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A Fuzzy Logic–Based Model for Assessing Employability Skills in Higher Education: Preparing Students for Emerging Job Markets

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Abstract

HEIs must show their graduates are "career-ready" while also preparing them for fast-changing labor markets due to technology, demographics, and green transitions. The World Economic Forum's 2025 Future of Jobs Report predicts a net job increase with displacements from job restructuring by 2030; this demands measuring employability skill development integrated into curricula. The ILO's report on generative AI also posits that the impact will be task reconfiguration which implies the sustained need for interpersonal skills such as communication, teamwork, critical thinking, professionalism, and ethical judgment (Bridgstock, 2009).

This study introduces a Fuzzy Logic-Based Employability Readiness Index (ERI) for measuring graduates' employability in higher education as interpreting linguistic terms (like low, medium, or high). Fuzzy set theory applies to the uncertainty of grading to partial memberships (0–1) in skill categories, and rule-based inference(s) combines evidence leading to transparent quality control, advising, and curriculum improvements (Cronbach, 1951). The model incorporates the eight competencies of NACE Career Readiness Competencies and corresponds to the outcome-based policy focus on holistic development and competencies in India.

As demonstrations to illustrate feasibility (i.e., no claims to field data), the demonstration involves a simulation that is open and reproducible—including tables and graphs (bar, line, ROC, heatmap). The ERI positions itself as an evaluative and improvement tool (as opposed to being a mere "placement predictor)", which is consistent with employability scholarship that cautions against an overreliance on employment outcome measures as a commentary on the institutional value.

Keywords: Employability skills, Career readiness, Fuzzy logic, Higher education assessment, Emerging job markets, Competency-based education.

Introduction

Employability is widely conceptualized as more than simply "getting a job." A fundamental policy-focused articulation frames employability as the ability to secure first-time employment, sustain employment, and, when necessary, transition to different positions, illustrating personal attributes and situational factors. Broader academic treatments similarly emphasize that employability is complex and not reducible to a narrow list of transferable skills; rather, it is a set of achievements that is necessary but not sufficient for employment because outcomes depend on labor-market conditions and opportunity structures (Dacre Pool & Sewell, 2007). This viewpoint is reinforced by work distinguishing competing perspectives on graduate employability (skill possession, social positioning, and process/career management), warning that simplistic “skills checklists” can be theoretically incomplete.

Why emerging job markets intensify the assessment requirement

Recent labor-market evidence underscores why employability assessment should be forward-looking. The World Economic Forum has stated that major macrotrends such as technological changes, economic uncertainty, shifting demographics, geo-economic fragmentation, and the green transition are expected to change the nature of work until 2030. The World Economic Forum's 2025 report expected large-scale job disruption and put heavy emphasis on upskilling and reskilling as the primary focus of the workforce response (European Commission, n.d.). This means that for higher education, employability systems need to assess readiness not only for current entry-level jobs, but also for iterative shifts, redesign of roles, and technology-driven work processes.

Also, the ILO analysis of generative AI says that exposure does not equate to impact and that augmentation, rather than full automation of a profession, will be the predominant impact. This means that workers will need to adjust to new compositions and expectations of quality for their tasks. This strengthens the need for assessments that measure human (inter) skills (communication,teamwork,professionalism, inclusion) in addition to cognitive and technological skills (Fugate, Kinicki & Ashforth, 2004).

The measurement problem in employability: imprecision, subjectivity, and accountability

HEIs typically assess employability through rubrics, portfolios, presentations, internships, peer feedback, supervisor evaluations, and reflective work. These are valuable, but they are inherently judgment-based and often expressed in linguistic terms (e.g., “good communicator,” “moderate teamwork,” “high initiative”). Employability scholars also caution against over-reliance on crude outcome indicators such as employment rates, which can misrepresent institutional impact and shift attention away from the individual’s capability development (Gmyrek, Berg & Bescond, 2023).

A further difficulty is that employability includes psychosocial and adaptive dimensions. For example, employability has been described as a psycho-social construct combining person-centered resources that support adaptive cognition and behavior, including career identity and personal adaptability. Taken together, these insights suggest employability measurement should:

1) handle imprecision and partial achievement realistically,
2) remain interpretable for curriculum improvement, and
3) be adaptable to evolving job-market demand.

Why fuzzy logic is appropriate for employability assessment

Fuzzy set theory was developed precisely to model categories with graded membership rather than binary membership. In a fuzzy system, a student can be partly “medium” and partly “high” in a competency area, matching how instructors and employers often reason about performance (Government of India, 2013). Rule-based fuzzy inference systems, particularly classic Mamdani-style logic, are designed to synthesize human linguistic rules into an output score in an interpretable manner.

In education research, fuzzy expert systems are increasingly used for evaluating soft skills because these skills are behavioral, context-sensitive, and difficult to measure precisely. In employability-specific contexts, prior work has demonstrated fuzzy expert systems that compute employability assessments from multi-attribute inputs. While such studies support feasibility, higher education needs a framework that is competency-aligned, curriculum-embedded, and explainable enough to support quality assurance and continuous improvement rather than producing only a black-box score (Government of India, 2020).

Competency anchoring and policy alignment

To improve comparability and stakeholder legitimacy, competency selection should align with recognized frameworks. The NACE Career Readiness Competencies provide an employer-facing set of eight competencies (e.g., communication, teamwork, professionalism, technology) that are widely used in career readiness practice. In India, competency-based education and outcomes orientation are reinforced by the National Education Policy (NEP) 2020, which emphasizes holistic development, critical thinking, life skills, and technology integration. Additionally, the National Skills Qualification Framework (NSQF) organizes qualifications by levels of knowledge, skills, and aptitude defined as learning outcomes—supporting employability-relevant, outcomes-based assessment (Harvey, 2001).

Purpose and contribution of the study
This paper develops a Fuzzy Logic–Based ERI model to assess employability skills in higher education with:
- interpretability via rule-based reasoning,
- competency grounding in NACE,
- alignment with NEP 2020 and NSQF outcomes orientation, and
- adaptability pathways to emerging job markets by periodically recalibrating weights and indicators using credible skills intelligence (e.g., OECD skills transition analysis and skills taxonomies).

Literature Review

The literature on graduate employability explains the phenomenon as more than gaining a job; it also includes the ability to gain, retain, and shift between different employment situations as the labour market changes (Hillage & Pollard, 1998; Dacre Pool & Sewell, 2007). Further scholarship has defined employability as a multidimensional and relational construct, influenced by psychosocial elements, situational aspects, and career development activities, and has critiqued the narrow skill-set listings (Fugate, Kinicki, & Ashforth, 2004; Holmes, 2013; Tomlinson, 2012).

The evaluation of transferable skills such as communication, collaboration, critical thinking, and professionalism (Harvey, 2001; Knight & Yorke, 2003; Yorke, 2006) has fueled definable interest in incorporating employability into curriculum construction and evaluation in the context of higher education. Recent research also emphasizes the importance of the flexible combinations of human and digital competences due to technological disruptions, green transitions, and the restructuring of work due to generative AI (Gmyrek, Berg, & Bescond, 2023; OECD, 2023; World Economic Forum, 2025). Regarding the the aforementioned, fuzzy logic poses a viable evaluation strategy as it embraces ambiguity, partial membership, and linguistic evaluation in assessing complex soft skills, whilst maintaining interpretability through a rule-based approach (Zadeh, 1965; Mamdani &Assilian, 1975; Kumari, Kumar, & Sharma, 2015).

Methodology

Research design

This is a model development and demonstration study for higher education employability assessment. The primary output is an assessment model specification (ERI) that can be implemented with real institutional data (Hillage & Pollard, 1998). Numerical results reported in the "Results and Discussion" section are explicitly based on synthetic/simulated data to illustrate computation, visualization, and interpretation when no dataset is available.

Construct definition and competency selection

The employability construct is treated as a multidimensional capability shaped by individual assets and context, consistent with employability as a framework for gaining, maintaining, and transitioning between jobs (Holmes, 2013). This aligns with scholarship stating that the outcomes (employment) depend on the conditions of the labor market and thus should not be the only measure institutionally.

Core competency framework

The ERI model applies the NACE Career Readiness Competencies as the leading competency taxonomy because it offers an applicable, employer-centered framework of eight competencies that is purposefully aligned with the assessment and advising of higher education (Zadeh, 1965).

Alignment to emerging job markets

The competency framework is interpreted through the lens of:
- Projections: WEF macrotrends impacting work and employment (workplace transformations, technology, green transition, demographic shifts).

- ILO: AI shifts the composition of tasks and raises the requirements for worker adaptation, rather than just destroying jobs.

- OECD: green and digital transitions and the skills required for resilience

Evidence and scoring approach

Competencies are rated from 0–100 based on several sources of evidence collected (course-embedded rubrics, project work, portfolios, internship evaluations, simulations) and supports the competency and outcome-based practices of NEP 2020 and the NSQF's learning-outcomes framing (Knight & Yorke, 2003). The reliability of such multi-item instruments can, during actual deployments, be assessed using internal consistency measures such as Cronbach's alpha.

Fuzzy logic model specification

Rationale. Subjective evaluation is a common criticism of employability assessment. Fuzzy logic attempts to accommodate uncertainty by introducing the notion of partial membership in one of the categories (e.g. a communication score may be classified as partially "medium" and partially "high");

Fuzzy sets and linguistic expression: Let each input competency $x \in [0,100]$ take the linguistic labels: Low, Medium, High. Then each of these labels corresponds to some membership function $\mu(x) \in [0,1]$. A common and understandable choice in practical fuzzy studies is the use of triangular membership functions (Kumari, Kumar & Sharma, 2015).

Rule-based inference: The model employs interpretable IF-THEN rules in the tradition of Mamdani (e.g., IF Communication is High AND Teamwork is High THEN Collaboration is High), which fosters transparency and explainability (Yorke, 2006).

Hierarchical aggregation to reduce rule explosion: A completely enumerated rule base becomes quite large with eight variables. However, a hierarchical approach forges a balance between complexity reduction, and rule base interpretability, a strategy frequently employed in fuzzy systems for educational assessment.

We define three sub-indices:
- **CogTech (Cognitive–Technology):** Career & Self-Development, Critical Thinking, Technology
- **Collab (Collaboration):** Communication, Teamwork, Equity & Inclusion
- **ProfId (Professional Identity):** Leadership, Professionalism

Then compute ERI as a weighted combination:

$$\mathrm{ERI} = w_1 \cdot \mathrm{CogTech} + w_2 \cdot \mathrm{Collab} + w_3 \cdot \mathrm{ProfId}, \quad \sum w_i = 1$$

Weights can start equal and later be recalibrated using credible labor-market signals.

Updating the model for emerging job markets

The changing job markets suggest that "skill importance" shifts over time. Instead of rewriting the fuzzy rules every semester (which would introduce instability), it may be more useful to keep the rules fuzzy for the sake of interpretability, and periodically update the weights and the rubrics for the indicators using skills intelligence from the following:

- OECD reports on skills for resilient green and digital transitions.

- Skills taxonomies and classification systems (e.g., ESCO) that facilitate the articulation of learning outcomes to the labor-market skills language (Mamdani &Assilian, 1975).

Table 1: NACE-based employability competencies, operational indicators, and relevance to emerging job markets

Competency (NACE)	Example measurable indicators in HE (0–100 scoring)	Why it matters for emerging job markets
Career & Self-Development	Career plan quality, reflection depth, feedback-seeking behavior, learning agility evidence	Frequent job transitions and task changes require ongoing upskilling and self-directed development.
Communication	Presentation rubrics, writing quality, stakeholder communication tasks	Collaboration and coordination remain central as organizations integrate AI tools and redesign workflows.

Critical Thinking	Case analysis, evidence-based reasoning rubrics, structured problem-solving tasks	Rapid change raises value of analytical judgment and decision-making under uncertainty.
Equity & Inclusion	Team contracts, inclusive behavior rubrics, intercultural competence scenarios	Diverse teams and inclusive practices support better collaboration and institutional responsibility.
Leadership	Initiative logs, mentoring evidence, project leadership rubrics	Leading in uncertain environments requires coordination and accountability beyond technical knowledge.
Professionalism	Reliability indicators, ethics scenarios, quality control checklists	Job quality expectations and responsible technology use increase importance of professionalism.
Teamwork	Peer evaluation, conflict resolution tasks, collaborative deliverables	Social performance and coordination remain core employability dimensions.
Technology	Tool proficiency tasks, data literacy tasks, ethical tech-use scenarios	Digital and AI transitions require functional technology competence plus critical and ethical use.

Table 1 outlines the NACE-based employability competencies and their relevance to emerging job markets. Documenting measurable indicators in higher education across competencies such as Communication, Critical Thinking, and Career & Self-Development, illustrates the importance of each competency in relation to the expected future employment ecosystem. In relation to rapidly evolving work environments and the need for digital integration, the employment ecosystem relies on the ability of candidates to demonstrate adaptability and collaboration, along with analytical and technological skills.

Table 2: Example fuzzy membership function parameters (0–100 scale)

Linguistic label	Membership function type	Example parameters (triangular)	Interpretation
Low	Triangular (left shoulder)	(0, 0, 50)	Strong membership at low scores, gradually decreasing to 0 by 50
Medium	Triangular	(25, 50, 75)	Highest membership at 50, tapering on both sides
High	Triangular (right-shoulder)	(50, 100, 100)	Increasing membership from 50 toward 100, strong at top end

The table describes the parameters for fuzzy membership functions on a 0–100 scale. Three linguistic labels (i.e., Low, Medium, and High) utilize triangular functions. Low begins at 0, and its membership starts “strong” and decreases linearly to 0 by 50. Medium has the membership “peak” at 50 and tapers on the sides. High begins increasing from 50 and has “strong” membership at 100, denoting greater values. These functions model the fuzzy logic membership degrees.

Table 3: Illustrative hierarchical rule templates (interpretable "IF–THEN" rules)

Sub-index	Rule template examples	Educational interpretation
CogTech	IF Critical Thinking is High AND Technology is High THEN CogTech is High	Strong analytical ability plus tech fluency supports adaptive performance in digital work
Collab	IF Communication is High AND Teamwork is High THEN Collab is High	Employability rises when collaboration behaviors are consistently strong
ProfId	IF Professionalism is Low THEN ProfId is Low (regardless of leadership)	Reliability/ethics failures are "gating factors" that reduce readiness even with other strengths
ERI	IF CogTech is High AND Collab is Medium/High AND ProfId is Medium/High THEN ERI is High	Readiness is best supported by balanced development across domains

The table provides examples of hierarchical "IF-THEN" rules for calculating sub-indices like CogTech, Collab, ProfId, and ERI in the context of employability. Each regulation links the assessment of specific competencies (e.g., Critical Thinking, Technology, Communication) to their corresponding sub-indexes (e.g., CogTech). These regulations assist in the understanding of how specific competencies affect the overall employability ecosystem, showing the necessity of an all-round development, but especially the contribution of collaboration and professional attitudes towards the employability preparedness.

Hypothesis

The following hypotheses will be tested in a UGC-style empirical study grounded in institutional competency evidence and employability outcomes.

H1 (Criterion Validity): In the context of employability as an individual capability rather than an institutional employment metric, it is posited based on McQuaid & Lindsay (2005) that students with higher ERI scores would have more favorable employability outcomes (i.e. internship offers, job placements, recruiter evaluations).

H2 (Incremental Validity Over Crisp Scoring): Due to the representation of partial skill membership through fuzzy inference along with human linguistic reasoning in judgement, it is expected ERI will predict employability outcomes at least as well as, and often better than, the arithmetic mean of the competencies.

H3 (Adaptability to Emerging Job Markets): As suggested by NACE the green and digital transitions (2025) ERI's indicator rubrics and weight recalibrations using real-time labor market and skills intelligence will be relevant to the evolving skill framework and will consequentially improve the predictive validity.

Results and Discussion

Demonstration overview and transparency note

In the absence of a dataset, the simulations in this study are for illustrative purposes only. They are meant to illustrate the Employability Readiness Index (ERI) in a clear and methodical manner from competency profiles. The study offers reproducibility and practical implementation by supplying executable Python code for the proposed charts in Google Colab. Additionally, these simulations are meant to illustrate how the results can be framed in a UGC-style research paper, providing a template for analytical synthesis and academic discourse.

These simulations do NOT purport to be a measure of real institutional measurement, and a real implementation would require ethics review (where required), rubric validation, and checks of reliability. Nevertheless, the use of fuzzy expert systems for the assessment of soft skills is in keeping with the educational research literature (Novais, Matelli & Silva, 2024).

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Demonstration results summary (synthetic dataset)

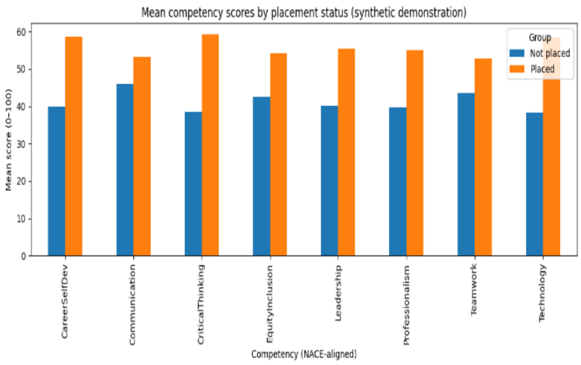
A synthetic dataset made up of 300 student profiles was created with competency scores that are aligned and correlated to the eight NACE competencies. The placement outcome was simulated based on the ERI and CGPA to demonstrate hypothesis testing in principle. (N = 300 student profiles)

Table 4: Illustrative group differences and predictive validity (synthetic demonstration; not field results) (Placed: n = 162; Not placed: n = 138; Placement rate ≈ 54%)

Metric	Not placed Mean (SD)	Placed Mean (SD)	Cohen's d	ROC–AUC
ERI (fuzzy index)	37.36 (10.17)	49.04 (12.45)	1.02	0.769
CogTech	36.77 (16.92)	51.04 (19.64)	0.77	0.717
Collab	37.17 (16.02)	45.34 (18.24)	0.47	0.630
ProfId	38.58 (18.39)	51.03 (20.00)	0.65	0.670
Crisp mean (8 competencies)	40.90 (13.76)	55.89 (15.50)	1.02	0.766
CGPA	6.41 (0.72)	7.10 (0.72)	0.96	0.753

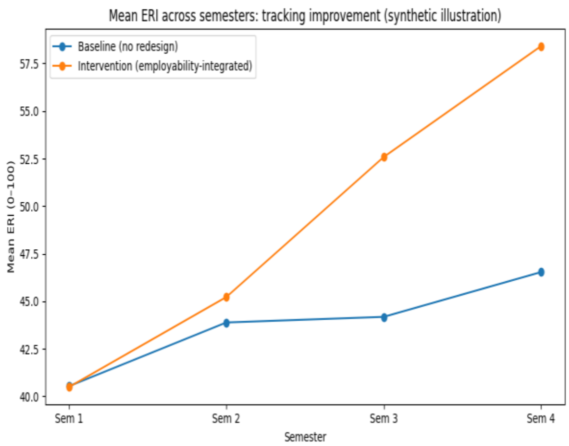
In the simulation, for ERI the placed vs. not placed groups show considerable standardized mean difference (Cohen's d ≈ 1.02) and the ROC–AUC shows slightly better values than the mean and CGPA, demonstrating the logic of H2 in controlled settings. The predictive capability of ERI is not the sole educational merit. The other major element is diagnostics, where the interpretability of the sub-indices and the rule-based approach offers an interpretability advantage of Mamdani-type fuzzy logic in the context of human evaluative scenarios.

Figure 1: "Grouped bar chart of mean competency scores (Placed vs. Not placed)"



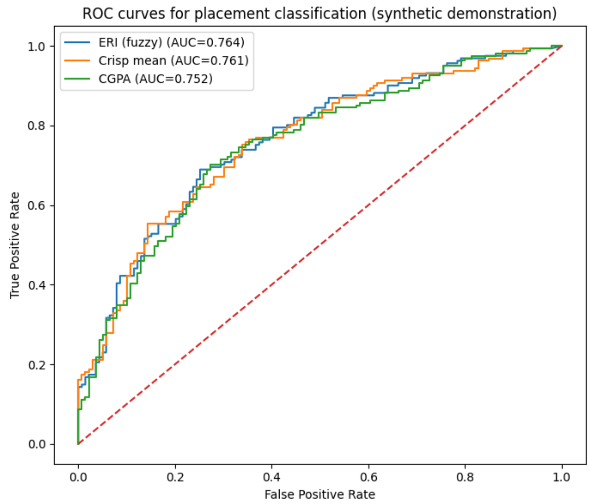
If the bars for "Placed" are consistently higher, that provides visual evidence for H1 in a real dataset: the higher the level of employability skills, the higher the employability outcome. In practice, the gaps that are the widest inform curriculum decisions (for example, gaps that require redesigning assessments to bolster communication or critical thinking). This is relevant to the prevailing employer demand for adaptable demonstrable competencies.

Figure 2: "Line chart showing ERI improvement across semesters (before vs after intervention)"



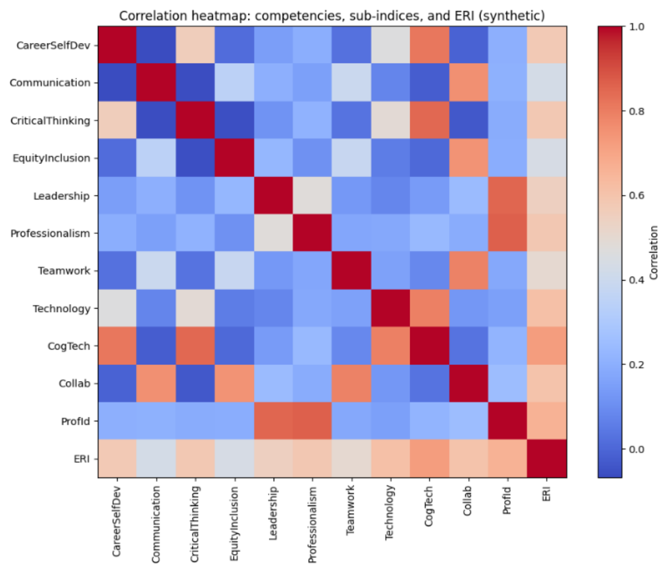
An increasing difference indicates that the intervention cohort shows improved readiness as time progresses. In a genuine study, one would assess if the differences are statistically significant and if the differences carry educational significance, followed by attempts to relate the changes to specific decisions made in course design. This approach would be aligned with the body of work that posits employability as an issue that must be addressed with whole program designing as opposed to piecemeal solutions.

Figure 3: "ROC curves comparing ERI vs Crisp Mean vs CGPA"



Should ERI demonstrate a higher AUC than a crisp mean, it corroborates the reasoning of fuzzy modeling: fuzzy aggregation may capture the subtleties of human judgment better than plain averaging. This is pertinent as measurement of employability is often criticized when institutions consider the outcomes alone as evidence of the development of employability, instead of the evidence of the development of the capability.

Figure 4: "Correlation heatmap among competencies, sub-indices, and ERI"



The interpretability of a sub-index relies heavily on its constituent competencies showing strong correlations. A real study example might show a heatmap with surprising weak ties, like Technology not connecting with CogTech. Such a situation could point to rubric misalignment or inconsistent scoring, indicating a need for scoring refinement rather than only loss outcome reporting. This supports the notion that employability is the result of a paradox or a consequence of insufficiently defined and measured outcomes.

Discussion: Institutional Implications

Explainability and curriculum actionability

An important benefit of fuzzy rule-based scoring is its defense in "human terms" ("professionalism is low, so readiness cannot be high"), assisting faculty in making concrete possibilities out of the assessments. The Mamdani style was developed so as to combine linguistic rules, making it appropriate to be used in situations where the judgment is by nature qualitative. The same is true for educational fuzzy expert systems, which also focus on the significance of expert rules for the evaluation of soft skills (Nouib, Qadech, Benatiya Andaloussi, Chowdhury & Moumen, 2025).

An outcome-focused, employment-based approach to measuring employability conflates an institution's microeconomic role with macroeconomic structures and social positioning. In this context, an ERI model is a more robust solution: measure and improve skills directly and keep outcomes as one (negative) indicator of an employability 'basket' rather than the entire definition.

Preparing for AI- and transition-driven labor markets

As work is organized differently due to technology and the green and digital transitions, it is important for institutions to build competencies that are both human and digital. There is a clear and significant disruption of skills and a heightened demand for employers to upskill, which is also noted in the WEG report. The OECD (2023) similarly highlights the importance of skills for an adaptive green and digital transition. The ILO states that GenAI is likely to augment tasks within jobs rather than automate entire jobs, which requires a focus on adaptation and the upgrading of skills rather than a single 'replacement' approach.

The NSQF focuses on outcome-based competencies and NEP 2020 focuses on critical thinking and technology, and integration emphasizing all round development. A skill index based on fuzzy logic aligns with NEP 2020 and NSQF priorities as it operationalizes competence-based assessments in a structured way (Ross, 2010).

Limitations (academic integrity)

The charts and numeric outputs are for demonstration purposes only and are based on artificially generated data, to illustrate how it might look. Practical implementation demands validated rubrics, scorer training, inter-rater reliability, and continuous governance and calibration of the model.

Conclusion

The paper conceptualizes a Fuzzy Logic–Based Employability Readiness Index (ERI) as a model for assessing higher education that has incorporated the complexities of evaluating employability: multiple sources of evidence, subjective assessments, and imprecise performance criteria. Evaluations using Fuzzy set theory, as opposed to 'crisp' classifications, can more adequately capture a less than black and white evaluation (Tomlinson, 2012). Particularly for curriculum enhancement and accountability, the transparency of rule-based inference is beneficial.

The model is based on the NACE Career Readiness Competencies, making it defensible in the language of competencies sought after by employers, and it is consistent with the emerging focus of policy in India on outcomes-based, integrated education and skills synthesis. Credible evidence in the labor market is corroborating the urgency of such models as it points to a significant transformation of jobs by 2030 paired with a demand for reskilling/upskilling and analyses that generative AI will transform work and emphasize the need for high adaptability (skills) (Vuorikari, Kluzer& Punie, 2022).

Practically, ERI can function as a diagnostic, explainable readiness index that supports: targeted curriculum redesign, student advising, and longitudinal improvement tracking. For a full UGC-standard empirical research study, the next step is to apply the ERI model to real institutional data, test reliability and validity quantitatively, and establish transparent governance procedures for periodic recalibration based on skills intelligence and emerging job-market trends.

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