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Beyond Qualifications Frameworks: Large Language Models and the Future of Global Skills Recognition

RESEARCH

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ABSTRACT

Global skills recognition has evolved through decades of innovation, spanning national and regional qualifications frameworks, international conventions, and more recently, digital credentials and artificial intelligence (AI)-assisted recognition systems. This paper brings together the insights of an international working group of researchers and practitioners who examined how AI, particularly large language models (LLMs), can enhance transparency, comparability, and equity in the global recognition of qualifications. The discussion explores how AI might assist in levelling frameworks and enabling job-matching systems that support mobility for diverse learners, including migrants and refugees, while emphasising the continuing need for human oversight, ethical governance, and contextual understanding. By situating these insights within the global discourse on the future of global skills recognition, the paper argues that the next era of recognition systems will depend on the co-evolution of humans and machines—combining computational pattern-detection and human oversight, contextual interpretation, and accountable governance to improve portability, comparability, and fairness, particularly for mobile learners, migrants, and refugees.

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INTRODUCTION

In an era defined by accelerating technological disruption and global interdependence, the recognition and validation of skills and qualifications across national and institutional boundaries have become a core enabling condition for both economic participation and educational mobility. The global recognition of skills and qualifications is essential for enabling labour mobility, fostering inclusive economic growth, and enabling people to learn and work across borders (UNESCO 2016; UNESCO 2019). As education and work become increasingly interconnected, recognition is increasingly central to lifelong learning, workforce adaptability, and equity, particularly for learners whose credentials originate outside the dominant system (Gallagher 2022).

Despite decades of international cooperation, achieving a harmonised system for global skills recognition remains a persistent challenge. Differences in educational structures, divergent policy logics, and inconsistent usage of terms such as skills, competence, and learning outcomes continue to limit interoperability (Bruno et al. 2010; Deane 2005). The result is a patchwork of national and sectoral frameworks that often function as silos, constraining the global flow of talent and knowledge. These inefficiencies not only undermine opportunities for individuals but also reinforce global inequities, leading to skills shortages amid surplus labour and restricting innovation in both developed and emerging economies. Without more adaptive, transparent, and connected systems, the potential of education to drive sustainable development remains unrealised.

At the same time, rapid advancements in artificial intelligence (AI), particularly in generative AI and large language models (LLMs), present new possibilities for addressing these systemic barriers (Dimari et al. 2025). Models such as OpenAI's ChatGPT-4, ChatGPT o1-preview, and most recently, ChatGPT-5 demonstrate unprecedented capacities to process, classify, and interpret large volumes of unstructured text, enabling more dynamic analysis of qualifications data, skills taxonomies, and occupational standards. When responsibly applied, such technologies could help standardise qualification descriptors, improve cross-framework levelling, and strengthen job and competency matching across national and regional systems (Abisha et al. 2024; Gan, Zhang & Mori 2024). However, these opportunities are tempered by critical challenges, including ethical risks, algorithmic bias, and the contextual sensitivity of educational meaning-making (de Almeida, dos Santos & Farias 2021).

This paper situates these developments within the broader discourse on the future of global skills recognition and lifelong learning (OECD 2018; UNESCO 2021; World Economic Forum 2020), exploring how AI-driven systems might transform global skills recognition from a static process of equivalence to a dynamic, learning-centered ecosystem. Drawing on the interdisciplinary expertise of an international working group specialising in higher education, qualifications frameworks, and educational technology, we propose a conceptual model for AI-assisted recognition that integrates technical feasibility with ethical and policy dimensions. Our analysis argues that, when guided by human oversight and grounded in principles of fairness, transparency, and contextual relevance, generative AI can serve as a catalyst for more adaptive, equitable, and future-ready systems of learning and work recognition. In this context, the paper serves both as a review of emerging approaches to global skills recognition and as a discursive exploration of what is needed to advance towards a more coherent, future-oriented system of learning validation.

Accordingly, the paper makes three contributions. First, it consolidates the core interoperability problems that constrain cross-border recognition (fragmentation, semantic drift, and governance gaps). Second, it advances a practical "AI-assisted recognition" logic by identifying where LLMs can add value, primarily in structuring and comparing text-based descriptors, without overstating automation. Third, it proposes governance guardrails and evaluation considerations to keep recognition systems transparent, contestable, and equity-oriented. Methodologically, we use a collective conceptual synthesis combining a structured review of recent literature, working-group deliberation, and validation through an early API prototype (Ascendra).

CONCEPTUAL METHODOLOGY

The methodology guiding this paper can be characterised as a collective conceptual synthesis grounded in professional expertise, critical literature engagement, validation through international dialogue, and solution prototyping. Interpretive rigour, professional experience, and comparative international insight were used as analytical filters to both assess existing literature and iteratively propose and develop theoretical AI solutions to persistent challenges in the learning validation space. Theoretical propositions were tested using a prototype application of AI, which was developed to demonstrate how LLMs might assist in credential comparison and qualification levelling.

The paper combines an analytical synthesis of recent literature with insights derived from the deliberations of an international working group of 12 experts in qualifications frameworks, credential innovation, AI, and education policy, spanning higher education, vocational training, continuing and lifelong learning, and workforce transformation. The combined capacity of the working group includes extensive experience in educational quality assurance and credentialing, computer science, competency-based learning, teacher professionalisation, education curriculum design, scientific and data literacy

education, and AI, including the application of AI and data science to educational systems, workforce initiatives, and skills recognition.

Members of the group have played leading roles in the design, governance, and evaluation of national and regional qualification frameworks across multiple continents, including Africa, Asia-Pacific, the Middle East, and the Americas, and have contributed to the development of three regional frameworks and advised on the African Continental Qualifications Framework (Keevy et al. 2021). Their work has directly supported or been commissioned by global agencies such as UNESCO (see Miao, Shiohira & Lao 2024), the Organisation for Economic Co-operation and Development (OECD) (see OECD 2018), the International Labour Organization (ILO), UNICEF and the World Bank (see ILO & UNICEF 2025; World Bank, UNESCO & ILO 2023), the Commonwealth Secretariat (see Osman & Keevy 2021), and most recently, the G20 (South Africa Department of Higher Education and Training [DHET] 2025), among others. This interdisciplinary foundation, linking research, policy, and technological innovation, provides a uniquely qualified perspective on how generative AI and LLMs can inform and enhance global approaches to skills recognition, credential transparency, and qualification interoperability.

FORMATION AND RESEARCH PROCESS

The working group began meeting in early 2024 with a shared interest in examining how generative AI, particularly LLMs, could support greater standardisation and recognition of skills across diverse qualification frameworks. The group's interdisciplinary composition enabled a multifaceted exploration of the topic, combining insights from policy, educational design, technology, and labour market analysis. Between January and June 2024, the team conducted a comprehensive literature review and meta-analysis of research and policy documents related to knowledge, skills, and competency development and their alignment with national and regional qualifications frameworks. This review synthesised findings from academic sources, organisational reports (e.g., UNESCO, the ILO, World Bank, OECD, European Centre for the Development of Vocational Training [Cedefop], and European Training Foundation [ETF]), and emerging literature on AI and skills recognition. The process identified major challenges in interoperability, semantic drift, and governance across systems, providing the conceptual basis for the current study. The initial outcomes of this phase led to several independent papers, one of which has already been published (see Lastra 2025), as well as the decision to consolidate the collective efforts into a single, integrative conceptual paper focused on the feasibility of conceptual use cases of technology for learning recognition, validation, and mobility.

COLLABORATIVE DELIBERATION AND REFINEMENT

Over the course of 2024–2025, the working group engaged in regular, virtual meetings to deliberate on findings, exchange regional and disciplinary perspectives, and synthesise emerging insights. The deliberative process was iterative and dialogic, emphasising theoretical alignment and practical applicability. The group's sustained engagement for more than a year reflects the rigour, reflexivity, and cumulative validation that underpin the conceptual framework proposed in this paper. The evolving ideas and frameworks were presented and refined through international peer engagement at two major global forums:

- The Global Digital TVET Transformation Summit (Kuala Lumpur, May 28–30, 2025), and
- The Global Development Network (GDN) Meeting (Oslo, October 29–31, 2025).

These convenings provided valuable opportunities to test and strengthen the paper's central arguments through expert feedback from policymakers, researchers, and practitioners in education and workforce development.

PROTOTYPING

To explore the potential role of AI in supporting cross-framework skills recognition, a prototype application, Ascendra, was developed to demonstrate how LLMs might assist in credential comparison and qualification levelling. Ascendra was designed as an application programming interface (API)-based prototype that applies generative language modelling to analyse and compare learning outcomes across diverse qualification artefacts and frameworks. The application's purpose is not to automate recognition decisions but to augment human expertise by identifying linguistic and conceptual similarities between outcome statements, curricula, or qualification descriptors.

TOWARD A FUTURE-READY FRAMEWORK FOR GLOBAL SKILLS RECOGNITION

Building on the collective expertise and structured deliberations described above, the discussion that follows integrates insights from the process to articulate how AI, particularly LLMs, can support a new logic for skills recognition and learning. The following sections move from a critical review of existing qualification frameworks towards a forward-looking exploration of AI-enabled pathways for levelling, recognition, and ethical governance.

CURRENT CHALLENGES IN GLOBAL SKILLS RECOGNITION: FRAGMENTATION, EQUITY, AND EVOLVING DEFINITIONS

The recognition of skills and qualifications on a global scale is vital. It enables individuals to transfer their educational and professional credentials across borders, thereby supporting labour mobility (Sha, Long & Windle 2007). Labour mobility is beneficial as countries can benefit from the influx of skilled workers, employers can access a diverse and skilled workforce, and individuals can pursue career opportunities that match their skills and aspirations. This in turn can lead to increased innovation, productivity, international cooperation, and/or regional competitiveness in global markets. Moreover, for migrants and refugees, recognised qualifications can mean the difference between meaningful employment and underemployment or unemployment, directly impacting their quality of life and ability to integrate into new societies (Iredale 1994). Additionally, global skills recognition upholds human rights by allowing individuals to fully utilise their talents and contribute to society, regardless of their country of origin.

Despite these benefits, the current landscape presents significant obstacles. Countries develop national qualifications frameworks (NQFs) for different reasons, such as to reflect the status quo of qualifications currently within the qualifications system or as an instrument to transform existing qualifications (or the lack thereof) (Bateman 2022). NQFs thus vary widely in structure and content, reflecting different educational philosophies, economic priorities, and cultural contexts (Haolader & Shimu 2024), and while they provide an essential mechanism for organising learning outcomes, their design and implementation vary extensively across countries (Coles et al. 2014).

Developing an NQF requires extensive consultation and research, particularly in determining the number of levels and the domains used to describe learning outcomes (Bateman 2022). The most common domains include knowledge, skills, application, and contextual competence but some countries also integrate digital, green, and social skills into their frameworks. Bhutan, for example, incorporates a values domain in its NQF, reflecting broader societal priorities (Bhutan Qualifications & Professionals Certification Authority 2023). While this diversity is valuable for preserving national identity and meeting local needs, it may create barriers to the mutual recognition of skills and/or qualifications. Furthermore, the lack of political will to adopt shared and standardised measures exacerbates these challenges, as countries often prioritise sovereignty over international harmonisation.

One of the central difficulties in global skills recognition is thus the lack of standardised methodologies for structuring and comparing qualifications. The key factors that hinder the seamless recognition of skills across borders contribute to fragmented and inefficient technical systems. Among the primary challenges is the absence of universally accepted taxonomies and frameworks for qualifications frameworks and qualifications (AUDA-NEPAD 2026; DPRU 2023). Each country or region may have its own system and definitions for categorising and describing skills and competencies, leading to confusion and misalignment when comparing qualifications internationally. This lack of standardisation makes it difficult for employers and educational institutions to assess the equivalence of foreign qualifications accurately.

Even when occupations share the same title across different countries, the underlying requirements, expectations, and cultural connotations may differ significantly (Massing 2024). For example, the role of a nurse in one country may entail different responsibilities and require different qualifications than in another. These variations make it challenging to assess the equivalence of qualifications and ensure that an individual's skills meet the specific demands of different labour markets (Kent & Haruta 2023).

Furthermore, while standardising the semantics and pragmatics of 'skills' and 'competencies' is crucial for the effective international comparison and recognition of qualifications (Lastra 2025), the terms have undergone significant evolution over time, resulting in a phenomenon known as semantic drift (Gilliland 2013). Originally, these terms were defined within specific contexts, often linked to the needs of industrialisation, and later, the knowledge economy (Winterton, Delamare-Le Deist & Stringfellow 2005). Skills were typically understood as specific abilities required to perform certain tasks, while competencies encompassed a broader range of attributes, including knowledge, skills, and attitudes necessary to perform effectively in a job or role (Mulder, Weigel & Collins 2007). These terms have since expanded to include soft skills, digital literacy, and lifelong learning competencies (OECD 2018), and their meanings have expanded and blurred over time. These shifts have contributed to inconsistencies in the application of different terms across educational and professional settings, as well as discrepancies in how qualifications are described and understood internationally. This in turn complicates the development of curricula, hinders the assessment and mutual recognition of qualifications, and affects the alignment of NQFs with international qualifications frameworks, as without consistent definitions, it becomes challenging to map qualifications from one system to another (ETF, Cedefop & UNESCO 2013). These inconsistencies can ultimately lead to underemployment or blocked professional pathways when qualified individuals are unable to demonstrate equivalences or meet locally interpreted requirements.

Despite these challenges, it is worth noting that reluctance to adopt centralised measures for skills recognition often stems from concerns over national sovereignty, economic protectionism, and differing policy priorities (Nicolaidis & Shaffer 2005). Countries may fear

that standardisation could undermine their educational systems or lead to an influx of foreign workers that could affect local employment (Busemeyer 2012). This lack of political will impedes the development of international standards that could facilitate the mutual recognition of qualifications and further demonstrates the need for a more adaptive model for comparison, rather than a specific call for uniformity.

LLMs AND THE NEW LOGIC OF SKILLS RECOGNITION

Generative AI, particularly LLMs, represents a significant advancement in the field of AI (Acemoglu & Restrepo 2019). These models can process and generate human-like text based on vast datasets, making them valuable tools for analysing and standardising complex information. Prominent LLMs operate using transformer architecture and can identify patterns, recognise relationships within text data, and generate structured outputs (Ferraris, Audrito & di Caro 2025). These abilities potentially make them well-suited for tasks such as parsing educational materials, mapping competencies, and aligning qualifications with industry requirements. Leveraging these capabilities, LLMs could potentially assist in creating more standardised descriptions of skills and qualifications, facilitating comparisons across different systems.

However, despite their strengths, LLMs have significant limitations that must be addressed. One major limitation is their lack of deep or contextual understanding. LLMs generate responses based on patterns in data rather than true comprehension, which means they may struggle with nuanced interpretations or the complex reasoning required in educational assessments (Rawther et al. 2024). In other words, LLMs primarily learn statistical regularities in language. They can be highly effective at summarizing, classifying, and mapping patterns across large corpora, but they do not 'understand' meaning in the way human experts do, and they may fail on cases that require contextual judgement, policy nuance, or tactic domain knowledge. Or as Daniel Dennett (2013) stated, 'competence without comprehension'. Their performance is also constrained by data quality and coverage (Lin et al. 2024); when training or evaluation data are biased, incomplete, or regionally skewed, model outputs may be systematically less reliable for underrepresented contexts.

These limitations align with broader ethical concerns when deploying LLMs. Issues such as perpetuating biases, generating misleading information (often referred to as 'hallucinations'), and a lack of transparency in decision-making processes raise significant questions. These concerns necessitate careful consideration and the implementation of strategies such as human oversight, review, and accountability, and the crowdsourcing of error reports for review to mitigate potential negative impacts (Marcus 2022).

ILLUSTRATIVE USE CASE: API PROTOTYPE

The prototype, referred to as Ascendra, used natural language processing (NLP) methods to evaluate semantic alignment between text-based qualification descriptors. By embedding these descriptors into a high-dimensional semantic space, the model estimates degrees of similarity based on context, intent, and skill-related terminology. The system allows users to upload or input learning outcomes and qualification descriptors, then returns ranked comparisons that suggest where semantic overlap is strongest across frameworks. These outputs are intended as decision support, an initial analytic lens to inform benchmarking, triage, and expert review, rather than an automated determination of equivalence. The value proposition is speed and consistency in first-pass comparison, coupled with traceable outputs that experts can interrogate and contest.

The prototype ingests CSV or PDF files as primary and secondary artefacts and then uses API-calls within the application code to extract learning outcome signals comparable across global systems. Below are two extracts of outputs from the Ascendra prototype illustrating the potential to guide and support expert interpretations. The first example is based on the comparison of two sets of level descriptors in the skills domain, Level 1 from the African Continental Qualifications Framework (ACQF), and Level 7 from the European Qualifications Framework (EQF). The second is an extract of the overall similarities and differences between Level 10 of the ACQF and Level 8 of the EQF.

Example 1: ACQF Level 1 & EQF Level 7, Skills domain.

Primary Level (Level 1):

- **Skills:**
- Cognitive: Simple cognitive skills such as recall and understanding basic concepts.
- Practical: Basic practical skills, often repetitive and structured.
- Problem-Solving: Basic problem-solving, typically requiring application of previously learned patterns in familiar contexts.

Secondary Level (Level 7):

- **Skills:**
- Cognitive: Advanced cognitive skills, including analysis, synthesis, and evaluation.
- Practical: Sophisticated practical skills requiring independent execution.

Degree of Equivalence and Recommendation: Due to the significant leaps in depth, complexity, and autonomy between the levels, they are not directly equivalent. The Primary Level at Level 1 is suggested to align with perhaps a preparatory or foundational

or foundational entry-level category, while the Secondary Level 7 corresponds to an advanced or mastery level of qualification or professional standard, such as a postgraduate qualification or equivalent advanced expertise.

Thus, the recommended alignment would place the Secondary Level 7 as an evolved extension of the foundational skills and knowledge of Primary Level 1, representing progression from beginner to expert.

Similarity score: 20/100

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Example 2: ACQF Level 10 & EQF Level 8, Similarities and differences.

Similarities:

- Both levels demonstrate a high degree of specialisation and require advanced cognitive and procedural skills.
- Autonomy is emphasised in both, with an ability to solve problems and make decisions independently to a certain extent.

Differences:

- **Complexity:** Level 10 requires broader integration and innovation, whereas Level 8 centers on in-depth mastery within a constrained scope.
- **Responsibility:** The difference in scope of responsibility, with Level 10 emphasising initiating changes and innovations, while Level 8 focuses on responsibility within specific boundaries.
- **Knowledge and Skills Application:** Level 10 involves creating new concepts, compared to Level 8's ability to manage and adapt established concepts.

Recommended Alignment:

Given the analysis above, Level 8 corresponds most closely to an underpinning for Level 10 but does not entirely meet the broader and more comprehensive expectations. Level 8 aligns well within the boundaries of a Level 10 framework primarily, when rigour is focused more on application than integration and creation. However, as the demands for innovation and strategic responsibility increase, the gap between Level 8 and Level 10 widens considerably.

Similarity Score: 75

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As an advisory tool, Ascendra's outputs must be interpreted cautiously. While LLMs are highly effective at identifying linguistic parallels, they may overlook policy nuances, regulatory distinctions, or contextual variations inherent to NQFs. The model's reliability therefore depends on continuous validation by human experts who can interpret results in light of specific socio-educational contexts and framework structures. The prototype underscores the importance of maintaining human oversight and interpretive authority, particularly when AI-generated insights could influence credential recognition or learner mobility outcomes.

Looking forward, the development of task-oriented, domain-specific language models, referred to as 'small language models' or 'SLMs', offers an important ethical and operational alternative to the generalised large-scale models currently in use. These smaller, purpose-built models can be trained on curated datasets specific to qualifications and competency frameworks, thereby reducing bias, improving contextual fidelity, and enhancing explainability (as well as reducing energy and water use). Although the Ascendra prototype is not itself an SLM, its design principles highlight the potential of such customised models to achieve greater accuracy, transparency, and ethical assurance in AI-assisted credential recognition. By combining targeted training data with constrained model architectures, SLMs may help reconcile the scalability of AI with the accountability and trust required for fair and equitable global skills recognition (see, for example, Hao 2025).

At the time of writing, the Ascendra API model remains under active development and fine-tuning, and the prototype should be viewed as an emerging example of a potential use case rather than a finalised system. Its refinement and validation will require further research, iterative testing in controlled environments, and continued interdisciplinary collaboration to evaluate its efficacy and ethical integrity in real-world applications.

TOWARDS ADAPTIVE LEVELLING AND JOB MATCHING: AI AS A MEDIATOR OF LEARNING AND WORK

LLMs can analyse the language used in qualifications frameworks by identifying commonalities and differences across countries, feeding into international conversations about standardisation. By processing large datasets of educational standards, job descriptions, and competency frameworks, AI can help develop consistent definitions of skills and mappings between skills, standards, and frameworks. However, because language evolves and terms and skills are context-dependent, AI must be used alongside human expertise to ensure accuracy and cultural sensitivity in qualifications framework comparisons.

With these deliberations in mind, we propose two considerations as a basis for exploring the applications of generative AI in a 'New Logic' for global skills recognition.

CONSIDERATION 1: A NEW LOGIC FOR LEVELLING

Levelling is the process of assigning educational qualifications to specific levels within a qualifications framework based on learning outcomes and competencies. This process is essential for maintaining the integrity and utility of qualifications frameworks but is currently challenged by subjectivity and complexity (EU 2011; Keevy, Mayet & Matlala 2017). In other words, the levelling of qualifications can be a complex and time-consuming process that is often prone to intuitive human judgements. Generative AI LLMs could be harnessed to at least partially automate the levelling process, while ensuring consistency and the comparability of qualifications within and across countries. The questions are: *How ethical would it be to do so?* and *What specific algorithms or models would need to be applied?*

Insights can be drawn from at least three statistical methods. Non-parametric statistical methods such as K-Nearest Neighbors (KNN) with text representation could be used to determine the closest matches between job profiles and qualifications profiles, for example, or between existing qualifications and an 'ideal' or 'standard' that is politically agreed. Unsupervised methods such as K-clustering could also be used to get the most common elements or groupings out of a set of qualifications frameworks, level descriptors, and job profiles to create a 'standard level profile'. Non-traditional statistical methods such as graph neural networks (GNNs) are modern and powerful machine learning methods that could also map and represent relationships. For example, GNNs could map the more nuanced alignment between learning outcomes located within qualifications descriptors and learning outcomes used to describe levels of learning.

Levelling of NQFs involves the consideration of two main components:

- Assigning levels based on level descriptors; and
- Evaluating the volume of learning, which may be expressed as a credit value.

While assigning credit value is a more straightforward task, assigning levels involves a more complex process. Levelling often relies on expert judgement, which can vary between individuals and contexts, introducing subjectivity into the process. Balancing vertical progression (the increasing complexity and depth of learning at higher levels) with horizontal comparability (equivalence across different fields of study) is also challenging. Additionally, the process is resource-intensive, requiring significant time and expertise, which can hinder timely updates and adaptations to evolving educational landscapes.

Cedefop indicates that the key purpose of NQF level descriptors is 'to indicate the location of a particular qualification' (Cedefop, 2018, p. 9). How countries use level descriptors to locate or place a qualification on the framework varies and depends on the purpose of the NQF within the qualifications system and the quality assurance arrangements applied to locating the qualifications. Deij (in Keevy & Chakroun, 2015, p. 60) notes that there are two main ways to apply the level descriptors:

- An 'end-point approach' (also referred to as a credit-based approach), where the qualification outcomes at the end of the qualification cycle inform the level; and
- A 'best-fit approach', where qualifications are placed according to the main focus of the knowledge, skills, and competence/application.

According to Bateman (2022), the credit-based approach involves developers allocating a level and credit value to the components of the qualifications and using an agreed formula to determine the type or level of the qualification. Examples of this approach include the New Zealand Qualifications and Credentials Framework and the Lesotho Qualifications Framework. The best-fit approach involves the evaluation of whether the qualification outcome (as a whole) meets, in broad terms, an NQF level. An example of this approach would be the Australian Qualifications Framework. Bateman explains that these approaches are not mutually exclusive but are on a continuum; a mix of these approaches may apply, and other external influences may also apply (Bateman 2021).

Our view is that generative AI could improve consistency in levelling by applying comparable criteria across large volumes of text, reducing interpretive drift, and lowering the operational burden of building fully structured datasets where such datasets do not yet exist. Through the training of LLMs, methods such as KNN, K-clustering, and GNNs, as mentioned above, could be refined to detect patterns and relationships that may not be immediately apparent to human analysts (Serino 2022; Sonstein et al. 2020), potentially uncovering new insights into how qualifications relate to one another (see Figure 1 below).

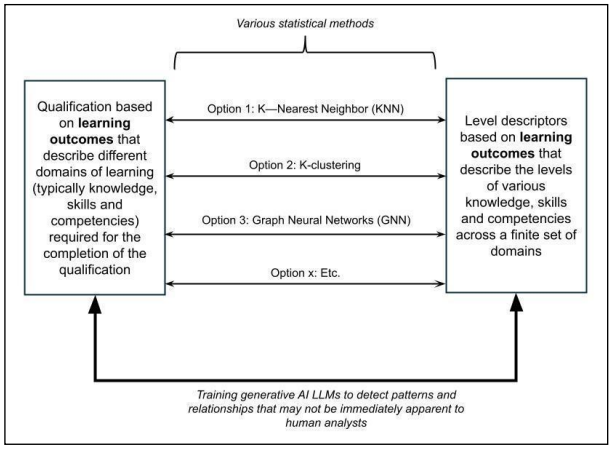

Figure 1 A new logic for levelling (Source: Authors).

Some cautions are important to note. While generative AI can process large volumes of textual data, and its language generation capabilities are widely acclaimed, there are varying opinions on its logical reasoning. While said to be able to solve logic puzzles, a study by Harvard found that generative AI's prowess with logical reasoning is around 58%, indicating a gap in its reasoning process (Pagidyala 2023). The various versions of ChatGPT are said to have a weakness in their deductive and propositional logic. As a result, AI may misinterpret definitions and terms within qualifications frameworks and qualifications without understanding cultural, institutional, or industry-specific contexts. Furthermore, certain aspects of levelling require nuanced decisions that AI is not equipped to make, such as assessing the quality of learning experiences or the relevance of specific competencies in different contexts. Human oversight is therefore essential to address these limitations and ensure that AI suggestions are accurate and appropriate.

CONSIDERATION 2: A NEW LOGIC FOR AI-DRIVEN JOB MATCHING

Migrants and refugees often face significant barriers to employment, including the non-recognition of their qualifications and limited access to job markets (Donlevy et al. 2016; Lantero & Finocchietti 2023). They frequently struggle to have their qualifications recognised in their new countries due to differences in educational systems, lack of verifiable documentation, and unfamiliarity with local labour markets. Recognition processes can be costly, time-consuming, and inaccessible, leading to underemployment or unemployment (Iredale 1994). Additionally, many migrants and refugees face a digital divide, with limited access to technology and digital platforms that facilitate job searches (Alam & Imran 2015). Nonetheless, AI-driven job-matching systems have the potential to mitigate these challenges by recognising and valuing migrants' and refugees' skills appropriately (Uribe et al. 2022) (see Figure 2 below).

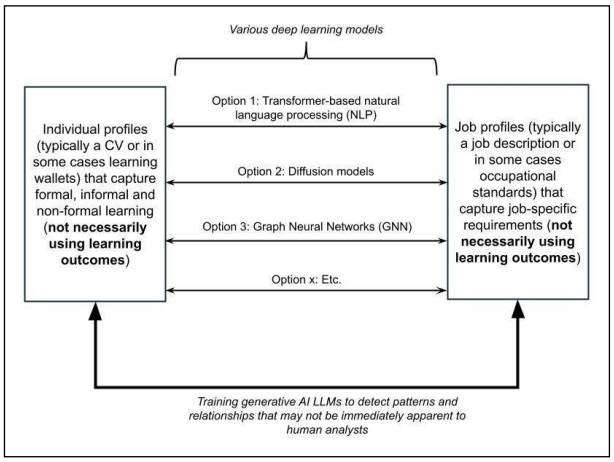

Figure 2 A new logic for AI-driven job matching (Source: Authors).

In our view, LLMs can potentially enhance job-matching systems (Zhang, van der Goot & Plank 2023; Zhao et al. 2024) by analysing individual profiles to identify transferable skills and competencies, even from non-traditional or informal learning experiences. Just as we argued in the preceding section on a new logic for levelling, we contend that generative AI could be used to support and improve job-matching systems, providing tailored job recommendations that align with an individual's unique background and strengths, thus improving the efficiency of the job search process. In theory at least, recognising a broader range of qualifications and experiences could improve opportunities for migrants and refugees, facilitating their integration into the workforce.

To ensure the effectiveness of AI-driven job-matching systems for migrants and refugees, several considerations must be addressed. Data quality and bias are critical concerns; AI systems must be trained on diverse and representative data to prevent reinforcing existing biases. Furthermore, additional considerations need to be made in the context of job matching. Accessibility is essential; platforms should be designed to be user-friendly and accessible to individuals with varying levels of digital literacy. Policy support is necessary to bridge the digital divide, including providing resources and infrastructure to ensure that migrants and refugees can access and benefit from these technologies.

ETHICS, TRUST, AND HUMAN OVERSIGHT IN AI-DRIVEN RECOGNITION

In this paper, we argued that the integration of generative AI into global skills recognition systems presents an opportunity to trial new approaches to longstanding challenges in transnational qualification recognition and employment mobility. LLMs can enhance the levelling process within qualifications frameworks, improve job-matching systems, and increase transparency in skills assessment, making the recognition of competencies more consistent, scalable, and inclusive. However, realising this potential requires a structured and ethically grounded approach that balances the computational power of AI with human expertise, contextual understanding, and trust-based governance.

One of the enduring challenges in global skills recognition has been the fragmentation of qualifications frameworks, resulting in inefficiencies, inequities, and barriers to labour mobility. AI-assisted levelling could help mitigate inconsistencies across national systems by providing automated recommendations, identifying patterns in qualification standards, and supporting cross-referencing between frameworks. Yet, AI alone

cannot resolve the deep cultural, institutional, and contextual differences that underpin qualification systems. Human oversight therefore remains essential, not only to validate AI-generated outputs but also to interpret them through the lens of local relevance, equity, and professional judgement. Similarly, AI-driven job matching holds promise for migrants, refugees, and informal learners by mapping transferable skills and aligning competencies with emerging labour demands. However, such applications must be designed inclusively and evaluated continually to ensure that they do not entrench existing inequities.

The deployment of AI in skills recognition raises three key ethical considerations: bias and fairness, privacy and data protection, and accountability and transparency. First, algorithmic bias remains a persistent risk. Because AI systems learn from historical data, they can inadvertently reproduce the inequalities embedded in those datasets, amplifying discrimination against marginalised or underrepresented groups (Hao 2025; Mao, Tan & Moieni 2023). Continuous auditing, open benchmarking, and explainability mechanisms must be implemented to detect and correct such biases.

Second, the handling of personal and professional data must comply with global privacy standards and ethical norms (Apsilyam, Shamsudinova & Ashrapova 2025). Individuals must be informed about how their data is collected, processed, and stored, with explicit consent obtained before use. Strong data governance frameworks, including encryption, anonymisation, and limited retention, are critical to safeguard trust in AI-enabled systems.

Third, accountability and transparency are essential in ensuring that AI decisions remain intelligible, challengeable, and auditable. Transparent documentation of model logic and decision pathways enables educators, policymakers, and credentialing bodies to understand how conclusions are derived. Without such transparency, AI systems risk becoming 'black boxes' that undermine confidence in global recognition processes.

Human oversight and collaborative governance thus become the cornerstone of ethical AI implementation. Experts can validate AI recommendations, interpret contextual nuances, and identify cases where automated reasoning diverges from educational or labour-market realities (Drori & Te'eni 2024). Effective oversight extends beyond validation; it requires human-in-the-loop systems where professionals are embedded throughout the AI lifecycle, from data curation and model training to output evaluation and feedback integration. Nevertheless, caution is warranted. Evidence suggests that human–AI collaboration is not universally beneficial. Vaccaro, Almaatouq, and Malone (2024) found that such combinations can underperform in decision-making contexts while showing gains in creative or generative tasks. This underscores the need to design governance structures that allocate responsibility appropriately, ensuring that humans intervene where ethical reasoning and contextual interpretation are indispensable.

We therefore propose that AI-enabled recognition approaches be evaluated in structured 'sandbox' environments, controlled, transparent, and participatory settings in which model outputs can be compared against expert judgement, audits for bias, and stress-tested across jurisdictions and learner profiles. Sandboxes should include clear escalation pathways for contested cases, documentation standards that make outputs explainable, and feedback loops that allow systemic error reporting and model refinement. This approach enables innovation without premature institutionalization, keeping recognition systems accountable to equity, due process, and contextual validity. They would also facilitate continuous improvement by integrating stakeholder feedback, aligning with emerging thinking from Cedefop (see Cedefop 2025), the African Union (see AU 2024), the European Commission (see Vesnic-Alujevic & Saitis 2025), UNESCO (see Miao & Holmes 2023), and the G20 (DHET 2025).

CONCLUSION AND CALL FOR ACTION

As education systems confront accelerating technological disruption and social change, the imperative is clear: to move beyond fragmented and siloed frameworks towards a shared, inclusive, and future-ready global ecosystem in which learning, wherever and however it occurs, is recognised for its capacity to empower individuals and strengthen societies.

The future of global skills recognition depends on reimagining how education systems, technologies, and human judgement interact to prepare learners for a rapidly changing and interconnected world. Generative AI offers more than a technical solution: it represents a paradigm shift in how learning is understood, validated, and shared across borders. When embedded within qualification and credentialing frameworks, AI can help translate diverse learning experiences into comparable, portable forms of recognition, enabling individuals to navigate complex career pathways with greater agency and confidence.

Yet realising this promise requires a fundamental shift in both governance and mindset. The integration of AI into education and credentialing must be guided by ethical frameworks that place human oversight, fairness, and transparency at the centre. Institutions must build capacity to engage critically with these technologies, ensuring that their use reinforces, rather than replaces, the professional judgement, contextual awareness, and pedagogical purpose that define meaningful education.

Such systems must be learner-centred, globally coherent, and adaptable to the evolving landscape of work, citizenship, and lifelong learning. This paper therefore calls for a coordinated global effort to design and test ethically governed, AI-enabled recognition systems that bridge national divides while safeguarding human dignity and autonomy. Doing so will require not only the development of specific technical tools that respond to desired use cases, but also collaboration across governments, international organisations, and educational providers to establish interoperable standards, shared data protocols, and common principles for trust and accountability.

The challenge is significant, but so too is the opportunity. Ultimately, the ethical future of global skills recognition depends not merely on technological advancement but on cultivating a culture of responsible innovation. If implemented with fairness, accountability, and inclusivity at its core, AI can enhance rather than replace human judgement, creating a more transparent, learner-centred, and future-ready ecosystem for skills and qualifications.

COMPETING INTERESTS

The authors have no competing interests to declare.

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