Artificial Intelligence Integration in Industrial Engineering Education: Competency Development, Process Optimization, and Industry Alignment in Costa Rica

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Abstract*– The widespread adoption of Artificial Intelligence (AI) across organizations is transforming professional competencies, organizational competitiveness, and process optimization in increasingly digital work environments. This mixed-methods study examines professionals' perceptions of the contribution of AI to competency development, organizational performance, and decision-making across diverse economic sectors in the Costa Rican labor market. The quantitative component applied Likert-scale questionnaires to 30 professionals representing Manufacturing and Service organizations. Descriptive statistics and the Mann–Whitney U test were used to compare perceptions between sectors. Key findings indicate that 70.0% of respondents use AI frequently or always in their work activities; 76.7% perceive that AI improves process efficiency; 76.7% consider AI an effective tool for supporting data-driven decision-making; 66.7% recognize its contribution to professional competency development; and 66.7% agree that AI helps reduce organizational errors and waste. The Mann–Whitney U test revealed no statistically significant differences between the Manufacturing and Service sectors ($p = 0.660$), indicating that AI is perceived as a strategic organizational resource regardless of the industrial context. In response to these findings, an ABP-STEM+E Professional Development Model consisting of four Integrated Professional Learning Units (IPLUs) and a competency-based assessment framework is proposed to support continuous learning, organizational improvement, and sustainable digital transformation. The model is grounded in the Model of Infusion [1], CDIO 3.0 standards [2], and the PAIIF framework [3].

Keywords*-- artificial intelligence; competency development; industrial engineering; Lean Manufacturing; Industry 4.0.

I. Introduction

The accelerating integration of Artificial Intelligence (AI) into organizational processes is transforming the way professionals perform their daily activities, make decisions, and develop competencies across multiple economic sectors. AI technologies are increasingly recognized as strategic resources for improving operational efficiency, supporting evidence-based decision-making, and strengthening organizational competitiveness in digitally driven environments [4], [5]. In Costa Rica, this transformation is particularly evident in technology-intensive industries such as medical device manufacturing, where exports exceeded USD 3,800 million in 2023 and more than 30 companies operate under ISO 13485 and FDA regulations, positioning the sector as one of the country's main drivers of innovation and digital transformation [6], [7].

Despite the growing adoption of AI in professional environments, empirical evidence regarding its contribution to competency development and organizational performance across different economic sectors remains limited, particularly within the Costa Rican context. Existing studies primarily focus on educational applications or isolated AI tools, with limited attention to how professionals perceive AI as a mechanism for strengthening competencies, improving organizational processes, and enhancing competitiveness in real workplace settings [1], [8]. Addressing this gap is essential for understanding how AI can support workforce development beyond formal educational environments [9], [10].

The objectives of this study are threefold: (i) to analyze professionals' perceptions of the contribution of Artificial Intelligence to competency development, organizational competitiveness, and process optimization within the Costa Rican labor market; (ii) to compare these perceptions between professionals working in the Manufacturing and Service sectors using nonparametric statistical analysis; and (iii) to propose an ABP-STEM+E Professional Development Model that promotes the structured integration of AI into continuous learning, organizational improvement, and professional competency development. These objectives respond to the increasing need for organizations to complement AI adoption with competency-based development strategies that support sustainable digital transformation across diverse productive sectors.

II. Background and Theoretical Framework

A. AI in Industrial Engineering: Machine Learning and Lean 4.0

Machine learning (ML) has become one of the most impactful AI branches in manufacturing contexts [11]. Psarommatis and May [4] documented that supervised ML algorithms achieved non-conformity detection rates exceeding 95% in automated visual inspection tasks, compared to 60–80% by human inspectors under industrial conditions, with reductions of 40% in false positives. The combination of IoT sensors with ML models for predictive maintenance achieved 87% anticipation of critical equipment failures, with a 14-month average payback period [12]. The denominated Lean 4.0 paradigm demonstrates that companies with high Lean maturity that adopted AI technologies obtained 31.2% improvements in OEE, compared to 12.4% for Lean-only and 14.7% for digitalization-only firms [13].

The irruption of Large Language Models (LLMs) — GPT-4 [14], Microsoft Copilot, Google Gemini — in 2022–2024 transformed the landscape of AI tools accessible to industrial engineers without advanced programming competencies. Kasneci et al. [15] identified seven impact dimensions of LLMs in engineering university training, with comparative use of multiple AI systems generating effect sizes of d = 0.54 in critical thinking, d = 0.41 in knowledge transfer, and d = 0.67 in technical error detection, significantly superior to single-tool or conventional learning [15], [16], [17].

B. Pedagogical Frameworks for AI Integration

The TPACK framework [18] establishes that effective AI integration in engineering teaching requires the simultaneous articulation of Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK); the absence of any intersection generates superficial integrations that increase cognitive load without improving learning outcomes [18]. The Constructionism principle [19], [20] complements TPACK by postulating that the deepest and most lasting learning occurs when students construct tangible, meaningful artifacts using AI as a tool: real process capability analyses, digital value stream maps fed by IIoT data, and ML models trained on manufacturing defect datasets [19].

Active learning methodologies — Project-Based Learning (PBL), Problem-Based Learning, flipped classroom, collaborative learning — show average 22% improvement in technical competency performance indicators when adopted as the central axis of industrial engineering program design [1], [21], [22], [23], [24], [25], [26]. The PAIIF framework, developed by 16 educators from 9 Australian universities under the CDIO approach, confirms that open-ended project work is the optimal context for integrating generative AI, identifying four AI integration levels: as consultation tool, as analysis assistant, as alternative generator, and as critical evaluator [3]. The present study situates AI use at levels 3 and 4.

C. Costa Rican Industry Context: Medical Device Sector Demands

The medical device manufacturing sector, Costa Rica's leading export sector (USD 3,800M in 2023), provides the authentic context that grounds this study. Companies including Boston Scientific, Baxter, Viant Medical, Moog Medical, and Biomedics operate certified manufacturing lines under ISO 13485:2016 [27] and FDA 21 CFR Part 820, where Statistical Process Control (SPC) [28] is not an efficiency tool but an ethical and regulatory obligation, given that process deviations can have direct lethal consequences for patients [29]. CINDE [6] data indicates that 76% of these companies report that Lean Manufacturing and SPC competencies in AI-assisted, ISO 13485-regulated contexts are a determinant criterion for hiring industrial engineering graduates, and 58% identify data analysis with normative criteria as the hardest competency to find in Costa Rican graduates [6].

Industry validation conducted for this study with representatives of the aforementioned companies confirms three priority competency gaps: (1) capacity to operate SPC tools in digitalized environments with real-time data; (2) ability to validate AI-generated outputs against primary normative sources (ISO 13485, Western Electric rules); and (3) critical judgment to distinguish statistically sound recommendations from AI hallucinations in highly regulated manufacturing contexts. These gaps directly informed the design of the proposed ABP-STEM+E model and its evaluation rubric RACI-IA+.

III. METHODOLOGY

A mixed-methods research design with a descriptive scope and a propositional component was adopted, following Hernández Sampieri and Mendoza Torres [30]. The quantitative component consisted of a structured Likert-scale questionnaire administered to 30 professionals employed in organizations across the Costa Rican labor market. Participants represented a wide range of economic sectors, including medical device manufacturing, information technology, healthcare, higher education, financial services, business consulting, construction, agribusiness, transportation, laboratories, research, private security, and international organizations. For comparative purposes, respondents were grouped into two major economic sectors: Manufacturing (n = 7) and Services (n = 23).

The study examined professionals' perceptions regarding the contribution of Artificial Intelligence to competency development, organizational competitiveness, process optimization, data-driven decision-making, and the reduction of organizational errors and waste. The independent variable was the perceived use of Artificial Intelligence in professional activities, while the dependent variables included competency development, organizational efficiency, decision-making, and continuous improvement. Data were collected using a structured questionnaire composed of demographic information and five-point Likert-scale items designed to measure perceptions across these organizational dimensions.

Statistical analysis was performed using Minitab 22 with a significance level of $\alpha = 0.05$. Descriptive statistics were used to summarize respondents' characteristics and perceptions. Because the dependent variables were measured using ordinal Likert-scale data and the comparison involved two independent groups, the Mann–Whitney U test was selected as the appropriate nonparametric inferential procedure to compare perceptions between professionals working in the Manufacturing and Service sectors. This approach provided a robust assessment of potential sectoral differences without requiring the assumption of normality.

IV. RESULTS

To analyze the perception of the use of Artificial Intelligence (AI) applied to competency development and its contribution to organizational competitiveness, data were collected from 30 professionals employed in a diverse range of organizations within the Costa Rican market. The sample included participants from strategic sectors such as medical device manufacturing, information technology, higher education, financial services, healthcare, business consulting, construction, agribusiness, transportation, research,

laboratories, private security, and international organizations, providing broad representation across different professional environments. For comparative purposes, the organizations were grouped into two major economic sectors: Manufacturing (7 participants; 23.3%) and Services (23 participants; 76.7%). This classification enables the examination of potential differences in perceptions regarding the impact of Artificial Intelligence between sectors with distinct operational characteristics, providing evidence of its adoption and application across diverse professional settings in the Costa Rican labor market.

A. Frequency of Artificial Intelligence Use in Work Activities

The results indicate that Artificial Intelligence (AI) is frequently incorporated into professionals' daily work activities (Fig. 1). Among the 30 respondents, 15 participants (50.0%) reported using AI frequently, while 6 respondents (20.0%) indicated that they use it always, meaning that 70.0% of the sample relies on AI on a regular basis during their professional activities. In contrast, 5 participants (16.7%) reported using AI occasionally, and only 4 respondents (13.3%) stated that they rarely use these technologies. Overall, these findings demonstrate a high level of AI adoption within the Costa Rican labor market, suggesting that AI has become an integral tool for supporting everyday professional tasks and organizational processes across diverse economic sectors.

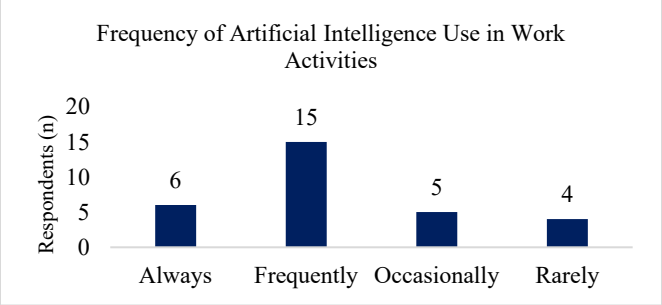


Fig. 1 AI Use Frequency.

B. Sample Distribution Across Industrial Sectors

This item recorded each respondent's primary industrial sector as a single-choice demographic question (one sector per participant, summing to n = 30), not a multiple-value perception item; values in Fig. 2 are therefore reported as absolute counts rather than percentages to avoid ambiguity. The resulting distribution demonstrates that the study captures perspectives from a diverse cross-section of the Costa Rican labor market, although the representation is concentrated in specific sectors. Higher Education accounts for the largest proportion of the sample (17%), followed by Medical Device Manufacturing (13%), reflecting the relevance of these sectors in the adoption and application of Artificial Intelligence (AI). Healthcare, Information Technology (IT), Business Consulting, and Financial Services each contribute approximately 7% of the sample, while the remaining sectors—including Research and Engineering, Entrepreneurship/Services, International Organizations, Private Security, Agribusiness, ERP Consulting, Certification and Quality, Laboratories and Pharmaceuticals, Software, Transportation and Aviation, and Construction—represent approximately 3% each. This heterogeneous distribution enhances the external validity of the findings by incorporating professionals from multiple economic sectors with distinct operational characteristics. However, the higher representation of education and medical device manufacturing suggests that the overall results may be more strongly influenced by industries that have demonstrated greater digital transformation and AI adoption, an aspect that should be considered when interpreting and generalizing the study's findings.

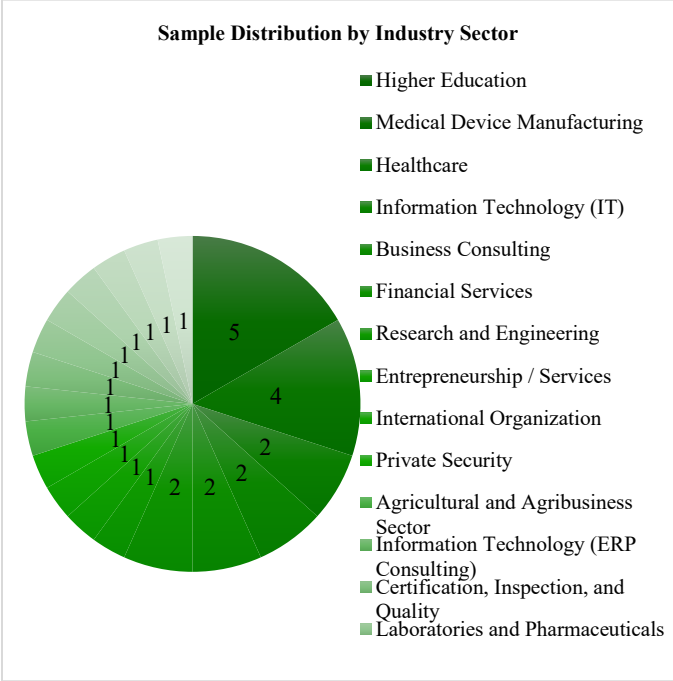


Fig. 2 Sample Distribution by Industry Sector.

C. Artificial Intelligence Improves the Efficiency of Processes Within My Organization

The results reveal a strong positive perception of the contribution of Artificial Intelligence (AI) to improving organizational process efficiency (Fig. 3). Among the 30 professionals surveyed, 23 respondents (76.7%) either agreed (40.0%) or strongly agreed (36.7%) that AI enhances the efficiency of processes within their organizations, indicating widespread confidence in its ability to optimize operations and improve overall organizational performance. In addition, 5 participants (16.7%) expressed a neutral opinion, suggesting that the benefits of AI may not yet be fully evident across all organizational contexts or that implementation levels vary among organizations. Only 2 respondents (6.7%) disagreed with the statement, while no participants selected strongly disagree, reflecting minimal resistance to AI adoption. Collectively, these findings suggest that AI is increasingly perceived as a strategic enabler of operational excellence, supporting process optimization, improving productivity, and strengthening organizations' capacity to achieve continuous improvement in an increasingly competitive business environment.



Fig. 3 AI and Process Efficiency.

D. Artificial Intelligence Facilitates Data-Driven Decision-Making

The results indicate a strong positive perception of the role of Artificial Intelligence (AI) in supporting data-driven decision-making within organizations (Fig. 4). Of the 30 professionals surveyed, 23 respondents (76.7%) either agreed (50.0%) or strongly agreed (26.7%) that AI facilitates decision-making based on data, reflecting a high level of confidence in its ability to transform data into valuable insights for organizational management. Meanwhile, 5 participants (16.7%) selected the neutral response, suggesting that AI implementation or its perceived impact on decision-making may still be limited in some organizational contexts. Only 2 respondents (6.7%) disagreed with the statement, and none reported strong disagreement, indicating minimal skepticism toward AI-enabled decision support. Overall, these findings highlight that AI is widely perceived as a strategic resource for enhancing analytical capabilities, improving the quality and timeliness of managerial decisions, and strengthening evidence-based decision-making processes that contribute to organizational competitiveness and digital transformation.

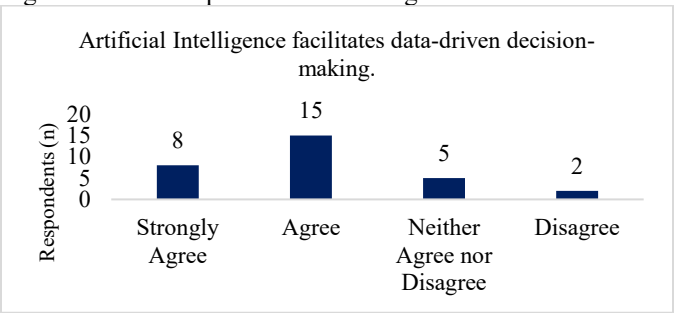


Fig. 4 AI and Data-Driven Decision-Making.

E. Artificial Intelligence Contributes to the Development of Employees' Professional Competencies

The results indicate a generally favorable perception of the contribution of Artificial Intelligence (AI) to the development of employees' professional competencies (Fig. 5), although the responses exhibit greater variability than those observed for the previous dimensions. Of the 30 professionals surveyed, 20 respondents (66.7%) either agreed (43.3%) or strongly agreed (23.3%) that AI contributes to the development of professional competencies, suggesting that most participants recognize its value as a tool for enhancing knowledge acquisition, technical skills, and continuous learning. However, 5 respondents (16.7%) expressed a neutral position, while 5 participants (16.7%) disagreed (13.3%) or strongly disagreed (3.3%) with the statement, indicating that a segment of the sample does not yet perceive AI as an effective mechanism for competency development. These findings suggest that although AI is widely recognized as a valuable resource for professional development, its perceived effectiveness may depend on factors such as organizational support, employee training, digital maturity, and the extent to which AI tools are integrated into learning and talent development strategies.

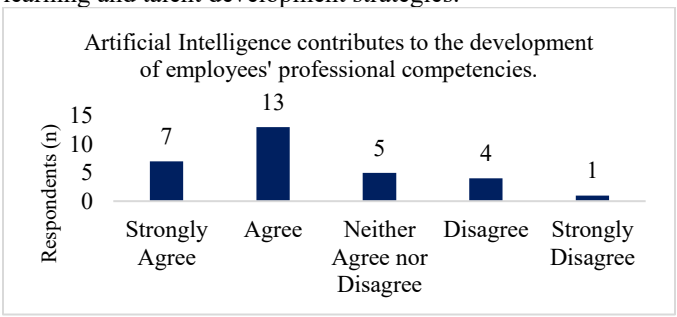


Fig. 5 AI and Professional Competency Development.

F. Artificial Intelligence Helps Reduce Errors and Waste in Organizational Processes

The findings indicate a predominantly positive perception of the role of Artificial Intelligence (AI) in reducing errors and waste within organizational processes (Fig. 6). Among the 30 professionals surveyed, 20 respondents (66.7%) either agreed (36.7%) or strongly agreed (30.0%) that AI contributes to minimizing operational errors and reducing process waste, reflecting substantial confidence in its ability to improve process quality and operational efficiency. Additionally, 9 participants (30.0%) selected the neutral response, suggesting that the benefits of AI in waste reduction may vary depending on the degree of implementation, organizational maturity, or employees' direct experience with AI-enabled process improvements. Only 1 respondent (3.3%) disagreed with the statement, while no participants expressed strong disagreement, indicating very limited resistance to the perceived effectiveness of AI in this area. Overall, these results suggest that AI is widely regarded as a valuable technological enabler for enhancing process reliability, supporting continuous improvement initiatives, and promoting operational excellence through the reduction of errors and non-value-added activities.

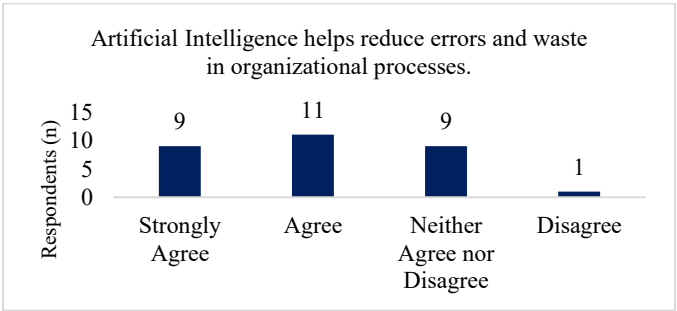


Fig. 6 AI and Error and Waste Reduction.

G. Comparison Between Manufacturing and Service Sectors

The comparative boxplot in Fig. 7 reveals that professionals from both the Manufacturing and Service sectors exhibit highly similar perceptions regarding the contribution of Artificial Intelligence (AI) to organizational performance. Both

groups present the same median score of 4 (Agree), indicating a consistently positive perception across sectors. Furthermore, the interquartile range (IQR) extends from 3 (Neither Agree nor Disagree) to 5 (Strongly Agree) in both groups, suggesting comparable variability in respondents' opinions. Although the Service sector displays a slightly wider overall range, with responses extending to 1 (Strongly Disagree), this lower score appears to represent an isolated observation rather than a general trend. The absence of substantial differences in the central tendency and dispersion between the two boxplots suggests that the perceived benefits of AI are relatively independent of the industrial sector. These findings support the notion that Artificial Intelligence is broadly recognized as a strategic resource capable of improving organizational processes, facilitating decision-making, fostering professional competency development, and enhancing operational performance across both Manufacturing and Service organizations in the Costa Rican context.

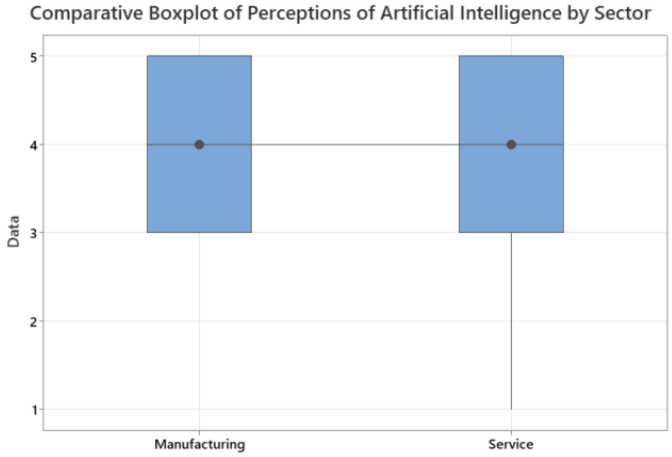


Fig. 7 AI Perceptions by Economic Sector.

Nonparametric Hypothesis Test: Comparison Between Manufacturing and Service Sectors

Given that the dependent variable was measured using a five-point Likert scale, which represents ordinal data, and the comparison involved two independent groups (Manufacturing and Service sectors), the Mann–Whitney U test was selected as the most appropriate nonparametric statistical procedure; the Minitab output is shown in Fig. 8. Unlike the independent samples t-test, the Mann–Whitney U test does not require the assumption of normality and is therefore suitable for comparing the central tendency of two independent samples when the response variable is ordinal. This approach allows for a robust evaluation of whether significant differences exist in participants' perceptions according to the industrial sector in which they work.

The hypotheses for the statistical test were as follows:

- *Null Hypothesis (H_0):* There is no statistically significant difference in the perception of the impact of Artificial Intelligence between professionals working in the Manufacturing and Service sectors ($\eta_1 = \eta_2$).
- *Alternative Hypothesis (H_1):* There is a statistically significant difference in the perception of the impact of Artificial Intelligence between professionals working in the Manufacturing and Service sectors ($\eta_1 \neq \eta_2$).

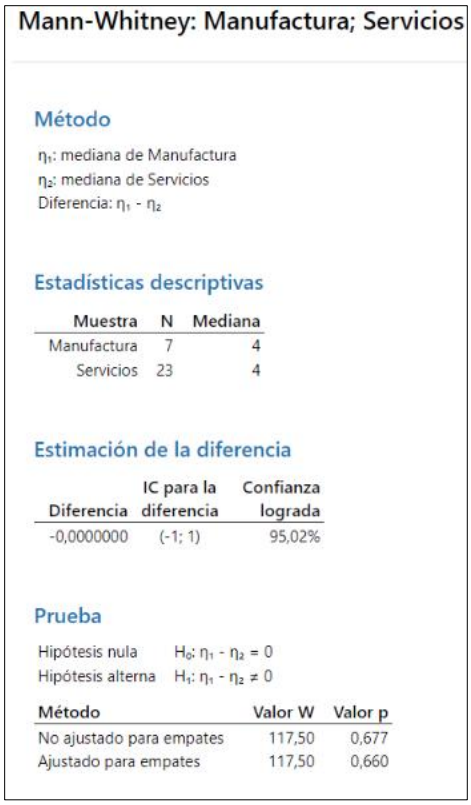


Fig. 8 Nonparametric Comparison Between Sectors.

The results of the Mann–Whitney U test indicate that both groups presented the same median score of 4 (Agree), suggesting a similar overall perception of Artificial Intelligence across sectors. The estimated median difference between Manufacturing and Services was 0.00, with a 95% confidence interval ranging from −1 to 1, indicating substantial overlap between the two distributions. Furthermore, the adjusted test for ties yielded a W statistic of 117.50 and a p-value of 0.660, which is considerably higher than the established significance level ($\alpha = 0.05$). Consequently, the null hypothesis cannot be rejected, providing no statistical evidence of significant differences between the Manufacturing and Service sectors regarding their perceptions of Artificial Intelligence. These findings reinforce the descriptive analyses and boxplot interpretation, suggesting that professionals from both sectors share a similarly favorable perception of AI as a strategic tool for enhancing organizational efficiency, supporting data-driven decision-making, fostering professional competency development, and promoting continuous improvement.

V. Proposed ABP-STEM+E Didactic Model

A. Design Rationale and Theoretical Foundation

The results demonstrate that Artificial Intelligence (AI) is widely perceived as a strategic resource for improving organizational performance across the Costa Rican labor market. Most professionals agreed that AI contributes to process efficiency, data-driven decision-making, and

organizational competitiveness. Furthermore, the Mann–Whitney U test revealed no statistically significant differences between the Manufacturing and Service sectors ($p = 0.660$), indicating that AI adoption is perceived similarly regardless of the industrial context.

Despite these positive perceptions, competency development obtained the lowest level of agreement among the evaluated dimensions. Although two-thirds of respondents recognized AI as a valuable tool for professional learning, a considerable proportion remained neutral or disagreed. This finding suggests that organizations have successfully adopted AI to improve operational performance but have not yet fully integrated it into structured competency development initiatives.

The four IPLUs were derived directly from this evidence rather than proposed independently of it. IPLU 1 (AI Fundamentals and Comparative Exploration) responds to the lower and more variable agreement observed for competency development (66.7%), by building foundational, critical AI-validation skills first. IPLU 2 (Problem-Based Learning through Organizational Analytics) operationalizes the strong perceived contribution of AI to data-driven decision-making (76.7% agreement) into a structured analytical practice. IPLU 3 (ABP-STEM+E Organizational Improvement Project) targets the equally strong perception of AI's contribution to process efficiency (76.7%) and directly addresses the three priority competency gaps identified through industry validation with medical-device sector representatives. IPLU 4 (Innovation Challenge and Organizational Transfer) extends these competencies toward the organizational-competitiveness dimension, consistent with the absence of significant sector differences ($p = 0.660$), which suggests that a single, sector-independent transfer unit is appropriate. This explicit mapping between perception results, industry-identified gaps, and unit design addresses the need to ground the four-unit structure in the data and literature discussed, rather than presenting it as an independently motivated framework.

Based on these findings, an updated ABP-STEM+E Professional Development Model, building on the institutional CDIO/ABPCS-STEM+E framework [31], is proposed. The model combines Project-Based Learning, active learning methodologies, STEM+E principles, and AI-assisted problem solving to strengthen professional competencies while promoting organizational competitiveness, continuous improvement, and evidence-based decision-making.

B. Four Integrated Professional Learning Units (IPLUs)

The proposed model consists of four sequential Integrated Professional Learning Units (IPLUs), summarized in Table I. Each unit progressively develops AI competencies while encouraging participants to apply their knowledge to authentic organizational challenges. The learning process moves from AI literacy toward organizational innovation, ensuring that competency development generates measurable value for both employees and organizations, using Bloom's Taxonomy [32] to define increasing cognitive-complexity outcomes across units.

TABLE I
Four Integrated Professional Learning Units (IPLUs) of the ABP-STEM+E Model

IPLU	Methodology	Main Objective	Bloom Level
IPLU 1	AI Fundamentals and Comparative Exploration	Develop responsible AI literacy and critical evaluation of AI outputs	AI Adoption Readiness
IPLU 2	Problem-Based Learning with AI	Improve analytical decision-making through organizational data analysis	Data-Driven Decision Competency
IPLU 3	ABP-STEM+E Improvement Project	Solve authentic organizational problems using AI-supported methodologies	Process Optimization
IPLU 4	Innovation Challenge and Organizational Transfer	Design innovative AI-enabled improvement proposals applicable to the workplace	Organizational Competitiveness

IPLU 1 – AI Fundamentals and Comparative Exploration

The first learning unit develops foundational AI competencies by exposing participants to multiple generative AI platforms when solving identical organizational scenarios. Rather than relying on a single AI system, professionals compare responses generated by ChatGPT, Microsoft Copilot, Gemini, and Claude [33] using equivalent prompts related to operational management, process optimization, quality improvement, and organizational decision-making. Participants identify differences in recommendations, evaluate response consistency, verify factual accuracy, and contrast AI-generated information with organizational procedures and industry best practices. This comparative approach promotes critical thinking while reducing excessive dependence on a single AI platform and strengthening professionals' ability to validate AI-generated outputs before applying them in real organizational environments.

IPLU 2 – Problem-Based Learning Through Organizational Analytics

The second unit focuses on developing analytical competencies through authentic organizational datasets. Participants employ AI-assisted tools to analyze operational indicators such as productivity, quality performance, customer satisfaction, process cycle time, resource utilization, and organizational efficiency. AI supports data visualization, statistical interpretation, trend identification, and scenario generation; however, participants remain responsible for validating conclusions and selecting the most appropriate improvement strategies. Collaborative discussions encourage professionals to justify recommendations using empirical evidence rather than AI suggestions alone, reinforcing evidence-based managerial decision-making and strengthening analytical competency development.

IPLU 3 – ABP-STEM+E Organizational Improvement Project

The third learning unit constitutes the central component of the proposed model. Working in multidisciplinary teams, participants address authentic organizational challenges identified within their own institutions or companies. AI

functions as an assistant throughout the project lifecycle, supporting problem definition, literature exploration, root-cause analysis, alternative generation, risk assessment, implementation planning, and performance evaluation. Participants integrate Lean Thinking, continuous improvement methodologies, quality management principles, process mapping, and data analytics into comprehensive organizational improvement proposals. Throughout the project, AI-generated recommendations must be critically evaluated against organizational objectives, operational feasibility, and available evidence to ensure that technological support complements rather than replaces professional judgment.

IPLU 4 – Innovation Challenge and Organizational Transfer

The final learning unit promotes organizational innovation by encouraging participants to design AI-enabled improvement initiatives capable of generating measurable organizational value. Teams present their projects before organizational leaders or peer evaluation committees, demonstrating not only technical feasibility but also strategic alignment with organizational objectives, competitiveness, process optimization, and employee competency development. Participants reflect upon the opportunities, limitations, ethical implications, and implementation challenges associated with AI adoption, generating organizational learning that extends beyond the completion of the training program and supports long-term digital transformation.

C. Competency-Based Assessment Framework

To ensure that competency development remains aligned with organizational needs, the model incorporates a multidimensional assessment framework emphasizing both learning outcomes and organizational impact. Evaluation is distributed across the four learning units according to increasing levels of complexity, as shown in Table II.

VI. Discussion

The findings indicate that Artificial Intelligence has become an established component of professional practice across the Costa Rican labor market. Most respondents reported frequent or permanent use of AI and recognized its positive contribution to process efficiency, data-driven decision-making, and organizational performance. These results suggest that AI is no longer perceived solely as an emerging technology but as a strategic resource that supports operational excellence and organizational competitiveness across diverse economic sectors.

Although perceptions were predominantly positive, professional competency development received the lowest level of agreement among the evaluated dimensions. This finding indicates that organizations have been more successful in adopting AI to optimize operational activities than in integrating it into structured learning and talent development strategies. Consequently, organizations should complement technological adoption with competency-based training models that promote critical thinking, continuous learning, and the responsible use of AI in professional environments.

TABLE II
Professional Development Assessment Weighting by IPLU

IPLU	Methodology	Key Products	Weight	RACI-IA+ Dimensions
IPLU 1	AI Fundamentals + Comparative AI Exploration	Comparative AI Analysis Report + AI Validation Matrix + Critical Reflection Log	20%	Responsible AI use; Critical evaluation of AI outputs; Information validation
IPLU 2	Problem-Based Learning + Organizational Analytics	Organizational Data Analysis Report + Evidence-Based Decision Proposal + Performance Dashboard	25%	Data-driven decision-making; Analytical reasoning; Organizational problem solving
IPLU 3	ABP-STEM+E (5 stages)	Process Improvement Project + AI-Supported Improvement Plan + Implementation Roadmap + Executive Report	35%	Process optimization; Innovation; Organizational competitiveness; Integration of AI into professional practice
IPLU 4	Innovation Challenge + Organizational Transfer	Innovation Proposal + Executive Presentation + Organizational Transfer Plan + Reflective Portfolio Metacognitive Reflection	20%	Strategic thinking; Communication; Continuous learning; Professional reflection

Source: Authors' own elaboration. IPLU 3 receives the highest weighting because it integrates the application of Artificial Intelligence, competency development, organizational problem-solving, and process improvement within an authentic professional environment.

The absence of statistically significant differences between the Manufacturing and Service sectors reinforces the cross-sector applicability of AI for organizational improvement. The Mann–Whitney U test demonstrated that professionals from both sectors share similar perceptions regarding AI's contribution to efficiency, decision-making, competency development, and continuous improvement. This evidence supports the proposed ABP-STEM+E Professional Development Model as a flexible framework that can strengthen AI-related competencies and foster digital transformation regardless of the industrial sector in which professionals operate.

A. Limitations

Several limitations should be acknowledged. First, the sample (n = 30) is relatively small and unevenly distributed between Manufacturing (n = 7) and Services (n = 23), which limits the statistical power of the sectoral comparison [34]; therefore, the non-significant Mann–Whitney result (p = 0.660) should be interpreted as insufficient evidence to identify differences between the groups rather than as evidence of

equivalence between sectors. Future studies should employ larger and more balanced samples and report an appropriate effect-size measure. Second, all dependent variables reflect professionals' self-reported perceptions rather than objectively measured outcomes; consequently, findings related to efficiency, competency development, decision-making, and error or waste reduction represent perceived rather than empirically verified effects, and causal interpretations should be avoided. Third, although the study adopted a mixed-methods design, the qualitative component was limited to brief industry-validation interviews with company representatives rather than a fully documented qualitative strand; future research should provide detailed participant profiles, interview protocols, data collection procedures, and qualitative analysis methods. Fourth, the proposed ABP-STEM+E model and its RACI-IA+ assessment framework are conceptual proposals derived from the perception data and literature review and have not yet been empirically implemented or validated; therefore, their effectiveness should not be inferred from the present findings, and future research should include a structured pilot implementation with pre- and post-intervention competency measures and participant and instructor feedback. Fifth, the convenience sample is concentrated in Higher Education and Medical Device Manufacturing, which may introduce selection bias and limit the generalizability of the findings to other industries and the broader Costa Rican labor market. Finally, the questionnaire's content validity and internal consistency were not formally assessed, and a formal informed-consent procedure was not documented; future studies should incorporate systematic instrument validation, appropriate reliability assessment, and explicit ethical and informed-consent procedures.

VII. Conclusions

This study examined professionals' perceptions of Artificial Intelligence as a resource for professional competency development, organizational performance, and process optimization across different sectors represented in the Costa Rican labor market. The findings indicate generally favorable perceptions of AI among the professionals included in the study, while also highlighting opportunities for more structured competency development initiatives. Based on these findings and the supporting literature, the ABP-STEM+E Professional Development Model is proposed as a conceptual framework for integrating AI into continuous learning, organizational improvement, and digital transformation. Further empirical validation is required to assess its effectiveness and applicability across organizational contexts.

1. Artificial Intelligence showed a high level of use among the professionals surveyed, with 70.0% of respondents reporting frequent or permanent use of AI in their work activities. These results suggest that AI is regularly incorporated into the professional activities of a substantial proportion of the participants in this study.
2. A predominantly positive perception was observed regarding the organizational contribution of AI, with 76.7% of respondents agreeing or strongly agreeing that AI improves process efficiency and 76.7% indicating that it facilitates data-driven decision-making. These findings suggest that the professionals surveyed perceive AI as a valuable resource for supporting operational performance and evidence-based decision-making.
3. The Mann–Whitney U test did not identify statistically significant differences between the Manufacturing and Service groups ($p = 0.660$). Given the small and unevenly distributed sample, this result should be interpreted as insufficient statistical evidence to identify sectoral differences rather than as evidence of equivalence between sectors. Larger and more balanced samples are required to determine whether sector-related differences exist.
4. Professional competency development received lower agreement than process efficiency and data-driven decision-making, with 66.7% of respondents agreeing or strongly agreeing that AI contributes to competency development. This finding suggests an opportunity to strengthen the structured integration of AI into professional learning and competency development initiatives.
5. The participation of professionals from multiple industries provides evidence of favorable perceptions of AI across the organizational contexts represented in the sample. However, because the study used a small convenience sample with greater representation from Higher Education and Medical Device Manufacturing, these findings should not be generalized to the entire Costa Rican labor market or interpreted as evidence of uniform effects across sectors.
6. Based on the identified perceptions, competency-development opportunities, industry-validation input, and supporting literature, the proposed ABP-STEM+E Professional Development Model provides a structured conceptual framework comprising four Integrated Professional Learning Units (IPLUs) that progressively address AI literacy, data-driven decision-making, process optimization, and organizational transfer. As the model has not yet been empirically implemented or validated, future research should evaluate its effectiveness through pilot implementation and competency-based assessment.

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References

[1] E. Euler, "Vocational and Educational Training in the Era of Digitalization," UNESCO-UNEVOC, Bonn, Germany, 2021.

[2] O. Malmqvist, K. Edström, and A. Rosén, "CDIO Standards 3.0 — An Update of the CDIO Standards," in Proc. 16th Int. CDIO Conference, pp. 60–76, 2020.

[3] S. Nikolic, M. Grundy, S. Cvetanovic, J. Perera, D. Husić, and V. Johnson, "PAIIF: Project-work Artificial Intelligence Integration Framework," Australasian J. Eng. Educ., vol. 31, no. 1, pp. 1–22, 2025.

[4] F. Psarommatis and G. May, "A literature review and design methodology for digital twins in the era of zero-defect manufacturing," Int. J. Prod. Res., vol. 60, no. 16, pp. 5093–5113, 2022.
[5] M. Ghobakhloo, M. Iranmanesh, A. Grybauskas, M. Vilkas, and A. Petraitė, "Industry 4.0, innovation, and sustainable development: A systematic review and a roadmap to sustainable innovation," Bus. Strategy Environ., vol. 30, no. 8, pp. 4237–4257, 2021.
[6] CINDE, "Reporte de inversión y empleo: Sector manufactura de dispositivos médicos en Costa Rica 2023–2024," Coalición Costarricense de Iniciativas de Desarrollo, San José, Costa Rica, 2024.
[7] G. Tortorella, D. Vergara, A. H. Garza-Reyes, and R. Sawhney, "Organizational learning pathways for Industry 4.0 adoption: An empirical study with Brazilian manufacturers," Int. J. Prod. Econ., vol. 234, art. 108044, 2021.
[8] E. Lo, "What Is the Impact of ChatGPT on Education? A Rapid Review of the Literature," Educ. Sci., vol. 13, no. 4, art. 410, 2023.
[9] UNESCO-UNEVOC, "Integrating Artificial Intelligence in Technical and Vocational Education and Training," UNESCO-UNEVOC, Bonn, Germany, 2022.
[10] E. Benito and A. Cruz (Eds.), Nuevas claves para la docencia universitaria en el Espacio Europeo de Educación Superior. Madrid: Narcea Ediciones, 2016.
[11] T. J. Wuest, D. Weimer, C. Irgens, and K.-D. Thoben, "Machine Learning in Manufacturing: Advantages, Challenges and Applications," Prod. Manuf. Res., vol. 4, no. 1, pp. 23–45, 2016.
[12] Y. Zhang, G. Liu, H. Qian, and Z. Yang, "Predictive Maintenance Using Machine Learning: A Systematic Review," J. Manuf. Syst., vol. 61, pp. 190–206, 2021.
[13] S. J. Buer, J. O. Strandhagen, and F. T. Chan, "The link between Industry 4.0 and lean manufacturing: Mapping current research and establishing a research agenda," Int. J. Prod. Res., vol. 56, no. 8, pp. 2924–2940, 2018.
[14] OpenAI, "GPT-4 Technical Report," arXiv:2303.08774, 2023.
[15] E. Kasneci et al., "ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education," Learning and Individual Differences, vol. 103, art. 102274, 2023.
[16] D. Baidoo-Anu and L. Owusu-Ansah, "Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting Teaching and Learning," J. AI, vol. 7, no. 1, pp. 52–62, 2023.
[17] E. Lo, G. Chan, and A. Yuen, "Artificial Intelligence-Supported Learning in Higher Education: Evidence from Experimental Studies," Int. J. Inf. Educ. Technol., vol. 13, no. 4, pp. 789–803, 2023.
[18] P. Mishra, "Considering Contextual Knowledge: The TPACK Diagram Gets an Upgrade," J. Digit. Learn. Teach. Educ., vol. 35, no. 2, pp. 76–78, 2019.
[19] H. Fardoun, C. Zafra Gómez, A. López-Moreno, and H. Alghazzawi, "Implications of COVID-19 on Education: Perspective of Technology," Sustainability, vol. 12, no. 18, art. 7528, 2020.
[20] M. C. Wittrock, "Generative processes of comprehension," Educational Psychologist, vol. 24, no. 4, pp. 345–376, 1989.
[21] J. Domènech-Casal, "Bringing Phenomena to the Fore: A Project-Based Learning Sequence for Introductory Genetics," J. Biol. Educ., vol. 52, no. 3, pp. 317–329, 2018.
[22] J. Porras, P. Khakurel, J. Mäkinen, J. Ikonen, A. Bankins, and L. Kaila, "Hackathons in Software Engineering Education: Lessons Learned from a Decade of Events," in Proc. Int. Conf. Softw. Eng.: Softw. Eng. Educ. Training, pp. 40–49, 2018.
[23] J. J. Johnson and R. T. Johnson, Energizing Learning: The Instructional Power of Conflict. ASCD, 2009.
[24] J. van Alten, C. Phielix, J. Janssen, and L. Kester, "Effects of Flipping the Classroom on Learning Outcomes and Satisfaction: A Meta-Analysis," Educ. Res. Rev., vol. 28, art. 100281, 2020.
[25] G. Akçayır and M. Akçayır, "The Flipped Classroom: A Review of Its Advantages and Challenges," Comput. Educ., vol. 122, pp. 334–345, 2018.
[26] J. O'Flaherty and C. Phillips, "The Use of Flipped Classrooms in Higher Education: A Scoping Review," Internet Higher Educ., vol. 25, pp. 85–95, 2015.
[27] J. Liu, Y. Lin, and M. Yin, "Digital Twin Architectures in ISO-Regulated Quality Management Systems," Int. J. Adv. Manuf. Technol., vol. 115, pp. 1203–1220, 2021.
[28] D. C. Montgomery, Introduction to Statistical Quality Control, 8th ed. New York: Wiley, 2020.
[29] ISO, ISO 13485:2016 — Medical Devices — Quality Management Systems — Requirements for Regulatory Purposes, International Organization for Standardization, Geneva, Switzerland, 2016.
[30] R. Hernández Sampieri and C. P. Mendoza Torres, Metodología de la Investigación: Las Rutas Cuantitativa, Cualitativa y Mixta, 1st ed. México: McGraw-Hill Education, 2018.
[31] Universidad Fidélitas, "Modelo pedagógico CDIO/ABPCS-STEM+E: Marco institucional de integración curricular," San José, Costa Rica: Universidad Fidélitas, 2022.
[32] D. Anderson and L. Krathwohl (Eds.), A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives. New York: Longman, 2001.
[33] E. Mollick and L. Mollick, "Assigning AI: Seven Approaches for Students, with Prompts," SSRN, 2023. DOI: 10.2139/ssrn.4475995.
[34] J. Cohen, Statistical Power Analysis for the Behavioral Sciences, 2nd ed. Hillsdale, NJ: Lawrence Erlbaum Associates, 1988.