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INTEGRATION OF GENERATIVE AI SKILLS IN JOB REQUIREMENTS: EVIDENCE FROM JOB ADVERTISEMENTS IN GEORGIA

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Abstract. The rapid diffusion of generative artificial intelligence (GenAI) tools has created a demand for new skills in labour markets. However, research into how employers articulate GenAI competencies in job advertisements has focused almost exclusively on large, technologically advanced economies. This study examines how employers in Georgia, a small upper-middle-income transitional economy, indicate GenAI skill requirements in job advertisements, considering four dimensions: skill visibility, linguistic framing, organisational readiness and skill depth. Deductive content analysis was applied to 94 job advertisements collected in January 2026 from three major Georgian labour market platforms (LinkedIn, Jobs.ge and HR.ge). Each advertisement was coded using a structured 20-indicator codebook derived from established theoretical frameworks. The results show that employers articulate GenAI skills in two ways: by explicitly naming the tool, which is present in 38.3 per cent of advertisements, and by using implicit task language, which is present in 61.7 per cent of advertisements and constitutes the dominant form of signalling. Regardless of occupation or skill depth, employers frame GenAI requirements as mandatory in 81.9 per cent of advertisements, indicating the rapid institutionalisation of GenAI literacy as a baseline labour market expectation. Signals of organisational readiness remain weak: only 21.3 per cent of job advertisements acknowledge any organisational role in enabling AI adoption, while the remaining 78.7 per cent present GenAI competence purely as a prerequisite for candidates. Skill complexity is almost evenly divided between basic and advanced requirements, and occupation strongly predicts this division, creating a clear distinction between a technically advanced group and a large group adopting AI on a more general operational level. Signals of organisational readiness remain weak: only 21.3 per cent of job advertisements acknowledge any organisational role in enabling AI adoption, while the remaining 78.7 per cent present GenAI competence purely as a prerequisite for candidates. Skill complexity is almost evenly divided between basic and advanced requirements, and occupation strongly predicts this division, creating a clear distinction between a technically advanced group and a large group adopting AI on a more general operational level.

Keywords: generative AI, job advertisements, labour market, skill demand, organisational readiness, content analysis, Georgia.

JEL Classification: J24, J40, O33

1. Introduction

The rapid diffusion of large language models and generative AI (GenAI) tools has introduced a new category of skills into labour markets worldwide. Unlike previous waves of automation, which primarily displaced routine manual and cognitive tasks (Autor et al., 2003), GenAI is penetrating high-skill, knowledge-intensive work. This is creating demand for competencies at the intersection of technical literacy, domain expertise, and the ability to provide critical oversight.

Labour market research has documented this shift primarily in large, technologically advanced economies (Acemoglu, 2024). Studies based on vacancy data from the US, Europe and China establish that mentions of GenAI skills in job postings are growing rapidly and are

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concentrated in specific occupational groups, carrying distinct patterns of framing and required depth. It is empirically unknown whether these patterns generalise to smaller, transitional economies with different institutional structures, digital adoption rates, and firm size distributions.

Georgia is an instructive case study: it is a small upper-middle-income economy that is undergoing rapid digitalisation. It has a growing technology sector, but its AI research infrastructure is limited. It is also situated between advanced economies that dominate existing research, and lower-income settings where AI adoption remains marginal. Understanding how GenAI skills are articulated by Georgian employers in job advertisements provides important evidence for workforce policy and makes a methodological contribution to comparative labour market literature.

This paper addresses four research questions:

RQ1. How are GenAI competencies articulated in Georgian job advertisements within GenAI-relevant occupations (Visibility)?

RQ2. How do employers linguistically frame GenAI competencies and what does this framing imply about skill urgency and expectations (Framing)?

RQ3. To what extent do job advertisements signal an organisation's readiness to adopt GenAI (Readiness)?

RQ4. What levels of GenAI skill depth and operational responsibility are required (Depth)?

2. Literature Review

2.1 Visibility of GenAI Skills in Job Advertisements

2.1.1 Job Advertisements as Labour Market Signals

Online job advertisements have become the main source of empirical evidence of labour market skill demand, offering real-time, large-scale data on how employers define their workforce needs. Pioneering research by Acemoglu et al. (2022) and subsequent studies has shown that technological change can be discerned from vacancy postings, as employers adapt the required competencies in response to automation pressures. Thanks to advances in natural language processing and large administrative datasets, the systematic analysis of job postings has become a standard methodology for tracking technology-induced shifts in skills (Bonin et al., 2015; Brynjolfsson and Mitchell, 2017).

Eloundou et al. (2024) developed occupational exposure frameworks, revealing that around 80% of U.S. workers perform at least 10% of their tasks that are potentially exposed to large language models. Both Babina et al. (2024) and Acemoglu et al. (2022) found independently that AI-related job advertisements are concentrated among a small number of large, technology-intensive firms and a narrow set of occupational categories. This selectivity is interpreted as a sign of market immaturity rather than limited relevance. This distinction is important for contextualising findings in smaller labour markets. Alekseeva et al. (2021) document a fourfold increase in the demand for AI skills in U.S. job advertisements over the decade up to 2019. This establishes the vacancy-based methodology as a valid and reliable measure of technology-driven labour market change across industries and occupational groups (see also Zarifhonarvar, 2023).

2.1.2 Competency Articulation in AI-Relevant Occupations

Research into AI skills mentioned in job advertisements reveals that the way they are expressed is varied and evolving. Acemoglu et al. (2022) compared task-based occupational exposure measures (Felten et al., 2023; Brynjolfsson et al., 2023) with the actual frequency of AI-related skills in U.S. online job advertisements. They documented a significant discrepancy between the theoretical level of AI exposure and the rate at which AI skills are explicitly listed. This suggests that employers either assume basic AI literacy without stating it, have not updated job descriptions, or are genuinely uncertain about which competencies to require.

In their 2026 study, Bluemelhuber and Langer (2026) analysed 22,352 job postings related to Generative AI (GenAI) from the German labour market platform Stepstone. Employing BERTopic modelling and expert classification, they found that employer demand for GenAI competencies clusters around prompt engineering, model selection, guardrail design and enterprise integration. The demand also exhibited a hybrid KSA profile, combining new GenAI-specific competencies with established technical, analytical and business expertise. Further evidence from Nakash and Peretz (2025), who studied LinkedIn postings globally in 2024, shows that communication, Python and machine learning are the most in-demand AI-adjacent skills. Data and analytics roles have the highest structural overlap with career development, quality and compliance functions. Crucially, their analysis confirms that AI-related job advertisements are increasingly seeking candidates with hybrid profiles, combining technical expertise with socio-emotional skills. In transitional economies, the visibility of GenAI skills is further limited by structural factors, such as smaller digital ecosystems, fewer large technology employers, and weaker institutional incentives to articulate new competency demands. Research into the Chinese labour market by Chen et al. (2025) and Ji et al. (2023) provides a useful parallel. LLM-related job advertisements increased rapidly, but remained concentrated in a small number of cities and companies,

with few explicit GenAI requirements in the wider occupational landscape.

2.1.3 Methodological Approaches

Lukauskas et al. (2023) developed an NLP-based segmentation and clustering approach, combining TF-IDF vectorization with topic modelling, that allows analysts to recover latent competency structures from unstructured text, distinguishing narrow technical AI skills from broader cognitive skills linked to AI collaboration. Critically, job advertisements are performative texts with their own rhetorical conventions (Fairclough, 2003). The visibility of GenAI skills is not a neutral reflection of employer demand, but rather a socially mediated signal that is shaped by hiring conventions and the dynamics of a competitive labour market.

2.2 Linguistic Framing of GenAI Skills

2.2.1 Framing Theory and Skill Communication

When applied to labour market communication, framing theory holds that the words and rhetorical structures used by employers to describe required competencies actively construct their social meaning, including their sense of urgency, status and organisational embeddedness (Benford and Snow, 2000; Fairclough, 2003). Research documents a systematic variation in the way in which employers frame technical requirements. Mandatory framing ('must have', 'required') carries a distinct signal about organisational urgency and candidate screening thresholds, as does preferred framing ('nice to have') (Deming and Noray, 2020; Deming and Kahn, 2018). Deming and Kahn (2018) demonstrate that the specificity and strength of skill framing in job advertisements varies systematically across firms and local labour markets. This reflects differences in organisational human capital strategy and competitive hiring intensity. Newly emerging technical skills tend to appear first with weaker framing, before becoming mandatory as the skill becomes established – a lifecycle that is expected to be condensed for GenAI, given the rapid public salience of tools such as ChatGPT and GitHub Copilot.

2.2.2 Urgency Signals and Normative Framing

Hershbein and Kahn (2018) demonstrated that the skill requirements listed in job advertisements intensify rapidly in response to technological shocks. In such situations, firms tend to add new skill terms and increase the specificity of existing ones. When applied to GenAI, this dynamic suggests that constructions such as 'rapidly evolving', 'cutting-edge' and 'at the forefront' are predictable features of job advertisements in emerging technology sectors. This allows employers to distinguish innovation-oriented roles and demonstrate their commitment to organisational innovation in an era of accelerating skill lifecycles. As technical skills shift from being desirable to mandatory as they become institutionalised, competence in GenAI is not merely desirable, but a baseline competitive expectation. Not adopting it is implicitly seen as a professional liability (Hershbein and Kahn, 2018; Deming and Noray, 2020).

Implicit framing, whereby postings presuppose GenAI literacy without naming specific tools, is currently more prevalent than explicit framing in sectors where the use of AI has become commonplace but not formalised (Marr, 2024). This makes vocabulary-based counting of mentions of GenAI skills a systematic undercount, which is why interpretive coding should be used alongside keyword analysis.

2.2.3 Occupational and Sectoral Variation

Brynjolfsson et al. (2023) found that, in creative occupations such as writing, design and marketing, GenAI skills were often presented as enhancing existing abilities, whereas in technical roles, the focus was more on specific tools. The labour market implications of this occupational stratification are empirically confirmed. Hui et al. (2024) demonstrate that it was precisely those workers in creatively framed, writing-adjacent occupations who suffered the sharpest employment losses following the release of ChatGPT. Examining 16 European countries over the period 2011–2019, Albanesi et al. (2025) found that occupations with greater exposure to AI experienced increases rather than decreases in employment shares – a positive association predominantly driven by high-skilled occupations, particularly those in the professional group (ISCO major group 2), which encompasses knowledge-intensive roles in science, law, business, and health.

2.3 Organisational Readiness for GenAI Adoption

2.3.1 Conceptualising Organisational Readiness

Organisational readiness for technology adoption encompasses technical infrastructure, human capital, leadership commitment, and cultural orientation (Holt et al., 2007; Armenakis and Harris, 2009). Tona et al. (2025) found that organisational readiness was a critical moderator of AI adoption outcomes when studying AI deployment for employee skill inference at Johnson and Johnson: firms with higher baseline readiness achieved more effective integration and reported fewer unintended consequences. Significantly, readiness signals were evident in the firm's recruitment practices prior to the formal adoption of AI, establishing job advertisements as leading indicators of organisational

preparedness. Applying signalling theory to the context of teams, Smith et al. (2025) demonstrate that congruence between human and AI signals is the strongest driver of AI adoption, showing that the way GenAI competence is framed in job advertisements signals both organisational enthusiasm and employee obligation.

2.3.2 Job Advertisements as Readiness Proxies

Babina et al. (2024) created a firm-level AI adoption index using vacancy postings. This index was found to be predictive of patenting activity, R&D investment, and productivity outcomes. Chen, Ge, et al. (2025) found that LLM-related postings in China were concentrated in firms with prior data infrastructure investment, suggesting GenAI readiness signals in job ads reflect genuine absorptive capacity (Cohen and Levinthal, 1990) rather than aspiration. Extending this analysis to a cross-country setting, Cazzaniga et al. (2024) demonstrate that the extent to which GenAI complements or displaces labour varies significantly according to national income level and employment structure. This has implications for how readiness signals should be interpreted in upper-middle-income economies such as Georgia. Organisational signalling theory (Spence, 1973; Connelly et al., 2011) offers an additional perspective by providing a complementary lens. While GenAI skill requirements may serve as credibility signals in competitive hiring markets, firms that include such requirements without the necessary infrastructure may experience misalignment, which has implications for employee retention (Brougham and Haar, 2018).

2.3.3 Readiness Dimensions and Workforce Restructuring

Noy and Zhang (2023) found that structured AI adoption policies moderated the effects of ChatGPT adoption on individual productivity; workers in organisations with clear policies demonstrated greater and more sustained improvements. Dell'Acqua et al. (2026), meanwhile, found that organisational task structure clarity moderated GenAI productivity outcomes, as reflected in the specificity of job advertisements for AI-relevant roles. Berger et al. (2024) provided evidence that, when adopting new technologies, firms modified job advertisements dynamically. They reduced the requirements for AI-substitutable skills and added AI oversight competencies. This process can be traced as a co-evolution of readiness signals and skill depth demands in real time. Meanwhile, Chen, Srinivasan et al. (2025) developed a taxonomy of reshaping modes – augmentation, automation, hybridisation and displacement – each of which maps onto distinct patterns of language in job advertisements.

2.4 GenAI Skill Depth and Operational Responsibility

2.4.1 Taxonomies of AI Skill Depth

The skill depth required for AI-adjacent roles can range from basic tool use to model governance, pipeline development, and ethical oversight. Early frameworks distinguished between AI developers, deployers and users, forming a three-level hierarchy that broadly aligns with deep, intermediate and surface AI literacy. Bluemelhuber and Langer (2026) empirically derived a granular, KSA-based taxonomy from a large corpus of GenAI job postings. They classified 32 competency topics into the business, technical, and analytical domains, and distinguished between knowledge, skill, and ability requirements. Knowledge requirements include an understanding of the foundations of the models and their capabilities. Skill requirements include practical proficiency in prompt engineering, model selection, and tool integration. Ability requirements include metacognitive capacities, such as output evaluation and responsible AI judgement. Eloundou et al. (2024) found that tasks involving information synthesis, structured writing, and code generation require the greatest level of AI interaction in residual human roles.

2.4.2 Operational Responsibility and the Division of AI Labour

Operational responsibility for AI refers to the extent to which a role involves active and significant functions relating to GenAI governance, output verification or process ownership, as opposed to merely using the technology as a tool. Bansal et al. (2019) found that effective AI integration requires clear delineation of roles, with humans retaining responsibility for high-stakes decisions and contextual adaptation. In a four-study experimental investigation of human–AI teams, Smith et al. (2025) demonstrate that this responsibility structure is dynamic. When employees choose to engage with AI advice rather than having it imposed on them, AI convergence is significantly higher. This suggests that the way in which organisations design AI roles, and particularly the amount of autonomy they grant employees, shapes the nature of AI oversight responsibilities at an individual level.

2.4.3 Higher-Order Skills, Training and Inequality

A distinctive feature of GenAI's impact on the labour market is its penetration into higher-order cognitive work. Brynjolfsson et al. (2023) found that

roles requiring complex reasoning and judgement exhibited higher AI exposure and a stronger demand for governance and verification metaskills. This creates a paradox whereby the roles most affected also experience the greatest increase in residual cognitive sophistication requirements. Consequently, skill depth is bifurcating: roles with shallow adoption require basic tool literacy, whereas those with deep adoption require sophisticated oversight competencies.

The question of who is responsible for developing GenAI skills has distributional implications. The training-within-firms research tradition of Berger et al. (2024) and Acemoglu et al. (2022) suggests that employers who invest in AI training signal a capacity-building orientation that is distinct from that of employers who recruit pre-formed skills from the external market. Gmyrek et al. (2023) found that high-level GenAI roles are predominantly held by high-wage workers in large, technology-intensive organisations. Meanwhile, lower-skilled workers are facing job displacement without the opportunity to develop new skills.

2.5 Synthesis and Research Gaps

In the first PRISMA-compliant systematic review of GenAI's labour market impacts, Salari et al. (2025) synthesise evidence from 14 empirical studies and conclude that GenAI is simultaneously increasing productivity and widening digital skill inequalities. They find that GenAI is creating new specialist roles while displacing workers in content-intensive occupations. The critical policy responses identified are reskilling and continuous monitoring. Within this broader landscape, the existing literature shows that GenAI skill visibility in job advertisements is real but uneven. It also shows that linguistic framing is performative, encoding urgency and organisational identity. Furthermore, it shows that job advertisements are valid proxies for organisational readiness and that demands for skill depth are heterogeneous and bifurcating across occupations. Drawing on 703 GenAI-related job postings from North America, the EEA and the UK, Khukhunaishvili and Zhghenti (2026) identified a clear competency hierarchy. This hierarchy saw cloud infrastructure, AI model deployment, security, and compliance form a shared backbone across GenAI use cases. Meanwhile, prompt engineering and front-end development remained niche skills concentrated in specific domains.

However, the vast majority of existing research focuses on large, technologically advanced labour markets. There is almost no empirical research on GenAI skill articulation in small, transitional, or lower-middle-income labour markets, such as that in Georgia.

Another issue is the lack of longitudinal data: most studies only provide snapshots at specific points in time over short periods (2022–2024). Finally, it remains unclear whether GenAI skill signals in job postings are credible, aspirational or merely performative, particularly in markets with limited accountability mechanisms. The present study addresses these gaps within the Georgian context.

3. Method

This study primarily employs a deductive content analysis of job advertisements. Content analysis of job advertisements is a well-established way of inferring latent skill demand structures from texts generated by employers. Deductive coding based on a theory-derived codebook enables the systematic and replicable classification of skill signals across a body of work.

Job advertisements were collected from three major Georgian-language and bilingual online labor market platforms: LinkedIn, Jobs.ge and HR.ge. Data collection was conducted in January 2026. An initial corpus was assembled by searching each platform using a predefined set of GenAI-related keywords, including but not limited to: artificial intelligence, generative AI, ChatGPT, LLM, large language model, prompt engineering, AI tools and machine learning. Searches were conducted in both Georgian and English to capture the full range of postings in the bilingual labor market. Advertisements were filtered based on the ISCO-08 occupational classification to include only roles where GenAI exposure was theoretically plausible. Of these, 94 advertisements containing at least one identifiable GenAI competency signal were selected for analysis.

A structured codebook comprising 20 binary and categorical indicators was developed across four analytical dimensions that correspond to the four research questions: (1) explicit vs. implicit GenAI skill signaling; (2) mandatory vs. preferred framing and description granularity; (3) organizational tone, training support and readiness communication; and (4) skill complexity level and specific task types. The full codebook is presented in Table 1.

Limitations. The sample is drawn from advertisements that already contain GenAI signals, which precludes any inference about the broader population of postings. The cross-sectional design also prevents the framing lifecycle from being traced over time. The moderate sample size (n = 94) restricts the ability to conduct in-depth or subgroup analyses. Furthermore, job advertisement text may not perfectly correspond to actual workplace AI practices due to its reflection of employer communication norms and competitive signalling strategies.

Table 1
Codebook: Coding Dimensions, Indicators and Measurement Rules

Dimension	Indicator	Measurement Type	Coding Rules
Visibility of GenAI Skills	Explicit tool mentions	Binary	0 = No named GenAI tool; 1 = Named GenAI tool or model mentioned
	Implicit task mentions	Binary	0 = No GenAI-related tasks mentioned; 1 = At least one GenAI-related task mentioned
	Task types	Multi-select categorical	1 = Content generation; 2 = Summarization; 3 = Translation; 4 = Research/Q&A; 5 = Prompt writing; 6 = Data analysis; 7 = Code assistance; 8 = AI output review; 9 = Workflow integration; 10 = Governance/compliance
Linguistic Framing of Skills	Framing language	Categorical	0 = Not mentioned/not required; 1 = Preferred/nice-to-have; 2 = Required/mandatory
	Description granularity	Categorical	0 = Vague mention only; 1 = One specific GenAI task or tool; 2 = Multiple GenAI tasks, tools or details
	Placement in ad	Multi-select categorical	1 = Job title or opening section; 2 = Responsibilities or requirements; 3 = Other sections (e.g., benefits, footer)
Organisational Readiness and Integration	Training/integration mention	Binary	0 = No GenAI training or integration mentioned; 1 = GenAI training or integration support mentioned
	Framing tone	Binary	0 = Neutral or unspecified tone; 1 = Positive or encouraging tone toward GenAI use in organisation
GenAI Skill Depth and Operational Responsibility	Skill complexity	Categorical	0 = Cannot determine skill level from ad; 1 = Basic GenAI use required; 2 = Advanced GenAI use required
	Certification or education mentions	Binary	0 = No GenAI-related certification or education mentioned; 1 = GenAI-related certification or education explicitly mentioned

4. Results

4.1 Visibility of GenAI Skills

All 94 advertisements contained at least one GenAI competency signal. Two qualitatively distinct modes were identified. The first mode, which involved explicit tool mentions where a named GenAI product, model or platform was referenced, was present in 36 advertisements (38.3%). The remaining 58 advertisements (61.7%) relied exclusively on implicit task language, describing GenAI-related activities without naming specific tools. No advertisement contained explicit tool mentions without also carrying implicit task language. Therefore, explicit naming co-occurs with, rather than replaces, broader task description.

Table 2
Distribution of Job Advertisements by Mode of GenAI Skill Visibility

Signal Type	n	% of Ads
Explicit tool or model named	36	38.3%
Implicit task only (no named tool)	58	61.7%

The named tools span four functional categories. Foundation model APIs and orchestration frameworks, such as OpenAI, Anthropic Claude, LangChain, LangGraph, LlamaIndex, Azure OpenAI and Amazon Bedrock, appeared predominantly in engineering and AI/ML roles. Creative generative tools such as Midjourney, Stable Diffusion, Runway, Pika and CapCut AI were used in design and multimedia roles. Consumer-facing assistants such as ChatGPT, Claude and Gemini appeared across roles, from content creation to legal research. Meanwhile, enterprise tools such as Microsoft Copilot, GitHub Copilot and ServiceNow GenAI were concentrated in DevOps, IT management and enterprise architecture.

Workflow integration was the most common task, featuring in 91.5% of all job advertisements, which confirms that GenAI is primarily represented as a competence embedded in processes. Advanced technical tasks, code assistance, research and Q&A were almost exclusively found in technical roles, whereas content generation was concentrated in creative and marketing positions.

Competency signals for GenAI appear across all ISCO-08 groups in the sample. However, explicit tool naming shows strong occupational stratification (Cramer's $V = 0.620$, $p = 0.002$). Rates are highest among systems architects (100%), systems administrators (83%), and designers (75%), and are absent among ICT managers and QA testers (0%).

4.2 Linguistic Framing of GenAI Competencies

Mandatory framing dominates the corpus: 77 advertisements (81.9%) present GenAI competencies as required, while only 17 (18.1%) treat them as preferred. This pattern is almost universal across most occupational groups, but there are variations at the extremes: content creators show 100% mandatory

Table 3
Distribution of Generative AI Task Types Mentioned in Job Advertisements

Task Type	n	% of Ads	Occupational Profile
Workflow integration	86	91.5%	Universal - all occupational groups
Data analysis	20	21.3%	AI/ML engineers, data scientists
Content generation	19	20.2%	Creative, marketing, content creators
Code assistance	12	12.8%	Software developers, AI/ML engineers
AI output review	10	10.6%	QA testers, AI test engineers
Prompt writing	6	6.4%	AI specialists, LLM engineers
Research / Q&A	6	6.4%	Advanced technical roles

Table 4
Generative AI Skill Demand Indicators by Occupation

Occupation (ISCO-08 Code)	n	Explicit Tool Named (%)	Mandatory Framing (%)
Systems Architects (2511)	5	100%	80%
AI/ML Engineers (2519)	25	44%	92%
Software Developers (2512)	9	44%	89%
Systems Administrators (2522)	6	83%	67%
Graphic & Multimedia Designers (2166)	8	75%	88%
QA Testers (3514)	7	0%	86%
ICT Managers (1330)	9	0%	44%
Content Creators (2641)	3	67%	100%
Marketers (2431)	6	17%	83%
Project Managers (2422)	5	20%	80%
Business Managers (1219)	3	33%	67%

Note: Occupation labels are taken directly from job advertisements and do not always exactly match official ISCO-08 titles. Assignments are based on described tasks. Groups with n < 3 excluded.

framing, while ICT managers show a preferred-majority pattern (44% required), which is consistent with senior roles that are assumed to require a broad range of competencies. Notably, no statistically significant association was observed between mandatory framing and skill complexity. The obligation to demonstrate GenAI competence is distributed uniformly, regardless of the required depth.

Advertisements are divided into two categories: single-detail and multi-detail Generative AI descriptions. Of the 52 advertisements (55.3%) that contain a single reference to a specific GenAI task or tool, 42 (44.7%) include multiple details. Multi-detail advertisements were more likely to include explicit tool naming and advanced task types. GenAI skills were present in the responsibilities or requirements section of 90 advertisements (95.7%), and in the job title or opening section of 41 advertisements (43.6%). Technical occupations used title placement in 63% of cases, compared to 35% for management roles and 22% for creative roles. This reflects the fact that, for technical roles, AI competence is constitutive of occupational identity.

Table 5
Linguistic Framing of GenAI Skills by Occupation

Occupation (Matched ISCO-08 Code)	n	Required (%)	Preferred (%)	Note
All Occupations	94	82%	18%	
Content Creators (2641)	3	100%	0%	All mandatory
AI/ML Engineers (2519)	25	92%	8%	Near-universal
Software Developers (2512)	9	89%	11%	Dominant mandatory
Designers (2166)	8	88%	12%	Dominant mandatory
QA Testers (3514)	7	86%	14%	Dominant mandatory
Marketers (2431)	6	83%	17%	Dominant mandatory
Systems Architects (2511)	5	80%	20%	Dominant mandatory
Project Managers (2422)	5	80%	20%	Dominant mandatory
Business Managers (1219)	3	67%	33%	Mixed
Systems Administrators (2522)	6	67%	33%	Mixed
ICT Managers (1330)	9	44%	56%	Preferred-majority

Note: Occupation labels are taken from job advertisements and matched with relevant ISCO codes. Groups with n < 3 excluded

Table 6
Description of Granularity of GenAI Skills in Job Advertisements

Granularity Level	n	% of Ads
Single GenAI task or tool reference	52	55.3%
Multiple GenAI tasks, tools, or details	42	44.7%

Table 7
Placement of GenAI Skill References Within Job Advertisements

Placement Location	n	% of Ads
Responsibilities / requirements section	90	95.7%
Job title or opening section	41	43.6%
Other sections (benefits, footer, etc.)	1	1.1%

Note: Percentages exceed 100% as advertisements may include GenAI references in multiple locations.

4.3 Organisational Readiness Signals

The majority of advertisements (63.8%) used positive or encouraging language in relation to AI adoption. The positive tone occurred significantly more frequently alongside mandatory than preferred framing (70% versus 35%), suggesting a deliberate rhetorical strategy of linking obligation with enthusiasm. This presents AI as both necessary and appealing, thereby attracting candidates who might otherwise be ambivalent about AI-intensive roles.

Table 8
Association Between Mandatory Framing and Positive Organisational Tone

Framing Type	Neutral Tone	Positive Tone	Total
Preferred framing	11 (65%)	6 (35%)	17
Required framing	23 (30%)	54 (70%)	77

Only 20 advertisements (21.3%) acknowledge an organisational role in enabling AI adoption through the provision of training, access to tools, onboarding or the mention of an organisational AI transformation programme. The remaining 74 advertisements (78.7%) present AI competence as something that candidates must already possess. Consequently, positive tone is largely decoupled from concrete training support: 45.7% used positive framing without offering any training, while only 18.1% offered both.

Table 9
Organisational Tone and Training Support Patterns

Pattern	n	% of Ads
Positive tone only (no training mention)	43	45.7%
Neither positive tone nor training support	31	33.0%
Both positive tone and training mention	17	18.1%
Training mention only (neutral tone)	3	3.2%

Note: Training mentions were more common in advertisements that explicitly named AI tools, suggesting training support reflects concrete tooling commitment rather than simply a response to higher technical demands.

4.4 GenAI Skill Depth and Operational Complexity

The skill complexity is almost evenly divided: 49 advertisements (52.1%) require the basic use of GenAI, while 45 (47.9%) require an advanced level of use. The occupational group is the strongest predictor of skill complexity (Cramer's V = 0.755, $p < 0.001$). All Systems Architects were required to have advanced skills, but none of the Designers, Marketing Professionals, Project Managers, Content Creators or Business Managers were. There is a clear distinction between technical depth roles and operational adoption roles, which are occupation-specific.

Table 10
GenAI Skill Complexity by Occupation

Occupation (Matched ISCO-08 Code)	n	Advanced (%)	**Basic (%)**
All Occupations	94	52%	48%
Systems Architects (2511)	5	100%	0%
AI/ML Engineers (2519)	25	88%	12%
Software Developers (2512)	9	67%	33%
ICT Managers (1330)	9	67%	33%
System Administrators (2522)	6	50%	50%
QA Testers (3514)	7	29%	71%
Designers (2166)	8	0%	100%
Marketers (2431)	6	0%	100%
Project Managers (2422)	5	0%	100%
Content Creators (2641)	3	0%	100%
Business Managers (1219)	3	0%	100%

Note: Occupation labels are taken from job advertisements and matched with relevant ISCO codes. Groups with n < 3 excluded.

Workflow integration is almost universal at both levels. Content generation is basic-dominant (32.7% versus 6.7%), which is consistent with its concentration in non-technical adoption roles. In contrast, data analysis, code assistance and research/Q&A are strongly advanced-dominant, confirming their status as depth markers for technical roles. Consistent with global distribution patterns of deep technical AI talent, advanced advertisements were also more likely to be remote (82.2% of advanced-skill advertisements).

Only four advertisements (4.3%) mention GenAI-related certification or formal education requirements. Employers demand AI competence as a condition of employment, but do not specify how this should be acquired, verified or formalised. This, combined with low training provision (21.3%), creates a structural gap. GenAI competence is required, yet neither the pathway to achieving it nor the organisation's role in supporting this process is defined.

5. Discussion

The following section provides an analytical discussion of the study's findings regarding the integration of

Table 11
Task Type Distribution by Skill Complexity Level

Task Type	Basic (n=49)	Advanced (n=45)	Pattern
Workflow integration	85.7%	97.8%	Universal
Content generation	32.7%	6.7%	Basic-dominant
AI output review	12.2%	8.9%	Balanced
Data analysis	10.2%	33.3%	Advanced-dominant
Prompt writing	4.1%	8.9%	Advanced-skewed
Code assistance	2.0%	24.4%	Advanced-dominant
Research / Q&A	0.0%	13.3%	Advanced only

generative AI in the Georgian labour market. Across job advertisements, GenAI requirements tend to be expressed in broad and non-specific terms, with little operational detail regarding the expected level of competence, the required tools, or specific applications. This reflects a general demand for 'AI capability' rather than specific technical or task-level expectations. In this context, the prevalence of implicit task language over explicit tool naming further emphasises that employers are primarily signalling a general expectation of AI-enabled work practices rather than specifying precise technological skills or platforms. Consequently, GenAI competence is perceived as a flexible, cross-functional requirement rather than a structured, measurable skill set.

Signals of organisational readiness remain notably weak. While organisations project enthusiasm for AI adoption and use a positive tone, the majority present GenAI competence as a prerequisite that is already in place. Only a small proportion of advertisements acknowledge any organisational role in enabling AI capability. Firms express their intention to adopt without providing the structural accompaniments – training, infrastructure, governance frameworks and tool access – that characterise genuine organisational readiness.

The near-total absence of certification requirements exacerbates this issue. When employers do not specify how competence should be demonstrated or provide pathways for its development, candidates are left to their own devices, resulting in AI competence becoming a tacit and socially stratified credential that favours those with access to informal learning resources.

There are two clear segments of GenAI labour demand. The sharp occupational bifurcation in skill depth lends support to this model. The technical depth segment (Systems Architects, AI/ML Engineers and Software Developers) requires advanced competencies and specifies tools explicitly. This segment is concentrated in remote roles and shows a higher level of training provision. In contrast, the operational adoption segment (Designers, Marketers, Project Managers and Content Creators) requires basic workflow integration and uses implicit framing. This segment is predominantly office-based and shows near-zero training support.

6. Conclusions

This study is the first to provide a systematic analysis of GenAI skill demand as expressed in job advertisements in the Georgian labour market. Four key findings emerge. Firstly, GenAI competence has become a general labour market expectation, regardless of skill depth, across occupations. Secondly, the dominant mode of articulation is implicit – workflow integration language without specific tool naming – meaning that functional AI expectations exceed those revealed by explicit mentions. Thirdly, signals of organisational readiness are weak: employers express enthusiasm for AI while presenting competence as a prerequisite for candidates, with fewer than one in five advertisements acknowledging training provision. Fourthly, the demand for skill depth is sharply stratified by occupation, dividing the market into segments characterised by either broad operational adoption or technical depth.

The following evidence-based recommendations address the distinct needs of policy, practice, and research. With regard to workforce development policy, the discrepancy between the widespread mandatory requirement for AI competence and the minimal provision of training indicates a systemic market failure. If AI proficiency is universally required but there is no institutional pathway to it or funding for it, the supply will lag behind the demand, resulting in widening labour market inequalities. For educators, the dominance of implicit framing means that AI literacy programmes must address functional integration skills across a wide range of occupations. As for researchers, the Georgian case shows that the institutionalisation of GenAI in the labour market can happen quickly in smaller transitional economies. This calls for broader cross-national comparative analyses.

Future research should build on this analysis by examining the gap between advertised requirements and actual workplace AI practices, and investigating whether the organisational readiness deficit observed here reflects a temporary adoption lag or a permanent structural feature of smaller labour markets.

Author Contributions

Conceptualization: N.K., T.Z.; Methodology: N.K., T.Z.; Formal Analysis: N.K.; Investigation: N.K.; Writing – original draft: N.K.; Writing – review and editing: T.Z.; Supervision: T.Z.

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