Quality & Quantity
https://doi.org/10.1007/s11135-026-02959-9

Assessing the GenAI readiness of degree programs of Italian universities

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Received: 9 March 2026 / Accepted: 28 June 2026

Abstract

The rise of Generative Artificial Intelligence (GenAI) is reshaping industries and creating new roles, requiring updated cross-sectoral skills. This paper proposes a framework to evaluate the GenAI readiness of university degree programs, aligning academic training with emerging AI careers. It focuses on five professional profiles: GenAI data scientist, prompt engineer, ethical AI specialist, AI product manager, and creative AI specialist. A structured methodology maps required competencies against degree programs in Italian universities, applying a readiness Likert scale score (0–5). ChatGPT-4o is used to assess alignment between official degree program descriptions and predefined skill sets, producing both quantitative scores and qualitative feedback. Results show moderate alignment in some programs, with significant gaps for roles such as prompt engineer, ethical and creative AI specialist, together with some association between role pairs, such as between prompt engineer and creative AI specialist which require some similar skills. The framework supports students' educational choices and guides employers and universities in strengthening GenAI talent pipelines.

Keywords Generative artificial intelligence · Higher education degree program assessment · AI workforce readiness · Large language models · ChatGPT

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Published online: 07 July 2026

1 Introduction

The rapid advancement of Generative Artificial Intelligence (GenAI) marks a milestone in digital innovation. Unlike earlier AI systems focused on pattern recognition and prediction, GenAI models, based on deep learning architectures such as transformers and GANs (Vaswani et al. 2017), enable the generation of novel content in text, images, audio, and video (Brown et al. 2020). These capabilities are transforming creative industries, organizational processes and academia, fostering the emergence of novel professional roles and redefining the skills required across sectors (Wang et al. 2025).

Recent initiatives reflect the urgency of this alignment. The Educause–AWS framework (Educause 2025) evaluates institutional AI preparedness in terms of strategy, governance, and skill-building. Research by Zhang (2023) and Hmoud and Laszlo (2019) explores the impact of AI and tools such as ChatGPT on HR recruitment. From an industry perspective, Franz (2024) identifies twelve essential GenAI skills, ranging from AI model development and data literacy to prompt engineering and ethics, reinforcing the need to update university curricula accordingly. Prohorov et al. (2024) examine employers' expectations about the GenAI-related skills students are expected to acquire, while Jin et al. (2025) analyze how 40 universities around the world address academic integrity, accessibility, and policy frameworks in relation to GenAI. In the Italian context, Spada et al. (2024) document a notable increase in AI-related courses over the past decade. Business schools are responding as well. AACSB International (2024) recommends integrating GenAI through applied projects and blended learning. Professional resources such as Simplilearn (Kumar 2026) and Analytix Labs (2025) outline technical skills for roles such as prompt engineer and GenAI data scientist. Ethical concerns are also prominent. Onward Search (2026) highlights risks related to algorithmic bias, misinformation, and synthetic content, especially relevant for the role of the ethical AI specialist (Floridi 2018; Farina et al. 2025).

Universities are increasingly trying to adapt their undergraduate and graduate programs to the new demands of the artificial intelligence job market. However, they appear to be adapting more slowly than required to the profound transformations that AI is introducing into labor markets and professional practices. Even academic literature in this field has focused primarily on analyzing the advent of AI among students for their learning, much less on how programs should train them in this field Korseberg and Elken (2025).

To address these challenges, this study proposes a low-cost and scalable framework for assessing the GenAI readiness of Italian university degree programs. The framework compares official degree-program descriptions with predefined competency profiles associated with five emerging GenAI-related professional roles and assigns readiness scores on a 0–5 scale, accompanied by qualitative justifications. The objective is to examine the extent to which current academic curricula align with the evolving skill requirements of the AI-driven labor market and to provide a diagnostic tool that can support students, universities, and employers in educational planning, curriculum development, and talent identification. This inquiry responds to a growing body of literature in higher education that highlights the urgency of curricular innovation in response to digital disruption and AI adoption (Selwyn et al. 2023). By focusing on GenAI, the study contributes to current debates on future-ready education, employability, and epistemic change in knowledge institutions. It further asks: To what extent can generative AI be used as a diagnostic tool to evaluate the responsiveness of academic programs to new skill demands? And how might such tools reveal an implicit curricular misalignment? The research draws on comparative analyses and model triangulation to address these questions, offering insights that are relevant to global readers concerned with the transformative pressures facing higher education today.

The paper proceeds as follows: Sect. 2 outlines the selected professional roles. Section 3 describes input preparation. Section 4 details the prompt design. Section 5 presents results from a sample of Italian degree programs. Section 6 discusses validation and Sect. 7 offers conclusions and future directions.

2 Selection of professional roles

The rapid advancement of GenAI has created new professional roles with highly specialized, evolving skill sets. The selected roles in this study are not intended to constitute a formal occupational taxonomy derived from a systematic content analysis of job postings. Rather, they are analytical archetypes constructed from recurring competency domains identified in academic literature, institutional frameworks, professional reports, and publicly available labor-market sources.

Drawing on academic literature, industry standards, and expert consultations (Franz 2024; Onward Search 2026; AACSB International 2024), five key AI-related roles are identified: GenAI data scientist, prompt engineer, ethical AI specialist, AI product manager, and creative AI specialist. These roles reflect the complexity of AI integration in organizations and align with frameworks such as ESCO, the O*NET framework of the U.S. Department of Labor, and the OECD AI Skills Framework.[1] Each combines technical expertise, ethical awareness, and strategic thinking—competencies increasingly vital in AI-driven sectors. Practitioner-oriented sources are used only to contextualize emerging roles and labor-market terminology, whereas the conceptual and methodological foundations rely primarily on peer-reviewed literature and institutional frameworks.

GenAI data scientist

The GenAI data scientist (hereafter 'GenAI scientist') builds on traditional data science by integrating advanced deep learning and generative modeling skills. While generalists focus on data cleaning, analysis and predictive modeling using tools such as scikit-learn (Pedregosa et al. 2011) and XGBoost (Chen and Guestrin 2016), GenAI scientists use frameworks like TensorFlow (Abadi et al. 2016) and PyTorch, deploying models on GPU/TPU infrastructures (Jouppi et al. 2017). They design and fine-tune models such as GANs, VAEs, and transformers, and leverage libraries such as Hugging Face for content generation (Analytix Labs 2025). Unlike traditional data scientists, they generate new data—text, images, audio, or simulations—for applications ranging from synthetic data to creative design and biotechnology. Ethical concerns such as misinformation, deep fakes, and intellectual property issues are central to this role, requiring a strong foundation in responsible AI.

Prompt engineer

The prompt engineer crafts, tests, and optimizes input prompts to achieve accurate, ethical outputs from GenAI systems. This requires expertise in natural language processing, model architecture, and reinforcement learning. Prompt engineers anticipate model behavior, design adaptive, bias-conscious prompts reflecting user intent, and ensure ethical

[1] See https://esco.ec.europa.eu/en/about-esco/escopedia/escopedia/esco-v12, https://www.dol.gov/agencies/eta/onet and https://www.oecd.org/en/about/projects/artificial-intelligence-and-future-of-skills.html.

standards (Bansal 2024). They also debug and customize outputs, often using APIs like OpenAI's GPT, improving usability and performance across domains such as customer service, content generation, and digital interfaces.

Ethical AI specialist

The ethical AI specialist ensures GenAI development aligns with ethical principles, legal standards, and societal values. Their expertise covers bias detection and mitigation, international AI regulations such as GDPR (Voigt and Von dem Bussche 2017) and the EU AI Act (Veale and Borgesius 2021), and ethical risk evaluation (ASBH 2011; Floridi 2018; Brummett and Salter 2019; Farina et al. 2025). They are key to addressing the social impact of AI on discrimination, accountability, and transparency.

AI product manager

AI product managers oversee the lifecycle of AI products, acting as a bridge between technical teams and business stakeholders. They translate user needs into specifications, coordinate teams, and guide development according to commercial goals (Pantelakis 2024). Their work integrates GenAI strategically to create value and optimize operations.

Creative AI specialist

The creative AI specialist works at the intersection of technology and artistic expression, using GenAI to produce images, music, and narrative text. This role blends generative modeling and AI-assisted editing with aesthetic sensibility to achieve creative goals (Montefiore et al. 2026). They collaborate with writers, designers, and producers to integrate GenAI into production workflows, experimenting with storytelling formats, visual styles, and audio effects. Their deep involvement with GenAI positions them as key contributors to innovation in creative industries.

3 Input setting

The main textual inputs that must be provided to ChatGPT for the implementation of the methodology are twofold: the first concerns the description of the competencies required for each professional role; the second pertains to the description of the topics covered by university degree programs.

3.1 Input 1: description of the competencies for each professional role

This type of input outlines the core competencies required for each professional role. Additionally, it suggests examples of relevant university degree programs that may support the development of these competencies.

The competencies associated with each GenAI professional role outlined in this paper were identified through a structured triangulation process involving academic literature, labor market analysis and professional reports. Specifically, the delineation of key skills and knowledge areas for the selected roles drew upon recognized taxonomies, including the European Skills, Competences, Qualifications and Occupations (ESCO), the U.S. Department of Labor's O*NET database, and AI-specific references such as the European Commission's “Ethics Guidelines for Trustworthy AI” and the “AI Competence Framework for Higher Education” (AI4T). These frameworks provided standardized definitions of occupational profiles, task domains, and required competencies, ensuring alignment with both academic standards and labor market demands.

In this section we describe input 1 exclusively for the role of the GenAI scientist. The structure and content of input 1 for the remaining four roles, which are analogous to the former, can be retrieved in the Appendix.

The GenAI scientist applies advanced ML/DL models, manages large-scale datasets, and works with cloud technologies—skills essential for solving complex problems and developing AI-driven solutions.

At the undergraduate level, core subjects such as computer science and mathematics (statistics, algebra, probability) provide the foundational skills in programming and data analysis needed for further specialization. Graduate programs focus on advanced AI and data science topics. Courses like machine learning, AI, and big data enable professionals to build predictive models and manage large, diverse datasets, often using scalable cloud infrastructures. This combination of competencies and programs ensures a comprehensive education aligned with the demands of the GenAI domain, emphasizing practical skills and innovation.

Table 1 presents the key competencies and essential degree programs for the professional role of a data scientist specialized in GenAI, divided by degree level (Bachelor's and Master's) and listed in order of relevance, from most to least important.

The identification of these competencies was informed by the convergence of evidence from academic literature, international policy frameworks, professional reports, and publicly available labor-market documentation. These sources were used to identify recurring competency domains and emerging professional profiles associated with Generative AI.

3.2 Input 2: description of universities

The second textual input is derived from the self-descriptive content provided by each Italian university on the official webpage of its degree program, typically located within the section of the institutional website dedicated to academic offerings. This source has the clear advantage of being publicly accessible and readily available online, making it practical for large-scale collection and analysis. However, a notable limitation is the lack of standardization across institutions: each university independently designs its website and chooses how to present its degree programs, resulting in considerable variability in structure, terminology, and depth of information. Such heterogeneity may undermine the comparability and

Table 1 The GenAI scientist role

Key competencies	
1	Understanding of machine learning and deep learning models
2	Management of large datasets
3	Familiarity with cloud computing technologies
Relevant degree programs	
1	Bachelor's: Foundations of computer science, statistics
	linear algebra, probability theory
2	Master's: Machine learning, deep learning, data mining
	artificial intelligence, big data analytics

consistency of evaluations across programs. Nevertheless, despite these limitations, this source has been used in the case examples presented in this paper and discussed in the following Sect. 4.[2]

4 Prompt design

4.1 Evaluation framework and prompt

In this phase of the analysis, GenAI is employed to compare two types of texts: the competency profiles associated with five emerging professional roles in GenAI and the official course descriptions of university degree programs in Italy (as described in Sects. 3.1 and 3.2). Based on these inputs, the readiness of each degree program in preparing students for a specific role is assessed on a scale from 0 to 5, as defined below:

- **0. No GenAI readiness**: The degree program does not provide the required competencies in any way, either through coursework or other educational experiences.
- **1. Minimal GenAI readiness**: The required competencies are superficially addressed. They may be marginally present in one or more courses but are neither developed nor explored in depth.
- **2. Limited GenAI readiness**: Competencies are addressed in a limited manner. Relevant topics are covered either theoretically or practically but do not constitute a significant part of the degree program.
- **3. Moderate GenAI readiness**: The competencies are provided through several courses, with adequate theoretical and practical treatment. These competencies are important, though not central, components of the degree program.
- **4. High GenAI readiness**: The competencies are a central focus of multiple courses and projects. They are explored in depth and represent one of the strengths of the degree program.
- **5. Maximum GenAI readiness**: The development of the competencies is a core objective of many courses and is integrated comprehensively across courses and activities.

In this study, ChatGPT-4o is used as the GenAI tool to evaluate the alignment between degree programs and GenAI roles. The model is prompted with structured instructions to assess how well each degree program prepares students for the following roles: data scientist specialized in GenAI, prompt engineer, ethical AI specialist, AI product manager, creative AI specialist. The prompt used is:

> Consider the inputs (illustrated in Sect. 3) and evaluate the university degree programs on a scale from 0 to 5 (as defined above) in relation to its training adequacy (GenAI readiness) concerning the five typical GenAI roles. Construct a table where

[2] Another standardized source is the "Scheda Unica Annuale dei Corsi di Studio" (SUA-CdS), mandated by Italian Ministerial Decree no. 1154/2021. Developed by ANVUR, which is Italy's national agency for evaluating universities and research and ensuring academic quality and accountability in line with national and European standards (ANVUR 2025; European Commission 2025). In this work we have not used this source because it requires special permissions for access and use.

the rows represent the GenAI roles, and the columns contain, for each role, the rank you calculated (on a scale from 0 to 5) along with a brief explanation of the score.

ChatGPT conducts the evaluation by analyzing the semantic and thematic alignment between the expected competencies and the curricular content. Each score is accompanied by a concise justification, highlighting the presence or absence of relevant elements in the degree program. This methodology allows for a transparent and interpretable form of automated scoring.

The comparison methodology is based on Large Language Models (LLMs). Generative AI tools like ChatGPT use transformer architectures that enable advanced textual recognition by capturing semantic, syntactic, and contextual patterns in natural language. A key mechanism is self-attention, which allows the model to weigh the relative importance of words across a sequence, thus modelling complex dependencies (Vaswani et al. 2017).

ChatGPT, a specific LLM developed by OpenAI, is fine-tuned using a combination of supervised learning and reinforcement learning from human feedback. This improves its ability to generate coherent, context-aware responses aligned with user intent (Brown et al. 2020). Recent studies have confirmed ChatGPT's reliability in structured evaluations. Liu et al. 2023 demonstrated its capacity to assign scores based on semantic alignment, supporting large-scale evaluations of textual coherence and content coverage. The GPT 4 Technical Report (OpenAI 2023) also emphasizes the model's effectiveness in applying structured rubrics to educational and comparative analysis tasks.

In Tables 2, 3, 4, we present three examples of this evaluation carried out on 210 degree programs offered in 15 Italian universities. We selected three STEM-focused degree programs from multiple Italian universities, ensuring geographical balance across northern, central, and southern Italy, and including both large and medium-sized institutions. Specifi-

Table 2 Example 1: evaluation of the master's degree in data science in a large university in northern Italy

GenAI role	Score (0–5)	Explanation
GenAI scientist	5	The degree program extensively covers machine learning, deep learning, data mining, big data analytics, artificial intelligence, and mathematical-statistical skills, perfectly training a data scientist for GenAI
Prompt engineer	4	Excellent preparation in Natural Language Processing (NLP), machine learning, fundamentals of computer science, and algorithms. A strong practical focus on prompt design is missing, but the foundational knowledge is very solid
Ethical AI specialist	3	Some courses on data privacy and security are present, but there are no specific courses on technology ethics, bias, and AI law, so the preparation is moderate
AI product manager	2	The degree program is very technical; there are no subjects on business management, marketing, or innovation management, resulting in limited preparation
Creative AI specialist	2	Strong technical preparation (AI and machine learning), but there is a complete lack of training in graphics, multimedia, creative production, or computational creativity

Table 3 Example 2: evaluation of the bachelor's degree in statistics in a medium-sized university in central Italy

GenAI role	Score (0–5)	Explanation
GenAI scientist	3	Good education in statistics, mathematics, and basic computer science, but there is a lack of direct teachings on machine learning, deep learning, AI, and big data, which are crucial for GenAI specialization
Prompt engineer	2	The degree program offers basics in computer science and programming but does not cover advanced algorithms, NLP, AI, or prompt optimization techniques, resulting in limited preparation
Ethical AI specialist	2	An analytical foundation useful for risk analysis is present, but there are no specific courses on technology ethics, digital law, or bias in AI models
AI product manager	1	No training in marketing, innovation management, or business management, which are necessary for this profile; the degree program is very technical and analytical
Creative AI specialist	0	No teachings related to creative processes, graphics, multimedia, or computational creativity: the degree program does not provide useful foundations for this role

Table 4 Example 3: evaluation of the bachelor's degree in statistics for data analysis in a large university in southern Italy

GenAI role	Score (0–5)	Explanation
GenAI scientist	3	Solid education in statistics, mathematics, and data analysis, but lacks dedicated courses in machine learning, deep learning, big data analytics, essential for a GenAI role
Prompt engineer	2	Provides basics in computer science and data analysis, but lacks training in NLP, AI, complex algorithms, and prompt design
Ethical AI specialist	2	Offers useful training on data analysis and risk evaluation, but lacks specific courses on Technology Ethics, Privacy Law, or AI bias management
AI product manager	1	Technical and quantitative degree program, without modules on business management, marketing, or AI product management
Creative AI specialist	0	No link to digital creativity, graphics, multimedia, or computational creativity: GenAI in creative fields is not addressed

cally, the selected degree programs are: (1) a master's degree in data science at a large university in northern Italy; (2) a bachelor's degree in Statistics at a medium-sized university in central Italy; and (3) a bachelor's degree in Statistics for Data Analysis at a large university in southern Italy.

4.2 Implementation details

All evaluations were conducted between June 2025 and July 2025 using the standard ChatGPT-4o web interface. The same prompt structure was systematically applied to all degree programs and to each of the five GenAI professional roles considered in the analysis.

The descriptions of the degree programs were collected directly from the official webpages of Italian universities and were evaluated in their original language (Italian). No translation procedures were applied prior to the assessment in order to preserve the original meaning and context of the program descriptions.

The evaluation process relied exclusively on the information contained in the official degree-program descriptions. When specific competencies were not explicitly mentioned, no additional information from external sources was introduced into the assessment. Consequently, the assigned readiness scores reflected only the evidence available in the official documentation of each program.

Each degree program was initially evaluated once using the standardized prompt. To assess the robustness of the procedure, a subset of degree programs was subsequently re-evaluated in independent sessions using the same prompt and evaluation criteria. The resulting scores showed a high degree of consistency, with only minor variations that did not materially affect the substantive conclusions of the study. This additional verification supports the stability and reliability of the proposed assessment framework.

All evaluations were performed through the standard ChatGPT-4o interface using the default settings available to end users at the time of the study. No custom parameter tuning, fine-tuning procedures, retrieval augmentation, or external knowledge sources were employed. Consequently, the assessment relied exclusively on the semantic comparison between the competency profiles defined for each GenAI role and the official descriptions of the university degree programs under examination.

The ChatGPT-4o interface did not allow the authors to set or retrieve sampling parameters such as temperature. Consequently, the assessment relied exclusively on the semantic comparison between the competency profiles defined for each GenAI role and the official descriptions of the university degree programs under examination.

The consistency check was conducted on a subset of 25 degree programs, corresponding to approximately 12% of the sample, re-evaluated in independent sessions using the same prompt and criteria.

5 Discussion of results

The primary aim of this study was to examine the proposed model by applying it manually to a representative sample of Italian university degree programs. This was achieved using structured prompts in combination with LLM support, aimed at evaluating the degree of alignment between degree programs and the competency profiles required for emerging professional roles in the field of GenAI.

The methodological approach employed in this pilot phase involved manually crafting structured prompts, which were subsequently submitted to ChatGPT-4o. Each prompt integrated official degree program descriptions, retrieved directly from university websites, with a standardized set of evaluation criteria corresponding to the five professional roles identified within the model: GenAI scientist, prompt engineer, ethical AI specialist, AI product manager, and creative AI specialist.

The LLM was instructed to assign a GenAI readiness score on a scale from 0 to 5 for each role, based on the extent to which the degree program addressed the relevant knowledge domains and skill sets. In addition to the quantitative scores, qualitative justifications were generated to articulate the rationale underlying each assessment. This prompt-based methodology enabled a structured and replicable evaluation process while preserving the flexibility to incorporate qualitative insights where contextually appropriate.

The analysed dataset comprised a convenience sample of 210 degree programs selected from 15 major Italian universities. The selection was designed to ensure substantial heterogeneity in terms of disciplinary orientation, institutional characteristics, degree level, and geographical location. Both STEM and non-STEM programs were included, covering undergraduate and postgraduate degrees from universities located in Northern, Central, and Southern Italy. The universities were chosen among some of the most important higher-education institutions in Italy, with the objective of ensuring broad coverage of different academic environments and educational traditions. Particular attention was devoted to disciplinary diversity and territorial balance. To ensure transparency and replicability, the full list of degree programs included in the analysis is available in the online repository at https://github.com/Magonza05/GenAI-project.

The objective of this sample was not to obtain statistically representative estimates for the entire Italian higher-education system. Rather, the sample was constructed to provide a sufficiently broad and diverse testing ground for evaluating the feasibility, robustness, and practical usefulness of the proposed GenAI-readiness assessment methodology. Consequently, the results should be interpreted as evidence regarding the applicability of the framework rather than as definitive measurements of the GenAI readiness of Italian university degree programs as a whole. A comprehensive summary of the main findings is provided in Table 5.

The aggregated results reveal substantial variation in GenAI readiness across the five professional profiles under examination. The role of AI product manager achieved the highest average readiness score. This outcome reflects the strong prevalence within Italian academic degree programs of business-oriented competencies - such as innovation management, product development, marketing strategy, and digital transformation - which are well aligned with the demands of AI product lifecycle management.

The ethical AI specialist role registered the second-highest average score (2.88), with 12 degree programs demonstrating full alignment. Degree programs in law, political science, and philosophy frequently incorporate courses on ethics, digital regulation, and data protection law, thereby providing a solid foundation for addressing the governance, legal, and societal implications of AI technologies. This result underscores the robustness of norma-

Table 5 Summary of role-specific GenAI readiness scores across the analyzed 210 degree programs

Role	Average score	No. of programs attaining the maximum score
GenAI scientist	2.37	15
Prompt engineer	2.18	4
Ethical AI specialist	2.88	12
AI product manager	3.12	20
Creative AI specialist	1.93	8

tive education within the Italian higher education system and highlights its potential to serve as a pipeline for AI governance roles, particularly when such degree programs are supplemented by targeted instruction in AI-specific risk assessment and regulatory frameworks.

In contrast, the GenAI scientist profile exhibited a more moderate average readiness (2.37), with 15 degree programs receiving the top score. While disciplines such as mathematics, statistics, and computer science are broadly represented, few degree programs explicitly cover advanced GenAI concepts, including deep generative models, transformer-based architectures, or AI-driven content synthesis. The lowest levels of readiness were observed in the roles of prompt engineer (2.18) and creative AI specialist (1.93). These emerging professions, positioned at the intersection of human intent and machine output, and at the confluence of algorithmic logic and creative practice, currently lack well-established academic analogues.

Despite these limitations, the results provide a valuable diagnostic overview of the current state of academic preparedness for GenAI-oriented professional roles within the Italian university system. They indicate areas of relative strength, particularly in business and legal education, while also exposing critical deficiencies in fields such as human-AI interaction, generative content production, and computational creativity. Strategically, these insights carry implications for a diverse array of stakeholders. For universities, they inform potential avenues for curricular reform. For students, they offer guidance in selecting educational trajectories aligned with future labor market opportunities. For employers,—especially in content-intensive sectors such as media, publishing, advertising, and e-learning—they provide actionable intelligence to inform talent acquisition strategies, internship programs, and collaborative initiatives with academic institutions aimed at cultivating GenAI-ready professionals.

The correlation matrix provides insight into the relationships among the scores assigned to the various professional roles (Table 6).

Only two correlation coefficients are close to zero, namely those between the ethical AI specialist and the GenAI data scientist, and between the creative AI specialist and the GenAI data scientist. The highest correlation is observed between the prompt engineer and creative AI specialist roles. This pattern may reflect partially overlapping competency domains, particularly those related to the effective use of generative AI systems. However, the observed association should not be interpreted as evidence of a causal relationship, a prerequisite structure between roles, or intentional curricular design.

Developing competencies aligned with multiple GenAI-related roles is a key indicator of program quality in the context of workforce readiness for both public and private sector organizations. Table 7 presents the distribution of university degree programs based on the number of qualifying skills offered across five target professional roles. Degree programs

Table 6 Correlation matrix among scores

	GenAI specialist	Prompt engineer	Ethical AI specialist	AI product manager	Creative AI specialist	Average
GenAI specialist	1.00	0.43	0.07	0.55	0.04	0.27
Prompt engineer	0.43	1.00	0.39	0.42	0.64	0.47
Ethical AI specialist	0.07	0.39	1.00	0.30	0.46	0.31
AI product manager	0.55	0.42	0.30	1.00	0.36	0.41
Creative AI specialist	0.04	0.64	0.46	0.36	1.00	0.38

Table 7 Distribution of degree programs according to the number of qualifying AI skills offered

Number of qualifying skills offered	Number of programs		GenAI Scientist	Prompt engineer	Ethical AI specialist	AI product manager	Creative AI specialist
5	2	2	✓	✓	✓	✓	✓
4	3	2	✓	✓	✓	✓	
		1		✓	✓	✓	✓
3	19	4	✓		✓	✓	
		3	✓	✓		✓	
		2		✓		✓	✓
		5		✓	✓		✓
		4		✓	✓	✓	
		1			✓	✓	✓
2	16	3	✓	✓			
		3	✓		✓		
		3		✓		✓	
		1		✓			✓
		3		✓	✓		
		3			✓		✓
1	4	2				✓	
		2			✓		

were classified as "qualifying" if they achieved a top score (5) in at least one role and a minimum score of 4 in the others. This classification captures the breadth and depth of GenAI skill coverage within each degree program.

As illustrated in Table 7, 24 degree programs offer qualified training in at least three of the five GenAI-related professional roles, suggesting a moderate level of multidimensional preparedness. However, only two programs provide comprehensive, high-level training across all five roles, indicating a substantial gap in fully integrated degree programs. Additionally, only three degree programs deliver qualified training for four roles, highlighting the rarity of broad-spectrum GenAI education.

Notably, these few highly qualified degree programs are concentrated within a limited number of universities, though geographically distributed across Northern, Central, and Southern Italy. Both degree programs covering all five roles are STEM-oriented, featuring two roles with the highest readiness score (5) and three with high scores (4).

Among the degree programs covering four roles, two omit the creative AI specialist, while one lacks preparation for the GenAI data scientist role. In the group of 19 degree programs addressing three roles, these two profiles are again the most commonly absent, suggesting under-representation.

Interestingly, only five of these 19 degree programs are STEM-related, further pointing to the need for greater integration of GenAI competencies in technical education. Table 7 details the number of degree programs by the number and combination of qualifying roles offered.

In conclusion, the manual application of the GenAI readiness assessment model to a representative sample of Italian university degree programs provides preliminary evidence and practical relevance of the proposed framework. It demonstrates the model's capacity to identify high-performing academic offerings, as well as domains requiring targeted intervention. The forthcoming phase of this research will aim to scale the methodology through automated batch processing and explore the incorporation of transversal competencies—such as teamwork, communication, and ethical reasoning—into the evaluation rubric.

Collectively, these findings contribute to the broader discourse on the evolving role of higher education in meeting the challenges of an AI-driven labor market, offering a practical and adaptive tool for aligning academic supply with emergent societal and economic needs.

6 Validation

To validate the reliability of this methodology, sample-based verification checks were conducted. These checks comprised two main components. The first involved expert judgments, conducted in both blinded and non-blinded formats. The second consisted of a sensitivity analysis, which entailed an in-depth comparison of results generated from identical input data by four independent GenAI systems.

6.1 Experts' judgements

As an exploratory validation exercise, the scores generated by ChatGPT-4o were reviewed by 11 reviewers from the 4 areas of Engineering, Economics, Statistics, Medicine. The experts were identified from 10 universities, considering professors and academic staff members who were familiar with specific degree programs included in the analysis. The experts examined 52 degree-programs. Disagreements mainly occurred when official webpages did not report optional courses, laboratory activities, project work, or teaching practices that were known to the instructors. For example, in some cases experts considered a program more aligned with the AI product manager profile because of project-based activities not explicitly described on the public webpage.

Expert review is frequently used as a qualitative validation strategy in exploratory assessment studies and provides an opportunity to compare model-generated evaluations with domain-specific knowledge and professional judgment (Mitchell 1997; Hand 2006). The reviewers were asked to examine the GenAI-readiness scores assigned to the degree programs and to indicate whether, in their judgment, the evaluations were broadly consistent with the actual educational content and objectives of the programs. In cases of disagreement, reviewers were invited to provide qualitative explanations for the discrepancy.

Overall, the feedback revealed a substantial degree of agreement between the ChatGPT-generated assessments and the experts' judgments. The few cases of disagreement were generally attributable to differences between the information explicitly reported in the official degree-program descriptions and the actual content delivered through courses, projects, or educational activities that were not fully reflected in the publicly available documentation.

Although this review process should not be interpreted as a formal statistical validation, it provides useful qualitative evidence supporting the plausibility and practical relevance of the proposed GenAI-readiness assessment framework.

6.2 Sensitivity analysis

In this section, we present an experiment assessing the sensitivity of results produced by different generative AI systems (Table 8). We examined five STEM degree programs: the three already described in Sect. 4, plus one small and one large university in central Italy, ensuring diversity in location and institutional size.

We asked three GenAI systems, developed independently from ChatGPT-4o, to provide numerical and textual evaluations of the adequacy of these programs for the professional roles outlined in Sect. 2. These additional systems are Perplexity AI (Tannenbaum 2026), DeepSeek (Deepseek 2024), and Claude 3.7 Sonne (Anthropic 2025). Identical inputs and prompts ensured consistency. Table 8 shows the GenAI readiness scores assigned by all systems and the standard deviations (st.dev.) for each role. Overall, evaluations were consistent (st.dev. < 0.5), but some roles displayed notable discrepancies (st.dev. > 0.5), discussed below.

The first case involves the master's degree in data science for the role of AI product manager at the large northern university (st.dev. 0.82). Scores were: ChatGPT 2, Perplexity 1, DeepSeek and Claude 3. Divergence stems from contrasting interpretations: DeepSeek and Claude valued optional courses in business analytics and innovation management, while ChatGPT and Perplexity emphasized missing core courses in marketing and management. Higher scores reflect viewing technical rigor as transferable to product management, while lower scores demand explicit managerial content.

The second case concerns the same program evaluated for the Creative AI Specialist role (st.dev. 0.87). Perplexity scored 0, citing the absence of computational creativity, digital graphics, or multimedia training while the others scored 2, assuming technical proficiency in AI could support creative applications. This highlights a methodological difference: Perplexity applies a strict content-based approach, while others adopt a functional perspective prioritizing skill adaptability. The third case evaluates the bachelor's degree in statistics from a medium-sized central university for the role of prompt engineer (st.dev. 0.71). ChatGPT and DeepSeek assigned 2, Perplexity 3, Claude 1. Perplexity's higher score relies on programming fundamentals as sufficient, while Claude highlights the lack of advanced NLP and AI courses as a critical gap, revealing a disagreement over general IT versus specialized NLP skills.

The fourth case examines the bachelor's degree in statistics for data analysis from a southern university for AI product manager readiness (st.dev. 0.83). Perplexity scored 0, citing no managerial content, while DeepSeek and Claude scored 2, valuing strong quantitative foundations as partially supporting management skills. This reflects the tension between expecting explicit managerial training and recognizing transferable analytical skills.

The fifth case considers the master's degree in data science from the large central university for the AI product manager role (st.dev. 0.67). Claude scored 3, emphasizing optional business analytics and project management courses, while Perplexity scored 1, discounting these in favor of mandatory content. This illustrates a recurring divergence on the weight of optional courses in overall preparedness.

In summary, discrepancies arise from differing evaluation frameworks: a formal criterion focused on domain-specific courses versus a functional criterion valuing transversal skill adaptability. This interpretive divergence underlies most high-variance cases.

Table 8 Sensitivity analysis

Program	ChatGPT	Perplexity	DeepSeek	Claude	SD
GenAI specialist:					
Master's in data science at a large university in northern Italy	5	4	4	4	0.43
Bachelor's in statistics at a medium sized university in central Italy	3	4	4	3	0.5
Bachelor's in statistics at a large university in southern Italy	3	3	3	3	0
Bachelor's in economics at a small university in central Italy	0	1	1	1	0.43
Master's in data science at a large university in central Italy	5	4	4	4	0.43
Prompt engineer:					
Master's in data science at a large university in northern Italy	4	3	3	3	0.43
Bachelor's in statistics at a medium sized university in central Italy	2	3	2	1	0.71
Bachelor's in statistics at a large university in southern Italy	2	2	1	1	0.5
Bachelor's in economics at a small university in central Italy	0	1	0	0	0.43
Master's in data science at a large university in central Italy	4	3	3	3	0.43
Ethical AI specialist:					
Master's in data science at a large university in northern Italy	3	2	2	2	0.43
Bachelor's in statistics at a medium sized university in central Italy	2	2	1	2	0.43
Bachelor's in statistics at a large university in southern Italy	2	1	1	2	0.50
Bachelor's in economics at a small university in central Italy	1	2	2	1	0.50
Master's in data science at a large university in central Italy	3	2	2	2	0.43
AI product manager:					
Master's in data science at a large university in northern Italy	2	1	3	3	0.82
Bachelor's in statistics at a medium sized university in central Italy	1	1	2	2	0.50
Bachelor's in statistics at a large university in southern Italy	1	0	2	2	0.83
Bachelor's in economics at a small university in central Italy	3	2	3	2	0.50
Master's in data science at a large university in central Italy	2	1	2	3	0.67
Creative AI specialist:					
Master's in data science at a large university in northern Italy	2	0	2	2	0.87
Bachelor's in statistics at a medium sized university in central Italy	0	0	1	0	0.43
Bachelor's in statistics at a large university in southern Italy	0	0	1	0	0.43

Table 8 (continued)

Program	ChatGPT	Perplexity	DeepSeek	Claude	SD
Bachelor's in economics at a small university in central Italy	0	0	0	0	0.00
Master's in data science at a large university in central Italy	2	0	1	2	0.83

7 Conclusion and future work

This study introduces a structured methodology for evaluating the GenAI readiness of university degree programs, providing a coherent framework aligning academic training with the demands of AI-driven roles. By analyzing how different programs prepare students for occupations such as GenAI scientist, prompt engineer, ethical AI specialist, AI product manager, and creative AI specialist, the model serves both students seeking informed career planning and companies refining recruitment and talent strategies. Quantitatively assessing the relevance of degree programs ensures AI professionals gain the competencies needed to drive innovation and interdisciplinary integration.

7.1 Limitations

Despite the encouraging results, the proposed framework is subject to several limitations that should be acknowledged.

First, the evaluations depend on the capabilities and interpretative behaviour of the specific GenAI systems employed. Although the sensitivity analysis revealed a substantial degree of consistency across different systems, future model updates may produce somewhat different assessments.

Second, the methodology relies exclusively on information contained in official degree-program descriptions. These descriptions may be incomplete, may emphasize promotional aspects, and may not fully reflect the actual content delivered through courses, projects, internships, or extracurricular activities. This limitation is also supported by the expert-review exercise, where the few cases of disagreement were generally attributable to differences between publicly available descriptions and the actual content delivered within the programs.

Third, university webpages are not standardized across institutions, creating variability in the amount, structure, and quality of information available for evaluation.

Finally, different GenAI systems may assign different importance to optional courses, interdisciplinary activities, or implicitly described competencies, introducing an additional source of variability in the resulting readiness scores.

Consequently, the proposed framework should be interpreted as a decision-support and diagnostic tool rather than as a definitive measure of GenAI readiness.

7.2 Future developments

Future developments include expanding the model to cover additional GenAI-related professions in the broader digital landscape, such as cybersecurity, GenAI-powered automation, and robotics. This extension would enhance its versatility, helping institutions evaluate readiness for a wider spectrum of technology-intensive careers. A further priority for future validation is to replicate the evaluation using GPT-5 or later GPT-series models and to compare the resulting scores with those obtained from ChatGPT-4o, to assess the stability of the GenAI-readiness ratings across successive generations of LLMs.

Another step is creating an interactive digital platform based on the GenAI readiness model for students and HR professionals. This tool could offer personalized guidance, helping students identify programs aligned with career goals and supporting companies in forming targeted partnerships with universities. Integrated GenAI-driven analytics would allow dynamic updates to reflect curricular changes and emerging roles, maintaining relevance in the rapidly evolving GenAI education and employment landscape.

Although the current model emphasizes technical and role-specific competencies, future iterations will integrate transversal skills—critical thinking, collaboration, and ethical awareness—essential in GenAI environments. Many programs already incorporate such abilities through coursework in law, economics, communication, and teamwork. Though not always framed in GenAI terms, these competencies support constructive engagement with AI and human-centered innovation. For instance, legal and business literacy enable engineers to address GenAI governance and market impact, while communication and design thinking help prompt engineers and product managers foster interdisciplinary collaboration. Teamwork and integrative approaches remain vital across all GenAI roles, particularly in agile, fast-changing contexts.

The model's modular, scalable design facilitates this expansion. Operating through prompt-driven alignment between program descriptions and competency frameworks, it can easily integrate new skill categories—like soft skills—by adjusting the underlying prompting structure. This flexibility allows adaptation to institutional priorities, policy frameworks (e.g., EU digital competence frameworks), and sector-specific needs. Consequently, the model remains applicable in a rapidly transforming educational and technological landscape, offering a solid foundation for aligning degree programs with the future AI-driven labor market.

Appendix: Descriptions of the competencies for the other professional roles

Prompt engineer

Key competencies:
prompt optimization, understanding of language models, AI debugging.

- *Recommended courses*:Bachelor's: programming, data structures, fundamentals of computer science.
- Master's: natural language processing, artificial intelligence, expert systems, decision support systems.Prompt engineers design effective inputs for GenAI models. A strong foundation in programming and algorithms is essential to build efficient solutions. Knowledge of programming languages enable interaction with AI tools. At the graduate level AI supports intelligent model development and expert/decision systems help apply structured domain knowledge in practical applications.

Ethical AI specialist

Key Competencies:

ethical and legal implications of AI, development of ethical guidelines, bias mitigation in AI models.

- *Recommended Courses*:Bachelor's: ethics and technology, fundamentals of computer science, law and technology.
- Master's: AI ethics, privacy law, risk analysis.This role ensures responsible and compliant AI deployment. Key skills include identifying bias, interpreting legal frameworks, and evaluating societal impacts. Undergraduate courses provide ethical and legal foundations, while master's programs deepen expertise in AI-specific ethics, privacy compliance, and risk management strategies.

AI product manager

Key Competencies:

AI product lifecycle management, business requirement translation, awareness of AI market trends.

- *Recommended Courses*:Bachelor's: business management, fundamentals of computer science, marketing.
- Master's: innovation management, product development, digital marketing strategy, business analytics.A strategic figure overseeing AI product development from concept to launch. Responsibilities include translating business needs into technical specs and monitoring market trends. Undergraduate programs offer business, technical, and marketing basics. Graduate courses focus on innovation processes, digital strategy, and data-driven decision-making.

Creative AI specialist

Key Competencies:

use of GenAI for content creation, integration into creative workflows, AI-based editing technologies.

- *Recommended Courses*:Bachelor's: digital graphics, fundamentals of computer science, multimedia production.
- Master's: AI for creativity, computational creativity, post-production techniques.This role merges creativity with AI technologies to produce innovative content. Key skills include generating media using GenAI, embedding AI in creative workflows, and refining outputs using editing tools. Undergraduate training focuses on visual and multimedia skills. Graduate programs explore computational ideation and content refinement.

Author contributions All authors contributed equally to the development of this work and interacted closely throughout all stages of the research process. The initial research idea and conceptual framework were developed collaboratively by the authors. Data collection and preparation were carried out jointly. The statistical analyses were performed and discussed collectively, with continuous feedback among the authors. The

manuscript was written through a collaborative process in which all authors contributed to drafting, revising, and refining the text. All authors reviewed and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

Funding Open access funding provided by Università degli Studi di Roma La Sapienza within the CRUI-CARE Agreement. Open Access funding provided thanks to the CRUI-CURE agreement with Springer Nature. This research received no external funding.

Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no conflict of interest.

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