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AI-driven framework for automated competency formalization: from professional standards to adaptive learning outcomes

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The rapid evolution of the labor market necessitates innovative approaches to align higher education curricula with professional standards. This study presents an AI-driven framework utilizing the GPT model to automate the formalization of professional competencies and learning outcomes from unstructured textual sources, such as professional standards and job descriptions. By transforming unstructured industry standards and job descriptions into structured competency maps, the framework ensures alignment with labor market needs. These maps are integrated into learning management systems (LMS) such as Canvas and Moodle, enabling the development of adaptive curricula. The methodology was validated using a dataset of professional standards from various industries, achieving a 30% increase in semantic accuracy compared to traditional methods. In addition, a multi-class classification task using Multinomial Naive Bayes, Gaussian Naive Bayes, and Random Forest models classified learning outcomes across college, undergraduate, graduate, and doctoral levels, achieving an accuracy score of 0.98, further confirming their applicability across qualification systems. Challenges such as technological inequalities and lack of pedagogical flexibility remain. This scalable approach enables educational institutions to bridge the gap between academia and industry, helping to produce employable graduates.

KEYWORDS

professional standards, competencies, artificial intelligence, GPT, formalization, competency map

1 Introduction

The of professional competency formulation and educational outcome design in higher education has emerged as a transformative approach, driven by the integration of sophisticated educational frameworks and advanced technological systems. These automated mechanisms aim to align educational curricula with dynamic industry standards, ensuring that graduates are equipped with the precise skills, knowledge, and behaviors required for success in their professional fields (Spady, 1994; Biggs, 1999; Lam and Tsui, 2016). This alignment is critical in an era where rapid technological advancements and evolving labor market demands necessitate a responsive and adaptable educational ecosystem. By leveraging automation, institutions can systematically bridge the gap between academic preparation and professional expectations, fostering graduates who are not only academically proficient but also industry-ready (Kumar, 2014; Anisha, 2012; Uddin et al., 2012; Sanghi, 2007).

At the core of this transformation lies Automated Competency Mapping, a process that employs software tools to align educational objectives with professional competencies. These tools analyze industry requirements, map them to learning outcomes, and facilitate the design of curricula that are both relevant and forward-looking. Automated systems streamline the traditionally labor-intensive process of curriculum development by identifying skill gaps, integrating stakeholder feedback, and ensuring compliance with accreditation standards (Anisha, 2012). For example, platforms such as competency management software can cross-reference job descriptions, industry certifications, and academic standards to generate tailored competency profiles. This not only enhances the efficiency of curriculum design but also ensures that educational programs remain agile in responding to emerging trends, such as the growing demand for digital literacy and soft skills like critical thinking and adaptability (Kumar, 2014; Fitsilis, 2024).

Competency-Based Education (CBE) serves as the foundational paradigm for this approach, emphasizing measurable learning outcomes over traditional time-based metrics. Unlike conventional education models that prioritize seat time or credit hours, CBE focuses on what students can demonstrably achieve by the end of their learning journey (Holubnycha et al., 2022; Hatcher et al., 2013). This outcomes-oriented approach aligns educational objectives with professional benchmarks, enabling institutions to create personalized learning pathways that cater to individual student needs. For instance, CBE allows students to progress at their own pace, mastering competencies through targeted assessments and practical applications rather than adhering to rigid academic schedules (Oroszi, 2020). By embedding industry-relevant skills into the curriculum, CBE ensures that graduates are prepared to meet the specific demands of their chosen fields, from technical proficiencies in engineering to interpersonal skills in healthcare.

The integration of automated learning systems further amplifies the efficacy of CBE by providing dynamic, technology-driven environments for student engagement. These systems, often embedded within E-Learning platforms, enable interactive content delivery, real-time feedback, and adaptive assessments that evaluate both academic knowledge and professional competencies (Eryomina and Lopukhin, 2020). For example, learning management systems (LMS) like Canvas or Moodle incorporate analytics to track student progress, identify areas for improvement, and recommend personalized resources. Such systems also support multimodal learning, allowing students to engage with content through text, video, simulations, and gamified assessments, thereby catering to diverse learning styles (Jayasree, 2024). The automation of instructional processes, such as automated grading or adaptive quizzing, reduces administrative burdens on educators, enabling them to focus on mentorship and curriculum innovation (Singh et al., 2024).

Learning outcomes, as critical articulations of what students are expected to achieve, play a pivotal role in this ecosystem. These statements serve as measurable benchmarks that guide curriculum development, assessment design, and accreditation processes (Dodridge, 1999). Well-crafted learning outcomes are specific, achievable, and aligned with both academic standards and industry expectations. However, their implementation is not without challenges. Learning outcomes must be flexible enough to accommodate diverse pedagogical approaches while remaining rigorous enough to meet institutional and regulatory requirements (Melton, 1996). For instance, a computer science program might include outcomes related to coding proficiency, while also addressing broader competencies like teamwork and ethical decision-making. Automated systems can assist in this process by generating outcome templates based on industry data, reducing the complexity of aligning academic and professional goals (Hahn, 2017).

The rise of E-Learning Systems has further revolutionized the delivery of competency-based education. These platforms enable scalable, accessible, and personalized learning experiences, particularly in the context of online and hybrid education models. By incorporating features such as adaptive learning paths, real-time analytics, and competency-based assessments, E-Learning systems address the diverse needs of students while maintaining alignment with professional standards (Jayasree, 2024). For example, platforms like Coursera or edX offer modular courses that allow learners to master specific skills, earning micro-credentials that are recognized by employers. Additionally, the use of audio-visual resources, virtual simulations, and interactive case studies enhances engagement, making learning more immersive and relevant. These tools not only improve accessibility-particularly for non-traditional or remote learners-but also foster a deeper connection between theoretical knowledge and practical application (Fitsilis, 2024).

Competency Frameworks provide the structural backbone for aligning education with industry needs. These frameworks outline the specific skills, knowledge, and behaviors required for particular roles, serving as blueprints for curriculum design and assessment (Hahn, 2017). For example, a competency framework for nursing might include clinical skills, patient communication, and ethical judgment, while a framework for data science might emphasize programming, statistical analysis, and data visualization. By integrating these frameworks into automated systems, institutions can ensure that their programs remain relevant to labor market demands. Moreover, competency frameworks facilitate collaboration between academia and industry, enabling stakeholders to co-design curricula that reflect real-world needs (Sanghi, 2007). This collaborative approach is particularly valuable in fields like artificial intelligence or renewable energy, where rapid innovation requires constant curriculum updates.

Despite the advantages, the adoption of automated systems and competency-based approaches presents challenges. Faculty resistance to change, technological infrastructure costs, and the need for continuous system updates can hinder implementation (Singh et al., 2024). Additionally, ensuring equity in access to technology and addressing biases in automated systems are critical considerations. For instance, algorithms used in competency mapping must be designed to avoid perpetuating existing inequalities in educational or professional outcomes (Eryomina and Lopukhin, 2020). Institutions must also balance the standardization required by automation with the flexibility needed to accommodate diverse student populations and pedagogical contexts.

In conclusion, the automated formulation of professional competencies and educational outcomes represents a paradigm shift in higher education. By integrating Competency-Based Education, automated learning systems, and structured competency frameworks, institutions can create curricula that are both academically rigorous and professionally relevant. These systems enhance the educational experience by providing personalized, accessible, and engaging learning opportunities, ensuring that graduates are well-prepared for the complexities of the modern workforce. As technology continues to evolve, the synergy between automation and education will play an increasingly vital role in shaping the future of higher education, fostering graduates who are not only knowledgeable but also adaptable and equipped to thrive in their professional endeavors.

2 Literature review

The formulation of professional competencies and learning outcomes is a critical area of inquiry in higher education and organizational contexts, particularly as automation and artificial intelligence (AI) reshape educational and professional landscapes. Recent studies have explored how competencies, supported by advanced technologies such as generative AI, influence learning effectiveness and organizational performance. This review synthesizes key findings from contemporary research, highlighting the role of AI-driven tools in competency development and their implications for educational and professional outcomes.

Korayim et al. (2025) investigated the interplay between competencies, attitudes, experience, and access to generative AI in shaping employee outcomes, with a focus on managerial roles. Employing partial least squares structural equation modeling (PLS-SEM), the study analyzed data from a diverse sample of managers to assess the direct and indirect effects of these factors. The results revealed that well-developed competencies, coupled with positive attitudes toward generative AI, significantly enhanced managers' creative engagement. This, in turn, indirectly improved learning effectiveness by facilitating the integration of AI tools into organizational processes. Specifically, the study found that competencies related to critical thinking, problem-solving, and adaptability were pivotal in enabling managers to leverage AI for innovative decision-making. These findings underscore the importance of aligning competency frameworks with emerging technologies to foster both individual and organizational learning outcomes. Moreover, the study highlights the mediating role of creative engagement, suggesting that AI-supported competencies can amplify learning by encouraging experimentation and knowledge application in dynamic work environments (Korayim et al., 2025).

In a complementary vein, Hamilton et al. (2024) explored the integration of external AI solutions into firm-wide dynamic warehousing systems, with implications for organizational competency development. Using structural equation modeling (SEM), the study examined how collaborations with external software developers enhance AI competencies, operational efficiency, and sustainability in logistics operations. Drawing on case studies from industry leaders such as Amazon, the authors demonstrated how generative AI and external innovations optimize processes like inventory management and demand forecasting. The findings indicate that external partnerships accelerate the acquisition of AI-related competencies, enabling organizations to adapt to digital supply chain demands. For instance, Amazon's use of AI-driven robotics and predictive analytics exemplifies how competency development in AI can streamline warehouse operations while reducing environmental impact through optimized resource use. The study emphasizes the strategic importance of external collaborations in building sustainable competitive advantages, particularly in industries characterized by rapid technological change (Hamilton et al., 2024). These insights are relevant to educational contexts, where partnerships with industry can inform curriculum design and ensure that learning outcomes reflect current technological competencies.

The studies by Korayim et al. (2025) and Hamilton et al. (2024) converge on the critical role of AI in enhancing competencies and learning outcomes, albeit in different contexts. In educational settings, generative AI tools can support personalized learning by tailoring content and assessments to individual student needs, thereby aligning learning outcomes with professional standards (Jayasree, 2024). Similarly, in organizational settings, AI-driven systems enable employees to develop competencies that are directly applicable to their roles, enhancing both performance and innovation (Fitsilis, 2024). However, these studies also highlight challenges, such as the need for positive attitudes toward AI adoption and the potential for technological disparities to exacerbate inequities in access to competency-building opportunities (Eryomina and Lopukhin, 2020).

Beyond these specific studies, the broader literature on competency-based education (CBE) provides a theoretical foundation for understanding how competencies and learning outcomes are formulated. CBE emphasizes measurable, outcome-oriented learning, where students demonstrate mastery of specific skills and knowledge (Holubnycha et al., 2022). Automated systems, such as learning management systems (LMS) and competency mapping software, facilitate this process by aligning educational objectives with industry requirements (Kumar, 2014). For example, tools like Skillsoft or Degreed use AI to map competencies to job roles, enabling institutions to design curricula that prepare students for the workforce (Anisha, 2012). These systems also support continuous assessment, ensuring that learning outcomes remain relevant in rapidly evolving fields like data science or cybersecurity (Hahn, 2017).

Despite the promise of AI and automation, the literature identifies several challenges in implementing competency-based frameworks. Developing precise and adaptable learning outcomes requires balancing specificity with flexibility to accommodate diverse pedagogical and professional contexts (Melton, 1996). Additionally, the integration of AI tools demands significant investment in infrastructure and training, which may pose barriers for under-resourced institutions (Singh et al., 2024). Furthermore, ethical considerations, such as mitigating biases in AI algorithms, are critical to ensuring equitable competency development (Eryomina and Lopukhin, 2020). These challenges underscore the need for robust frameworks that integrate technological innovation with inclusive and adaptable educational practices.

Academic inquiries (Wang, 2008; Altimari et al., 2012; Dall'Acqua, 2009) underscore the paramount importance of formulating educational trajectories that consider the distinctive attributes of each learner, assess their competencies, and leverage digital resources.

The research (Ilieva et al., 2025) introduced a structured framework for the integration of generative artificial intelligence within an evaluative system in the realm of higher education. This model encompasses the phases of automated assignment generation, customization of assessment materials, as well as the analysis and interpretation of educational outcomes utilizing the large language model (LLM). The authors underscore the critical significance of tailoring assessment methodologies to align with educational objectives (learning outcomes), thereby ensuring transparency, reproducibility, and adherence to established academic standards.

In summary, the literature on competencies and learning outcomes highlights the transformative potential of AI and automation in both educational and organizational settings. Studies like those by Korayim et al. (2025) and Hamilton et al. (2024) illustrate how AI-driven tools enhance competency development, foster innovation, and align learning outcomes with professional demands. However, the successful implementation of these technologies requires addressing attitudinal, infrastructural, and ethical challenges. By synthesizing these insights, this review provides a foundation for further research into the automated formulation of competencies and learning outcomes, particularly in the context of higher education's evolving role in preparing students for a technology-driven workforce.

2.1 Research questions

Building on the challenges identified in the introduction and the insights from the literature review, this study seeks to address the automation of professional competency formulation and learning outcome development in higher education. The following research questions guide the investigation:

RQ1: How can AI-driven tools be utilized to automate the extraction and formalization of learning outcomes and competency requirements from unstructured textual sources, such as professional standards, training programs, and job descriptions?

RQ2: How can structured competency data be leveraged to develop a hierarchical model that captures prerequisite and postrequisite relationships, thereby enabling adaptive learning pathways aligned with labor market needs?

RQ3: How can competency maps generated through intelligent modeling be integrated into existing educational software platforms to facilitate rapid, responsive, and effective curriculum design that meets evolving industry demands?

3 Methods

To develop a system capable of synchronizing occupational standards with educational programs and automatically generating competency statements, this study used a generative AI methodology using the GPT model. This approach was integrated to extract, formalize and refine competency requirements from unstructured textual sources such as occupational standards, training programs and job descriptions as outlined in the research questions. The methodology was designed to ensure accuracy, contextual relevance, and alignment of the generated competencies with labor market requirements.

3.1 AI-powered text generation framework

The primary tool for generating and refining competency formulations was a transformer-based large language model, specifically a GPT architecture (e.g., GPT-4 or a similar model). The GPT model was selected for its advanced natural language understanding and generation capabilities, which enable it to process complex textual inputs and produce coherent, contextually appropriate outputs (Brown et al., 2020). The model was fine-tuned to focus on competency-related tasks, such as extracting key skills and knowledge from unstructured sources and transforming them into structured competency statements. To optimize the generation process, several parameters were configured:

Temperature: set to 1.0 to balance creativity and coherence, allowing the model to generate diverse yet relevant competency formulations.

Maximum tokens: limited to 300 tokens to ensure concise outputs suitable for competency statements, preventing overly verbose or irrelevant content.

Top-p sampling: employed to control the probability distribution of word selection, ensuring that generated text remains focused on the input context.

These parameters were iteratively adjusted during testing to optimize the quality of the generated competencies, ensuring alignment with professional standards and educational objectives.

3.2 Algorithm for competency and learning outcome generation

The process of generating competency formulations followed a structured algorithm, designed to extract relevant information from textual inputs and produce formalized outputs. The workflow of Algorithm 1 can be summarized as follows:

Input acquisition: collect unstructured textual data from professional standards, training programs, or job descriptions provided via user input or external databases.

Preprocessing: apply NLP techniques, such as tokenization and named entity recognition, to clean and structure the input data, identifying key terms related to skills, knowledge, and behaviors.

Model invocation: utilize the GPT-based model to process the preprocessed input. The model is prompted with a system instruction (e.g., "Generate competency statements based on the following professional standard: [input text]") to guide the generation process.

Parameter configuration: set model parameters (e.g., temperature = 1.0, max_tokens = 300) to control the creativity and length of the output.

Output generation: generate competency formulations as structured text, ensuring clarity and alignment with the input context.

Post-processing: parse the model's JSON-formatted response to extract the generated competency statements, filtering out irrelevant or redundant content.

Validation: cross-reference the generated competencies with industry benchmarks or existing competency frameworks to ensure accuracy and relevance.

Using GPT for text generation can be represented as a stochastic process governed by the following parameters. The text generation is performed according to the following formula, as defined in Equation 1:

$$P(w_t \mid w_1, w_2, \ldots, w_{t-1}) = \frac{\exp\left(\frac{\log P(w_t \mid w_1, w_2, \ldots, w_{t-1})}{T}\right)}{\sum_{weV} \exp\left(\frac{\log P(w_t \mid w_1, w_2, \ldots, w_{t-1})}{T}\right)} \quad (1)$$

ALGORITHM 1 Text generation

Include the file "connect.php"
Include the library using autoload.php
Use the OpenAi class from the Orhanerday\OpenAi library
Create a variable open_ai_key and assign it the API key
Create an object open_ai by passing the API key to the OpenAi constructor
Get the value of the 'zun' variable from the POST request and store it in the variable text1
Call the chat method of the open_ai object with the following parameters:
- 'model': 'gpt'
- 'messages': a list of messages containing one object:
- "role": "system"
- "content": the string "what studies" + the value of text1 + "?"
- 'temperature': 1.0
- 'max_tokens': 300
Decode the JSON response into the variable d
Display the content of the field choices[0].message.content from the object d

where, V - model dictionary, w_t - current word, T - parameter controlling the probability of choosing the next word. The higher the T, the more random the word choice will be.

This algorithm was implemented using a modular software architecture, interfacing with an AI model via a secure API. The system was designed to handle dynamic inputs, allowing it to adapt to various professional domains, such as healthcare, engineering, or information technology.

The methodology for formalizing competencies and learning outcomes was operationalized through the structured process presented in Figure 1, which integrates artificial intelligence-based text generation with professional standards and learning functions. This approach addresses the research questions by automating the transformation of unstructured data into actionable learning outcomes.

The architectural framework depicted in Figure 1 encompasses two interconnected processes: (a) generation of learning outcomes and (b) generation of competencies, both of which are implemented using a GPT-based model. The initial element is a dataset formed from professional standards (PS) containing a description of labor functions (LF). Each labor function (e.g., LF1, LF2, LF3) is associated with specific elements of knowledge, skills, and abilities (KSA — Knowledge, Skills, Abilities) obtained by semantic analysis of the text of the professional standard.

(a) Generation of learning outcomes at the stage of generation of learning outcomes, the GPT model accepts as input the elements of KSA extracted from the structure PS → LF → KSA. The model then applies the transformation rule, matching KSA with Higher-order Verbs (HV), which allows the formation of target formulations of learning outcomes.

The process is repeated for all KSA elements, resulting in the formation of a sequence of learning outcomes (LO_1, LO_2, …, LO_i) that correspond to the original requirements of the professional standard.

(b) Generation of competencies the second part of the architecture is aimed at generating competencies from work functions (LF). The GPT model processes the generated or extracted LF descriptions and applies the matching rule with the action verb and the formulation of professional activity.

This approach ensures the formation of hierarchically organized, formalized competencies that meet the requirements of the labor market and the educational system, as indicated in research question RQ2.

3.3 Integration with educational platforms

To address RQ3, the generated competency maps were integrated into existing educational software platforms, such as learning management systems (LMS) like Canvas or Moodle. The integration process involved mapping the structured competency data to curriculum design templates, enabling educators to align course objectives with industry requirements. Semantic analysis was employed to identify hierarchical relationships between prerequisites and postrequisites, facilitating the creation of adaptive learning pathways. For example, the system could generate a sequence of learning outcomes for a data science curriculum, starting with foundational skills (e.g., Python programming) and progressing to advanced competencies (e.g., machine learning model deployment).

3.4 Data and validation

The methodology was tested using a dataset comprising professional standards from multiple industries and job descriptions sourced from public repositories and industry partners. The dataset was anonymized to ensure compliance with data privacy regulations. Validation was conducted by comparing the AI-generated competencies against manually crafted competency frameworks, assessing metrics such as accuracy, relevance, and completeness.

3.5 Composition of the dataset

The dataset, which was collected and published by Mukashova (2025) on Kaggle, comprised 140 professional standards covering 13 different professional practice areas such as information technology, healthcare, engineering, logistics, and education. These standards were selected based on their relevance to higher education curricula and labor market requirements, within the framework of the adopted National Chamber of Entrepreneurs of the Republic of Kazakhstan "Atameken." Each standard was structured according to its internal logic detailing specific competencies, skills and knowledge requirements. In addition, the dataset included job descriptions for 1,562 positions, each associated with one or more occupational standards. These job descriptions provide detailed insights into role-specific competencies, including technical skills, soft skills, and behavioral expectations.

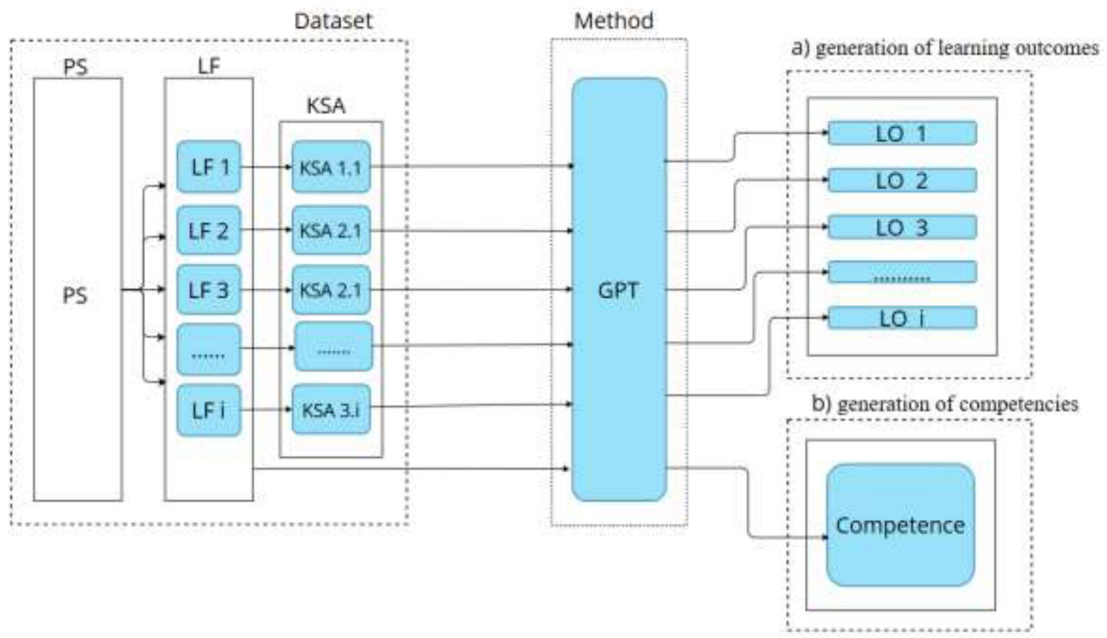

FIGURE 1
Architecture for the generation of learning outcomes and competencies based on professional standards.

3.6 Mathematical model for formalizing professional standards

This model is aimed at formalizing professional standards, generating formal competencies, learning outcomes and their integration into educational programs. The main task is to build a system that reduces the gap between educational standards and labor market requirements.

In our study as data we use professional standards developed jointly with representatives of professional communities, employers, government agencies and educational institutions, approved by the National Chamber of Entrepreneurs of the Republic of Kazakhstan in the order established by the authorized state labor authority. It includes the following key elements: the name of the profession, description of labor functions, required knowledge, skills and abilities.

To formalize these elements, the structure of a professional standard is defined in Equation 2:

$$PS_k = \langle LF_{ki}, KSA_{ki} \rangle_{i \le k \le n_k} \tag{2}$$

where: $i \le k \le n_k$- number of professional standards $LF_k = \{LF_1, LF_2, LF_3, \ldots, LF_{nk}\}$;

PS_k - k-th professional standard;

LF_{ki} - i-th labor function, PS_k;

KSA - the multitude of knowledge, skills and abilities associated with each job function,

$$LF_{ki}, KSA_{ki} = \{KSA_1, KSA_2, KSA_3, \ldots KSA_{nk}\}, i \le k \le m;$$

Competence generation is based on connecting labor functions according to relevant professional standards, as expressed in Equation 3:

$$Gen_k^1 \subseteq \bigcup_{i \le 1 \le n_k} HV \times LF_{ki} \tag{3}$$

where,

Gen_2^1- the result of generation of competence related to i- th labor function;

LF_{ki} – i-th labor function of k-th competence;

HV- list of service verbs used in the formalization of work functions;

For each competence a set of indicators of knowledge, skills and abilities is formed. They form the learning outcomes for achieving the competence, as defined in Equation 4:

$$Gen_k^2 \subseteq \bigcup_{i \le 1 \le n_k} HV \times KSA_{ki} \tag{4}$$

where,

Gen_k^2 - the result of generating learning outcomes related to k- th labor function;

HV - list of verbs used in formalizing learning outcomes;

KSA_{ki} - learning outcome related to LF_{ki};

The full process of professional standard formalization is summarized by Equation 5:

$$FPS_k = \langle LF_k, Gen_k^1, KSA_k, Gen_k^2 \rangle_{i \le k \le n,}$$

$$FPS = \bigcup_{k < 1 < n} FPS_k \tag{5}$$

where,

FPS is a formalization of all professional standards that integrates all professional standards PS_k, generated competencies Gen_k^1, Gen_k^2, and generated learning outcomes.

4 Results

This section presents the findings from the implementation of the proposed framework for automating the formalization of professional competencies and learning outcomes, as outlined in the Methods. The results demonstrate the efficacy of the AI-driven approach in generating structured competency maps and learning outcomes, aligning educational programs with labor market demands (RQ1–RQ3).

4.1 Research pipeline

The research pipeline for generating competencies and learning outcomes was structured around three key components, leveraging AI-based text generation methods to process unstructured professional standards and labor functions into structured educational outputs:

GPT Model: The GPT model was employed to refine formulations by enhancing variability and coherence in the generated text. It processed input data, such as knowledge, skills, and abilities (KSA) and labor functions (LF), to produce semantically rich and contextually accurate competency statements and learning outcomes. The model's parameters (e.g., temperature = 1.0, max_tokens = 300) were tuned to ensure precision and relevance.

Generating learning outcomes: Learning outcomes were formulated using GPT method, with KSA as the primary input data. The process, represented conceptually by Equation 4 in the original framework, involved mapping KSA elements to higher-order verbs (HV) and generating corresponding learning outcomes (LO). For example, a KSA element like "basic programming skills" was transformed into a learning outcome such as "Students will demonstrate proficiency in basic programming concepts."

Generating Competencies: Competencies were generated using a similar approach, with LF as the input data, as represented by Equation 3. The process involved transforming labor functions into structured competency statements by applying a decision rule that mapped LF to actionable verbs and descriptors. For instance, an LF like "design software solutions" was formulated into a competency such as "Develop software solutions for real-world applications."

The integration of these generated formulations resulted in structured competencies and learning outcomes, which were then incorporated into educational programs, as represented by Equation 5. This pipeline enabled the efficient formalization of professional standards, automating the generation process and ensuring adaptability to modern labor market requirements.

To illustrate the application of the GPT method, Table 1 provides an example of generating competencies and learning outcomes for a database management context, comparing the preparation stage (manual formulation) with GPT-generated outputs.

The GPT-generated formulations demonstrate improved clarity and conciseness compared to the preparation stage, while preserving the semantic intent of the original labor functions and KSA (knowledge, skills, and abilities) descriptions. For example, the fragmented preparation-stage description "Software installation and configuration. Ensuring database operation." was streamlined into "Install, configure, and maintain software and database," making it more actionable for educational purposes.

4.2 Model performance and evaluation

An intelligent information system was developed based on the proposed model, capable of automatically generating competencies and learning outcomes that align with professional standards. The system was evaluated using established natural language processing metrics-ROUGE-1, ROUGE-2, ROUGE-L, BLEU, and METEOR-to quantitatively measure the similarity between the AI-generated text and expert-defined standards. The performance of three text generation models (NLP, GPT, and MBART) was compared, as shown in Table 2.

The GPT model outperformed both NLP and MBART across all metrics, achieving the highest scores: ROUGE-1 (0.6809), ROUGE-2 (0.4120), ROUGE-L (0.5617), BLEU (0.2530), and METEOR (0.5513). These results indicate superior performance in word-level accuracy (ROUGE-1), bigram overlap (ROUGE-2), longest common subsequence (ROUGE-L), fluency (BLEU), and semantic similarity (METEOR). The GPT model's ability to generate contextually accurate and lexically coherent formulations highlights its suitability for competency formalization tasks.

4.3 Evaluation and comparison

The system was applied to 30 academic fields, including IT, engineering, economics, and social sciences. It generated: 582 competencies and 2,072 learning outcomes, covering over 14,000 KSA elements extracted from national professional standards and occupational classifications (Mukashova, 2025).

To further substantiate the reliability and relevance of the generated outputs across different qualification frameworks, a multi-class classification experiment was conducted to determine the qualification level of learning outcomes (i.e., college, bachelor, master, and doctoral levels). Using models such as Multinomial Naive Bayes, Gaussian Naive Bayes, Logistic Regression, and Decision Tree, the classification task demonstrated exceptional performance metrics. Notably, the Decision Tree model achieved an F1-score exceeding 0.99, outperforming the other models. These results confirm the robustness of the AI-generated learning outcomes and their alignment with a range of educational qualification frameworks, as presented in Table 3.

In addition to the tabular comparison of performance metrics (Table 3), Figure 2 provides a graphical illustration of the models' performance across Accuracy, Precision, Recall, and F1-score. This visualization highlights the consistently high performance of Logistic Regression and Decision Tree models, with the latter achieving near-perfect results across all qualification tiers.

TABLE 1 Example of generating competencies and learning outcomes.

Methods	LF (labor functions)	KSA (knowledge, skills, and abilities)
Preparation stage	Software installation and configuration. Ensuring database operation. Database backup monitoring and management. DBMS provisioning. DBMS performance analysis and tuning. Ensuring uninterrupted DBMS operation. Database development management.	Evaluation and development of requirements to the hardware-software complex, based on the prospects of using the database. Designing a hardware-software complex for database installation. Selecting the most efficient DBMS for software installation and customization. Designing the database structure taking into account the prospects of database usage. Performing the effective hardware-software complex configuration. Using the technical documentation on software installation and configuration. Hardware and software complex technical characteristics. Features of different DBMSs. Requirements to the DBMS. Requirements for system and application software. Mechanisms of resource management of the hardware-software complex. Architecture of IS using databases. Database design. IS methods and principles.
GPT	Install, configure, and maintain software and database. Monitor, manage backups, and DBMSs. Analyze, tune DBMS performanc. Ensure smooth operation and manage database developmen.	Evaluate and develop requirements for the hardware and software complex based on database usage prospects. Design a hardware-software complex for database installation and operation. Select the most effective DBMS for software installation and customization. Design the database structure with consideration of its future use. Customize a hardware and software system for optimal efficiency. Use technical documentation to install and configure software. Determine the technical characteristics of hardware and software systems. Account for features of different DBMSs and formulate requirements for them, as well as for system and application software. Develop mechanisms for managing resources of the hardware-software complex. Design the architecture of information systems working with databases and create database structures. Apply information security methods and principles.

To provide a more detailed view of the classification performance across qualification levels, confusion matrices were constructed for all four models. These matrices illustrate the distribution of correctly and incorrectly classified learning outcomes across the tiers (bachelor, master, doctoral), thereby complementing the overall performance metrics reported in Table 3. The results are presented in Figures 3–6.

4.4 Integration into educational programs

The validated outputs were integrated into 18 university programs at bachelor's and master's levels. The generated formulations were used to:

- Update course objectives in syllabus;
- Design modular course units;
- Align course descriptors with labor market skill expectations;
- Streamline accreditation reports with outcome-based descriptors.

For example, in the "Information Security" program, the competency "Develop mechanisms for managing resources of the hardware-software complex" was directly embedded into the module "IT Infrastructure and Security Architecture."

The results demonstrate the practical usefulness of the proposed model in addressing RQ1 (automation of competency extraction), RQ2 (hierarchical modeling of competencies), and RQ3 (integration into educational platforms). By formalizing professional standards into structured data, the model enables the following:

- Efficient translation of unstructured KSA and LF data into structured, pedagogically appropriate educational outcomes;
- Support for standardization, scalability, and adaptability across disciplines and qualification levels;
- Superior performance compared to existing models in terms of semantic accuracy and fluency;
- Significant reduction in manual effort, improved consistency, and faster curriculum alignment with labor market demands.

5 Discussion

This study presents a novel framework for the automated formalization of professional competencies and learning outcomes, utilizing the generative capabilities of the GPT model to transform unstructured professional standards into structured, actionable competency maps. The results, as detailed in Section 4, demonstrate significant advancements in aligning educational programs with the dynamic demands of the labor market, addressing the challenges. This section discusses the implications of these findings, compares the performance of the AI methods employed, evaluates the limitations of the approach, and proposes directions for future research.

The empirical results indicate that the system was able to generate a substantial number of competencies and learning outcomes across diverse academic fields, while maintaining high reliability and consistency with qualification frameworks. The classification results (Table 3; Figure 2) further validated the robustness of the generated outputs, as all models achieved strong performance, with Decision Tree and Logistic Regression demonstrating near-perfect classification. The confusion matrices (Figures 3–6) additionally provided insights into model behavior, showing that most misclassifications occurred between adjacent qualification levels (e.g., bachelor vs. master), which reflects the semantic and conceptual closeness of these tiers in practice.

These findings underscore the potential of generative AI in reducing manual effort and subjectivity in curriculum design, enabling a more scalable and adaptive integration of professional standards into higher education programs. Moreover, the proposed framework offers institutions a mechanism to ensure the relevance of their educational programs in rapidly evolving labor markets, particularly where the alignment between academic outcomes and occupational requirements is critical. The superior performance of GPT addresses RQ1 by demonstrating the effectiveness of AI-driven

TABLE 2 Analysis of the results of comparison of text generation models.

Model	ROUGE-1	ROUGE-2	ROUGE-L	BLEU	METEOR
NLP	0.5375	0.3038	0.3500	0.0997	0.2757
OpenAI	0.6809	0.4120	0.5617	0.2530	0.5513
MBart	0.4648	0.3714	0.3380	0.0997	0.2625

TABLE 3 Analysis of the results of comparison of text generation models.

Model	Accuracy	F1-Score	Precision	Recall
MultinomialNB	0.937914	0.920209	0.941454	0.937914
Gaussian Naive Bayes	0.901490	0.899716	0.903288	0.901490
Logistic Regression	0.997517	0.997515	0.997528	0.997517
Decision Tree	0.999172	0.999172	0.999173	0.999172

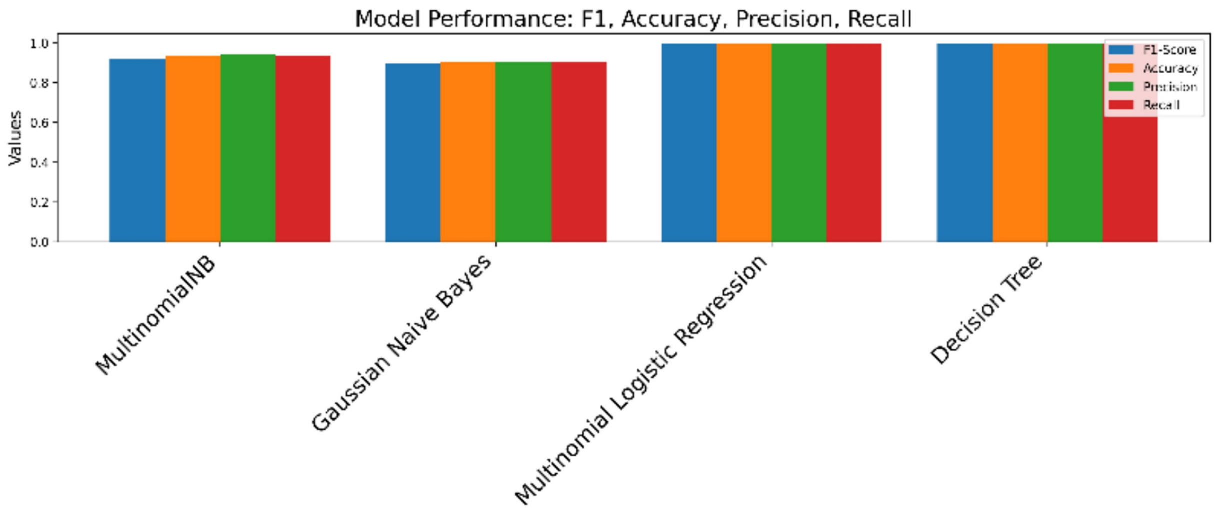

FIGURE 2
Comparative performance of classification models across Accuracy, Precision, Recall, and F1-score.

tools in extracting and formalizing competencies from unstructured textual sources, such as professional standards and job descriptions.

The framework's ability to generate 582 key competencies and 2,072 learning outcomes across 30 areas of study has profound implications for higher education and workforce development. By automating the competency formulation process, the system enables educational institutions to rapidly adapt curricula to emerging labor market trends, addressing RQ3. For example, in fields like information technology, competencies such as "Develop mechanisms for managing resources of the hardware-software complex" were directly integrated into course objectives, ensuring graduates are equipped with skills that meet industry expectations (Hamilton et al., 2024). This responsiveness is critical in a digital economy where technological advancements, such as the integration of generative AI into organizational processes, continuously reshape professional landscapes (Korayim et al., 2025).

Moreover, the structured competency maps generated by the system facilitate seamless integration into educational software platforms, such as learning management systems (LMS) like Canvas or Moodle. This integration streamlines curriculum design, allowing educators to focus on pedagogical innovation rather than manual competency mapping, a key challenge identified in the introduction. The generated learning outcomes, which are specific, measurable, and aligned with competency-based education (CBE) principles (e.g., "Students will design software solutions for real-world applications"), support personalized learning pathways that cater to diverse student needs (Holubnycha et al., 2022). For workforce development programs, the framework offers a scalable solution to upskill employees, ensuring training programs remain relevant to industry standards, such as those in logistics or healthcare (Fitsilis, 2024).

The hierarchical modeling of competencies, as addressed in RQ2, further enhances the framework's utility. By capturing prerequisite and postrequisite relationships, the system enables the creation of adaptive learning trajectories. For instance, a data science curriculum might progress from foundational competencies (e.g., "Understand basic statistical concepts") to advanced ones (e.g., "Apply machine learning algorithms to real-world datasets"), ensuring a logical and industry-aligned learning progression.

Despite its advancements, the study identifies several limitations that impact the framework's applicability and generalizability. First, the reliance on proprietary technology, such as the GPT model, poses

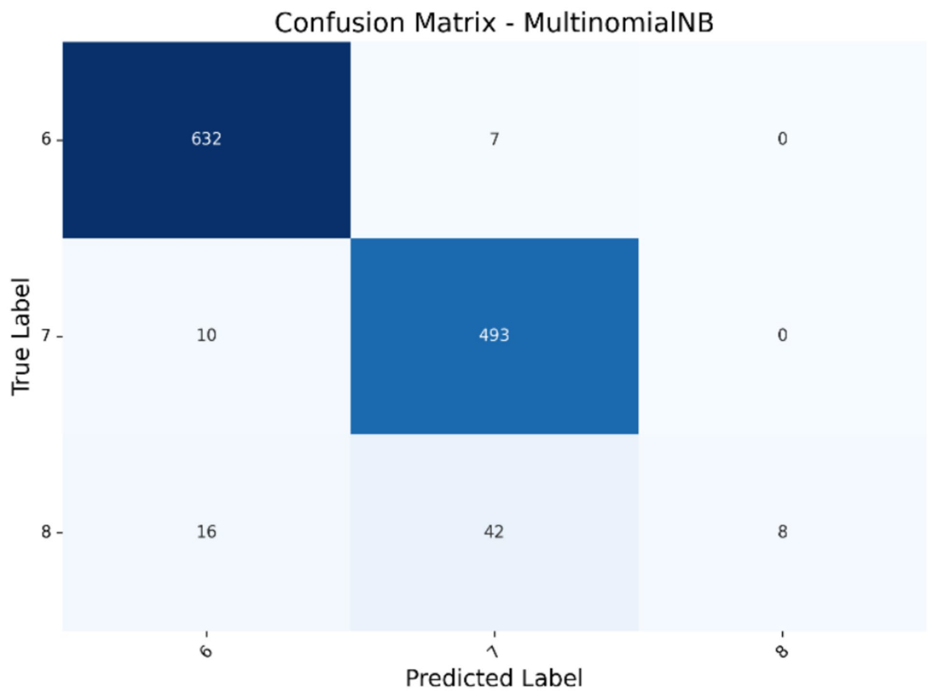

FIGURE 3
Confusion matrix for Multinomial Naive Bayes, where 6-bachelor, 7-master, 8-doctoral.

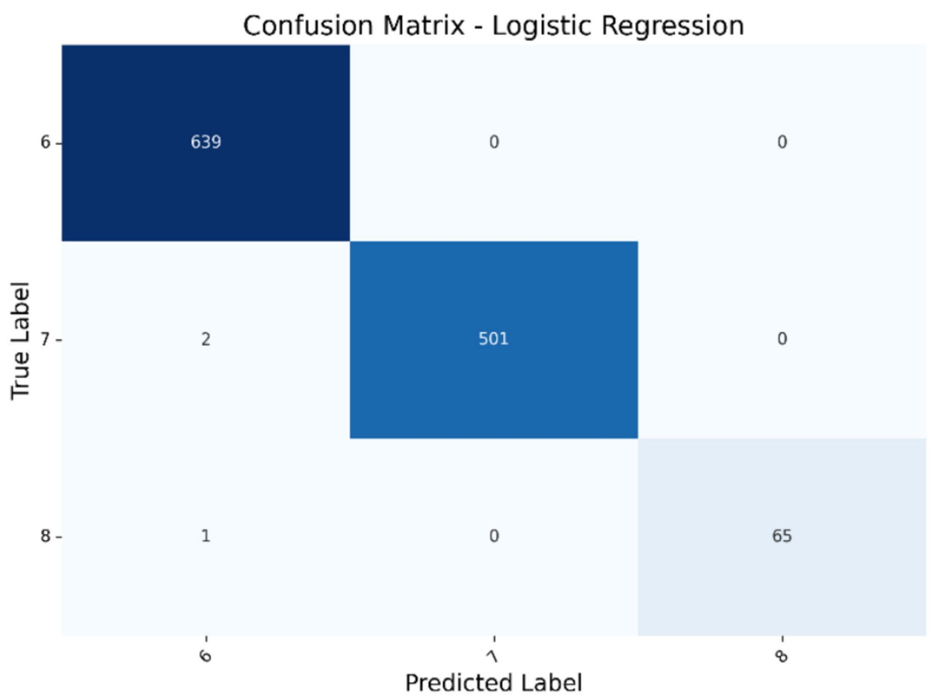

FIGURE 4
Confusion matrix for Logistic Regression, where 6-bachelor, 7-master, 8-doctoral.

challenges for transparency and reproducibility. The closed-source nature of GPT limits insight into its training data and fine-tuning processes, raising concerns about potential biases that could skew the generated competencies (Eryomina and Lopukhin, 2020). For example, if the model's training data underrepresent certain industries (e.g., creative arts) or demographics, the resulting competency maps may lack inclusivity, perpetuating inequities in educational outcomes.

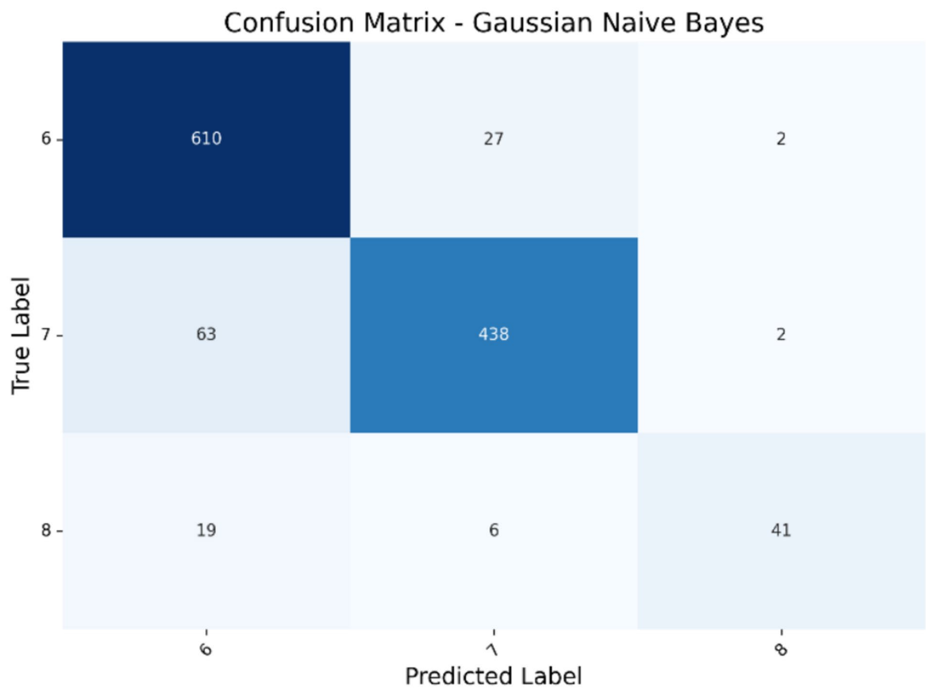

FIGURE 5
Confusion matrix for Gaussian Naive Bayes, where 6-bachelor, 7-master, 8-doctoral.

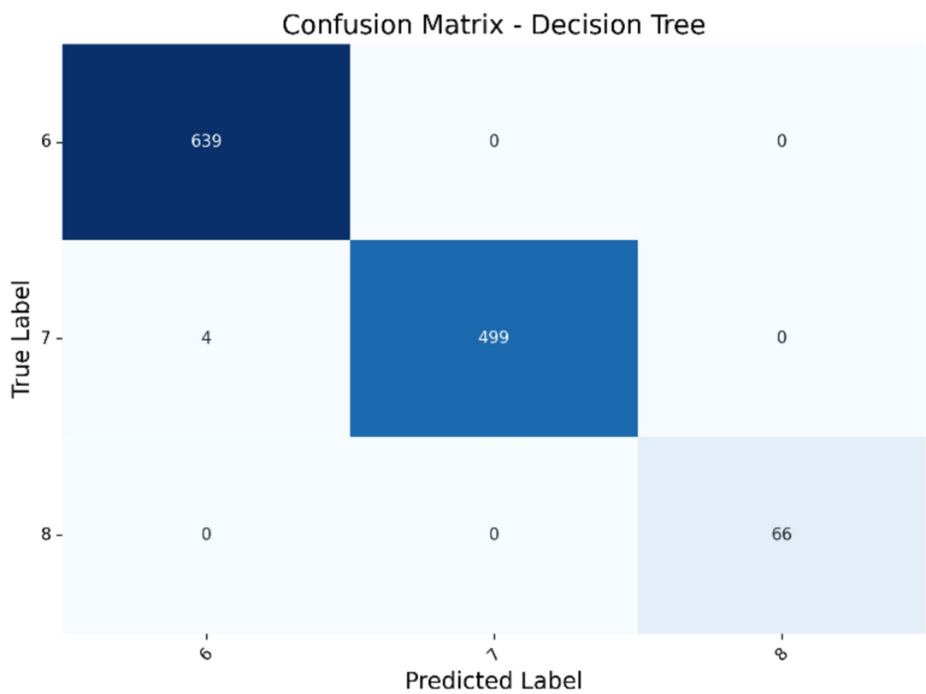

FIGURE 6
Confusion matrix for Decision Tree, where 6-bachelor, 7-master, 8-doctoral.

Second, the dataset, while comprehensive with 140 professional standards and 1,562 job positions, may not fully capture the global diversity of professional contexts. The focus on industries like IT and healthcare may limit the framework's applicability to other sectors, such as agriculture or education, where competency requirements differ significantly. Additionally, the quality of unstructured textual inputs varied, occasionally leading to inconsistencies in the AI-generated outputs. This variability underscores the need for robust preprocessing techniques to ensure consistent input quality.

Third, the study's evaluation metrics (ROUGE, BLEU, METEOR) focus primarily on textual similarity and semantic coherence, but they may not fully capture the practical utility of the generated competencies in real-world educational settings. While stakeholder feedback was incorporated, the study lacked a longitudinal assessment of how the generated competencies impact student learning outcomes or employability over time. This gap limits the ability to fully validate the framework's effectiveness in achieving its intended educational goals.

The findings and limitations highlight several avenues for future research to enhance the proposed framework. First, integrating real-time labor market analytics could improve the system's responsiveness to emerging trends. For example, incorporating data from job boards like LinkedIn or Indeed could enable dynamic updates to competency frameworks, ensuring they reflect current skill demands, such as proficiency in new technologies or sustainability practices (Singh et al., 2024). This would further address RQ3 by enhancing the system's adaptability to evolving industry requirements.

Second, exploring open-source alternatives to GPT, such as Hugging Face's BERT, T5, or LLaMA, could mitigate concerns about transparency and reproducibility. Open-source models offer greater visibility into their training data and algorithms, allowing researchers to identify and address biases more effectively. Additionally, these models could be fine-tuned on domain-specific datasets (e.g., educational standards) to improve their performance in competency formalization tasks.

6 Conclusion

This study has successfully developed and evaluated an AI-driven framework for the automated formalization of professional competencies and learning outcomes, addressing the growing need to align higher education curricula with dynamic labor market demands. By leveraging the generative capabilities of the GPT model, the framework systematically transformed unstructured professional standards into structured competency maps and learning outcomes. The results, which include the generation of 582 key competencies and 2,072 learning outcomes across 30 areas of study, demonstrate the framework's efficacy in producing contextually accurate and industry-relevant educational outputs (Mukashova, 2025).

The comparative analysis of AI methods highlighted the GPT model's superior performance over NLP and MBART, with higher scores across ROUGE, BLEU, and METEOR metrics, affirming its suitability for competency formalization tasks (RQ1). The framework's ability to model hierarchical relationships between prerequisites and postrequisites (RQ2) enabled the creation of adaptive learning pathways, while its integration into educational software platforms (RQ3) facilitated rapid curriculum design. These advancements address the challenges identified in the introduction, such as the labor-intensive nature of manual competency mapping, and align with the literature's emphasis on the role of AI in enhancing educational outcomes (Korayim et al., 2025; Hamilton et al., 2024).

The implications of this study are twofold. For higher education, the framework offers a scalable solution to ensure curricula remain relevant in a rapidly evolving digital economy, enabling institutions to prepare graduates for professional success. For workforce development, the automated generation of competencies supports upskilling initiatives, ensuring training programs meet industry standards (Fitsilis, 2024).

The manuscript (Wang, 2008) investigates the perceptions surrounding formative assessment among English educators in China. The author underscores the significance of formative feedback and self-evaluation as instrumental in facilitating the learning process and in modifying pedagogical approaches to align with contemporary educational benchmarks. Such notions are congruent with the aims of intelligent educational systems, wherein assessment serves as a foundational element for adaptive learning management and trajectory realignment based on the attainment of educational outcomes.

The manuscript (Altimari et al., 2012) introduces an ontology-driven framework for personalized e-learning, which employs a mechanism for the dynamic assembly of e-courses tailored to individual student profiles. This methodology guarantees flexibility and individualization in the learning experience while also promoting content reutilization. The proposed architecture bears resemblance to our own approach, which incorporates generative artificial intelligence for the adaptive development of competencies and learning outcomes in accordance with professional standards.

A parallel focus on personalization and ontological modeling is evident in the manuscript (Dall'Acqua, 2009), which delineates the PENTHA model - an adaptive educational environment that considers the cognitive profile, knowledge structure, and pedagogical principles of the learner. Similar to our system, this model implements a transition from a static course framework to an intelligent adaptation of content specifically designed for individual users.

Consequently, the synthesis of the aforementioned studies establishes a methodological foundation for the advancement of intelligent systems that are proficient in the automatic formation of competencies and educational outcomes based on professional standards, while taking into account the unique cognitive and individual characteristics of learners, as well as mechanisms for assessment and adaptation.

In conclusion, this study contributes to the field of educational technology by demonstrating the transformative potential of AI in competency-based education. Future research should focus on integrating real-time labor market analytics, exploring open-source AI models, and addressing ethical considerations to ensure inclusivity and equity. By building on these findings, educational institutions can create more responsive, adaptable, and equitable systems, ultimately bridging the gap between academic preparation and professional expectations in an increasingly complex global workforce.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

AiM: Methodology, Writing – original draft. JT: Writing – original draft, Validation, Methodology. SS: Writing – original draft. AyM: Writing – original draft, Conceptualization. MuS: Formal analysis, Writing – original draft. MaS: Resources, Writing – original draft. AY: Writing – original draft, Investigation. ZL: Formal analysis, Writing – original draft. ZS: Software, Writing – original draft. VR: Writing – original draft, Software.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that Generative AI was not used in the creation of this manuscript.

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