itself. Core terms such as competency, skill, qualification, standards, and literacy are often used interchangeably. Competency is described as tacit (Norris, 1991), fuzzy (van Klink and Boon, 2003), and context-dependent. Weinert (2001), within the OECD DeSeCo project, highlighted the multiple and sometimes contradictory meanings of competency. Likewise, Le Deist and Winterton (2005) argued that a unified theory is unattainable. Some traditions view competencies functionally, often in the plural, while others equate them with occupational competence (McClelland, 1998).

National approaches further illustrate these divergences. In the UK, Vocational Qualifications based on functional analysis were criticised for lacking theoretical depth (Mansfield and Mitchell, 1996), prompting a turn towards systematic knowledge acquisition. Since 1996, a more holistic model has emerged, integrating cognitive, functional, personal, ethical, and meta-competencies (Cheetham and Chivers, 1996). In continental Europe, particularly France and Germany, competency developed independently. Deist and Winterton (2005), notes that while the US focuses on individual behavioural traits and the UK on functional standards, France and Germany emphasize a multidimensional, analytically rich concept of competence. For this reason, it has become essential to initiate a discussion on key competencies that are context-independent and equivalent in their use and effectiveness across different institutions, tasks, and demand conditions, especially given that the KE is no longer confined to any specific economic sector (Unger, 2022).

3.1 Key Competencies

Similar terminological ambiguities arose when trying to determine key competencies. These include competencies such as oral and written mastery of the mother tongue, mathematical knowledge, reading competence for rapid acquisition and accurate processing of written information, knowledge of at least one foreign language, media competence, independent learning strategies, social competences, and divergent thinking, critical judgement, and self-criticism (Weinert, 2001).

International and national education systems often use terms like "key skills", "key competencies", "core competencies", "life skills", "essential/basic skills", or "21st century skills", though the semantic perception of these concepts often differs from country to country. Efforts to define key competence uniformly and explore possibilities for its measurement were preceded by various initiatives in different countries. A significant milestone was the debate on "key qualifications" and competencies, launched in Germany in 1974 (Mertens, 1974), in response to labour market changes brought by the new economy (Dörge, 2010).

3.2 The Problem of a Uniform Definition

Similarly to the challenge of defining the "knowledge economy and society," the OECD has sought to establish a uniform conceptualisation of competencies, alongside internationally comparable indicators to capture their role in supporting individual, social, and economic prosperity. The growing interest in competencies and the demand for data on educational outcomes in OECD countries gave rise to numerous projects that were often independent and conceptually inconsistent. Salganik et al. (1999) highlighted the need for a unified theoretical basis for assessing skills and competencies. Against this background, the OECD launched the DeSeCo (Definition and Selection of Key Competencies) initiative, widely regarded as fundamental. Its objectives were to provide a coherent conceptual framework, identify the competencies required for successful life in democratic societies, and strengthen the theoretical foundation for more reliable measurement and interpretation (Salganik et al. 1999; Rychen and Salganik, 2003). The programme also stressed the importance of individual responsibility for continuous learning and subsequent action (Ananiadou and Claro, 2009).

The DeSeCo definition drew heavily on Weinert (2002), who prioritised measurability and the development of indicators. However, some scholars challenged this, arguing that competencies are not outcome-oriented and therefore cannot be fully measured (Rychen and Salganik, 2002).

DeSeCo sought to reconcile diverse conceptual approaches and expert views by incorporating insights not only from psychology but also from philosophy, sociology, anthropology, and economics. A key contribution of DeSeCo lies in its holistic view of competencies, which are not reducible to cognitive abilities. Competency and skill are not treated as synonyms; rather, competencies involve the mobilisation of cognitive and practical skills, creative capacities, and psychosocial resources such as attitudes, motivation, and values (Rychen and Salganik, 2003). Key competencies are defined as those that "involve a mobilisation of cognitive and practical skills, creative abilities and other psychosocial resources such as attitudes, motivation and values." More specifically, the OECD describes them using three "competency categories":

- *Using Tools Interactively*: including the use of language, symbols, and texts; knowledge and IT; and technology in interactive ways.
- *Interacting in Heterogeneous Groups*: encompassing the ability to relate well to others, cooperate, and manage or resolve conflicts.
- *Acting Autonomously*: covering the capacity to act within a broader context, pursue life plans and personal projects, and assert rights, interests, and needs (OECD, 2005).

3.3 Key Competencies for Knowledge Society

Despite the conceptual and methodological difficulties of defining both the KS/KE and key competencies, their interconnection requires systematic examination. A KS/KE cannot develop without adequately educated, skilled, and experienced people. Without such human capital, it would face stagnation and information overload, with individuals unable to transform vast amounts of digital information into usable knowledge - the primary economic and social asset of the new economy. This dynamic is reflected in the World Bank's Knowledge Economy Index (2009), which revealed that despite Slovakia's relatively high standing in ICT adoption compared to regional counterparts, the nation's lag in education metrics directly contributed to weaker overall output indicators, particularly in the domain of innovation (see Figure 1).

KAM 2009

Comparator: None 1995 2000

Sort by: Most recent 2000

Comparison Group: **All Countries**

Export to Excel

Country	KEI		Economic Incentive and Institutional Regime		Innovation		Education		ICT	
	recent	2000	recent	2000	recent	2000	recent	2000	recent	2000
Germany	8.96	8.98	9.06	9.02	8.94	9.08	8.36	8.79	9.47	9.02
Hungary	8.00	7.64	8.35	7.76	8.21	8.04	7.73	7.52	7.70	7.26
Czech Republic	7.97	7.45	8.17	7.10	7.78	7.51	8.23	7.55	7.70	7.63
Slovak Republic	7.47	7.12	7.78	6.48	6.89	7.09	7.26	7.39	7.95	7.52

Figure 1: Result of a comparison of the KEIs of four countries in the World Bank database of 2009 (recent) and 2000

The relationship between competencies and KE was explicitly addressed by the OECD (Pont, 2001). Drucker's (1992) prediction from the 1960s materialised: white-collar and highly skilled jobs (knowledge workers) became the main drivers of employment growth across industries. This prompted the OECD to ask which competencies and skills were most essential for the KS/KE. From the perspective of education, the goal was to ensure the highest possible attainment levels and the development of broad, transferable competencies for lifelong learning. From the labour market perspective, however, emphasis was placed on ICT skills, problem solving, teamwork, and continuous learning. The OECD (Pont, 2001) stressed the importance of foundational education and literacy as prerequisites for knowledge work, while also identifying further skills increasingly required in the new economy. Based on expert analyses and employers' hiring criteria, three clusters of competencies were highlighted:

- Interpersonal skills: teamwork, leadership, collaboration.
- Intrapersonal skills: motivation, learning ability, problem solving, communication, analytical skills, systems thinking.
- Technological/ICT skills.

Generally, the identification of key competencies relies on methods such as analyses of professional literature, job descriptions, behavioural studies, expert consultations (e.g., Delphi studies), focus groups, or empirical surveys (Zhu et al. 2024; Batt, Tavares and Williams, 2019; Geng et al. 2018). In our research on competencies for KS/KE, we applied a different methodological approach, aiming to capture more precisely the interplay between competencies and the dynamics of the KS/KE.

4. Methodology

The initial part of the methodology delineates the framework for constructing a key competency model for the KS/KE. This framework is subsequently operationalized in the Results section through its pilot application utilizing data derived from four KEIs to construct the pilot key competency model for the KS/KE. The second part details the procedural approach and findings regarding the anticipation of key competency trends for the forthcoming three-year horizon.

4.1 Methodological Framework for the Development of the Key Competency Model for KS/KE

Identification of relevant economic indices

The initial phase of the research addressed the methodological step designated as the Identification of relevant economic indices. The primary objective of this phase was to select specific economic indices, developed and published by respected international authorities, which demonstrate alignment with the established main pillars of the KE. In our specific application, this analysis was initiated in 2017, focusing on the evaluation of measurement initiatives that correlate with the core pillars of the World Bank framework (Chen and Dahlman, 2006).

Construction of a tailored database of indicators

The subsequent phase entails the extraction of indicators from the identified indices to populate a proprietary database structured according to specific research objectives. A critical imperative in this phase is the continuous and incremental archiving of data, as retrospective access to historical datasets within source repositories is often limited or subject to removal.

To address these requirements, a customised dataset was developed, comprising the variables index, country, year, value, and rank. This structured approach enabled robust longitudinal and comparative analyses across different KE indicators.

Content analysis and categorization

Indicators derived from the selected KEI must be subjected to content analysis, followed by semantic categorization. This analytical step is indispensable for establishing a unified categorization of all indicators into the designated KE pillars, particularly because identical indicators can be classified divergently across different KEIs or presented under slightly varying nomenclatures.

We employed the method of intellectual and cognitive categorisation from the field of knowledge organisation to group related entities and phenomena into shared categories. Unlike strict classification, which requires exclusive membership, categorisation is flexible and allows associations based on perceived similarities among entities. Category composition may vary across contexts, which constitutes the core strength of cognitive categorisation. Moreover, the possibility of assigning an entity to multiple categories (Jacob, 2004) was considered essential for the objective categorisation of semantically related indicators.

This approach facilitates the grouping of related entities based on recognised similarities. Each indicator was assessed in terms of its definitional scope, measurement method, and contextual application, before being assigned to a category.

Division into input and output indicators

A critical subsequent procedural step involves the dichotomization of identified indicators within each KE pillar into two distinct categories: input and output indicators. This classification process must strictly adhere to a defined conceptual framework to ensure analytical rigor. Input indicators (resources and investments) - these metrics quantify the volume of invested resources, the availability of enabling infrastructure, and the latent potential within a specific domain. Conceptually, inputs are regarded as essential antecedents and investments that serve as precursors to performance. Output Indicators (results and outcomes) - these metrics evaluate the resultant efficacy, tangible outcomes, or broader impacts generated by the preceding investments. Outputs represent the realized performance and actualized value within a given domain.

Compilation of required key competencies

A subsequent methodological recommendation involves the parallel continuous compilation of a reference key competency database. This can be achieved through the systematic extraction and categorization of competencies derived from authoritative international documents that conceptualize or define such frameworks. Crucially, this process necessitates semantic harmonization to address the challenge of diverse nomenclature.

Mapping of key competencies to KE categories

The primary objective of this phase is to identify specific competencies that facilitate the effective conversion of input indicators into high-performing output indicators within each KE pillar. Achieving this mapping necessitates a systematic content analysis of official documentation and definitions encompassing both the KE indicators and the targeted key competencies. This mapping also facilitated evaluation of the representativeness of competencies identified by the model in comparison with established frameworks.

Model visualization

The methodological process can culminate in the visualization of key competency model for the KS/KE. We recommend that the graphical representation explicitly delineates the functional role of competencies as mediating mechanisms that facilitate the transformation of KE resource inputs into tangible performance outputs.

4.2 Model-based Analysis of Anticipated Trends in Key Competency Development for the Forthcoming Three-Year Period

Recognising the dynamic nature of the KS/KE, the study also sought to incorporate a forward-looking perspective. The aim was to forecast the development of KE-related factors likely to influence society over the next three years, integrating these assumptions into the competency model.

Data from KE indicators served as the basis for predictive modelling in RapidMiner software. Multiple prediction techniques were tested, including: Generalised Linear Model (GLM), Deep Learning, Decision Tree, Random Forest, Gradient Boosted Trees, Support Vector Machine (SVM). Performance of these models was evaluated according to relative error rates (RE) and standard deviation (STDEV). Results indicated that the Generalised Linear Model (GLM) provided the most effective performance, with RE = 0.4% and STDEV = 0.1%. Despite its conceptual simplicity, GLM proved suitable for predicting short-term economic and competency-related trends. Its assumption of a linear relationship between input and output variables is often a reasonable approximation in economic contexts, thereby reinforcing its applicability to the forecasting task.

5. Results

In this section, we present a specific pilot application of our methodology, utilizing data derived from four relevant KEIs and official documents analysing 21st-century key competencies, culminating in the construction of the key competency model for the KS/KE.

5.1 Pilot Construction of the Key Competency Model for the KS/KE

Identification of relevant economic indices

The selection of these four aforementioned indices was predicated upon a preliminary evaluation of several salient structural determinants, encompassing: the core conceptual framework and institutional custodianship; the scope of national coverage; the hierarchical index architecture, ranging from constituent indicators to defined pillars/sub-indices; the evolution of indicator properties (i.e., selection, enumeration, and weighting) alongside overall structural modifications; and the underlying principles that govern index aggregation. The following indices met the selection criteria: Global Knowledge Index (GKI) and Global Innovation Index (GII) from global indices; European Innovation Scoreboard – Summary Innovation Index (EIS- SII), and Digital Economy and Society Index (DESI) from European indices.

The creators of GKI state that because the World Bank's KAM measurements (KEI, KI) have been discontinued, GKI is the sole index measuring knowledge at the global level (UNDP and MBRF, 2019)The EIS -SII and GII indices are primarily perceived as innovation indices but can also be seen as KE indices, as they capture key KE drivers and use indicators such as employment in knowledge-intensive activities. Our view is supported by authors like Karahan (2012) and Leogrande (2022). DESI was included because, at the beginning of our analysis in 2017, it extended beyond ICT to cover research, innovation, and education. An initial comparison showed that, despite shared thematic orientation, the indices differ considerably in the selection of pillars, sub-pillars, weighting of indicators, and interpretation of KE concepts.

Construction of a tailored database of indicators

A dataset was built using data collected since 2017 from all indicators of the four identified KE indices. Much of the data used since 2017 is no longer publicly available, making it important to continuously build our own dataset (Github), structured as: index, country, year, value, rank (Katuščáková, Capková and Grečnár, 2023b). The data used in this research is from 2022, consisting of 301 indicators from the Global Knowledge Index, Global Innovation Index, and European Innovation Scoreboard – Summary Innovation Index, recorded as: indicator name, description, parent index, and assigned weight, based on 2022 data.

Content analysis and categorization

After constructing the database, we carried out a comprehensive content analysis of the 301 indicators. The analysis revealed varying levels of granularity in indicator categorisation across indices, accompanied by notable semantic differences, even among identical indicators. Several unique and newly introduced indicators were identified, including university - industry collaboration, exports of knowledge and creative services, development of creative industries (film, media, gaming, Wikipedia editors), as well as environment, health, and gender equality. Furthermore, the indices applied different weights to similar or overlapping indicators and frequently revised their methodologies, underscoring divergent interpretations of KE principles. This demonstrated the necessity of applying semantic categorisation through a uniform framework.

Drawing on the content analysis of KE indices and their internal structures (sub-pillars, pillars, sub-indices), in combination with relevant scholarly literature on fundamental KE pillars, we derived four, or in some cases five, shared core KE categories observable across all indices—though under different names or levels of detail. These largely correspond to the KE pillars defined by the World Bank in 2005/2006 (Chen and Dahlman, 2006).

The shared categories identified were: (1) Research, development, and innovation; (2) Education; and (3) ICT. In response to rapid developments in KE-related areas, a fourth category, Others (lately renamed to Society & Environment), was created to cover contextual indicators potentially influencing KE performance. Finally, a fifth category, Economy, was introduced to encompass broader indicators not assignable elsewhere. Categorisation was thus based on semantic similarities within each group.

The Education category included both formal and informal learning; quality and accessibility of pre-university and higher education; PISA results; lifelong learning; and graduate employability. Research, development, and innovation encompassed state and private R&D expenditure, scientific publications, patents, university–industry cooperation, quality of research institutions, employment rate in knowledge-intensive activities, and business innovation. ICT covered internet access and usage, digital skills, ICT employment, and software investment. The Other (lately renamed to Society & Environment) category addressed specific or emerging KE-related dimensions, while Economy included indicators such as GDP per capita, foreign direct investment, business density, industrial diversification, and export complexity.

In order to identify the principal indicators for each of the five KE pillars, we had to address several challenges like intersecting or semantically linked indicators. Such indicators were assigned to all relevant categories, with its weight divided by the number of categories, in which it was included, to increase the objectivity of categorisation. Examples include indicators focused on doctoral students, which can be categorised in both Education and Research, development and innovation, or the digital skills indicator, which can be categorised in both ICT and Education; the Enterprises providing ICT training indicator can be categorised in both Education and ICT, or the Female ICT specialists indicator can be categorised into Others (gender equality), ICT and Education. This means that in the case of assigning an indicator to one category, the indicator is added to that category with its weight assigned in the given index together with the name of the index, from which it originates. If an indicator is assigned to more than one category, that indicator is assigned to each relevant category, along with the corresponding fraction of its original weight. In the first round of classification, indicators were assigned to one of the four primary categories: Research, development, and innovation; Education; ICT; or Others (lately renamed to Society & Environment). When this was not feasible, they were placed in the Economy category. This approach enabled consistent categorisation of all 301 indicators. Within Education, further subcategories were created: primary and secondary schooling, Technical and Vocational Education and Training (TVET), and tertiary education.

Input and output indicator sets

Our classification was theoretically grounded in a rigorous semantic analysis of indicator definitions and their functional role within the KE value chain. For instance, within the ICT pillar input indicators included parameters such as financial investments, infrastructure quality, and accessibility metrics. These metrics measure the deployment of resources. Output indicators comprised measurable achievements, such as ICT employment rates, the number of ICT patents, and the number of PhDs in ICT. These reflect the actual performance.

Compilation of required key competencies

In parallel with the database of KE indices, we developed a database of key competencies. These were extracted from authoritative documents addressing key competencies, core competencies, life skills, essential/basic skills, and 21st-century skills, produced by organizations such as the OECD (2005; 2019), UNESCO (2015; 2017; 2018), the European Commission (Council of the European Union 2018), the World Economic Forum (2020), and the Partnership for 21st Century Learning (Battelle for Kids, 2019). As definitions and categories of competencies differ across these sources, overlaps and terminological inconsistencies were frequent. Therefore, after building the database, we conducted an analysis and semantic clustering of competencies. The contextual orientation of the documents was also considered, as some were sector-specific (e.g., education, employment, civic engagement) and contained corresponding competences.

Mapping of key competencies to KE categories

Following the preparation of both the indicator and competency databases, we proceeded to the crucial task of mapping competencies to the respective KE indicators and categories. We systematically analysed the functional description of each KE indicator. If an indicator required specific knowledge, skill, or attitude for its successful realization or improvement, the corresponding key competency was mapped to that indicator.

Since many competencies are relevant across multiple pillars, we structured the model progressively, beginning with education and R&D as foundational domains and moving towards competencies specific to ICT, the economy, and socio-environmental contexts.

In *education* and *R&D*, the key competencies identified as central to knowledge processes include:

- Basic literacy (particularly in primary and secondary education), recognized as foundational building blocks that enable children to develop to their full potential (UNESCO, 2015; OECD, 2005; Council of the European Union, 2018)
- Cognitive competencies: analytical, creative, critical, and abstract thinking; problem-solving; information and media literacy; mathematical and data literacy; domain-specific knowledge; and systems thinking (OECD, 2005, 2018; WEF, 2020; Battelle for Kids, 2019). These reflect both higher education and research needs.
- Soft skills: intrapersonal competencies such as self-motivation, curiosity, attention to detail, resilience, and flexibility (WEF, 2020, 2023; OECD, 2019); and interpersonal competencies including teamwork, communication, leadership, empathy, and lifelong learning (WEF, 2020, 2023; Council of the European Union, 2018).
- Ethics: essential in handling sensitive data, developing AI, and aligning with social justice and sustainability (OECD, 2005, 2019; UNESCO, 2015).

In *ICT*, competencies span digital and technical skills, from basic usage to programming, networking, big data, cloud computing, and artificial intelligence, again complemented by ethical considerations (WEF, 2020).

In the *economic* sphere, key competencies include economic and financial literacy, strategic and innovative thinking, and ethics (OECD, 2018; Council of the European Union, 2018). In the *social* and *natural* environment, essential competencies include active citizenship, intercultural knowledge, tolerance, environmental awareness, sustainability, health literacy, and ethics (UNESCO, 2015, 2017; Council of the European Union, 2018).

Drawing on these findings, we created a Key Competency Model for the KS/KE, linking competencies to the transformation of KE inputs into outputs. This model aligns with Weinert's and the OECD DeSeCo project's recommendations, emphasising a holistic and dynamic perspective. It integrates both cognitive and non-cognitive elements and reflects the complexity of knowledge processes in contemporary societies.

Representativeness of the Key Competency Model for KS/KE:

An important finding was that the database of extracted key competencies was sufficient to cover all categories of KE, which confirms the overlap of the currently required key competencies and the main areas of KE, but mainly that the model of key competencies generated by the proposed method can be considered sufficiently representative.

Model visualization (see Figure 2)

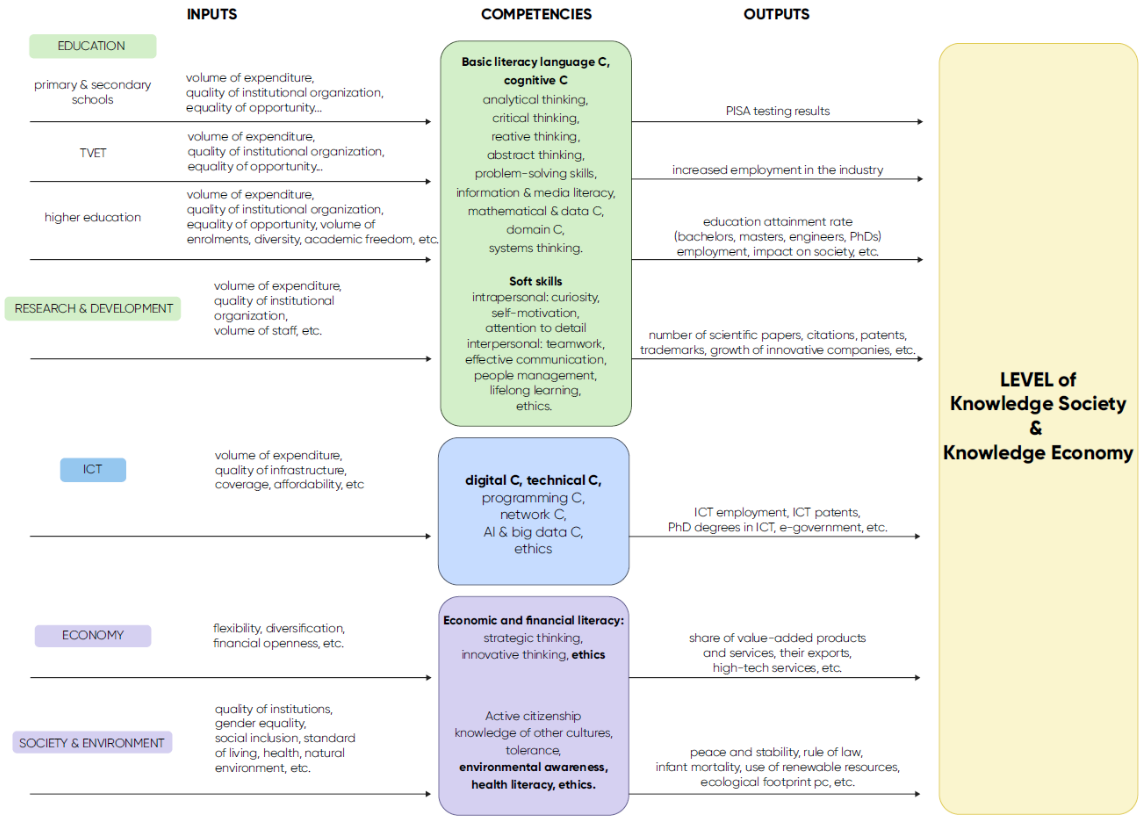

Figure 2: Key Competency Model for KS/KE

5.2 Model-based Analysis of Anticipated Trends in Key Competency Development for the Forthcoming Three-Year Period

Given the continuous evolution of indices and their indicators, variations in the key competencies required to transform input into output indicators can be anticipated. To address this, we forecasted the future development of the KS/KE and the factors most likely to influence it in the coming years. For this purpose, we used data from our repository (2017–2022) derived from four indices: the *Global Knowledge Index*, *Global Innovation Index*, *European Innovation Scoreboard – Summary Innovation Index*, and *Digital Economy and Society Index*. These data were used to train predictive models in RapidMiner, including generalized linear models (GLM), deep learning, decision trees, and support vector machines. The GLM (Nelder and Wedderburn 1972; Faraway 2016) proved most effective, yielding the lowest relative error and standard deviation.

Based on the selected model, the most significant predictors of future performance in knowledge indices are: ***research, development and innovation*** (w: 0.499); (current level) ***economy*** (w: 0.368) and (current level) ***ICT*** (w: 0.351); (current level) ***technical and vocational education*** (w: 0.332); (future level) ***secondary education level*** (w: 0.331) (future level). At the same time, we calculated the factors with the greatest impact on the quality of the prediction, where the factors of ***research, development and innovation*** and ***ICT and technical and vocational education*** were identified as the most important ones.

To complement our analysis, we also drew on forecasts from the *World Economic Forum* (2023) for 2023–2027. Based on a survey of 803 companies employing 11.3 million people across 45 economies, the WEF identified technology adoption and the expansion of digital access as the main drivers of business transformation. Over 75% of companies reported high adoption potential for big data, cloud computing, and AI. The World Economic Forum bases its forecasts on a large-scale employer survey (Future of Jobs Survey), complemented by expert judgement, internationally standardised occupational and skills classification frameworks (ISCO and ONET), and analytical extrapolation of expected trends contextualised with external labour market data.

From the perspective of the KS/KE, most technologies are expected to have a slightly positive impact on jobs. In particular, big data analytics, climate and environmental management technologies, and cybersecurity are likely to play key roles.

The World Economic Forum also identified the competencies most in demand for 2023–2027. Cognitive skills, notably analytical and creative thinking, are paramount. Creative thinking, ranked tenth in 2015, has risen to second place. Interpersonal competencies—resilience and flexibility, self-motivation, and curiosity with lifelong learning—are also projected to be crucial, particularly in navigating labour market disruptions. Additional competencies include technological literacy, reliability and attention to detail, empathy, active listening, and managerial abilities such as quality control.

Therefore, we have tried to innovate our model to include a forecast of the KS/KE development and the necessary key competencies, considering the results of prediction using the GLM model together with the WEF forecasts over a five-year horizon. We expect that the main factors influencing the future level of the KS/KE will be the internally interconnected areas of ***R&D*** and ***ICT*** (see Figure 3), while their impact on society's transformation will gradually strengthen.

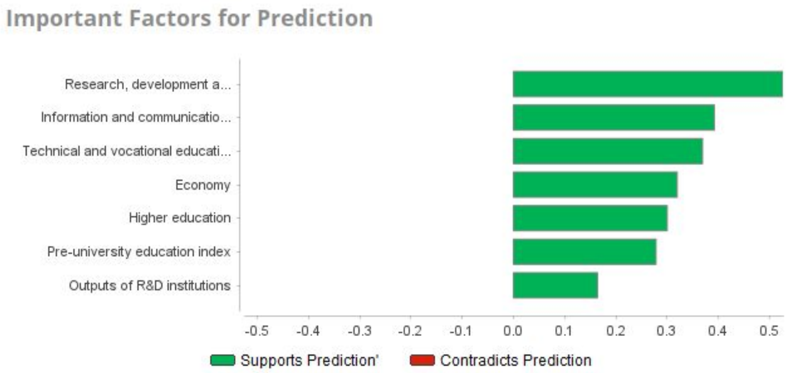

Figure 3: Important Factors for Prediction (Rapid Miner)

At the same time, the key competencies forecasting model (see Figure 4) highlighted those competencies that are linked to the development of science and research and ICT, and that overlap with the competencies that will be most important in the 2023-2027 horizon according to WEF: basic *literacy*, *language* competencies, *cognitive* competencies, especially *analytical* thinking, *creative* thinking, *abstract* thinking, *problem-solving* capability, *soft* skills such as *curiosity*, *self-motivation*, *lifelong learning*, *digital* and *technical* competencies.

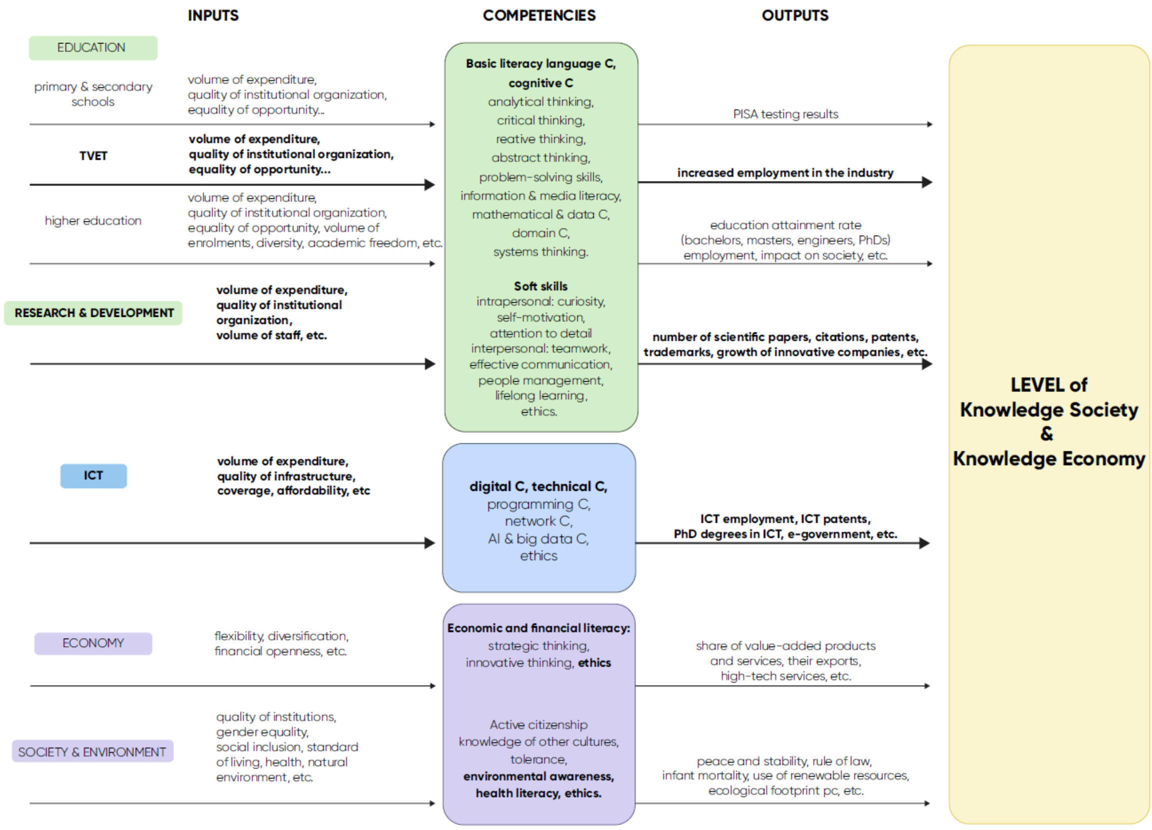

Figure 4: Key Competencies Forecasting Model

6. Discussion and Conclusion

Our analysis of key performance metrics revealed that certain countries significantly outperform their neighbours in information society measures but simultaneously lag behind in critical KS/KE outputs, such as patents, trademarks, and high-impact publications. This demonstrable disparity underscored the essential role of human competencies in effectively transforming information and invested resources (inputs) into measurable knowledge-based outcomes (outputs). Consequently, this paper aims to interconnect the concepts of the KS/KE, KE indices, and the specific key competencies required for this transformation, thereby linking these concepts through the development of a unified model directly derived from the KE indices.

This study advances the research landscape by contributing to the development of a novel methodological framework for constructing a model of key competencies specific to the KS/KE. This framework is systematically built upon the content analysis of indicators derived from major, internationally recognized KEI. The core methodological innovation resides in the uniform and empirically justified categorization of all analysed KEI indicators, which culminated in their systematic division into input (quantifying prerequisites and investments) and output (quantifying achieved results and performance) subsets. This crucial segmentation enabled the precise and structured mapping of key competencies, identifying those, that are demonstrably responsible for mediating the transformation of invested resources (inputs) into measurable and desirable outcomes (outputs).

The key competency model for KS/KE derived from our collected and analysed KEI indicator data was subsequently subjected to a validation process. Specifically, the generated model was benchmarked against a comprehensive, authoritatively curated compilation of required key competencies. This compilation was meticulously extracted from influential documents addressing key competencies, core competencies, life skills, essential/basic skills, and 21st-century skills, produced by leading global organizations such as the OECD, UNESCO, the European Commission, the Council of the European Union, the World Economic Forum, and the Partnership for 21st Century Learning.

The comparative analysis confirmed that the competencies contained within this compilation were sufficiently broad and exhaustive to cover all categories identified within our KE framework. This alignment confirmed that the model of key competencies generated by the proposed methodology can be considered sufficiently representative and valid for addressing the competency requirements across the entire spectrum of the KS/KE.

Furthermore, the resultant key competencies model was subsequently utilized to perform a model-based analysis of anticipated trends in competency development, thereby providing actionable insights into the strategic skill demands required by the KS/KE for the forthcoming three-year period.

The methodological framework development encountered several challenges. For instance, the selection of four prominent KE indices, while based on declared objectives, necessitates researchers to prioritize indices whose goals align with the KE. Essential for data integrity was the construction of a dedicated, custom database (Katuščáková, Capková and Grečnár 2023b), mitigating issues arising from frequent index revisions and obscure methodologies. A critical challenge was the non-uniform categorization of identical indicators across different indices. To overcome this, we implemented a precise, uniform approach to categorization.

Compared to traditional competency modelling approaches based on expert studies, job analyses, behavioural observations, Delphi methods, or surveys, *the proposed model* leverages indicators from KEI, enabling *greater flexibility and responsiveness to rapid socio-economic change*. Unlike conventional models, which are typically developed over extended periods and tend to stabilise competencies over time, the use of dynamically updated indicators and shifting weights allows the model to continuously reflect evolving societal, technological, and economic conditions. However, this approach is inherently dependent on the availability, quality, and conceptual validity of macro-level indicators, which may limit its ability to capture context-specific or tacit competencies at the organisational or individual level.

Moreover, the practical significance of this type of key competency model is that, by processing the KEI indicators, individual countries can identify which input and, more importantly, output indicators are performing poorly. This allows them to strategically focus their solutions not only on supporting the input indicators within that KE pillar but also on targeting the development of specific competencies necessary to improve the performance of those output indicators.

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