
MAPPING GENERATIVE AI EXPOSURE IN BUSINESS AND ECONOMICS HIGHER EDUCATION: EVIDENCE FROM ROMANIAN PUBLIC UNIVERSITIES

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Abstract:

Generative Artificial Intelligence (GenAI) is reshaping labour markets and creating new challenges for higher education. This study develops an analytical framework for assessing the occupational exposure associated with university study programmes. The framework maps university qualifications to occupational profiles and applies the ILO Global Occupational Exposure Index to estimate the occupational exposure of future graduates. A database was developed by integrating information from the Romanian National Qualifications Register (RNCIS), official data on enrolment capacity, COR, ISCO-08 and occupational exposure data from the ILO Global Occupational Exposure Index. The database covers 263 Business and Economics Bachelor's programmes and 27,690 potential graduates from Romanian public universities. The findings show that 66.9% of potential graduates are associated with occupations characterised by high exposure to Generative AI, while no study programmes are linked to occupations classified as Not Exposed, Minimal Exposure or Gradient 1. The study provides the first systematic assessment of occupational exposure associated with university study programmes through the analysis of Business and Economics Bachelor's programmes in Romanian public universities. The proposed framework is transparent, replicable and can be applied to other ISCED fields and national higher education systems.

Key words: *Generative Artificial Intelligence; Occupational Exposure; Higher Education; Business and Economics; Labour Market*

1. Introduction

Recent advances in Generative Artificial Intelligence (GenAI) have intensified interest in the implications of artificial intelligence for labour markets, occupations and

skills. The rapid progress of large language models has expanded AI capabilities beyond routine automation towards a growing range of cognitive tasks, raising new questions about how work may evolve and how workers can adapt to technological change (Acemoglu, 2025; Gmyrek et al., 2023). These developments have attracted growing attention not only in academic research but also among international organisations such as the International Labour Organization (ILO), the Organisation for Economic Co-operation and Development (OECD) and the International Monetary Fund (IMF), which increasingly emphasise both the opportunities and the challenges associated with the widespread adoption of Generative AI for labour markets, productivity and skills (Cazzaniga et al., 2025; Lorenz et al., 2023).

Higher education institutions play a central role in preparing future graduates for occupations that are increasingly influenced by Generative AI. As labour market requirements evolve, universities face growing pressure to ensure that graduates acquire the knowledge, skills and competencies needed to work effectively alongside AI technologies. Recent studies suggest that responding to these challenges requires more than simply incorporating AI tools into teaching. Universities need to reconsider teaching, learning and assessment practices while ensuring that graduates develop the digital and professional competencies required in AI-enabled workplaces (Leite, 2025; Tharapos et al., 2025). Evidence also suggests that the educational benefits of Generative AI depend not only on access to the technology itself but also on the development of complementary competencies and supportive institutional environments. Technological self-efficacy, domain-specific competencies and appropriate pedagogical support are therefore essential for enabling effective and responsible AI use in higher education (Lelescu et al., 2025; Zhang et al., 2026).

Despite the growing body of research on Generative AI and the increasing availability of occupational exposure measures, limited attention has been devoted to the implications of occupational exposure for higher education. Existing studies have primarily examined workers, occupations and labour markets (Gmyrek et al., 2023), while universities have been discussed mainly in terms of teaching practices, AI adoption and curriculum adaptation. Consequently, little is currently known about the occupational exposure associated with university study programmes and the future graduates they prepare. This lack of evidence makes it difficult for higher education institutions and policymakers to anticipate how AI-driven changes in occupational requirements may affect different fields of study and to develop informed educational responses.

To address this gap, the present study examines the extent to which Business and Economics Bachelor's programmes offered by Romanian public universities are associated with occupational profiles exposed to Generative AI. The analysis links university study programmes to the occupational profiles associated with the qualifications registered in the Romanian National Qualifications Register (RNCIS) and applies the ILO Global Occupational Exposure Index to estimate the occupational exposure of future graduates. Specifically, the study maps university study programmes to occupational profiles, estimates occupational exposure using the ILO framework and analyses its distribution across Business and Economics higher education in Romania.

The study makes three main contributions. First, it extends the application of occupational exposure assessment to higher education by examining university study programmes through the occupational profiles associated with the qualifications they award. Second, it provides the first systematic evidence on the occupational exposure associated with Business and Economics Bachelor's programmes in Romanian public universities. Third, it develops a newly constructed analytical database integrating the Romanian National Qualifications Register (RNCIS), COR, ISCO-08 and the ILO Global Occupational Exposure Index into a transparent and replicable analytical framework that can be applied to other ISCED fields and national higher education systems.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature and identifies the research gap. Section 3 presents the methodology and data. Section 4 reports the empirical findings. Section 5 discusses the results, and the final section concludes the paper.

2. Literature review

2.1. Artificial Intelligence, Generative AI and the Transformation of Knowledge Work

The rapid development of Artificial Intelligence (AI), particularly Generative Artificial Intelligence (GenAI), has transformed academic and policy discussions on the future of work. While earlier waves of digital technologies primarily automated routine physical and cognitive tasks, recent advances in large language models (LLMs) have considerably expanded the range of activities that can be performed or supported by AI. Eloundou et al. (2023) demonstrate that the capabilities of LLMs extend beyond routine automation to a broad spectrum of knowledge-intensive activities, including writing, information synthesis, coding and analytical reasoning. Consequently, the potential impact of AI is no longer confined to low-skilled occupations but increasingly affects highly educated professionals performing cognitive, analytical and creative tasks. Recent evidence suggests that occupations requiring higher levels of education and cognitive skills are among those with the greatest potential exposure to Generative AI, although the effects are expected to differ substantially depending on task composition and the complementarity between human capabilities and AI systems (Eloundou et al., 2023; P. Gmyrek et al., 2025).

Rather than asking whether occupations will disappear, recent research increasingly focuses on how AI transforms the tasks performed within occupations (Acemoglu et al., 2020; P. Gmyrek et al., 2025). Building on the task-based framework originally developed by Acemoglu and Restrepo (2018), recent studies recognise that occupations consist of heterogeneous bundles of tasks, which may be automated, augmented or remain largely unaffected depending on the capabilities of AI systems and the potential for human-machine complementarity (P. Gmyrek et al., 2025). This shift from occupations to tasks has led to the emergence of the concept of occupational exposure as a proxy for estimating the extent to which different occupations may be affected by AI according to their task composition. Several methodological approaches have subsequently been proposed to operationalise occupational exposure. Capability-based measures compare AI capabilities with occupational abilities (Felten et al., 2021), patent-based approaches infer exposure from the overlap between patented AI technologies and occupational tasks

(Webb, 2019), while more recent frameworks rely on large language models to evaluate task-level exposure directly from occupational descriptions (Pawel Gmyrek et al., 2025; Tolan et al., 2021).

Although these approaches differ in their underlying assumptions and measurement strategies, they all estimate occupational exposure at the occupation level rather than at the level of educational qualifications.

2.2 Measuring Occupational Exposure to AI

Because direct evidence on AI adoption at the occupational level remains limited, recent research has increasingly relied on occupational exposure as a proxy for estimating the potential effects of AI on work. Rather than measuring observed adoption, exposure indices assess the extent to which the tasks associated with different occupations overlap with current AI capabilities. Consequently, occupational exposure has emerged as one of the principal analytical tools for examining the labour market implications of AI, while different methodological approaches capture complementary dimensions of this phenomenon (Frank et al., 2025; Green et al., 2025; Jaccoud, 2025).

Several methodological approaches have been developed to estimate occupational exposure to AI, reflecting different conceptualisations of how AI capabilities interact with occupational tasks. Existing measures differ with respect to the underlying data sources, the definition of exposure and the mechanisms through which AI is assumed to affect work. Consequently, occupational exposure indices should be viewed as complementary rather than competing approaches, each capturing distinct dimensions of the relationship between AI technologies and occupations (Green et al., 2025; Jaccoud, 2025).

Among the earliest and most influential measures of occupational exposure is the AI Occupational Exposure (AIOE) index developed by Felten et al. (2021). Rather than measuring the actual adoption of AI technologies, the AIOE framework estimates potential occupational exposure by comparing AI capabilities with the abilities required to perform different occupations. The underlying assumption is that occupations relying more heavily on abilities that can be replicated by AI systems exhibit higher levels of potential occupational exposure. Owing to its transparent methodology and compatibility with standard occupational classifications, the AIOE framework has been widely adopted in subsequent empirical research and provides the foundation for several later occupational exposure measures (Green et al., 2025; Jaccoud, 2025).

An alternative perspective is provided by the patent-based approach introduced by Webb (2019), which measures occupational exposure by matching the content of patent documents with occupational task descriptions. The methodology extracts verb–noun pairs from patent titles and O*NET task descriptions to quantify the overlap between technological applications and the tasks performed within occupations. Unlike capability-based approaches, the Webb’s approach infers occupational exposure from technological innovation reflected in patent activity, thereby providing a complementary perspective for assessing the potential labour market impact of artificial intelligence.

More recent methodological developments have extended occupational exposure analysis by modelling more explicitly the relationship between occupational tasks and AI capabilities. Tolan et al. (2021) develop a framework that links occupations to work tasks,

cognitive abilities and AI benchmarks through an intermediate layer of cognitive abilities, allowing occupational exposure to be assessed beyond traditional automation measures. This framework captures the potential impact of AI on occupations without assuming direct labour substitution and provides a more detailed understanding of how different cognitive abilities contribute to occupational exposure. Building on these developments, Eloundou et al.(2023) estimate occupational exposure to large language models, while Gmyrek et al.(2025) further refine this approach by constructing an internationally comparable Global Occupational Exposure Index based on ISCO-08 occupations.

The methodological evolution of occupational exposure research has progressively moved from capability- and patent-based measures towards task-oriented frameworks supported by large language models. Despite differences in their underlying assumptions and measurement strategies, these approaches share the common objective of estimating the potential effects of AI on occupations before widespread adoption can be directly observed. Among them, the refined ILO Global Occupational Exposure Index provides one of the most comprehensive and internationally comparable frameworks, making it particularly suitable for studies based on ISCO-08 occupational classifications, including the present study.

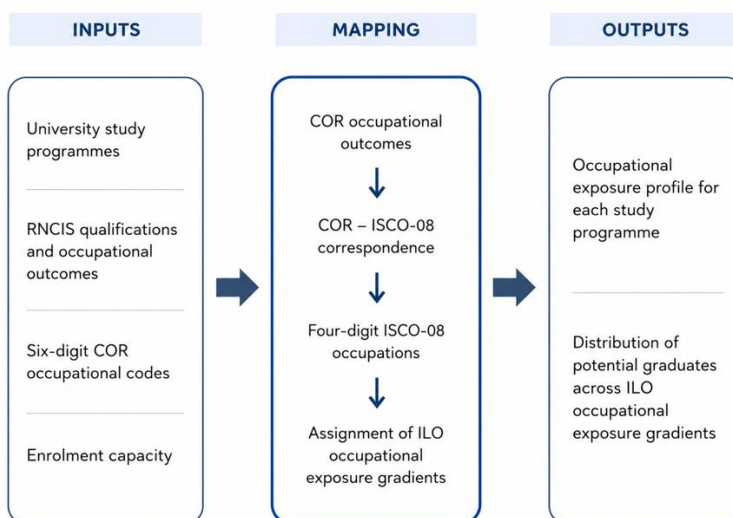
2.3 Higher Education and Graduate Employability in the Age of AI

Growing evidence suggests that the labour market implications of Generative AI extend well beyond routine occupations and increasingly affect highly educated workers performing cognitive and knowledge-intensive tasks. Recent studies consistently show that AI exposure rises with educational attainment, with college graduates and professionals among the occupational groups exhibiting the highest levels of potential exposure (Lábaj et al., 2025). Moreover, evidence from cross-country analyses indicates that highly educated workers are more likely to transition from AI-vulnerable occupations towards occupations where AI complements human capabilities, although these technological changes may simultaneously disrupt labour market entry by reducing traditional stepping-stone jobs for young graduates (Cazzaniga et al., 2025). These developments are already influencing educational and occupational decisions, as the emergence of Generative AI has altered young people's occupational preferences, particularly for occupations characterised by cognitive and language-intensive tasks (Goller et al., 2025).

These developments have important implications for higher education institutions, which are increasingly expected to prepare graduates for a labour market transformed by Generative AI. Rather than simply integrating Generative AI into educational processes, universities are challenged to redesign curricula, assessment methods and learning outcomes to ensure that graduates develop the analytical, critical thinking and professional judgement skills required to work effectively alongside AI technologies (Leite, 2025; Tharapos et al., 2025). Recent evidence also suggests that the integration of Generative AI in higher education remains at an early stage and requires coherent institutional strategies, educator preparedness and the development of AI literacy across the academic community (Lelescu et al., 2025). Consequently, higher education is increasingly viewed not only as a provider of disciplinary knowledge but also as a key actor in supporting graduates' long-term employability in an AI-driven economy.

Research on occupational exposure has expanded rapidly alongside a growing body of literature examining the implications of Generative AI for higher education. Nevertheless, these two research streams have evolved independently. Occupational exposure studies primarily analyse workers, occupations and labour markets, whereas higher education research focuses on curriculum adaptation, teaching practices, AI competencies and graduate employability. As a result, universities are generally examined as educational institutions rather than as providers of future occupational profiles. While occupational exposure has been extensively assessed at the occupation level, a methodological gap remains in translating occupational exposure assessment into the higher education context. To address this gap, the present study develops a transparent and replicable analytical framework that links university qualifications to occupational profiles and applies the ILO Global Occupational Exposure Index to assess the occupational exposure associated with university study programmes. The proposed framework is summarised in Figure 1.

Figure 1. Analytical framework for translating occupational exposure assessment into the higher education context



Source: Developed by the authors

3. Methodology

3.1. ILO occupational exposure framework

The first ILO Global Index of Occupational Exposure to Generative AI was developed by (Gmyrek et al., 2023) to assess the potential exposure of occupations and tasks to GenAI technologies. The study adopted a task-based approach using occupational and task descriptions from the four-digit ISCO-08 classification and GPT-4 to estimate task-level exposure scores. These scores were subsequently aggregated at occupational level and linked to ILO labour market data to estimate the potential

employment effects of GenAI exposure. Importantly, the framework measures potential technological exposure rather than observed automation or employment displacement.

In response to rapid advances in GenAI capabilities, the ILO developed a refined version of the index in 2025. The updated framework used three large language models to generate initial synthetic assessments of the potential automation of occupational tasks, compared with the use of GPT-4 in the original study. Worker assessments and expert validation were subsequently incorporated into the scoring procedure. The empirical basis was also substantially expanded by using the Polish six-digit occupational classification, comprising 2,541 occupations and 29,753 associated tasks. This classification provided more detailed and up-to-date occupational information than the four-digit ISCO-08 task structure used in the original study. The resulting evaluations were incorporated into an AI-assisted adjustment and prediction procedure used to generate exposure scores for the complete set of occupational tasks (Pawel Gmyrek et al., 2025).

The refined index aggregates task-level exposure scores at occupational level by calculating the mean and standard deviation of task scores for each four-digit ISCO-08 occupation, with all tasks receiving equal weight. While the mean captures the overall level of potential exposure within an occupation, the standard deviation reflects the variation in exposure across its constituent tasks. Based on the combination of these two measures, occupations are classified into four progressively increasing exposure gradients, in addition to the categories of Minimal Exposure and Not Exposed (Pawel Gmyrek et al., 2025). The classification criteria and interpretation of these categories are presented in Table 1.

Table 1. GenAI exposure gradients: classification criteria and interpretation

Exposure category	Classification criteria	Interpretation
Not Exposed	Occupations not meeting the criteria for any of the exposure categories below	Most tasks remain relatively unaffected by GenAI, with low mean exposure and low variability across tasks
Minimal Exposure	Mean < 0.5 and Mean + SD > 0.4	Some tasks show moderate automation potential, while overall occupational exposure remains limited
Gradient 1	Mean < 0.4 and Mean + SD ≥ 0.5	Low average exposure combined with high variability across tasks; some tasks have substantially higher automation potential
Gradient 2	0.4 ≤ Mean < 0.5 and Mean + SD ≥ 0.5	Moderate average exposure and high variability across tasks
Gradient 3	0.5 ≤ Mean < 0.6 and Mean + SD ≥ 0.5	Higher average exposure and high variability across tasks
Gradient 4	Mean ≥ 0.6 and Mean - SD ≥ 0.5	High average exposure and relatively low variability across tasks, indicating consistently high exposure across occupational tasks

Note: Mean represents the arithmetic mean of task-level exposure scores within an occupation, and SD represents their standard deviation. All tasks are equally weighted.

Source: Authors' adaptation based on Gmyrek et al. (2025), Table 5, ILO Working Paper 140.

The exposure gradients represent progressively increasing levels of potential occupational exposure to GenAI, while also accounting for differences in the distribution of exposure across tasks within occupations. At the highest level, Gradient 4 identifies

occupations characterised by both high average exposure and consistently high exposure across tasks.

The Polish six-digit occupational classification, which served as the empirical basis for developing the refined ILO occupational exposure index, is hierarchically aligned with ISCO-08, allowing the resulting task-level assessments to be aggregated to the internationally harmonised four-digit ISCO-08 occupational level. This compatibility enables the refined exposure index to be applied across countries and linked to national occupational classifications that provide an official correspondence with ISCO-08 (Pawel Gmyrek et al., 2025). In the present study, this feature provides the methodological basis for applying the refined ILO index to Romania, where occupational outcomes associated with higher education qualifications are officially classified using six-digit COR codes and can be mapped to the corresponding four-digit ISCO-08 occupations.

3.2. Data sources and construction of the analytical database

To apply the refined ILO occupational exposure framework to Romanian higher education, a new analytical database was constructed covering all Romanian public universities offering Bachelor's degree programmes in the field of Business and Economics for the 2026–2027 academic year. The primary data source was Government Decision No. 191/2026, which officially establishes the structure of Romanian higher education institutions, accredited study programmes, modes of study and the maximum authorised enrolment capacity for each Bachelor's programme for the 2026–2027 academic year (Government of Romania, 2026). Additional programme-level information, including officially registered occupational outcomes, was collected from the Romanian National Register of Qualifications (RNCIS) (National Authority for Qualifications, 2026).

First, all Romanian public universities were identified. Subsequently, universities offering Bachelor's programmes in Business and Economics were selected. The database covers the complete population of Bachelor's programmes across all eight officially recognised Business and Economics fields of study in Romania, resulting in a final population of 24 public universities and 263 accredited study programmes.

For each study programme, information was collected on the university, field of study, mode of study, maximum authorised enrolment capacity and officially registered occupational outcomes. The final database comprises 263 Bachelor's study programmes with a total authorised enrolment capacity of 27,690 study places, including programmes delivered in full-time, distance-learning and reduced-frequency formats. While each study programme constitutes a distinct observation in the database, aggregate exposure distributions were calculated using authorised enrolment capacity to account for differences in programme size.

To assess whether restricting the main analysis to public universities could materially affect the overall exposure patterns, a complementary analysis of private universities was also conducted. The complementary dataset covers all private universities offering Bachelor's degree programmes in Economic Sciences and includes all 113 programmes across the same eight fields of study, representing 23 institutions and a total authorised enrolment capacity of 8,335 study places. Together, public and private

universities account for 35,845 authorised study places, of which public universities represent approximately 77%.

Occupational outcomes associated with each Bachelor's study programme were extracted from the Romanian National Register of Qualifications (RNCIS), which specifies the occupational profiles officially linked to each qualification (National Authority for Qualifications, 2026). Occupational outcomes were recorded using the corresponding six-digit Romanian Classification of Occupations (COR) codes together with their official occupational titles. Where multiple occupational outcomes were listed for the same study programme, only the first listed occupational outcome was retained for the subsequent mapping procedure.

The resulting database comprised 93 distinct six-digit COR occupational outcomes associated with the analysed study programmes. These occupational outcomes constitute the starting point for the subsequent mapping to the international ISCO-08 classification.

During the construction and validation of the occupational database, two minor inconsistencies between official data sources required additional verification. First, the newly established Bachelor's programme *Artificial Intelligence Applied in Economics and Business*, introduced by the Bucharest University of Economic Studies (ASE), was not yet registered in the Romanian National Register of Qualifications (RNCIS) at the time of data collection. Its occupational outcomes were therefore provisionally assigned based on the official programme description and the occupational profiles of comparable programmes offered by the same faculty. Second, the study programme *Economic Statistics and Data Science* appeared in RNCIS under its previous title, *Statistics and Economic Forecasting*. As all three universities offering this programme were associated with identical COR occupational outcomes and the same ISCO-08 occupation, the difference was treated as a programme name update rather than as a methodological difference.

3.3. Occupational mapping and assignment of exposure measures

The six-digit COR occupational outcomes were mapped to the corresponding four-digit ISCO-08 groups using the official correspondence between the Romanian Classification of Occupations (COR) and the International Standard Classification of Occupations (ISCO-08) (National Authority for Qualifications, 2026). This mapping provided the methodological link between the Romanian higher education data and the occupational exposure measures reported in the ILO Global Index of Occupational Exposure to Generative AI. The use of six-digit COR occupational codes ensured consistency with the Romanian qualification framework, while the official COR–ISCO correspondence enabled the application of the ILO Global Index of Occupational Exposure to Generative AI at the internationally harmonised four-digit ISCO-08 level (Pawel Gmyrek et al., 2025).

The 93 distinct COR occupational outcomes identified in the database were successfully mapped to 10 four-digit ISCO-08 occupations. Where multiple COR occupations corresponded to the same ISCO-08 occupation, they were assigned the same occupational exposure measures, reflecting the occupational level at which exposure scores and gradients are reported in the ILO index.

With the exception of the newly established programme discussed above, the mapping procedure relied exclusively on the official COR–ISCO correspondence, ensuring methodological consistency, transparency and full reproducibility of the classification process.

Each four-digit ISCO-08 occupation identified in the Romanian dataset was matched with the pre-calculated occupational mean exposure score and exposure gradient reported in Annex Table A1 of the refined 2025 ILO Global Index of Occupational Exposure to Generative AI (Pawel Gmyrek et al., 2025). These externally derived occupational exposure measures were assigned to all public university study programmes linked to the corresponding ISCO-08 occupation. Because exposure measures are defined at the four-digit ISCO-08 level, study programmes linked to the same ISCO-08 occupation received identical occupational exposure indicators.

The ILO exposure indicators were treated as externally derived occupational-level measures and were not recalculated using Romanian task-level data. Accordingly, the present study does not estimate new occupational exposure scores, reproduce the ILO methodology or predict the impact of Generative AI on Romanian occupations. Instead, it applies the published ILO occupational exposure framework to a newly constructed database linking higher education study programmes, officially registered occupational outcomes and authorised enrolment capacity.

Although both occupational mean exposure scores and exposure gradients were retained in the analytical database, the empirical analysis primarily relies on exposure gradients. The categorical classification provided by the gradients facilitates the aggregation of authorised enrolment capacity and the comparison of exposure patterns across study programmes, fields of study and higher education sectors. Mean exposure scores were included as supplementary occupational-level information but were not used as the primary basis for the aggregate analysis.

For the complementary analysis of private universities, only exposure gradients were assigned. The gradients were initially assigned based on the exposure classification of the corresponding specialisation in the public university dataset. Where the same specialisation was associated with different exposure gradients across public universities, the occupational outcomes registered in RNCIS were examined for the corresponding private university programmes to determine the appropriate exposure gradient. The complementary analysis was used to assess whether restricting the main analysis to public universities materially affected the overall distribution of GenAI exposure levels.

3.4. Aggregation and analytical procedure

Following the assignment of occupational exposure measures to individual study programmes, authorised enrolment capacity was aggregated to examine the distribution of GenAI exposure across the analysed higher education system. Depending on the analytical dimension considered, enrolment capacity was aggregated by ISCO-08 occupation, exposure gradient, field of study and mode of study. For each analytical category, the corresponding authorised enrolment capacities were summed and expressed as a percentage of the relevant total authorised enrolment capacity. The reported

percentages therefore reflect the distribution of authorised enrolment capacity rather than the distribution of study programmes.

The analysis also examined the relationship between specialisations and occupational profiles. Study programmes belonging to the same officially recognized specialisation were grouped using the standardised specialisation categories defined in the Romanian higher education nomenclature. Distinct ISCO-08 occupations associated with each specialisation were identified, and authorised enrolment capacity was aggregated separately for each specialisation–occupation combination. This procedure allowed the analysis to identify occupational heterogeneity within specialisations associated with multiple ISCO-08 occupations and, where applicable, different exposure gradients, as well as the concentration of authorised enrolment capacity across occupational profiles.

Finally, a complementary analysis was conducted for private universities. Authorised enrolment capacity was aggregated by exposure gradient and compared with the distribution observed for public universities. This analysis was used to assess whether restricting the main analysis to public universities materially affected the overall pattern of occupational exposure to GenAI.

4. Results/findings

4.1. Overview of Business and Economics Higher Education in Romanian Public Universities

The analytical dataset covers all Romanian public universities offering Bachelor's degree programmes in the eight officially recognised Business and Economics fields of study. Of the 52 public universities operating in Romania during the 2026–2027 academic year, 24 offer at least one Bachelor's programme in this field. Together, these universities provide 263 accredited study programmes with a total authorised enrolment capacity of 27,690 study places, representing approximately 15.4% of the total authorised enrolment capacity of Romanian public Bachelor's education (180,285 study places). The position of Business and Economics within the Romanian public higher education system is summarised in Table 2.

Table 2. Position of Business and Economics Bachelor's Education within the Romanian Public Higher Education System

Indicator	Value
Public universities in Romania	52
Public universities offering Business and Economics Bachelor's programmes	24
Total authorised enrolment capacity (all Bachelor's programmes)	180285
Authorised enrolment capacity (Business and Economics)	27690
Business and Economics share of total authorised enrolment capacity	15.4%

Source: Authors' compilation and calculations based on HG No. 191/2026.

The analysed Business and Economics dataset comprises 263 accredited Bachelor's study programmes delivered by 24 public universities across the eight officially recognised fields of study. The programmes include 191 full-time, 65 distance-learning and

7 reduced-frequency programmes, with a total authorised enrolment capacity of 27,690 study places. Overall, the analysed programmes are associated with 93 distinct occupational outcomes defined in the Romanian Classification of Occupations (COR), which were subsequently mapped to ten four-digit ISCO-08 occupations. The main characteristics of the analytical dataset are presented in Table 3.

Table 3. Characteristics of the analysed Business and Economics dataset

Characteristic	Value
Public universities offering Business and Economics programmes	24
Business and Economics fields of study	8
Bachelor's study programmes	263
Full-time programmes	191
Distance-learning programmes	65
Reduced-frequency programmes	7
Total authorised enrolment capacity	27690
Full-time authorised enrolment capacity	21520
Distance-learning authorised enrolment capacity	5535
Reduced-frequency authorised enrolment capacity	455
Distinct occupational outcomes (COR)	93
Four-digit ISCO-08 occupations	10

Source: Authors' compilation and calculations based on HG No. 191/2026 and RNCIS.

The institutional distribution of Business and Economics study programmes across Romanian public universities is presented in Table 4. While a relatively small group of traditional programmes is widely established across the higher education system, the institutional diversity within several fields of study reflects the gradual expansion and specialisation of the educational offer. The resulting programme structure provides the institutional context for the occupational mapping and GenAI exposure analysis presented in the following sections.

Table 4. Distribution of Business and Economics Study Programmes Across Romanian Public Universities

Field of study	Study programme	Number of universities
Accounting	Accounting and Management Information Systems	21
Business Administration	Economics of Commerce, Tourism and Services	18
Business Administration	Business Administration	14
Business Administration	Business Economics	3
Business Administration	Business Administration in Public Food	1
Business Administration	Business Administration in Commerce, Tourism, Services, Commodity Science and Quality Management	1
Business Administration	Business Administration in Hospitality Services	1
Cybernetics, Statistics and Economic Informatics	Economic Informatics	12
Cybernetics, Statistics and Economic Informatics	Economic Statistics and Data Science	3

Cybernetics, Statistics and Economic Informatics	Economic Cybernetics	2
Cybernetics, Statistics and Economic Informatics	Artificial Intelligence Applied in Economics and Business	1
Economics	Agri-food and Environmental Economics	2
Economics	General Economics and Economic Communication	2
Economics	General Economics	1
Finance	Finance and Banking	19
International Economics and Business	International Business	5
International Economics and Business	International Economics and Business	5
Management	Management	20
Marketing	Marketing	14

Source: Authors' compilation and calculations based on HG No. 191/2026

The resulting programme structure provides the institutional context for the occupational mapping and GenAI exposure analysis presented in the following sections.

4.2. Occupational Profiles Associated with Business and Economics Study Programmes

The 263 Business and Economics Bachelor's study programmes included in the analytical dataset were associated with 93 distinct occupational outcomes defined in the Romanian Classification of Occupations (COR). Using the official COR–ISCO correspondence, these occupational outcomes were mapped to ten four-digit ISCO-08 occupations, providing the basis for assigning the occupational mean exposure scores and GenAI exposure gradients reported in the refined ILO Global Index of Occupational Exposure to Generative AI. The resulting occupational profiles and assigned GenAI exposure measures are presented in Table 5.

Table 5. Occupational Profiles and Assigned GenAI Exposure Measures

ISCO-08 code	Four-digit ISCO-08 occupations	GenAI exposure gradient	Study programmes (no.)	Authorised enrolment capacity (places)	Share of authorised enrolment capacity (%)
2411	Accountants	Gradient 3	46	4815	17,4
2412	Financial and investment advisers	Gradient 3	25	2670	9,6
2413	Financial analysts	Gradient 4	4	425	1,5
2421	Management and organization analysts	Gradient 2	88	7830	28,3
2431	Advertising and marketing professionals	Gradient 3	22	2485	9,0
2432	Public relations professionals	Gradient 2	5	410	1,5
2511	Systems analysts	Gradient 2	4	420	1,5
2512	Software developers	Gradient 3	14	1840	6,6
2631	Economists	Gradient 3	54	6705	24,2
2632	Sociologists, anthropologists and	Gradient 2	1	90	0,3

	related professionals				
Total			263	27690	100.0

Source: Authors' calculations.

The mapping reveals that multiple officially recognised occupational outcomes frequently converge into the same four-digit ISCO-08 occupation. Consequently, study programmes associated with different COR occupational outcomes may receive identical GenAI exposure measures when these occupations correspond to the same ISCO-08 category. This reflects the methodological design of the ILO framework, which evaluates occupational exposure at the internationally harmonised ISCO-08 level rather than at the level of national occupational classifications or individual study programmes. The occupational profiles presented in Table 5 constitute the analytical basis for the aggregate exposure analysis reported in the following section.

4.3. Distribution of GenAI Exposure Across Business and Economics Higher Education

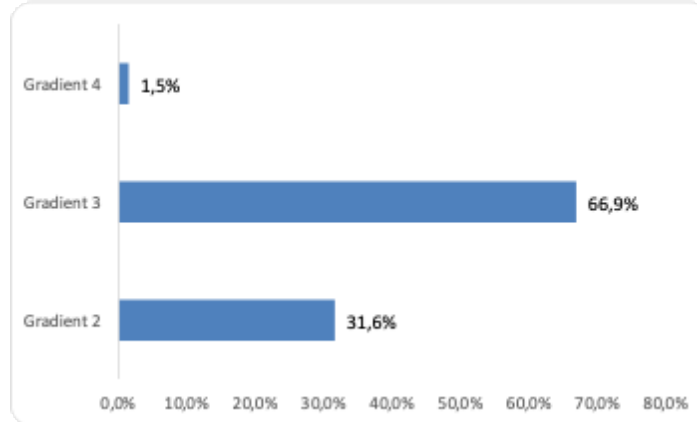
The distribution of authorised enrolment capacity across the ILO GenAI exposure gradients indicates that Romanian Business and Economics higher education is highly concentrated in occupations characterised by moderate to high potential exposure to Generative AI. As shown in Table 6, almost two-thirds of the total authorised enrolment capacity (66.9%) is associated with Gradient 3 occupations, while a further 31.6% corresponds to Gradient 2. Only 1.5% of authorised enrolment capacity is linked to Gradient 4 occupations, and no study programmes are associated with the categories Minimal Exposure, Gradient 1 or Not Exposed.

Table 6. Distribution of enrolment capacity by exposure gradient

Exposure gradient	Authorised enrolment capacity (study places)	Share of enrolment capacity (%)
Gradient 2	8750	31,6
Gradient 3	18515	66,9
Gradient 4	425	1,5
Total	27690	100,0

Source: Authors' calculations.

Figure 2 illustrates the highly concentrated distribution of authorised enrolment capacity across the three identified exposure gradients. Nearly all Business and Economics study places are associated with occupations classified in Gradients 2 and 3, indicating that future graduates are expected to enter occupations with at least moderate potential exposure to Generative AI. At the same time, the very limited share of authorized enrolment capacity assigned to Gradient 4 suggests that occupations characterised by consistently high exposure across most occupational tasks remain relatively uncommon within the analysed higher education system.

Figure 2. Distribution of enrolment capacity across Generative AI exposure gradients

Source: Authors' calculations.

5. Discussions

5.1. Interpretation of the main findings

The findings provide a clear answer to the research question by showing that the vast majority of Business and Economics Bachelor's study programmes in Romanian public universities are associated with occupational profiles classified in the intermediate and higher GenAI exposure gradients. This distribution suggests that a substantial share of future graduates are currently being prepared for occupations whose task composition is likely to be significantly influenced by Generative AI technologies.

These findings should not be interpreted as indicating that the corresponding occupations are likely to disappear or be fully automated. Consistent with the conceptual framework underlying the ILO Global Index of Occupational Exposure to Generative AI, occupational exposure reflects the potential for changes in the composition of occupational tasks rather than the replacement of entire occupations. Because occupations comprise heterogeneous bundles of tasks, higher exposure is expected to translate primarily into changes in work organisation and human–AI interaction rather than complete occupational substitution.

The main contribution of the present study lies in applying the refined ILO occupational exposure framework to higher education by using the published occupational exposure measures to assess the potential GenAI exposure of graduates from Business and Economics Bachelor's programmes. Rather than developing new occupational exposure measures, the study builds on the exposure gradients reported by the ILO for four-digit ISCO-08 occupations and links them to the officially registered occupational outcomes associated with Romanian Bachelor's study programmes. This approach provides the first systematic assessment of the potential GenAI exposure of graduates from Romanian Business and Economics higher education.

5.2. Implications for Business and Economics Higher Education

The findings of this study have several implications for Business and Economics higher education. Although Bachelor's study programmes are formally linked to stable

occupational profiles through the Romanian qualifications framework, the tasks associated with these occupations are expected to evolve continuously under the influence of Generative AI. Consequently, maintaining the alignment between higher education programmes and labour market requirements is likely to become an increasingly dynamic process, requiring regular adaptation of curricula, learning activities and graduate knowledge, skills and learning outcomes to reflect changing occupational task profiles.

At the same time, the transformation of existing occupations is unlikely to represent the only consequence of Generative AI. Alongside changes in the task composition of established professions, new occupational profiles and professional roles are expected to emerge as organisations increasingly integrate AI technologies into business processes. From this perspective, higher education institutions face the challenge not only of preparing graduates for the evolution of existing occupations, but also of equipping them with transferable knowledge, digital competences and adaptive capabilities that remain relevant in an evolving occupational landscape.

The educational implications of these findings should also be interpreted in the context of the Romanian labour market, which comprised more than 5.56 million active employees in June 2026 (Ministry of Labor, 2026). Against this background, the transformation of knowledge-intensive occupations under the influence of Generative AI has implications that extend beyond higher education, affecting the preparation of future graduates entering the labour market.

Evidence that Romanian higher education has already begun to respond to these developments can be observed in the introduction of the Bachelor's programme *Artificial Intelligence Applied in Economics and Business*, launched in the 2026–2027 academic year and currently offered only by the Bucharest University of Economic Studies. Among the 19 distinct Business and Economics Bachelor's study programmes identified in the national higher education system, it is the only programme explicitly centred on Artificial Intelligence. Although currently unique, it may represent an early institutional response to the growing importance of AI-related knowledge and competences within Business and Economics education, potentially signalling broader curricular developments in the coming years.

5.3. Application of an Occupational Exposure Framework to Higher Education

The present findings should be interpreted within the broader evolution of occupational exposure research. Initial studies primarily focused on developing alternative approaches for measuring occupational exposure to AI, including capability-based, patent-based and task-oriented frameworks (Felten et al., 2021; Gmyrek et al., 2023; Tolan et al., 2021; Webb, 2019). More recent research has increasingly applied these measures to investigate AI exposure across countries, industries and labour market outcomes, demonstrating their value for analysing diverse economic contexts (Baek & Lee, 2025; Frank et al., 2025; Georgieff & Hyee, 2022; Williamson et al., 2025). Building on this emerging body of research, the present study demonstrates that an established occupational exposure framework can also be applied to higher education through university study programmes. This application demonstrates that occupational exposure assessment can be applied to university study programmes.

The findings also complement the growing literature on Generative AI in higher education. Existing studies have primarily emphasised the need to redesign curricula, develop AI-related competencies and strengthen graduate employability in response to rapid technological change (Leite et al., 2026; Lelescu et al., 2025; Tharapos et al., 2025). The present results provide an empirical perspective to these discussions by identifying the university study programmes associated with occupational profiles characterised by higher levels of AI exposure. Rather than relying exclusively on conceptual arguments for curriculum adaptation, the proposed framework offers a transparent approach for identifying programmes where the potential impact of Generative AI may be greater and where curriculum review and competency development may deserve particular attention.

The proposed approach also contributes to connecting occupational exposure research with higher education by introducing university study programmes as a new unit of analysis. Instead of evaluating existing workers or occupations, the framework enables the assessment of the potential AI exposure associated with future graduates before labour market entry. This perspective may support more informed decisions regarding curriculum revision, strategic programme development and higher education policy, while providing a transparent approach that can be replicated across other ISCED fields and national higher education systems.

5.4. Complementary Analysis of Romanian Private Universities

Although the main analysis focuses on Romanian public universities, a complementary analysis was also conducted for private higher education institutions to examine whether the observed exposure patterns are specific to the public sector or reflect broader characteristics of Business and Economics higher education in Romania. The complementary dataset comprised 23 private universities offering 113 Business and Economics Bachelor's study programmes with a total authorised enrolment capacity of 8,335 study places (Table 7).

Table 7. Distribution of authorised enrolment capacity by GenAI exposure gradient – private universities

GenAI exposure gradient	Number of study programmes	Authorised enrolment capacity	Share of total capacity (%)
Gradient 2	45	3,435	41.2
Gradient 3	68	4,9	58.8
Gradient 4	0	0	0.0
Total	113	8,335	100.0

Source: Authors' calculations based on HG No. 191/2026.

Similar to the public university sector, the authorised enrolment capacity of private universities is concentrated primarily in Exposure Gradients 2 and 3. Specifically, 58.8% of the authorised enrolment capacity is associated with Gradient 3 occupations, while the remaining 41.2% falls within Gradient 2. No study programmes were linked to occupations classified in Exposure Gradient 4 (Table 8).

Table 8. Comparison of Authorised Enrolment Capacity by GenAI Exposure Gradient in Public and Private Universities

Gradient	Public universities (%)	Private universities (%)	Difference (pp)
Gradient 2	0,316	0,412	9,6
Gradient 3	0,669	0,588	-8,1
Gradient 4	0,015	0	-1,5

Source: Authors' calculations

The comparison between public and private universities confirms that the overall exposure profile of Business and Economics higher education remains highly consistent across institutional sectors. Although private universities display a somewhat higher share of programmes associated with Exposure Gradient 2 and no programmes linked to Gradient 4 occupations, both sectors are characterised by a clear predominance of Gradient 3 (Table 8). These differences are likely to reflect variations in programme portfolios rather than fundamentally different patterns of occupational exposure. More importantly, the similarity between the two sectors suggests that the observed exposure profile is primarily related to the occupational outcomes associated with Business and Economics study programmes rather than to whether programmes are offered by public or private universities. Overall, the complementary analysis reinforces the robustness of the main findings by demonstrating that the identified exposure patterns are not limited to Romanian public universities.

6. Conclusions

This study examined the occupational exposure to Generative AI associated with Business and Economics study programmes offered by Romanian public universities. The analysis included 263 Bachelor's programmes, representing 27,690 potential graduates. Occupational exposure was estimated by linking the qualifications registered in the Romanian National Qualifications Register (RNCIS) to their corresponding occupational profiles and applying the ILO Global Occupational Exposure Index. The findings reveal a distinct occupational exposure profile across the analysed programmes, with no study programme associated with occupations classified as Not Exposed or Minimal Exposure. Instead, the vast majority of potential graduates were linked to occupations characterised by moderate to high levels of occupational exposure. These findings highlight the importance of incorporating occupational exposure into discussions on curriculum development, graduate employability and higher education policy in the context of Generative AI.

Beyond its empirical findings, the study makes three main contributions. First, it demonstrates that an established occupational exposure framework can be applied to higher education through the occupational profiles associated with the qualifications awarded by university study programmes, offering a proof of concept for applying occupational exposure assessment to higher education. Second, it provides the first systematic evidence on the occupational exposure associated with Business and Economics Bachelor's programmes in Romanian public universities. Third, it develops an analytical database developed for this study linking university qualifications to occupational

profiles and occupational exposure measures through the integration of the Romanian National Qualifications Register (RNCIS), COR, ISCO-08 and the ILO Global Occupational Exposure Index. The resulting framework is transparent, replicable and can be applied to other ISCED fields and national higher education systems.

The findings also have important implications for higher education institutions and policymakers. For universities, occupational exposure assessment offers an additional perspective for curriculum revision and strategic programme development by identifying fields where graduates are more likely to encounter AI-driven changes in occupational requirements. In the short term, the results may support curriculum adaptation through new courses, the integration of AI-related competencies into existing courses and the redesign of learning outcomes to better reflect evolving labour market requirements. At the institutional level, universities may also strengthen their role as lifelong learning providers by expanding master's programmes, postgraduate programmes, microcredentials and other flexible learning formats. These initiatives can support graduates in continuously updating their knowledge and competencies throughout their careers. At the policy level, the proposed framework may contribute to evidence-informed decision-making regarding higher education planning and the alignment between educational provision and future labour market needs.

The study is subject to several limitations that also open potential directions for future research. The analysis focuses exclusively on Business and Economics Bachelor's programmes offered by Romanian public universities and estimates occupational exposure using authorised enrolment capacity as a proxy for the population of potential graduates. Future research could refine the proposed framework by incorporating data on enrolled students and graduates, providing a more accurate representation of the population associated with each study programme. The framework can also be extended to other ISCED fields and national higher education systems, enabling broader comparative analyses of occupational exposure across higher education. Annual updates of the analytical database would enable longitudinal analyses of occupational exposure across higher education.

7. References

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