“Developing human capital through innovative competencies in the context of Industry 4.0: Insights from Kazakhstan”

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DEVELOPING HUMAN CAPITAL THROUGH INNOVATIVE COMPETENCIES IN THE CONTEXT OF INDUSTRY 4.0: INSIGHTS FROM KAZAKHSTAN

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Abstract

The purpose of this study is to identify the factors influencing human capital development through the integration of key innovative competencies and to assess their contribution to readiness for Industry 4.0. A quantitative survey was conducted among 1,447 respondents aged 18–63 across Kazakhstan between September and October 2025. This population was selected because individuals aged 18–63 represent the core economically active workforce in Kazakhstan and are directly involved in human capital formation. The survey method was selected to capture a large and diverse sample and to examine relationships between latent constructs within the proposed model. Structural equation modeling using the partial least squares method (PLS-SEM) was employed to examine the relationships between innovative competencies and human capital development. The results demonstrate that all examined innovative competencies have positive and statistically significant effects on human capital development ($p < 0.001$). Creativity shows the strongest influence ($\beta = 0.333$), followed by emotional intelligence ($\beta = 0.241$), artificial intelligence ($\beta = 0.135$), and critical thinking ($\beta = 0.129$). Human capital, in turn, exerts a strong positive effect on readiness for Industry 4.0 ($\beta = 0.650$, $p < 0.001$), thereby demonstrating that developing human capital is essential for the effective adoption and coherent integration of Industry 4.0 technologies. These results provide valuable direction for policymakers, educators, and organizations aiming to enhance workforce readiness for Industry 4.0 by strategically investing in innovative skill development initiatives.

Keywords human capital, innovative competencies, Industry 4.0, AI-related competencies, emotional intelligence, creativity, critical thinking

JEL Classification J24, O15, O33

INTRODUCTION

Developing human capital through values, competencies, and employee motivation is a key condition for the successful adaptation of organizations to the challenges of Industry 4.0 (Štaffenová & Kucharčíková, 2024). In the context of rapid digitalization, this adaptation is impossible without mastering new skills, since it is competencies that are becoming the determining factor in preparing the workforce of the future (Alhloul & Kiss, 2022). However, the modern reality requires not just training, but a deep strategic rethinking of approaches to human capital development with an emphasis on digital skills, cognitive flexibility, and continuous learning in the context of sustainable economic transformation (Marku, 2024). This need is particularly acute in developing economies, where the implementation of strategic human resource management becomes crucial for ensuring organizations' readiness for digital transformation and strengthening their competitiveness in the new industrial reality (Vong et al., 2025). Innovative competencies such as creativity, critical thinking, and the ability to

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solve non-standard problems are particularly significant, becoming essential tools for adapting personnel to the rapidly changing conditions of the digital economy (Lanvin & Monteiro, 2020).

At the same time, it is important to develop not only technical but also social competencies, as they ensure the formation of a qualified, flexible, and resilient workforce capable of effectively responding to the challenges of technological change (L. Chen et al., 2024). Moreover, innovative competencies represent not just a set of skills, but a holistic system of opportunities, resources, and capabilities aimed at implementing new ideas and adapting socio-economic systems to ongoing transformations (Khakimova, 2023). The successful implementation of Industry 4.0 directly depends on the quality of human capital; the next analytical step is to identify which specific competencies become decisive within the emerging technological paradigm.

1. LITERATURE REVIEW

Research into the nature of innovative competencies is a key factor in the sustainable development of society, the economy, and human capital in the context of Industry 4.0. Although the research focuses on innovative competencies, understanding their essence requires considering broader theoretical frameworks. First and foremost, the research field of innovative competencies is grounded in the competency-based approach, which defines competencies as the integration of knowledge, skills, abilities, and personal characteristics that ensure the effective performance of professional tasks (Baartman & De Bruijn, 2011). The competency-based approach, in turn, is based on the theory of human capital, which views competencies as an investment in the development of the individual, increasing productivity, competitiveness, and value to society (Pant et al., 2022). To uncover the innovative component of competencies, it is also necessary to turn to J. Schumpeter's theory of innovation, which explains the role of creativity, unconventional thinking, and the implementation of new ideas in economic development (Śledzik, 2013). Thus, the study of innovative competencies requires an analysis of the competency-based approach, human capital theory, and innovation theory as interconnected elements of a unified theoretical framework.

Understanding the role of human capital is essential for explaining economic growth and workforce development in the context of modern technological and societal changes. Human capital theory, developed by Schultz (1961) and Becker (1964), considers education, professional training, and health as key forms of investment that increase productivity, explain income differences, and are the main source of economic growth (Pant et al., 2022). Goldin (2014) notes that the key factor in economic development is the accumulation of human capital based on knowledge, education, and skills, while long-term growth depends on the ability of the education system and competencies to adapt to technological changes. Kucharčíková et al. (2015) clarify that the effectiveness of human capital is determined by strategic knowledge management and continuous development of competencies, ensuring the competitiveness and innovative growth of organizations. Kozioł et al. (2014) add that the value of human capital is formed through investments in knowledge and skills, and that the incentive system should reflect employees' contributions to the growth of organizational and national efficiency. Coduras et al. (2016) develop this idea at the micro level, showing that the knowledge, experience, and training of employees directly influence the innovative activity of small and medium-sized enterprises, contributing to their sustainable development and competitiveness. Taken together, these studies demonstrate that human capital, based on the development of knowledge and competencies, is a key resource for innovation and economic progress. Therefore, in the digital economy, human capital development is impossible without developing innovative competencies that help people master new technologies, adapt to change, and create innovations.

Within the framework of the digital economy, the development of human capital is inconceivable without the cultivation of innovative competencies that enable individuals to master new technologies, adapt to dynamic changes, and generate innovations. In this context, the ideas of

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J. Schumpeter are of particular relevance, as he regarded innovation as a key driver of economic development and a crucial mechanism for transforming human capital into a source of entrepreneurial and technological advancement (Śledzik, 2013). Schumpeterian innovation theory laid the foundation for understanding innovation as a driving force for economic growth, but contemporary research expands its scope, focusing on the role of human capital and organizational capabilities (Śledzik, 2013). While Schumpeter viewed the entrepreneur as a central figure creating 'creative destruction' through the introduction of new combinations, Moreira et al. (2024) show that today this function is realized through the collective innovative capabilities of organizations based on knowledge, learning, and strategic management. In turn, Śledzik's (2013) interpretation confirms the relevance of Schumpeterian ideas, but points to their evolution: innovation is becoming not only the result of individual initiative, but also a systemic process that ensures competitiveness and sustainable development of the economy. Thus, the combination of human capital theory and innovation theory leads to the concept of innovation competencies, which reflect a person's ability to apply knowledge and skills to create and implement innovations.

In the era of Industry 4.0, developing innovative competencies has become a critical priority for both organizations and public institutions. De Barros et al. (2025) emphasize that developing creative and innovative competencies grounded in critical thinking, collaboration, and adaptability is crucial for organizations in the context of Industry 4.0. This idea resonates with Mykolaichuk et al. (2024), who emphasized the importance of innovative competencies in public administration as the foundation of sustainability and national security. Both studies trace the connection between innovative competence and the ability to think systems-wise, be flexible, and change management, which forms the basis for a trans-sectoral understanding of innovation. An important contribution to the methodological development of this topic is the ICDC tool (Bittencourt et al., 2025), based on the Kolb cycle and the principles of innovation pedagogy. This approach focuses on the practice-oriented development of competencies, including creative thinking, initiative, and networking.

A similar role is played by the model of Ma et al. (2024), developed in the context of healthcare, where the 4Ps (person, process, environment, product) system demonstrates the importance of both personal and structural factors. Both models emphasize the need for a supportive organizational environment to realize innovative potential, which is also confirmed by Khakimova (2023), as the importance of the resource base and the socio-economic context is highlighted as the foundation of innovative capability. Against the backdrop of the development of such models, the issue of measuring innovative manifestations becomes particularly relevant, requiring tools capable of capturing behavioral indicators in both educational and professional settings. A significant tool for measuring innovative behavioral indicators in education is the NCODE Barometer (Watts et al., 2013), which identifies three dimensions of innovative activity: individual, interpersonal, and network. In turn, Pérez-Peñalver et al. (2018) expand on this classification, proposing five key components: creativity, critical thinking, initiative, teamwork, and networking. This underscores the trend toward shifting focus from assessing personality traits to observable behavioral manifestations, which facilitates the development of educational and managerial strategies.

Continuing the analysis of behavioral manifestations, it is important to turn to the individual determinants of innovative activity, which reveal the psychological and cognitive foundations underlying the development of these competencies. An analysis of individual determinants of innovative behavior is presented by Jussila (2007), who developed a self-assessment instrument for diagnosing innovative competence, and Hero et al. (2017), who identify six categories of personal innovative capacity. These categories (personality traits, future orientation, creative and analytical thinking, social and managerial skills, and subject-matter knowledge) resonate with the 4C competency model and emphasize the complex nature of innovation competence. The shift from the individual to the managerial level is demonstrated by Asumeng (2014), who proposes a Holistic-Domain Model, which examines innovation capacity through the lens of managerial effectiveness. This development logically extends to digital leadership research, such as that of Ren et

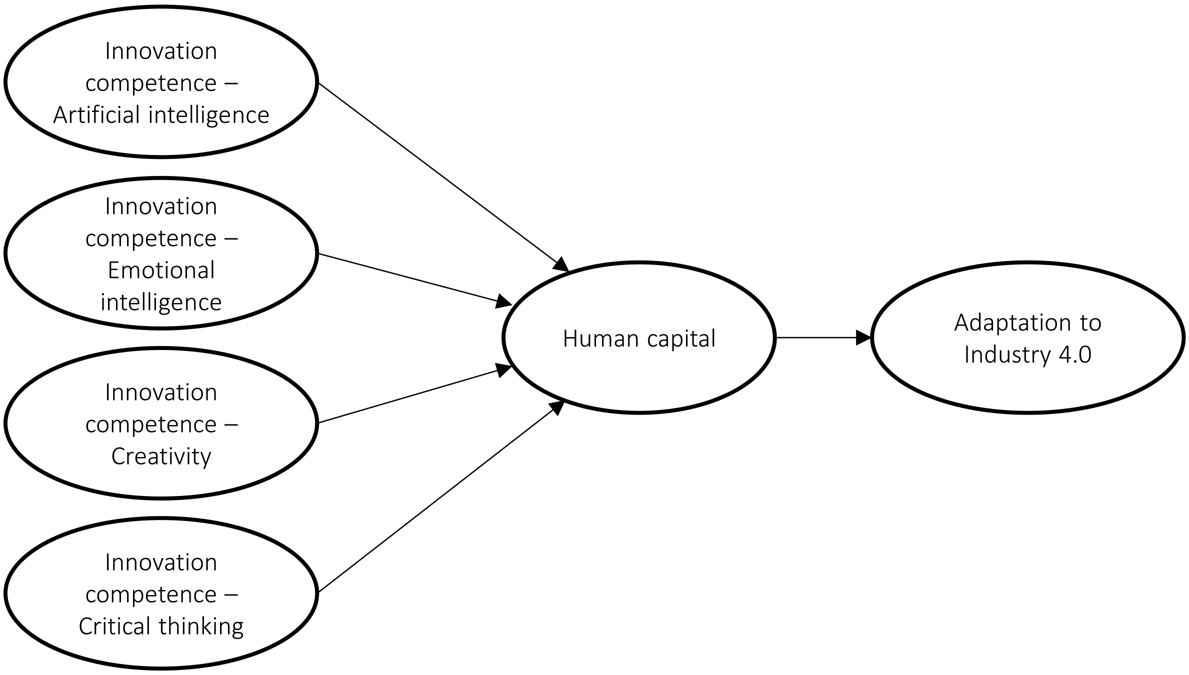

Figure 1. Proposed research model

al. (2025), where innovation competence is closely linked to management in the context of digital transformation.

Against the backdrop of these managerial and digital aspects, it becomes evident that the sustainable development of innovation competencies is impossible without a systemic reliance on education as the key mechanism for their formation. The role of education occupies a central place in a number of studies. Watts et al. (2013) emphasize that developing innovative competencies should be a key goal of educational programs, including the development of an entrepreneurial approach, creative thinking, and learning ability. This idea is further developed by Akimov et al. (2023), who note the insufficient attention to meta-skills, character, and critical thinking within the Education 4.0 concept. This trend is empirically supported by Ovbiagbonhia et al. (2023), where the implementation of a systemic educational intervention in engineering education demonstrated the effectiveness of integrating innovative competencies into the educational process. Of particular interest is the study by X. M. Chen et al. (2024) that conducts a multilevel analysis of the factors shaping the development of innovative competence among children and adolescents. The use of Bandura's social cognitive theory allows for the interpretation of student behavior in the context of not only personal but also socioeconomic and digital conditions, opening up new horizons in pedagogical approaches.

Thus, these studies provide a foundation for the proposed research model (Figure 1), conceptualizing innovative competence as a multi-dimensional phenomenon encompassing personal, behavioral, organizational, and institutional aspects. An analysis of contemporary research reveals a persistent focus on developing components of innovation competence such as critical thinking, emotional intelligence, creativity, and teamwork (de Barros et al., 2025; Hero et al., 2017; Pérez-Peñalver et al., 2018). However, despite the rapid spread of artificial intelligence, the existing literature lacks a holistic analysis of its role in developing these skills. There is a lack of research on how interaction with AI affects the development of critical thinking, the transformation of creative processes, and changes in the emotional and communicative domain. This indicates a significant research gap, which is highly relevant in the context of digital transformation and calls for a reconsideration of approaches to developing innovative competencies within the human–technology environment.

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In this regard, the purpose of this study is to identify the factors influencing human capital development through the integration of key innovative competencies and to assess their contribution to readiness for Industry 4.0. Therefore, this study investigates factors that influence human capital development through the inclusion of key innovation competencies, such as working with AI, emotional intelligence, creativity, and critical thinking. In particular, the study assesses how these competencies contribute to an individual's adaptability to Industry 4.0. conditions. The study adopts a competency-based approach and is implemented within the framework of the developed research model (see Figure 1). Therefore, this study proposes the following hypotheses:

H1: *The development of competencies related to interaction with artificial intelligence has a positive impact on the level of human capital.*

H2: *Emotional intelligence as a component of innovation competencies contributes to the strengthening of human capital.*

H3: *Personal creativity is positively related to human capital development.*

H4: *Critical thinking has a significant positive effect on the level of human capital.*

H5: *Human capital positively influences an individual's adaptability to changes characteristic of the Industry 4.0 environment.*

2. METHODS

2.1. Sample and data collection

A quantitative survey was conducted among respondents aged 18–63 across Kazakhstan between September and October 2025. This population was selected because individuals aged 18–63 constitute the core economically active workforce in Kazakhstan and are directly involved in human capital formation and Industry 4.0–related skill development, making them highly relevant for examining innovative competencies and readiness for Industry 4.0. A quantitative survey was chosen as the most appropriate method for identifying relationships between latent variables and testing the proposed model. PLS-SEM method was used due to its effectiveness in analyzing complex models with multiple constructs, as well as for estimating both the measurement and structural models simultaneously (Hair et al., 2022).

The final sample size of 1,447 respondents fully meets and significantly exceeds the methodological requirements of PLS-SEM. According to the "10-fold threshold" rule (Hair et al., 2019), the minimum sample size should be at least ten times larger than the maximum number of structural paths leading to any latent variable in the model. In this study, the most complex variable included fewer than 10 indicators, meaning that even a sample of 100–150 respondents would have been statistically sufficient for a reliable estimate. Furthermore, Tabachnick and Fidell (2014) indicate that the number of observations should be at least ten times the total number of observed items across all variables. Since this model used 29 indicators, the minimum required sample size would have been approximately 290 participants. Thus, the 1,447 valid responses obtained not only significantly exceed these theoretical thresholds but also ensure high statistical power, robust parameter estimates, and representativeness across regional subgroups of Kazakhstan, enabling robust multigroup analysis.

To ensure representativeness of the study's regional and demographic characteristics across Kazakhstan's population, stratified quota sampling was used across five macroregions (Eastern, Western, Northern, Southern, and Central) and gender. This approach allowed us to account for territorial, socioeconomic, and cultural differences, which is particularly important when analyzing human capital and innovative competencies. The use of stratification ensured an even representation of subgroups, reduced the risk of data bias, and made it possible to identify gender differences in the perception and development of competencies. Data were collected primarily online via Google Forms, which enabled us to include respondents from different regions of the country. The final sample included 1,447 valid responses (Eastern – 117, Western – 251, Northern – 308, Southern – 635, Central – 136), ensuring geographic balance and reliability for conducting a multigroup analysis using the PLS-SEM model. Before beginning the questionnaire, respondents were provided with information about the study objectives, the approximate duration, and the format of their responses. The questionnaire included attention/validity control questions, and incorrect and incomplete responses were excluded (including cases with atypically short completion times).

2.2. Instrument design and analysis

In the second part of the survey, the indicators were measured using validated scales adapted from previous studies: innovation competence – AI (Ng et al., 2024); innovation competence – emotional intelligence (Schutte et al., 1998); innovation competence – creativity (Kaufman, 2012); innovation competence – critical thinking (Kobylarek et al., 2022); human capital (Jepkorir Inyangala et al., 2014); adaptation to Industry 4.0 (Sözbilir, 2021). Each construct was assessed using 1–5 statements on a five-point Likert scale (1 – "completely disagree", 5 – "completely agree").

The questionnaire was developed in Kazakh and Russian using forward and backward translation, ensuring conceptual and linguistic equivalence. Minor translation difficulties with terms related to innovation competencies were resolved after expert review. To assess the clarity and reliability of the formulations, pilot testing was conducted among 40 respondents from various regions of Kazakhstan; minor adjustments were made based on the results.

The reliability and validity of the scales were assessed using Cronbach's α, Composite Reliability (CR), and Average Variance Extracted (AVE). Participation was voluntary and anonymous, with prior informed consent obtained. After excluding incomplete and invalid questionnaires, the final dataset comprised 1,447 valid responses. Statistical analysis was conducted using the PLS-SEM method in SmartPLS 4.

2.3. Participants' profile

Key socio-demographic data are presented in Table 1. The majority of respondents were women (92.8%), while men accounted for 7.2%. The largest number of participants was aged 35–44 (42.0%) and 25–33 (33.5%). The 45–54, 18–24, and 55–63 age groups accounted for 15.8%, 5.3%, and 3.5%, respectively.

In terms of education level, the majority of respondents had higher education (77.3%). Secondary specialized education was reported by 11.7% of re-

Table 1. Participants' demographic profile

No.	Variable definition	Frequency	%
	Age range		
1	18–24	77	5.3
	25–33	484	33.5
	35–44	607	42.0
	45–54	229	15.8
	55–63	50	3.5
	Gender		
2	Male	104	7.2
	Female	1343	92.8
	Education level		
3	General secondary education	40	2.8
	Secondary specialized education (technical and vocational schools, college)	169	11.7
	Incomplete higher education	88	6.1
	Higher education (including Bachelor's and Master's degrees)	1119	77.3
	Academic degree (Ph.D., Candidate, or Doctor of Sciences)	31	2.1
	Region of KZ		
4	Eastern Kazakhstan (East Kazakhstan and Abai regions)	117	8.1
	Southern Kazakhstan (Turkistan, Zhetisu, and Almaty regions, Shymkent and Almaty cities)	635	43.9
	Central Kazakhstan (Karagandy and Ulytau Regions)	136	9.4
	Western Kazakhstan (Atyrau, Mangystau,West Kazakhstan, and Aktobe Regions)	251	17.3
	Northern Kazakhstan (Akmola, Kostanay, Pavlodar, and North Kazakhstan Regions, Astana city)	308	21.3

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spondents, incomplete higher education by 6.1%, general secondary education by 2.8%, and an academic degree by 2.1%.

The majority of respondents resided in Southern Kazakhstan (43.9%), followed by Northern Kazakhstan (21.3%), Western Kazakhstan (17.3%), Central Kazakhstan (9.4%), and Eastern Kazakhstan (8.1%). This shows that representatives from all regions of the country participated in the study.

3. RESULTS

3.1. Measurement model assessment

Before data collection, pretesting and pilot testing were conducted to ensure the accuracy and reliability of the measurement instruments used. Following the methodology of Hair et al. (2019), the assessment of the measurement model involves four stages: analysis of indicator loadings, testing construct reliability, and assessment of convergent and discriminant validity. As shown in Table 2, all indicators were consistent with their theoretical constructs and had values above the minimum threshold of 0.708 (Hair et al., 2019). The reliability of the constructs is confirmed by high Cronbach's alpha and composite reliability (rho_a and rho_c) values, which exceed the threshold of 0.70 (Hair et al., 2019)

AVE values range from 0.712 to 0.820, exceeding the threshold of 0.50 (Hair et al., 2019), confirming that the corresponding constructs explain more than 50% of the indicator variance. Thus, all constructs demonstrate high convergent validity and internal reliability, confirming the robustness and appropriateness of the measurement model.

Table 3 presents the Fornell–Larcker criterion for discriminant validity. According to this criterion, a research model is considered properly specified if, for each latent variable, the square root of the AVE exceeds its correlations with other constructs.

In this study, the square root of the AVE for each construct was higher than its correlations with other variables, confirming the presence of discriminant validity for all indicators. Specifically, the diagonal values were as follows: human capital = 0.878, innovation competence – artificial intelligence = 0.884, innovation competence – creativity = 0.844, innovation competence – critical thinking = 0.906, innovation competence – emotional

Table 2. Measurement model results

Construct	Item	Factor loading	OuterVIF	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Human capital	HC1 HC2 HC3 HC4	0.872 0.883 0.908 0.846	2.586 2.780 3.128 2.148	0.901	0.902	0.931	0.771
Innovation competence – Artificial intelligence	IC-AI1 IC-AI2 IC-AI3 IC-AI4	0.863 0.919 0.889 0.865	2.381 3.713 3.659 2.854	0.908	0.916	0.935	0.782
Innovation competence – Creativity	IC-C1 IC-C2 IC-C3 IC-C4 IC-C5	0.854 0.831 0.837 0.839 0.858	2.437 2.259 2.278 2.313 2.461	0.899	0.900	0.925	0.712
Innovation competence – Critical thinking	IC-CTh IC-CTh IC-CTh	0.909 0.930 0.877	2.973 3.392 2.165	0.890	0.891	0.932	0.820
Innovation Competence –Emotional intelligence	IC-EI1 IC-EI2 IC-EI3 IC-EI4 IC-EI5	0.855 0.865 0.868 0.882 0.856	2.543 2.687 2.664 2.949 2.581	0.916	0.916	0.937	0.749
Adaptation to Industry 4.0	Industry 4.0-1 Industry 4.0-2 Industry 4.0-3	0.893 0.862 0.908	2.557 1.879 2.799	0.865	0.866	0.918	0.788

Table 3. Measurement model's discriminant validity

Constructs	HC	IC-AI	IC-C	IC-CTh	IC-EI	Adoption I-4.0
Human capital (HC)	0.878					
Innovation competence – artificial intelligence (IC–AI)	0.534	0.884				
Innovation competence – creativity (IC–C)	0.703	0.552	0.844			
Innovation competence – critical thinking (IC–CTh)	0.653	0.560	0.786	0.906		
Innovation competence –emotional intelligence (IC–EI)	0.690	0.595	0.806	0.774	0.865	
Adaptation to Industry 4.0 (Industry 4.0–)	0.650	0.658	0.627	0.619	0.650	0.888

intelligence = 0.865, and adaptation to Industry 4.0 = 0.888. They all exceed the corresponding inter-construct correlations presented in Table 3.

Thus, each construct is distinct from the others and measures a unique aspect of the proposed model.

3.2. Hypotheses testing

Table 4 and Figure 2 present the results of the structural model analysis, including path coefficients, standard deviations, *t*-statistics, and *p*-values for the proposed hypotheses. All proposed hypotheses were supported at a highly statistically significant level ($p < 0.001$), confirming the robustness of the model.

The relationship between human capital (HC) and Industry 4.0 adoption is strong and positive (β = 0.650, t = 35.630, $p < 0.001$), indicating that the development of human capital substantially facilitates the adoption and integration of Industry 4.0 technologies. This finding underscores the key role of human resources in digital transformation processes. Furthermore, all dimensions of innovative competencies (IC) exhibit a significant positive impact on human capital. Among them, creativity (IC–C) has the strongest effect (β = 0.333, t = 8.323, $p < 0.001$), suggesting that organizational collaboration and knowledge-sharing networks are critical mechanisms for developing and sustaining human capital potential.

The impact of innovation competence – emotional intelligence (IC–EI) is also significant (β = 0.241, t = 5.940, $p < 0.001$), indicating that employees' emotional awareness, empathy, and self-regulation contribute to a more resilient and adaptive workforce, enhancing overall human capital qual-

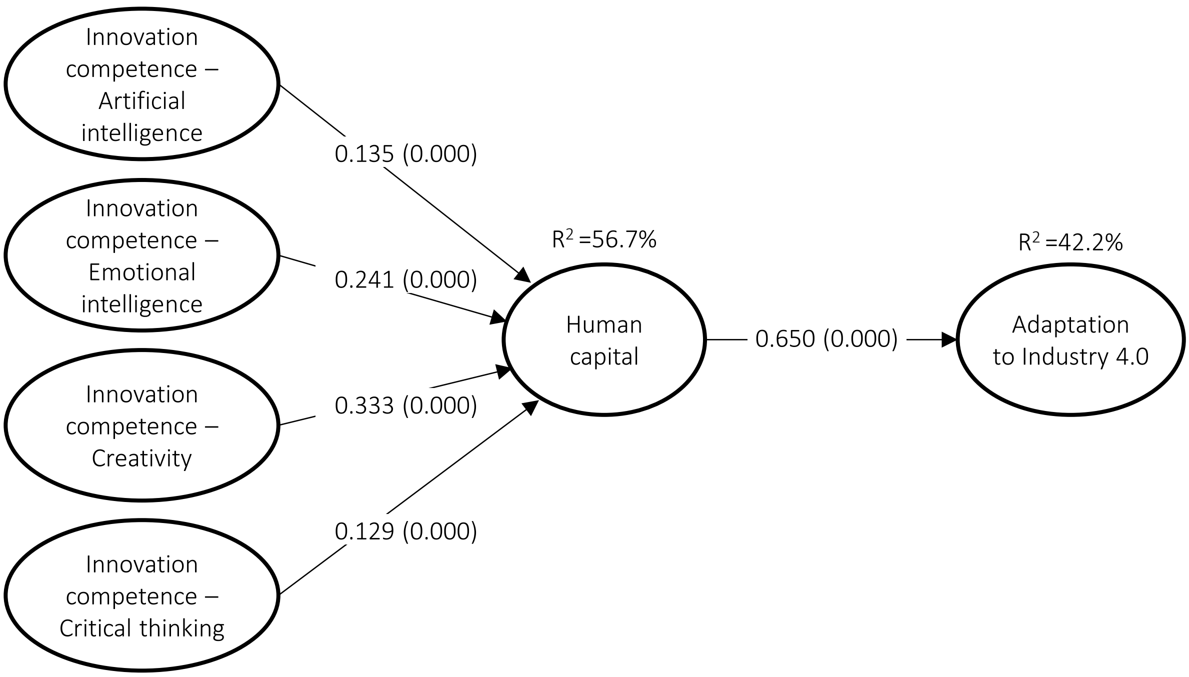

Figure 2. Testing the hypothesized model

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ity. Similarly, AI-related competencies (IC–AI) have a moderate but statistically significant effect on human capital (β = 0.135, $t = 5.696$, $p < 0.001$), implying that the development of AI competencies within organizations strengthens employees' knowledge, adaptability, and innovative potential. Finally, critical thinking (IC–CTh) exerts a positive, albeit relatively smaller, effect on human capital (β = 0.129, $t = 3.486$, $p < 0.001$). This suggests that while critical thinking remains an important factor in enhancing human capital, its impact may be more indirect or context-dependent than that of other dimensions of innovative competencies.

Overall, the results confirm that all dimensions of innovative competencies have a significant and positive influence on the development and strengthening of human capital, which, in turn, plays a decisive role in adapting to the demands of Industry 4.0.

Thus, all hypotheses were supported (see Table 4). The results indicate that all path coefficients are positive and statistically significant ($p < 0.001$), confirming the proposed relationships among the constructs. Among the innovative competencies, creativity (IC–C → HC) has the strongest positive effect on human capital (β = 0.333, $p < 0.000$), followed by emotional intelligence (IC–EI → HC, β = 0.241, $p < 0.000$), artificial intelligence (IC–AI → HC, β = 0.135, $p < 0.000$), and critical thinking (IC–CTh → HC, β = 0.129, $p < 0.000$). It should be noted that human capital (HC) exerts a strong and significant effect on Industry 4.0 readiness (β = 0.650, $p < 0.001$), indicating that the development of human capital is a key factor in adapting to the conditions of the Fourth Industrial Revolution.

Overall, the results suggest that the development of innovative competencies contributes to the strengthening of human capital, which, in turn, significantly enhances organizations' readiness to transition to Industry 4.0 standards.

A multigroup analysis (MGA) was conducted to determine whether the structural relationships between the constructs varied by region. The study identified five regional groups in Kazakhstan: Eastern, Western, Northern, Southern, and Central. The results presented in Table 5 reveal several notable cross-regional differences.

First, the relationship between human capital (HC) and Industry 4.0 implementation is positive and statistically significant across all regions, with the strongest effect observed in Central Kazakhstan (β = 0.739). The MGA results confirm that this path is significantly stronger in Central Kazakhstan compared to other regions, indicating a more critical role for the development and use of human capital in promoting Industry 4.0 practices in this region.

Second, intellectual capital related to artificial intelligence (IC–AI) exhibits a relatively weak but significant impact on human capital, rang-

Table 4. Hypotheses testing results

Hypothesis	β	$\overline{x}$	SD	*t*-statistics	*p*-value	InnerVIF	Result
H1 HC → Industry 4.0-	0.650	0.650	0.018	35.630	0.000	1.000	Supported
H2 IC–AI → HC	0.135	0.135	0.024	5.696	0.000	1.618	Supported
H3 IC–C → HC	0.333	0.332	0.040	8.323	0.000	3.535	Supported
H4 IC–CTh → HC	0.129	0.130	0.037	3.486	0.000	3.132	Supported
H5 IC–EI → HC	0.241	0.241	0.041	5.940	0.000	3.544	Supported

Table 5. Multi-group analysis across regions of Kazakhstan

Relationship	East KZ	West KZ	North KZ	South KZ	Central KZ	Significant group differences (MGA, p < 0.05)
HC → Adoption I- 4.0	0.662	0.644	0.635	0.643	0.739	Central KZ → all other regions
IC–AI → HC	0.131	0.103	0.140	0.140	0.212	Central KZ → West, East, South, North
IC–C → HC	0.304	0.374	0.284	0.347	0.404	Central & West → North & East
IC–CTh → HC	0.181	–0.052	0.111	0.173	0.255	Central → West; minor differences elsewhere
IC–EI → HC	0.279	0.433	0.270	0.170	0.026	West → Central, East, South; others non-sig.

ing from β = 0.103 (West) to β = 0.212 (Center). MGA shows that this effect is significantly stronger in Central Kazakhstan than in other regions, which may indicate a more effective use of AI-related intellectual resources for human capital development.

Third, the relationship between intellectual capital – collaboration (IC–C) and human capital is positive across all regions, with the strongest links observed in Central (β = 0.404) and Western (β = 0.374) Kazakhstan. MGA confirms that these two regions exhibit significantly stronger effects than North and East, highlighting the greater role of networking and collaboration in more industrialized regions.

Fourth, intellectual capital – creative thinking (IC–CTh) shows moderate effects in most regions, with a negative value in Western Kazakhstan (β = –0.052). MGA reveals that Central Kazakhstan has a significantly higher coefficient than Western Kazakhstan, although differences with other regions are not significant. This result reflects regional differences in how creative intellectual resources contribute to human capital formation.

Finally, the relationship between intellectual capital – emotional intelligence (IC–EI) and human capital varies significantly across regions. The strongest effect is observed in Western Kazakhstan (β = 0.433), while the weakest is in Central Kazakhstan (β = 0.026). MGA results reveal that Western Kazakhstan significantly outperforms Central, Eastern, and Southern Kazakhstan on this indicator, indicating regional advantages in developing emotional intelligence within the human capital system.

Overall, the MGA results demonstrate significant regional heterogeneity in structural relationships, highlighting that the determinants and intensity of Industry 4.0 readiness and human capital strengthening vary significantly across Kazakhstan's regions.

4. DISCUSSION

The empirical results demonstrate that the development of key innovative competencies (creativity, emotional intelligence, artificial intelligence-related, and critical thinking) has a positive and statistically significant effect on human capital. All hypothesized relationships were statistically supported, showing the strongest influence of a creativity factor. This finding underscores the importance of creative capacity in a rapidly changing technological environment, where non-standard thinking and flexibility are critical for adaptation. Furthermore, the results indicate that human capital directly enhances individual readiness for Industry 4.0, confirming its central role in navigating digital and institutional transformations.

The observed positive effect of human capital on the adoption of Industry 4.0 confirms its central role in facilitating digital and institutional transformations. This aligns with Štaffenová and Kucharčíková (2024), the value of human capital in Industry 4.0 is increasingly determined not only by professional knowledge but by personal qualities such as cognitive flexibility, motivation, and the capacity for continuous self-development. Our results suggest that these qualities serve as the foundation of innovative competencies, particularly creativity and emotional intelligence, which rely on adaptability, empathy, and lateral thinking rather than algorithmic problem-solving.

When compared with prior research, our findings are consistent with bibliometric evidence reported by Alhloul and Kiss (2022), which identified a growing scientific focus on the role of soft and digital skills in employment and productivity under Industry 4.0. Their results emphasize creativity and critical thinking as fundamental skills of the future. Importantly, the present study not only confirms this assumption but also empirically clarifies the hierarchy of their influence, positioning creativity as the most impactful competence for human capital development. Similarly, practice-oriented research, such as the strategic human resource model proposed by Vong et al. (2025), highlights emotional intelligence and interaction with artificial intelligence as foundations for sustainable human capital growth in emerging economies. In contrast to macro-level studies focusing on structural labor market changes (Marku, 2024), this paper contributes to the literature by

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examining individual-level adaptation, emphasizing psychological and cognitive dimensions of competencies.

Moreover, the findings support and extend the conclusions of the Global Talent Competitiveness Index (Lanvin & Monteiro, 2020), which links adaptability to digital technologies with the development of creativity, digital literacy, and emotional intelligence. By providing quantitative empirical evidence, this study substantiates these propositions and demonstrates how innovative competencies jointly strengthen human capital. From a theoretical perspective, the results further support contemporary approaches to human capital management that emphasize the quality and effectiveness of competencies rather than their mere presence (Štaffenová & Kučharčíková, 2024; Kozioł et al., 2014). Unlike prior studies that examined human competencies in isolation, this current analysis demonstrates their combined and hierarchical effects, identifying creativity as the most influential factor. This contribution refines existing theoretical models of innovation competence and human capital, including multi-level frameworks proposed by Hero et al. (2017), Pérez-Peñalver et al. (2018), and Bittencourt et al. (2025).

Additionally, the findings resonate with Schumpeterian ideas regarding innovation, entrepreneurial spirit, and adaptability as drivers of economic development (Śledzik, 2013), confirming that creativity and innovative thinking function as strategic assets enabling employee adaptation in the context of Industry 4.0.

CONCLUSION

The research objective was to identify the factors influencing human capital development through the integration of key innovative competencies and to assess their contribution to readiness for Industry 4.0. The results reveal that creativity, emotional intelligence, artificial intelligence-related skills, and critical thinking collectively strengthen human capital, which in turn enhances adaptability to technological and organizational change. The findings highlight the systemic importance of innovative competencies as a foundation for sustainable development in the digital economy. In this regard, the study provides recommendations for education systems, human resource management, and public policy. Educational institutions should prioritize the development of both technical and soft skills, while employers and HR professionals are encouraged to integrate creativity, emotional intelligence, critical thinking, and AI-related competencies into recruitment, training, and performance assessment practices. Such an approach can foster resilient, innovative, and adaptable workforces capable of supporting long-term competitiveness under Industry 4.0 conditions.

AUTHOR CONTRIBUTIONS

Conceptualization: Aliya Karakozhayeva.
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