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Shaping AI-related competencies for labor market and business. A PLS-SEM approach

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Abstract

In the era of digitalization and rapid technological advancement, artificial intelligence (AI) has emerged as a decisive factor in transforming the labor market, requiring the continuous adjustment of educational competencies to prepare students for the labor market demand. This study investigates the impact of AI on educational requirements, identifying the essential competencies that educational systems and the business sector must shape to equip future professionals for AI-driven challenges and opportunities. Employing Partial Least Squares Structural Equation Modeling (SEM), the research analyzed the survey data from a sample of 138 educators from various pre-university and university environments in Bihor county, Romania. to determine the relationships between the educational system, business sector, educational competencies, and AI career preparedness. The findings show significant influences from both sectors in shaping competencies that, in turn, affect labor market demands. This study highlights the imperative for educational systems the business sector to develop forward-thinking programs that anticipate future changes, thereby maximizing an AI-driven economy's economic and social benefits. The results indicate that both the educational system and the business sector are integral to developing the competencies required in the AI era, with AI career preparedness exerting the greatest influence on labor market demands.

Keywords: Artificial intelligence (AI), educator, competencies, labor market, business sector

1 Introduction

The rapid expansion of the new industrial revolution, supported by digitization, advanced knowledge and networks, has spectacularly highlighted the role of artificial intelligence (AI) in the world's economies, and especially in developed countries. Generous objectives such as the intelligent transformation of production, the use of AI for the benefit of humanity and the planet, the reshaping of the global industrial division of labor, imply a significant transformation of the labor market and the education of the workforce according to the challenging demands coming from the public and business sectors [12, 66]. According to [4], developed countries have been perceiving, for more than a decade, these changes and the polarization of the employment structure - an increase in the share of highly skilled jobs in sectors dominated until recently by personnel with medium and low qualifications and, respectively, a numerical decrease in jobs in sectors where medium qualifications were specific.

AI has a considerable impact on the labor market, it changes the trend of employment through substitution and creation effects: technological advances reduce equipment costs and make labor relatively more expensive and less controlled, causing management to look for ways to replace it with equipment, respectively AI programs and applications [1, 2, 11], accelerating substitution effects [61], generating, at least in the short term, the loss of some jobs [39] especially in productive sectors that required medium and low qualifications. There are positive consequences of the phenomenon of the expansion of AI in the economy and society as well - expanding the scale of production by reducing costs, increasing the productivity of equipment [10], increasing the skills of the workforce in research and development, design, communication [1], the emergence of new jobs and fields of activity [64], even if a large part of researchers differently understand the impact of AI on the fading, substitution, and creation of jobs, and, respectively, their qualification levels, desired by the business environment [1, 3, 36].

Although extensive literature exists on the relationship between AI and educational competencies, there is a conspicuous gap in research regarding teachers' perspectives on the roles of the educational system and the business sector in cultivating these competencies. Most current studies focus on students' perspectives and preparedness for AI integration. However, the pivotal role of educators in shaping and fostering AI-related competencies remains insufficiently explored. This research aims to fill this gap by investigating teachers' perceptions of the educational system's and business sectors' roles in cultivating educational competencies, evaluating their combined influence on labor market demands, and assessing the impact of preparedness for AI-based careers. The objectives are to identify key factors that contribute to effective competency development, analyze how these competencies align with current labor market needs, and determine strategies for enhancing educator and business sector collaboration, using a Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. The study is structured as follows: an extensive literature review establishes the theoretical foundation on

AI's role in education and skill development, followed by the formulation of research hypotheses. The study then outlines construction, model fit assessment, and validation of the PLS-SEM model, followed by the empirical results, discussion, limitations of the study, and policy implications.

2 Literature review and hypothesis development

2.1 AI and employment

According to Wang et al. (2024) [66], the first academic mention of the concept of AI appeared at the Dartmouth Conference in 1956, suggesting the competence of machines to emulate human actions and perform tasks intelligently, reflecting human activities. Subsequent definitions - to solve problems and make decisions [15], "machines with minds, in the full and literal sense" [40], or to do something that would normally be thought to require the intelligence of a human [52], reflects the gradual understanding and human experiences of this incredible and ever-evolving reality.

More recently, Xia et al. (2022) [71] or Chiu et al. (2023) [24] emphasizes AI as the ability of a digital machine to perform tasks by imitating human intelligence, to learn and think, while the definitions of some national or international organizations or institutions adopt a more general and flexible position - "a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments" [56], or "Artificial intelligence is more than the simple automation of existing processes: it involves, to greater or lesser degrees, setting an outcome and letting a computer program find its own way there. It is this creative capacity that gives artificial intelligence its power" [65]. The rapid growth and development of AI technology involves not only advances in digital technologies, production efficiency, or scientific advances, it has effects in most aspects of human society.

Regarding the impact of AI on labor supply and demand, the main theories focus on changes in skill structures (skill-bias) and respectively on changes in task structures (task-bias) [13, 66]. Thus, in the first stages of the expansion of AI in economies, increases the risk of losing medium-skilled jobs, based on procedural, repetitive tasks, and therefore easy to automatization [35]. Interestingly, low-skilled labor (mainly non-procedural and manual), presents a much lower risk of replacement, accentuating employment polarization, accelerating labor inequality [1, 3] and a polarized demand for human capital [19]. The second stage of the development of AI technology leads to an increase in the demand for skilled, knowledge-based workers [16, 66], negatively affecting low-skilled workers but not necessarily due to the specific demand coming from high-tech sub-fields or sectors affected by AI, but rather due to macro-economic transformations [31], directly and indirectly driven by AI technology and the new industrial revolution, exacerbating spatial and technological polarization on the labor market [20, 44].

By promoting the optimization of industrial structure, blurring differences between sectors, and increasing integration and diffusion in the real economy and society, AI nonlinearly influences economic transformation [45], total productivity factors [73], and the modernization of industrial structure [74]. In this regard, the impact of AI on the employment structure will be accelerated by the spillover effects of openness, diffusion, externalities, and extremely low marginal costs of information technology [66]. The widespread use of AI can significantly increase the demand for high-skilled labor in some sectors, while reducing the demand for low-skilled labor in others, causing a non-linear adjustment of the labor market, with some vulnerable groups affected by unemployment, while others enjoy high rewards in highly skilled fields. In sectoral terms, AI can accelerate the decline of certain traditional sectors and the emergence of new high-tech industries, which can cause a non-linear migration of workforce between industries, affecting the evolution of the employment structure [66].

The large-scale adoption of AI within companies is changing the way the skills needed for jobs are defined, but also the organization of work in these institutions, generating a change in the demand for skills, increasing the demand for workers with AI skills, i.e. people who have the knowledge and skills to actively develop and maintain AI models. However, workers with these qualifications are only a small part of the overall employment, despite the media, political and academic interest associated with the expansion of AI in the economy and society [37, 38]. According to recent OECD studies [37] most workers who will use AI in everyday work tasks will not need advanced AI skills or knowledge of how AI systems work. Of course, there are certain occupations heavily exposed to the development of AI, such as management, business processes and social activities that call for specific skills - project management, budgeting, accounting, administration, clerical tasks and customer support. Thus, a significant number of high-skilled occupations are highly exposed to AI input, among them OECD or EU reports mention genetic counsellors, financial advisors, insurance surveyors, purchasing agents, budget analysts [28, 37, 54]. The World Economic Forum points out that occupations such as 'AI and Machine Learning Specialists' and 'Data Analysts and Scientists' will be among the top 10 fastest growing jobs between 2023 and 2027 [68].

Social, emotional and digital competencies/skills are also in high demand, with over 50% of vacancies in high-exposure occupations requiring at least one skill from these skill groups [37, 38, 54]. Thus, in recent years there has been an increase in demand for positions that require at least one skill from each of these groups, among occupations with high exposure to AI, and especially for positions that require at least one cognitive, emotional or digital skill. According to recent studies, the adoption of AI can increase, for limited periods of time and in variable proportions, the demand for some skills specific to traditional industrial production, based on physical skills, "blue collar" type [30, 37]. All these data and studies clearly show that the use and expansion of AI in the economy require the development of new skills and competencies, from technological expertise to social, emotional and creative skills [59].

According to Bird [18] and the IBM Institute for Business Value [43], the effective use of AI means more than programs and advanced technologies, it also means understanding the existing skills within the organization, identifying and prioritizing the skills needed in the future and creating opportunities for employees to develop them. Of course, digital literacy and data processing abilities are essential for employees to understand how to interact with AI tools. Moreover, employees need to realize that generative AI is not a source of truth or miraculous solutions, but rather it uses various data to provide potential answers and solutions, and employees - using their experience, knowledge, critical thinking and social interactions - will interpret them to take the best decision. The power and potential of AI and personal technical skills must be complemented with the soft skills of employees – creativity, collaboration, social and communication skills. Adaptability and flexibility in changing organizations are also important in the world transformed by AI, which is increasingly taking over much routine tasks.

2.2 AI and the business sector

Farayola et al. [29] concluded that the business sector is shaped by AI integration, generating new business models. The positive change is possible by adapting the education technology (EdTEch) sector. The challenge would be to integrate and adapt the classical education system, so that businesses receive professionals that need less training and are better equipped to deal with AI related challenges in the business environment. The proliferation of the EdTech businesses is evoked by Alam and Mohanty (2023) [8], who claim that these businesses changed the educational sector, marking the influence of the business sector, that uses AI solutions. On this note, the tradition education goals are completely opposite to the novel notions of teaching. The necessity of recognising sector-specific challenges and opportunities in the business sector, was highlighted by Kaggwa et al. [47] who debate the issue of AI educational tools, that would enhance learning experiences, thus contributing to growth and diversity in the workplace. The business sector could contribute to aiding policy makers in adapting the AI in the education reform, in such a way that the educational system and the business environments benefit from changes, without lowering quality of teaching. Giuggioli and Pellegrini [32] argue that business driven AI solutions, implemented in the educational sector, would lead to innovation and entrepreneurship before students graduate, thus enabling them to have a head start in creating further digital education, when they are employed in the EdTech business sector. In similar research, Sollosy and McInerney [60] argue that the business sector will have significant changes in the workforce, jobs will be lost, but others will be created, and in the context of AI, these new jobs will be uniquely human. The role of the business sector would be to promote the concept of business needs into the education sector, so that graduates know what jobs and what needs they might pursue, with accuracy. The relationship between the expansion of AI in the business and the public sectors and, respectively, employment is becoming an insistent concern of international institutions and organizations (World Bank, 2019; OECD, 2022; OECD, 2023; WEF, 2023; WEF, 2024).

2.3 AI and labor force training

The rapid integration of generative AI in the economy and society, its accessibility and the increasing interest of the general public, the transformational perspectives brought, have determined the education system to re-evaluate its role in the educational process and develop strategies to prepare students to work and understand the principles of this technology [22]. The demand is complex and dynamic, it comes from productive/industrial sectors [12, 45, 74], finance [17, 21], health care [72], transport and communications [70], social services [27, 57].

Even education as such is subject to transformations carried by AI [6, 22, 24, 59, 71], to improve student learning, to provide personalized feedback in real-time and by adapting to individual learning styles [22, 34, 50]. It can be used to stimulate students' involvement in the development and implementation of AI technology, in discovering areas of application in economics, society, human relations and personal development, equipping them with sound tools and principles to navigate in various ethical, social and economic environments [7, 22].

Last but not least, the expansion of AI in education and assessment must be done while respecting and maintaining academic integrity [7, 22], warning and educating students about the ethical considerations surrounding AI, the potential consequences of the incorrect use of AI in current and future academic contexts, but also as employees or active citizens in the societies in which they will work and live. In conclusion, the use of AI in education is accompanied not only by benefits but also by risks, underlining the importance of appropriate and responsible AI education policies.

The issue of educational competencies is strongly connected with the quality of the educational system. Ghailani and Khan (2004) [33] argue that the secondary educational system should be realigned to the existing economic needs of contemporary society. The education system could be in a productive collaboration with the business sector, requiring reforms of the curriculum and the teaching methods, that would impact the development of educational competencies. In the same context, Herdan and Stuss (2019) [41] highlight that higher education's focus could be on lifelong learning competences, that encompass problem solving, communication and technological proficiency, in order to train students who are adaptable to labor market requirements. The labor market needs to inform higher education institutions, which adapt the curricula in such a way that it prepares students with competences in new and developing fields, such as technology, fintech, and AI. Terentyeva et al. (2018) [63] take the position that the collaboration between the educational system and the labor market leads to the development of tools for human resource management. In this situation, collaboration between higher education institutions allows for a flexible educational program, synchronized to the labor market dynamics and constant technological advancements. However, according to a UNESCO [58] study, the integration of AI into the labor market led to a significant reshaping of competences and workforce dynamics, by automating intermediate skills jobs. Technology design, critical thinking, and computer use are skills that universities should embed into their curriculum, by constantly collaborating with various industries, for adapting to new job requirements.

Chiu et al. (2024) [25] bring forth the idea that K-12 schools could emphasize AI literacy and competency, by combining technical skills with societal impact of AI, ethics in using AI and collaborations. AI skills should not be reduced to an engineering perspective, but should be related to lifelong learning. Adams et al. (2023) [5] offer the perspective that there are AI principles, such as transparency, fairness, and privacy, that students should be taught to use in their work with AI technologies. Their view highlights the flexibility of AI in shaping educational principles, such as pedagogical appropriateness, children's rights and professional integrity, which inform educational skills, used throughout the person's life.

Tedre et al. (2021) [62] argue that there needs to be a change in K-12 schools, namely a shift from traditional rule-based programming to data-driven approaches. The shift would allow machine learning in schools to develop on a path that enables students to fit into new labor market demands.

Machine learning principles would, therefore, be introduced and developed in K-12 schools through the use of age-appropriate tools and methods, that would allow for deep understanding and advanced computational thinking. The shift could foster entering on career paths and opportunities, that would otherwise be unattainable. Hossain Ka (2023) [46] highlights the fact that AI and machine learning require a reform or an adaptation of the K-12 educational system, as well as the higher education system, to labor market needs, which emphasize enhanced learning and an alignment of educational outcomes, with evolving employment opportunities. The educational adaptation would result in reduced unemployment and the promotion of socio-economic development.

2.4 Research hypotheses

Based on the theoretical framework and insights identified in previous research [9, 49, 53, 59] we developed a series of research hypotheses. The premises of this research assume that the roles of the educational system (ESR) and the business sector (BSR) have a positive and significant influences on the development of educational competencies (EC), which, in turn, affect labor market demands (LMD) in the AI era. We also consider that preparedness for AI-based careers (PCBA) significantly impacts labor market demands. The educational system's initiatives, together with the participation of the business sector, collaboratively develop the competencies needed to meet the modern job requirements shaped by artificial intelligence. The research hypotheses are:

–Hypothesis 1: The role of the educational system (ESR) has a positive and significant impact on developing educational competencies (EC).

–Hypothesis 2: The role of the business sector (BSR) has a positive and significant influence on developing educational competencies (EC).

–Hypothesis 3: The educational system (ESR) has a significant positive indirect effect on labor market demands (LMD), mediated by its influence on educational competencies (EC).

–Hypothesis 4: The business sector (BSR) has a significant positive indirect effect on labor market demands (LMD), mediated by its influence on educational competencies (EC).

–Hypothesis 5: Educational competencies (EC) have a positive and significant influence on labor market demands (LMD).

–Hypothesis 6: AI career preparedness (PCBA) has a significant and positive influence on labor market demands (LMD).

3 Methodology and model development

3.1 Data collection

The principal objective of this study is to construct and validate an exploratory model through the application of Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess the roles of the educational system (ESR) and the business sector (BSR) in influencing the development of educational competencies (EC) and their subsequent influence on labor market demands (LMD), as well as the preparedness for AI-based careers (PCBA). PLS-SEM is less restrictive regarding sample size compared to other structural modelling methods such as Covariance-Based SEM (CB-SEM). It can produce valid and reliable results even with smaller sample sizes, making it ideal for studies with a limited number of respondents. Specifically, this research aims to evaluate educators' perceptions regarding their contributions to fostering these competencies in the context of the increasing prominence of artificial intelligence (AI) systems. Through the application of PLS-SEM, the study explores the interconnected effects of the educational system and business sector roles on educational competencies, the alignment of these competencies with evolving labor market requirements, and the critical importance of preparing for careers influenced by AI. The research employed a survey method, starting with the design and online distribution of a questionnaire. This survey, created using Google Forms, was disseminated digitally and included two sections: demographic information collection and specific questions about the role of educators in the dynamic AI context. Data collection took place in August 2023, involving a convenience sample of 138 educators from pre-university and university levels in Bihor county, Romania. Convenience sampling, often based on voluntary participation, is a commonly used research technique [51] but can introduce bias due to its non-representative nature. To overcome this challenge, direct email contact and the "snowball" sampling method were employed to increase sample size and enhance diversity. Although Partial Least Squares Structural Equation Modeling (PLS-SEM) is suitable for smaller samples and offers valuable insights, we acknowledge the limitation that a larger sample would increase the statistical power and robustness of our findings. As such, the findings should be interpreted with caution, taking this limitation into account. Future research should aim for larger and more representative samples to enhance the generalizability of the results.

The profile of the 138 educators participating in the study offers a detailed demographic and professional overview, reflecting a balanced representation across various characteristics essential for understanding AI integration in education. Predominantly female (80%), in alignment with common trends in pre-university educational settings, the sample spans diverse age groups, with the majority aged between 40-50 years (42%), followed by 50-60 years (25%) and 30-40 years (24%), and includes smaller proportions aged 20-30 years (6%) and over 60 years (3%). Specialization among respondents is fairly divided between sciences (42%) and humanities (58%), providing a comprehensive view of competencies across disciplines. Teaching experience varies significantly, with most respondents having over 20 years (51%) or 10-20 years (33%) of experience, while 9% have 3-9 years and 7% have 0-3 years, bringing a mix of seasoned and fresh perspectives to the study. Participants represent all educational levels, including preschool (3%), primary school (21%), lower secondary school (11%), higher secondary school (32%), and university (33%), facilitating a thorough assessment of AI's impact across educational stages. Additionally, the majority are based in urban areas (86%) and teach in urban settings (91%), reflecting the concentration of educational resources and AI efforts in cities while also including valuable input from rural areas.

3.2 Reliability and validity of the model

The specific questions of the questionnaire, which consists of 31 items, are carefully designed to assess the roles of the educational system and the business sector in shaping educational competencies, and how these competencies influence labor market demands. Respondents rated each item on a five-point Likert scale (1 - Strongly Disagree to 5 - Strongly Agree). The questionnaire is based on essential variables for understanding the integration of AI in educational contexts: labor market demands (LMD) with 4 items measuring the alignment of competencies with AI-driven market needs; the educational system's role (ESR) with 5 items evaluating its ability to cultivate AI-related skills and knowledge; the business sector's role (BSR) with 5 items focusing on its support for integrating AI competencies within educational frameworks; preparedness for AI-based careers (PCBA) with 5 items assessing readiness for AI-oriented career opportunities; and educational competencies (EC) with 5 items capturing the skills necessary for incorporating AI into educational settings. Each item set effectively measures these variables, providing a detailed framework for analyzing the connections among educational preparation, business sector involvement, and labor market requirements in the AI era. To analyze the reliability of the latent variables in the study, we calculated the Composite Reliability (CR), Average Variance Extracted (AVE), and Cronbach's Alpha for each latent variable. Table 1 provides an overview of the results for each subscale.

The reliability analysis of the constructs is essential for evaluating the internal consistency and validity of the measurement model used in this study. Composite Reliability (CR) measures the coherence among a construct's items, with a value above 0.70 indicating strong internal consistency [23, 26]. Average Variance Extracted (AVE) assesses the proportion of variance captured by the latent variable relative to measurement error, with a value above 0.50 demonstrating adequate convergent validity [23]. Cronbach's Alpha further evaluates the internal consistency of the items within each construct, where values above 0.70 are generally considered acceptable. The data shows that the Educational Competencies (EC) construct achieved a CR of 0.929, an AVE of 0.768, and a Cronbach's Alpha of 0.924, demonstrating high internal consistency and good convergent validity. Labor Market Demands (LMD) showed similarly robust metrics, with a CR of 0.900, an AVE of 0.768, and a Cronbach's Alpha of 0.899. The Role of the Educational System (ESR) exhibited a CR of 0.931, an AVE of 0.775, and a Cronbach's Alpha of 0.927, while the Role of the Business Sector (BSR) had

Table 1: Reliability Analysis

Latent Variable	Item	Outer Loading	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Labor market demands (LMD)	LMD1	0.880	0.899	0.900	0.768
	LMD2	0.894			
	LMD3	0.871			
	LMD4	0.859			
Preparedness for AI-based careers(PCBA)	PCBA1	0.841	0.928	0.929	0.776
	PCBA2	0.914			
	PCBA3	0.878			
	PCBA4	0.872			
	PCBA5	0.899			
The role of educational system (ESR)	ESR1	0.830	0.927	0.931	0.775
	ESR2	0.836			
	ESR3	0.931			
	ESR4	0.924			
	ESR5	0.843			
The role of business sector (BSR)	BSR1	0.887	0.922	0.932	0.764
	BSR2	0.889			
	BSR3	0.832			
	BSR4	0.902			
	BSR5	0.890			
Educational competencies (EC)	EC1	0.862	0.924	0.929	0.768
	EC2	0.896			
	EC3	0.854			
	EC4	0.883			
	EC5	0.884			

a CR of 0.932, an AVE of 0.764, and a Cronbach's Alpha of 0.922. The Preparedness for AI-based Careers (PCBA) construct demonstrated a good reliability with a CR of 0.929, an AVE of 0.776, and a Cronbach's Alpha of 0.928. These metrics confirm the strong reliability and validity of the constructs, ensuring that the measurement model provides a robust foundation for analyzing the relationships between the educational system, business sector, and the development of competencies required for an AI-driven labor market.

3.3 Discriminant validity and model fit analysis

To evaluate the validity and fit of the Structural Equation Model (SEM) developed for assessing the impact of AI on educational competencies and labor market demands, it is important to assess both discriminant validity and overall model fit. This can be evaluated using the Fornell-Larcker criterion, which compares the square root of the Average Variance Extracted (AVE) of each construct with the highest correlation of the construct with any other construct.

Table 2: Discriminant validity

Latent variables	EC	LMD	ESR	BSR	PCBA
Educational Competencies (EC)	**0.832**	0.601	0.568	0.525	0.634
Labor Market Demands (LMD)	0.601	**0.846**	0.511	0.494	0.648
Role of the Educational System (ESR)	0.568	0.511	**0.865**	0.472	0.531
Role of the Business Sector (BSR)	0.525	0.494	0.472	**0.860**	0.546
Preparedness for AI-based Careers (PCBA)	0.634	0.648	0.531	0.546	**0.877**

The results presented in Table 2 indicate adequate discriminant validity, as the square root of AVE for each construct is greater than the highest correlation with any other construct. The SEM model presented in Figure 1, which includes the path coefficients, indicates that all estimated coefficients are positive. This suggests that the roles of the educational system (ESR) and the business sector (BSR) positively contribute to the development of educational competencies (EC). These competencies, along with preparedness for AI-based careers (PCBA), in turn, positively influence labor market demands (LMD).

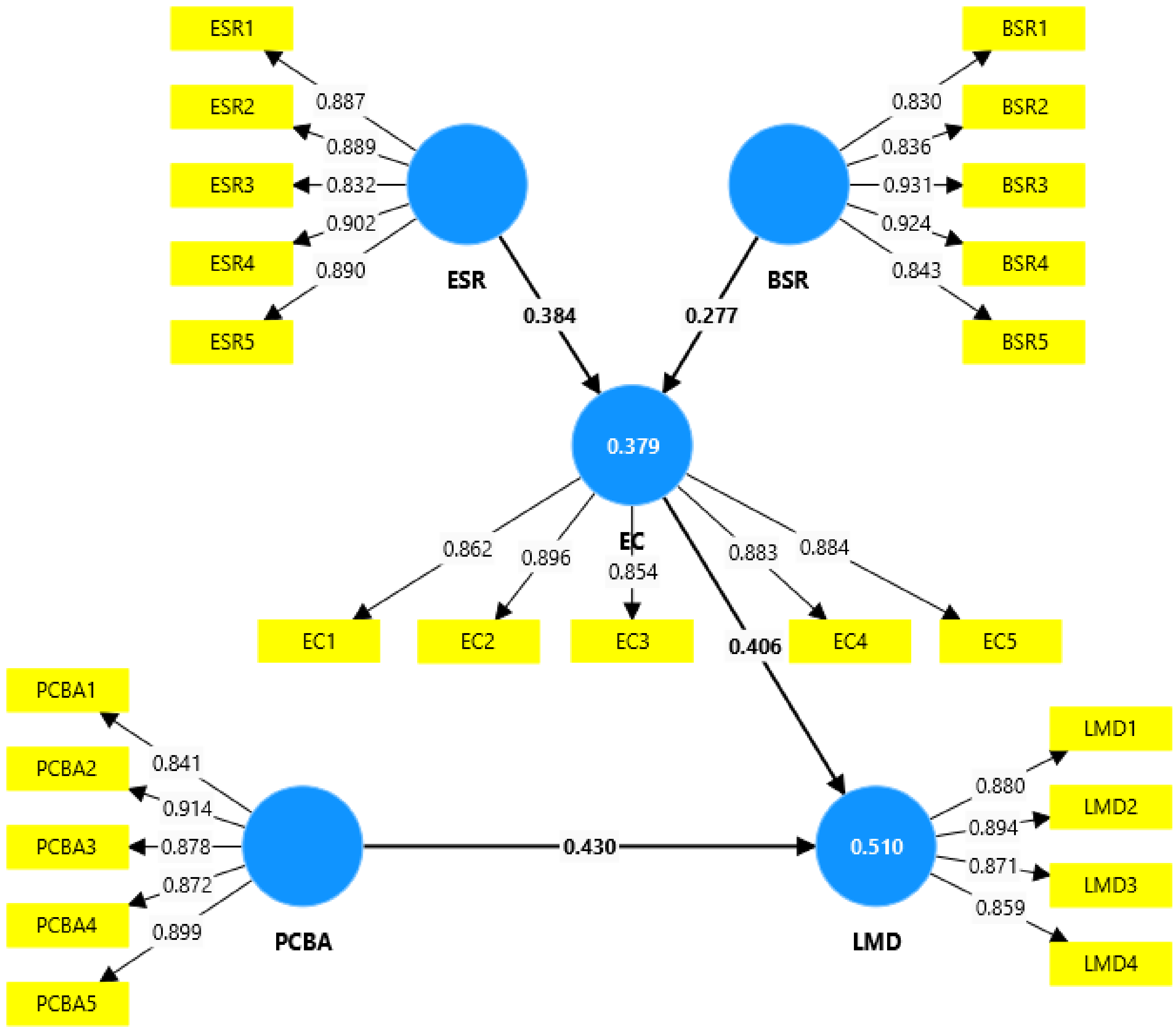

Figure 1: PLS-SEM

The assessment of model fit indices is essential for determining the alignment of the proposed SEM model with the observed data, thereby validating the hypothesized relationships between constructs. The R^2 values, which represent the explanatory power of the model, reveal that for Educational Competencies (EC), the model accounts for 37.9% of the variance ($R^2 = 0.379$), indicating a significant portion of the variability in educational competencies can be explained by factors such as the roles of the educational system (ESR) and the business sector (BSR). This underscores the substantial impact these factors have on shaping educational competencies. For Labor Market Demands (LMD), the model explains 51% of the variance ($R^2 = 0.51$), demonstrating strong explanatory power and highlighting the influence of educational competencies and preparedness for AI-based careers (PCBA) on labor market demands. The evaluation of fit indices further supports the model's adequacy: a Standardized Root Mean Square Residual (SRMR) of 0.060, which is below the threshold of 0.08, indicates a good fit, consistent with Hu and Bentler (1999) [42]. The Normed Fit Index (NFI) of 0.817, while slightly below the preferred threshold of 0.90, is acceptable, particularly in complex models, suggesting a reasonably good fit but indicating potential for further refinement [14, 48]. This comprehensive evaluation affirms the model's robustness in capturing the dynamics between educational and business sector roles, educational competencies, and labor market demands in the context of AI.

4 Results and discussion

4.1 Results and validation of the hypotheses

The analysis of the path coefficients provides detailed insights into how the educational system and business sector directly influence educational competencies and labor market demands. The path coefficients show the extent to which initiatives within the educational system enhance educational competencies, reflecting the significant role that educational policies, curricula, and instructional strategies play in developing the necessary skills for an AI-driven market. Similarly, the path coefficients highlight the direct contributions of the business sector, indicating how business engagement through partnerships, internships, and practical training programs supports the development of competencies that align with labor market needs. These coefficients also illustrate the dynamic interplay between educational and business practices in shaping a workforce prepared for the demands of an evolving labor market influenced by artificial intelligence.

Table 3: Results of testing direct and indirect statistical hypotheses

Path	**Direct effects**			**Indirect effects (MD:EC)**		**Decision**
	Coeff. (β)	**t-value**	**p-value**	**Coeff.(β)**	**p-value**	
H1: ESR → EC	0.384	7.25	$p < 0.01$			Accepted
H2: BSR → EC	0.277	5.6	$p < 0.01$			Accepted
H3: ESR → EC → LMD				0.154	$p < 0.01$	Accepted
H4: BSR → EC → LMD				0.111	$p < 0.01$	Accepted
H5: EC → LMD	0.4	8.1	$p < 0.01$			Accepted
H6: PCBA → LMD	0.428	8.45	$p < 0.01$			Accepted

*Note: * Coeff = Coefficient, MD = mediator, β = standardized coefficient*

Based on the data presented in the Table 3, we can argue that the roles of the educational system (ESR) and the business sector (BSR) have a positive and a significant influence on the development of educational competencies (EC), which, in turn, influence labor market demands (LMD) in the AI era. The educational system's influence on educational competencies is positive and significant, with a path coefficient of 0.384 (t-value = 7.25, $p < 0.01$), validating Hypothesis 1. This suggests that the policies, resources, and curricular frameworks established by the educational system are critical in shaping the competencies that educators need to integrate AI effectively into teaching practices. Also, the business sector has a meaningful influence on educational competencies, evidenced by a path coefficient of 0.277 (t-value = 5.60, $p < 0.01$), supporting Hypothesis 2. This underscores the importance of industry partnerships, practical insights, and resource support from the business sector in fostering relevant competencies. Educational competencies significantly influence labor market demands, as shown by a path coefficient of 0.400 (t-value = 8.10, $p < 0.01$), confirming Hypothesis 5. This indicates that the competencies developed within educational settings are important for aligning with the evolving requirements of the labor market influenced by AI. The direct effects show the immediate and tangible impacts of educational system policies and business sector engagement on the development of educational competencies, underscoring the critical role of well-formulated curricular frameworks and strategic industry partnerships in cultivating a workforce equipped with the necessary skills for the AI-driven landscape. In contrast, the indirect effects clarify the broader, influences these elements exert on labor market demands through the mediation of educational competencies, highlighting the necessity of an integrated approach that combines educational reforms with industry collaboration to foster comprehensive workforce development and adaptability in an evolving economic environment. Thus, the educational system indirectly impacts labor market demands through its effect on educational competencies, with an indirect path coefficient of 0.154 ($p < 0.01$), supporting Hypothesis 3. This suggests that the educational system's efforts to enhance competencies have a downstream effect on meeting labor market needs. Similarly, the business sector indirectly influences labor market demands through its contribution to educational competencies, with an indirect path coefficient of 0.111

($p < 0.01$), validating Hypothesis 4. This underlines the need for stronger collaborations between educational institutions and businesses to ensure that skills are relevant to the market. Furthermore, preparedness for AI-based careers (PCBA) shows the most significant direct influence on labor market demands, with a path coefficient of 0.428 (t-value = 8.45, $p < 0.01$), corroborating Hypothesis 6. This highlights the importance of AI-specific training and career preparation in meeting the demands of the labor market. The study underscores the impact of both educational system and business sector in shaping educational competencies, with effect sizes indicating meaningful contributions to AI-driven labor market demands. The educational system's influence is higher, demonstrating a strong capacity to equip educators with the necessary skills for AI integration through effective policies and comprehensive curricula. Likewise, the business sector plays a pivotal role, with effect sizes reflecting its significant contributions in providing practical insights and resources that enhance the relevance of educational competencies. Notably, preparedness for AI-based careers exhibits the largest effect size, underscoring its significant role in aligning educational outcomes with labor market needs. These findings highlight the importance of robust collaboration between educational institutions and industry partners to cultivate a workforce well-prepared for the challenges and opportunities presented by an AI-influenced economy.

4.2 Discussion

The significant influence of the educational system on developing educational competencies highlights the importance of curricular reforms that integrate AI technologies and promote continuous learning. Educational institutions must focus on creating programs that not only impart AI-related knowledge but also foster interdisciplinary learning and ethical considerations. Bird (2023) and the IBM Institute for Business Value (2024) [18, 43] developed a similar point of view, arguing for the development of specific educational competencies and adapting the educational curriculum to the new AI integration in the business sector. These programs should be designed to evolve with technological advancements, ensuring that students are equipped with the latest skills and are prepared for the dynamic demands of the AI-driven labor market. The business sector's role, while slightly less impactful compared to the educational system, remains important. Businesses can bridge the gap between educational outcomes and labor market needs by offering practical AI applications, internships, and training programs that align with industry requirements. Enhanced collaboration between educational institutions and the business sector can facilitate the development of competencies that are directly applicable to real-world scenarios, thereby improving the employability of graduates and ensuring that they are well-prepared for AI-related job roles. The direct impact of educational competencies on labor market demands suggests that a focus on competency development within educational frameworks is essential for meeting the modern job market's expectations. This necessitates a strategic approach to curriculum development that incorporates comprehensive AI-related content and practical experiences, allowing graduates to contribute effectively to an AI-driven workforce. Preparedness for AI-based careers stands out as the most influential factor on labor market demands, emphasizing the critical need for specialized AI training. Educational programs should prioritize career readiness, providing students with hands-on AI experiences and equipping them with skills that are directly applicable to AI-related careers. Adiguzel et al., (2023), Chan (2023), Xia et al. (2022), Simut et al. (2024), Chiu et al. (2023) [6, 22, 24, 59, 71] support the idea that there is an educational need to deepen the AI literacy among students, in order to develop specific competencies, through a collaboration between the business sector and policy makers.

To effectively prepare students for an AI-driven economy, educational institutions should enhance their curricula by integrating AI-focused content and practical experiences, ensuring that students acquire essential skills for modern job markets. Strengthening collaborations between educational institutions and the business sector is important to align educational competencies with labor market demands and facilitate a smoother transition from education to employment. Emphasizing AI career readiness in educational programs through real-world AI applications will better equip students for specific job roles driven by AI technologies. Additionally, educational policies should support continuous learning and adaptability, allowing for the integration of emerging AI technologies and responding to evolving industry needs. Including ethical considerations and interdisciplinary approaches in curricula is also necessary to prepare students for the complexities of AI integration in diverse professional contexts. The findings of this study offer significant insights for educational institutions and policymakers regarding the integration of AI into education and workforce preparation. Educational institutions should prioritize curricular reforms that emphasize AI literacy, interdisciplinary learning, and ethical considerations, thereby equipping students with the skills required for an AI-driven job market. This approach should encompass not only technical proficiency but also critical thinking, creativity, and adaptability. Policymakers are encouraged to foster partnerships between educational institutions and the business sector to ensure that educational outcomes align with industry demands, facilitating the development of internships, training programs, and research initiatives. Furthermore, the focus on AI career preparedness underscores the necessity for policies supporting lifelong learning and continuous skill development to keep pace with technological advancements. By adopting these strategies, educational institutions and policymakers can cultivate a workforce that is well-prepared to drive innovation and contribute to economic growth in the AI era. Thus, our outcomes align with the research of [33, 41] regarding an accentuated need for curriculum reform and consistent collaboration between the education and business sectors, to develop competencies and adaptability in the context of long-term learning.

5 Conclusions

This research highlights the significant roles that both the educational system and the business sector play in developing the educational competencies essential for success in an AI-driven era. The analysis through Structural Equation Modeling (SEM) shows that the educational system has a stronger influence on the development of competencies, reflecting the effectiveness of educational policies and programs in fostering AI-related skills and knowledge. The business sector, although having a slightly lesser impact, still contributes importantly through practical training and industry partnerships that enhance competency development. Educational competencies are shown to have a direct and substantial impact on labor market demands, suggesting that the skills and knowledge developed through educational initiatives are well-aligned with the needs of the modern labor market shaped by artificial intelligence. Furthermore, preparedness for AI-based careers emerges as the most influential factor on labor market demands, underscoring the critical need for targeted AI training and career preparation. Indirect effects in the model indicate that the contributions of the educational system and business sector to labor market demands are mediated through educational competencies. This underscores the important role of these competencies as a pathway through which educational and business sector influences translate into market readiness. The model effectively illustrates the multifaceted relationship between educational system initiatives, business sector involvement, educational competencies, and labor market demands, emphasizing the need for integrated strategies that combine efforts from both education and industry to address the evolving requirements of an AI-driven economy. The R^2 values for educational competencies and labor market demands (37.9% and 51% respectively) highlight the substantial explanatory power of the model, reinforcing the significance of these factors in preparing a workforce capable of meeting contemporary market needs. This research is not without limitations and acknowledges that variations in educational policies, business involvement, and AI adoption rates across different regions might lead to different outcomes. Consequently, the model's applicability may differ when considered in a national or international context. Additionally, changes in AI technology, educational policies, or economic conditions could alter the relationships observed in this study. A longitudinal approach would provide deeper insights into how these factors evolve and impact competencies and labor market demand over extended periods. While this article does not conduct a multi-group analysis to explore demographic differences such as age or teaching experience, future research will aim to incorporate these factors to gain deeper insights into how demographic variables may influence the roles of the educational system and business sector in shaping educational competencies in the AI era.

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Appendix

Description of the constructs

The constructs	Item	Description
Labor market demands (LMD)	LMD1	Ability to interpret and use AI information in decision-making.
	LMD2	Creativity and innovation to complement AI algorithms and models.
	LMD3	Ethical considerations in the oversight and implementation of AI systems.
	LMD4	Problem solving skills in AI workflows.
Preparedness for AI-based careers (PCBA)	PCBA1	Develop a solid foundation in data analysis.
	PCBA2	Integrate AI with domain-specific knowledge.
	PCBA3	Encourage critical thinking and problem-solving in AI-related contexts.
	PCBA4	Incorporate curricular aspects of AI ethics and societal impact.
	PCBA5	Gain practical experience in developing AI projects.
The role of educational system (ESR)	ESR1	Develop training programs focused on AI to improve workforce skills.
	ESR2	Promote AI education initiatives for all age groups.
	ESR3	Encourage the development of AI skills in disadvantaged communities.
	ESR4	Support AI research across all educational fields.
	ESR5	Encourage collaboration between the educational system and the business sector on AI projects.
The role of business sector (BSR)	BSR1	Promote curiosity and openness towards AI created opportunities.
	BSR2	Encourage collaboration and teamwork.
	BSR3	Develop best practices in AI implementation strategies.
	BSR4	Promote adaptability to changes brought about by AI.
	BSR5	Knowledge of AI applications in fintech (financial technology).
Educational competencies (EC)	EC1	Encourage ongoing learning and skill enhancement in AI-related fields.
	EC2	Develop interdisciplinary skills that combine AI with domain-specific knowledge.
	EC3	Cultivate expertise in AI regulations and its ethical use.
	EC4	Provide practical experience in developing AI applications and projects.
	EC5	Competence in using AI for data analysis.

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