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From digital access to workforce capability: a comparative documentary study of AI-relevant learning ecosystems in Singapore, Europe and India

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Abstract

Artificial intelligence is typically linked to the learning platform, the diagnosis of skills and employment services, but the advantages of AI to workforce training are still not even as the skills acquired in the learning platform are not automatically available for use. There is already a significant amount of published work that discusses automation risk, as well as digital competencies and the role of AI in learning and development, but less comparative focus on the institutions that transform learning resources into recognised skills and employability through the operation and use of AI enabled and/or AI relevant learning environments. By designing it around the theoretically motivated Capability Approach of Sen, this study analyzed SkillsFuture Singapore and the European Digital Skills and Jobs Coalition and India's National Career Service using a qualitative comparative documentary approach. Thematic analysis was performed using secondary data such as all documents of platforms, official documents, intergovernmental document and peer-reviewed literature, which were publicly available and interpreted each case one by one as a documentary thematic analysis. It suggests that the strength of workforce-learning ecosystems emerges when combined with trying to make digital accessible, within an affordable context, with digital skills, counselling, assisted access, language-sensitive design, recognition by employers, transparency in governance, and evidence of outcomes. With Singapore demonstrating coordinated lifelong learning, Europe demonstrates the good and bad of mobilising digital skills across multiple stakeholders and levels and India helps to show how to apply the reach of platforms to employment-related skills inclusion at large scale. The analysis of the study presents a framework for capability conversion, which attempts to simultaneously analyze the AI-relevant workforce's learning, even though the mere presence of the platform does not guarantee it is effective. The shocks are not "user" shocks or "platform-internal" shocks because of the documentary nature of the evidence, which leaves room for analytical interpretations of the findings as more representative of outcomes in the labour market rather than causal interpretations.

1 Introduction

The application of artificial intelligence (AI) in workplace learning is transforming in a practical, disparate and institutionally impactful manner. Organisations and public agencies increasingly rely on data driven systems to get a better picture of skill gaps, provide guidance on training areas, provide map of occupations, support with counselling and link workers with a job. They are closely connected to the interests of human resource development as they have an impact on the perception of learning needs by the workers, the perception of the role of credentials by the employer and the design of a learning pathway toward the job. Whether learning platforms will become more efficient with the help of AI is not the only matter to consider. It is whether and how digital workforce-learning ecosystems can transform access into meaningful access (in terms of skills, recognized credential and realistic employment opportunity) of different cohorts of workers (Bhatt and Muduli 2023; Jarrahi 2018; Salas et al. 2012; Van Laar et al. 2017). Recent HRD scholarship also considers AI-powered learning as a problem of system-based change and enables workforces as much as adopting new platforms, as the need to maintain

human capability, ethical considerations, and organizational support (Chuang et al. 2026; Ekuma 2024; Goel et al. 2024; Khandelwal et al. 2024).

Technological changes have stirred up labour markets in the past, certainly not in an even or impartial way. Based on task-based research, the jobs that involve more judgement,

interaction and coordination are becoming more often reorganised than eliminated (Acemoglu and Autor 2011; Autor 2015; Autor et al. 2003; Frey and Osborne 2017; Nedelkoska and Quintini 2018; Arntz et al. 2016; Acemoglu and Restrepo 2018). Jarrahi (2018) also highlights the implications of augmentation, complementarity and organisational redesign, alongside replacement, in newer research on AI and management. Other contributions to the recently developed field of AI and management bias towards augmentative, complementary and redesign rather than replacement (Brynjolfsson et al. 2018; Kellogg et al. 2020; Raisch and Krakowski 2021). For those who want to develop their knowledge and skills, it means that reskilling needs take different forms for workers and institutions, as work tasks, technologies, and employers' expectations evolve (OECD 2019; 2021; 2023; World Economic Forum 2023; 2025).

This makes training or development for a scholarship a specific problem. Digital platforms can increase access to jobs, information on jobs and credentials, but this access does not lead to skills transfer and the learning transfer does not necessarily lead to employability or decent work. Invasiveness can be achieved while workers are not able to participate, due to factors such as cost, time, language, disability, lack of digital confidence, connectivity and/or lack of employer trust in the platform credentials. On the other hand, a well-governed ecosystem can have a more practical application of learning, with course discovery, counselling, acknowledged credentials, companies involvement and outcome monitoring. It is therefore important to this research to highlight the difference between access to digital and the skills of the workforce. Another issue reflected in current studies regarding digital divide is the fact that successful use and the reported outcome of use are more important than the ability to connect and access a platform (Fisk et al. 2023; Lythratis et al. 2022; van Deursen and van Dijk 2014; Zheng et al. 2022; li et al. 2021; Bost et al. 2020).

Important explanations are available in the existing literature, but are partially isolated. Research on automation presumes the identification of tasks and occupations vulnerable to technological changes. Research on HRM uses of AI involves analysis and governance issues along with decision support. Analysis of skills, skills signaling, career adaptability and labour-market recognition is examined in the field of employability research. In research on digital inclusion, the question of whether the people have the genuine opportunity to access resources for desired lives is asked, (Kleine 2010; Robeyns 2005; Sen 1999; Zheng and Walsham 2008). In contrast to this, a comparative learning ecosystem report on how resources, conversion supports and governance conditions are organized in public AI-enabled and/or AI-relevant learning ecosystems is still in its infancy.

The problem is analyzed using Sen's Capability Approach as this approach distinguishes between resources that are available and opportunities people have to use available resources. The Course

Catalogue, Skills Framework, recommendation tool or job portal can be only a resource in a workforce-learning ecosystem. It's value in development is dependent on whether it's affordable, people have the education required, they're digitally literate, there's language access, counselling is provided, the employer recognises the value, is transparent and has institutional trust (Nussbaum 2011; Poquet and de Laat 2021; Robeyns 2005; Sen 1999). This viewpoint avoids an overstatement in digital skills policy – one that is to assume that the mere fact that a platform is available is an indicator of inclusion.

The present study comes across three related gaps. The functions of platforms are more commonly recognized as concepts in AI and L&D studies, where their description is limited without detailing what parts institutional supports play in moving the functionality to workforce opportunity. Empirically, there is an absence of comparative analysis across the diverse varieties of public workforce-learning-ecosystems in terms of scale and employment and governance orientations. Methodologically, indicators visible to the public, such as course availability, course registrations, and/or policy commitments, are more readily observable than indicators related to course credential use, employer recognition, similarly, mobility and inclusion. A qualitative comparison documentary analysis is justified, not statistical evaluation of the platform impact, because of these gaps.

For this reason, this research consists of 3 research questions. RQ1: What are the differences between public AI-enabled or AI-relevant workforce-learning ecosystems in terms of the resources and conversion supports that are offered? RQ2: What institutional conversion factors do seem to be most of key importance in the transition from access to digital learning to recognised workforce capability? RQ3: What are the governance and evidence challenges that limit claims in the selected ecosystems to include experiences of employability and inclusion? This research makes the following contributions by presenting an alternative perspective on workforce learning for AI: It considers AI-related workforce learning as a capability conversion problem, in contrast to the literature, which focuses on training or educating AI-related skills. Not that it's a surprise to anyone knowledgeable of the Capability Approach that it has been connected to AI era lifelong learning in advance, as has been done by the work of Poquet and de Laat (2021). In particular, it could help operationalize the concept of capability conversion in three very different public workforce-development systems, and demonstrate how the characteristics of the governance system, employer recognition, and counselling and outcome evidence contribute to or detract from the capacity of digital learning resources to serve as meaningful opportunities for the workforce. The article goes on to briefly explore literature regarding AI and digital learning, employability, capability theory, and responsible governance of AI, before sharing the design of the documentary study that yielded the findings, discussion, and conclusion.

2 Literature review

2.1 AI, digital learning and workforce transformation

Digital Learning and Workforce Transformation in Health Professions Education (Practice 2.1 AI) While job training, development, and the importance of AI is not as large of a topic to be discussed as the loss

of jobs, it has reignited the conversation regarding future jobs. It is the workers' process of acquiring knowledge and understanding of new skills and their transition to new and different work opportunities that are of special interest. AI can aid skills intelligence, profiling learners, course recommendations, evaluations of adaptive feedback, and evaluations of training. Bhatt and Muduli (2023) illustrate that there are many applications of AI in learning and development, which include: Identification of learners, their personalisation, monitoring, assessment and correction of their progress. Broad education-technology reviews also point to the data-driven school profiles, predictions, adaptive systems, assessment, and intelligent tutoring as frequent AI applications, while distinguishing that while often well-focused on technical performance, they are less likely to take the pedagogical and ethical dimensions into consideration (UNESCO 2021; Zawacki-Richter et al. 2019). Such functions can become effective in making workforce learning more responsive but to fulfil this, workforce learning organisational and institutional conditions must be able to avail these functions. This serves to highlight the need to link discussions on AI adoption to lesser high-profile but more early stage and practically relevant adult learning, reskilling, and institutional conversion support (Chuang et al. 2026; Ekuma 2024; Makarius et al. 2020; Pandya and Wang 2024).

The same difference exists in the realm of digital learning research between the concept of availability and effectiveness. While online delivery has the potential for expansion and a reduction of geographical barriers, and a flexible route to training, motivation, support, instructional quality, assessment design and opportunities to apply skills of the training are

still a critical means of ensuring learning outcomes (Billett 2001; Colquitt et al. 2000; Kraiger et al. 1993; Salas et al. 2012; Williamson et al. 2020). The results of the drop-out rates in online learning are also reflective of inequality if access is not accompanied by support (Kizilcec and Halawa 2015). So one can hardly ask a 'how' question about the role of digital platforms in the workforce development arena than how do they relate to learning design, institutional support, and labour-market recognition. The recent debates surrounding AI makes this more complex as digital learning is more and more enveloped in human, data and institutional ecosystems. AI-guided learning and skill development for the workforce can include worker information, skill classifications and taxonomies, recommendation algorithms, worker signals and training providers.

A recent scoping review of workplace learning in the corporate world revealed that AI and data-based technologies have been integrated into LMS platforms, communication channels, distribution platforms and simulation-based workplaces, and fragmentation, interoperability, privacy and autonomy with a learner remain unsolved (Pham et al. 2026). While these elements can be found in the context of improved ease of transaction or increased responsiveness, they can also evoke questions of the line between ‘assistance' and ‘surveillance' (Jarrahi 2018; Kellogg et al. 2020). AI is thus not just a technical layer for a public workforce-learning ecosystem. Exña is just one aspect of a larger system that has the potential to enhance or inhibit workforce capability and how that capability is expressed in learning opportunities.

2.2 Employability, credential recognition and skill conversion

Being involved in training doesn't necessarily lead to employability. It includes the ability to access, maintain and convert knowledge and skills in the work context, to adapt, adjust and move within work environment and get by using social capital and labour market signals

(Fugate et al. 2004; Hillage and Pollard 1998; McQuaid and Lindsay 2005; Tomlinson 2012). Additionally research on competencies indicates that in order to perform effectively in the workplace, people need cognitive, social and behavioural skills as well as possessing specific technical skills (Boyatzis 2008; Le Deist and Winterton 2005).

If learning is not visible and credible to the employers it does not have employment value for workers. Access to learning, participation, learning evidence, qualification assessment, recognition, employer's acceptance, mobilisation and/or decent jobs: this means that the pathway of learning access to employability is a process with consecutive stages. One of the key conversion factors in the credential recognition process is. The human capital theory of education and training considers education and training to be an investment that can expand productive capacity (Becker 1964), but the labour market value of learning is related to the ability of the employers to understand and rely on the signal. In addition to lack of training, skills gaps and mismatches are also often linked to a lack of information, a lack of training-worker connection, and a lack of recognition of skills (Cappelli 2015; Cedefop 2018; Deming 2017; Kato et al. 2020; Le Deist and Winterton 2005). It is therefore necessary for public learning platforms to offer more than just courses catalogues. They need a structure of credential frameworks, involvement of employers, credible assessment and feedback from the labour market.

There is another caution, which comes from research in the field of active labour-market and employment services. The impact of public employment and training programs depends significantly on the nature of the program, targeting, timing and quality of the local labor market supply chain (Card et al. 2018). These issues continue to exist in a digital ecosystem. A platform can report registrations, vacancy or availability of course but doesn't say anything about the value the user got from the work, jobs gained or their experience of having a positive impact on mobility for a longer time. The measure of the employability value of AI

learning ecosystems should be judged on quality, not scale – how much value is gained when learning is converted to outcomes from the resources.

Likewise, research on Artificial Intelligence and algorithmic tools in public employment services shows that if these tools are not designed and managed to ensure accuracy, fairness, participation and appeal mechanisms, then profiling and classification and recommender systems can impact the way users are accessed for counselling, training and support. (Allhutter et al. 2020; Desiere and Struyven 2021; OECD 2024; Scott et al. 2022).

2.3 Capability Approach and inclusive workforce development

The Capability Approach is especially well adapted to the study of digital learning ecosystems, as it de-couples the resources from the real freedoms that individuals have to reap the benefits of them. Sen (1999) speaks about development in terms of substantive freedoms, and Nussbaum (2011) adds to Robeyns (2005)'s discussion of the role of capabilities, functionings and conversion factors. In fact, digital-inclusion scholarship demonstrates the same precaution by revealing that access should permeate all three: that access is not just a given, but should be paired with skills and taught alongside support and social context, and with meaningful use (Helsper 2012; Kleine 2010; Warschauer 2004; Zheng and Walsham 2008). In the context of workforce learning, it can not be a capability by itself; a platform, a course, a skills framework or a job-matching service. It can be a resource whose value can be enjoyed only if people can make effective use of it to engage in desirable work and learning trajectories. There have been several warnings in digital inclusion scholarship to only assume it means access and devices leads to meaningful participation, as can be seen by the work of Eynon and Geniets (2016), Helsper (2012), Kleine (2010), Warschauer (2004) and Zheng and Walsham (2008). Poquet and de Laat (2021) directly come back into the current context of lifelong learning in times of Artificial Intelligence when they claim that learning policy needs to shift from human resources accumulation to

human development, agency of the learner and enabling conditions of the system. This study does not claim to be a novel study, but this study is following the above insight.

It aims at operationalizing the capability logic by establishing the documentary indicators to distinguish the resources, conversion conditions, capabilities and functionings in the comparative workforce-development cases. This argument has recently been extended to reveal further evidence that inequality can shift between access and levels of use / intensity of access, as well as between relation to access itself and relation to the actual economic or social benefits / support received (Fisk et al. 2023; Lythreatis et al. 2022; van Deursen and van Dijk 2014). There are multiple levels in the action of conversion factors. There is an individual measure of success to be discovered: previous schools, language, digital skills and time. Social conversion factors comprise of counselling, employer recognition, social networks and institutional trust. Connectivity, affordability, location and accessibility to devices are examples of environmental conversion factors. Governance may occur at these levels, because users trust and challenge the opportunities given to them via platforms based on criteria such as transparency and privacy protection, grievance procedures, and human oversight and reporting of outcomes. The table below (Table 1) helps to explain how the key concepts of the Capability Approach are ‘operationalised’ in this manuscript.

Table 1
Capability concepts and workforce-learning interpretation

Capability concept	**Workforce-learning interpretation**	**Observabledocumentary indicator**	**Illustrative case evidence**
Resource	Platform, course catalogue, skill taxonomy, credential, counselling service or job-matching information	Official descriptions of services, courses, skills frameworks,platform functions and user support	SkillsFuture course and skills information; Digital Skills and Jobs Platform resources; NCS vacancy, counselling and training-linkage services
Personal conversion factor	Learner-levelcondition affecting ability to use resources	References to digital literacy, language readiness, prior education, time or confidence	Digital-readiness barriers in employment-service settings; multilingual and skills-readiness issues in regional systems
Social conversion factor	Institutional and labour-market condition shaping recognition and use	Employerengagement, counselling, partnerships, credential acceptance and trust-building mechanisms	Employer-facingskills frameworks, stakeholder pledges and public counselling services
Environmentalconversion	Materialorcontextual	Affordability,connectivity,	Subsidies and national access

factor	condition affecting access	geography, device access or local service availability	infrastructure; rural, regional and connectivity challenges
Capability	Substantive opportunity to learn, gain recognition and pursue valued work	Evidence that resources are connected to support, recognition and employment pathways	Learning routes that link skillsinformation, credentials, counselling and employer demand
Functioning or outcome	Realised achievement such as completedlearning, credential use, job search, transition or mobility	Outcome data, completion records,employment transitions or published evaluation evidence	Public evidence is uneven; this study therefore avoids causal claims and treats outcome evidence cautiously

Note. Capability categories are interpreted from Sen's Capability Approach and adapted to the documentary analysis of workforce-learning ecosystems.

2.4 Governance and responsible artificial intelligence

Learning ecosystems need to be governed, as AI is becoming a crucial artefacts for shaping opportunities allocation. Inconsistent or inequitable treatment can occur because of protecting against inequities in the training data, failure to take responsibility or careful oversight by humans (Barocas and Selbst 2016; Kellogg et al. 2020; Mehrabi et al. 2021; Selbst et al. 2019; Tambe et al. 2019; Veale and Binns 2017). The issue of algorithmic opacity is particularly critical in the public workforce system, where users might not know why the courses they are shown are visible or why they cannot see an occupation or vacancy they might be interested in. The six principles of responsible AI – fairness, accountability, transparency, contestability and human oversight – are emphasized in responsible AI literature (Floridi et al. 2018; Gebru et al. 2021; Jobin et al. 2019; Kitchin 2017; Mitchell et al. 2019; Raji et al. 2020; UNESCO 2021).

The AI Act gives a broader regulatory framework to AI systems which can have an impact on opportunity allocation in Europe (European Parliament and Council of the European Union 2024). The same risks of profiling, surveillance, and automated exclusion that apply to private-sector AI and data systems do also apply to public-sector systems, as noted by Eubanks 2018; Pasquale 2015). Model biases, and the ability of workforce learners to understand recommendations, question errors and notice and evidence participation leads to better outcomes, are important issues to be considered when designing responsible governance in workforce learning. These principles are of particular relevance when it comes

to workforce development as algorithmic systems could affect the training offered, referral to training, decisions about work or caseworker perception of employability before a final job placement is determined (Allhutter et al. 2020; Desiere and Struyven 2021; OECD 2024; Scott et al. 2022; Wang and Pashmforoosh 2024).

The present comparison mainly concerns this governance issue. Some of the selected systems are specifically AI-based, and others are AI-related, since they are used to organize a digital environment of resources and skills information or their services, some of which could be adapted to data-driven service matching/recommendation. The manuscript, therefore, does not identify AI as merely and simply digitalisation, as such. It considers the three cases to be public workforce-learning ecosystems with levels of AI-applicability differing from one another and puts it to you that it investigates how well the documented governance conditions enable the capability conversion of the latter.

3. Methodology

3.1 Research design and case logic

The research design and the logic of the cases are discussed in 3.1 Research design and case logic. A qualitative comparative documentary design case study was used in the study. The paper focused on public workforce-learning ecosystems and looked at the ways in which these ecosystems organise and structure learning resources, governance arrangements and conversion supports across institutional settings and not tested the results of statistical relationships or the measures of individual measures. The close examination of bounded systems in their policy/institutional atmospheric context is facilitated by case-study logic, whereas the qualitative evaluation logic allows the purposive comparison of systems wherein the objective is an analytical insight, instead of statistical representation (Yin 2018; Patton 2015). The cases chosen for the study were those that were most differing for maximum variation and functional similarity. They're not comparable symbolic systems from the point

of view of institutions. SkillsFuture Singapore is a national ecosystem for lifelong learning, the European Digital Skills and Jobs Coalition is a multi-stakeholder mobilisation framework in the region, while India's NCS is a public employment-service platform that has links to counselling and training. All (except there is no institutional form at all in any of the examples on the scale of the European Cohesion Fund and no target population on the scale of the fund), are analytically comparable in that they all organise digital pathways between skills, learning and employment, but they vary with regard to governance scale, target population, the form of the institution, the visibility of the evidence. This variability is not simply considered a degree of organisational equivalence but one of theoretical leverage. The context is a public workforce-learning ecosystem and not a feature of a platform, country-level or users in total. The comparison therefore centres on the evidence of documented resources, in supporting the conversions, evidence of governance arrangements and evidence of outcome. The rationale for selecting the cases is summarised in Table 2.

Table 2
Case selection logic and comparative rationale

Case	Institutional form	Reason for inclusion	Capabilityquestion examined
Singapore: SkillsFuture	Nationallifelong-learning ecosystem	Represents a coordinated public strategy for adult learning, skills development and workforce adaptation	How coordinated policy design supports conversion from training access to recognisedworkforce capability
Europe: Digital Skills and Jobs Coalition	Regional multi-stakeholder digital-skills mobilisation ecosystem	Represents a governance model involving European institutions, member states, employers,education providers and civil-society actors	How multi-level coordination expands or constrains digital-skills opportunities across variedimplementation contexts
India:NationalCareer Service	National public employment-service platform with counselling and training linkages	Represents an employment-oriented public ecosystem operating at scale in a diverse labour market	How digital employment access becomes capability when users require assisted use, counselling and employer recognition

Note. The cases were selected for analytical contrast rather than statistical representation. They are compared functionally as public workforce-development ecosystems.

3.2 Documentary evidence and source protocol

The analysis was based entirely on secondary evidence. No interviews, surveys, experiments, field observations or participant-level data collection were conducted. The documentary corpus included official platform materials, government and intergovernmental policy documents, labour-market and skills reports, legal and governance documents, and peer-reviewed literature. These sources were used for different analytical purposes: official sources described the systems and their stated functions, while scholarly and intergovernmental sources supported theoretical framing, contextual interpretation and caution about outcome claims.

The source selection process was relevance-led rather than exhaustive. Searches were conducted across official platform and policy websites, Google Scholar and publisher databases using combinations of terms such as artificial intelligence, AI, workforce development, learning and development, digital skills, employability, SkillsFuture, Digital Skills and Jobs Coalition, National Career Service, Capability Approach, conversion factors, credential recognition and algorithmic governance. Sources were retained when they provided traceable evidence relevant to the cases, theoretical

framework or analytical dimensions. Sources were excluded when they were unrelated to workforce learning, duplicated stronger evidence, lacked traceability or made promotional claims that could not be linked to documented services or outcomes.

The design was not a systematic literature review, so PRISMA-style claims are not made. A documentary search flow or appendix would nevertheless strengthen reproducibility if the authors can provide final retrieval counts, dates, search strings, document date ranges and case-level corpus sizes. In the present manuscript, the evidence protocol is made explicit in Table 3 and the limitations section acknowledges the absence of platform-internal data and user-level evidence.

Table 3
Documentary evidence protocol

Evidence category	Use in the analysis	Inclusion standard	Boundary applied
Official platform materials	Described platform functions, stated objectives and service features	Included when published by the platform or responsible public authority and directly related to learning, skills or employment services	Used descriptively unless independentoutcome evidence was available
Policy and intergovernmental reports	Located the cases within broader digital-skills and labour-market debates	Included when issued by recognisedpublicor intergovernmental organisations and relevant to skills, employment, digital learning or AI governance	Not treated as proof of individual outcomes without supporting evidence
Peer-reviewed literature	Supportedtheoretical framing,methodology, employability concepts and responsible-AI interpretation	Included when traceable and relevant to AI, HRD, employability, capability theory, document analysis or governance	Used for analytical interpretation rather than as case evidence unless directly related to a case
Legalandgovernance documents	Supported analysis of accountability, transparency, privacy and responsible AI	Included when formally issued and relevant to digital, AI or employment governance	Used to define governance context, not to infer implementation effectiveness

Note. The protocol separates evidence of platform design from evidence of workforce outcomes.

3.3 Analytical procedure

The Capability Approach of Sen (1999) was followed to analyse the approach, defining resources as the capacity to use them to achieve desired effects, while real freedom to use them to create valued effects is practical freedom. Platform features which were both AI-driven and AI relevant were initially considered as resources. Analysis then focused on a group of conversion conditions which could help or hinder whether those resources were able to provide plausible support to workforce capability. These encompassed digital literacy, cost, language access, counselling, employer recognition, transparency, grievance route and reporting of outcomes.

A comparative matrix was created which looked at the cases in the following six dimensions:

1) Policy objective and target users; 2) AI-enabled or AI-relevant technological features; 3) Governance and stakeholder structure; 4) Equity and access mechanisms; 5) linkages to credentials and employability; 6) public evidence of outcomes or transparency. The coding and comparison of these dimensions was done via Documentary Thematic Analysis (Braun and Clarke 2006, 2022; Bowen 2009). Descriptive evidence was distinguished from possible interpretations. For instance, the words "counselling" on a platform's website was

interpreted as a feature of their service, and an interpretation that counselling enhances employability was regarded with a fair amount of scepticism unless backed up by outcome data.

The analytical procedure and quality control are summarised in Table 4. A single consolidated matrix was employed to ensure that the case descriptions, documentary sources, interpretive codes and comparative claims line up. The analysis also employed negative-case sensitivity—that is, uncovering instances where public evidence does not lend itself to make more robust claims, particularly on topics of algorithm transparency, differentiated outcomes and employer recognition.

Table 4
Analytical procedure and quality controls

Analytical activity	Procedure applied	Quality-control action
Document screening	Sources were screened against the six analytical dimensions	Documents were retained only when they provided traceable evidence relevant to a case or framework
Thematic coding	Text segments were coded for resources, conversion factors, governance arrangements and outcome evidence	Descriptive platform features were kept separate from interpretive capability claims
Cross-case comparison	Case-specific patterns were compared across governance, access, conversion supports and outcomes	Claims were checked against more than one source type where available
Capability mapping	Findings were mapped to resources, personal, social and environmental conversion factors, capabilities and functionings	Causal claims were avoided because the study did not use primary user data or statistical testing
Reporting and interpretation	Findings were written as qualitative case-based evidence	Limitations relating to secondary evidence, official-source positivity and algorithmic opacity were stated explicitly

Note. The procedure supports analytical consistency and documents how case evidence was screened, coded, compared and bounded.

3.4 Trustworthiness, ethics and methodological boundaries

Students are expected to distinguish between truth and error, and adhere to certain (scientific) boundaries in their practices. Criteria of trustworthiness were addressed in clear and adequate case logic, by triangulation of the types of documents, clear categories for theoretical coding and cautious reporting of strength of evidence. Official policy documents and platform

documents were not assumed to be evidence (neutral) of effectiveness. They were employed to capture explicit aspects of design but only appeared when evidence of its impact was noted or explicitly referenced texts. This difference is relevant as it can be more clearly identified in public programmes as an objective's documentation, rather than differentiated-effects across user groups. There were no human subjects, personal data or interviews/surveys or experiments or observations in the field.

The acceptance of this type of ethical approval and informed consent was therefore inappropriate. Ethical care, however, was still relevant as the analysis focused on public care systems which could

impact on opportunities for learning and employment. The document has thus refrained from a specific identification of people, unsupported assertions about the person or the articulation of public statements of platform desires as achieved results. The primary methodological limitation is that of causal inference. The research cannot provide answers on whether participation on the platform led to better employment, wages, mobility or inclusion outcomes; only answers are possible and what research gaps may exist. It further has no way of verifying proprietary algorithms, internal audit processes or user experiences. The limitations are discussed and future research agenda is raised to address these limitations.

4 Findings

The results are grouped both by case and by synthesizing results for the three ecosystems. The section documents feature in comparison and patterns of them; and it distinguishes features of the platform with policy intentions and inferences of their capability conversion.

4.1 Singapore: coordinated lifelong learning and skills pathways

SkillsFuture Singapore is a national initiative of coordinated efforts towards lifelong learning and skills upgrading in the country. Public documentation depicts SkillsFuture as a continuum connecting citizens, employers, training providers and government agencies --

providing course information, funding opportunities, skills frameworks and continuing education (SkillsFuture Singapore 2024, n.d.). The critical aspect is not just that there is a digital platform; its capabilities are key from a capability point of view. The relationship between public funding, identified training careers/certificates, skills information for employers and frequent policy signals make learning a common component of work. In Singapore, there appears to be relatively good fit of platform resources and conversion supports. These are visible to the public: functions of searching courses, skills-demand information, information about subsidies and guidance, addressed to employers. These features offer a way of making a connection between the learning intention and training participation.

In parallel, less detailed innovations exist at the public documentation level for long-term differentiated outcomes within worker groups. Meanwhile; at the level of public documentation, less innovation evidence exists for longer term differentiated outcomes by worker groups. This indicates a relatively well-embedded ecosystem with SkillsFuture but also illustrates the gaps that need to be filled with evidence regarding the impact on the workforce; who is being served by SkillsFuture and who is not; and how Skills are mobilizing.

4.2 Europe: multi-stakeholder digital-skills mobilisation

The Digital Skills and Jobs Coalition in Europe is a model of a multi-stakeholder model on the regional level. According to the European Commission, Coalition is a project which involves the EU Member States, companies, social partners, non-profit organisations and education providers to address the

digital-skills gaps (European Commission n.d.). Bigger policy activities such as the Digital Education Action Plan, the DigComp 2.2 and Digital Decade targets (European Commission 2021, 2024) are also important in supporting the

ecosystem. It is successful because of its mobilisation, as it raises digital skills as a policy priority for everyone and brings visibility of pledges, partnerships and national initiatives to the public. The importance of solving problems with the design is highlighted with similar conversion challenges. There are varying aspects of the adult learning system, the infrastructure, funding capacity, language context and employer involvement in my member states. There is a need for a regional project to classify priorities and expectations similar and to pass those to the national and local level in terms of training opportunities.

Additionally, OECD evidence explodes the idea of digital skills being developed as a standalone measure, by focusing on the need for coordinated digital education, labour-market and social policies rather than on training (OECD 2019). The governance aspect of “capability conversion” can thus be illustrated in a European way. Coordination can bring in more resources, but the challenge is if workers can be trained in a relevant way across different areas, and if the power to recognise the skills acquired is distributed across workers, employers and academics, and outcome evidence can be shared across institutional settings.

4.3 India: employment-oriented inclusion at scale

The inclusion problem at scale is listed as India's National Career Service says. It is on the platform that the opportunity encounters the job seeker and the employer as well as the counsellor and training providers communicate. The various components of the platform serve as a channel for the interaction of the different stakeholders such as vacancy updates, job fairs, training linkages, etc. (National Career Service n.d.; National Government Services Portal n.d.). The Indian case is quite different from the Singapore and European cases as it is set in an ultra-dynamic setting with an informally dominated labour market, a large share of the population that is not fluent in English, rural-urban divide, and high levels of inequality in technology adoption. Additionally, evidence on platform-work and digital-labour reveals that

mediation as a form of labor through digital platforms offer a new avenue to access work while challenging the question on the protection of laborers, their visibility, platform design and aspects of decent work (International Labour Organisation, 2021).

Under these circumstances, conversion support is particularly important. The importance of the National Career Service is that it brings the access to work, counselling and training linkages under a single public facing ecosystem. But it also demonstrates the downsides of scale if the users' connectivity is spread out or they might not speak English well, or they lack digital confidence or certifications they know are respected. Research on Digital-inclusion has identified these barriers as not simply marginal technical issues, but instead as "key factors" which influence whether or not access translates into Digital-

inclusion (Eynon and Geniets 2016; Helsper 2012; and Warschauer 2004). Digital employment platforms provide meaning and value for users if they are supported by counselling, local help, employer trust and pathways in to decent work. The Indian case thus clarifies that the mere presence on a platform does not mean that it has to be included. It depends on the extent of which some elements of the ecosystem diminish certain barriers to those with less favourable starting conditions.

Insert Table 5 about here

Table 5
Comparative profile of the three learning ecosystems

Dimension	Singapore	Europe	India
Dominant policy logic	Coordinated lifelong learning and skills upgrading	Digital-skillsmobilisation throughpartnershipsand national initiatives	Employment-service access, counsellingandtraining linkages
Primary resource form	Skills frameworks, course discovery, subsidies and training pathways	Coalitionplatform, stakeholder pledges, policy targets and digital-skills resources	Vacancy information, job matching, counselling, job fairs and training linkages
Main conversion strength	Institutional coordination and visible connection between skills policy and training opportunities	Multi-level mobilisation and employer or stakeholder participation	Scaleandpublic employment-service orientationfordiverse labour-market users
Main conversion risk	Limited public evidence on differentiatedlong-term outcomes	Unevenimplementation capacityandoutcome comparability across member states	Digital literacy, language, informality, rural access and uncertainemployer recognition
Governance visibility	Publicly visible policy architecture, with limited publicalgorithmic transparency	Strong regulatory and policy context, but varied implementation visibility	Public service information is visible, but detailed audit, ranking and grievance evidence is limited
Evidence boundary	Design and policy alignment are clearer than causal outcome evidence	Mobilisation is clearer than comparableuser-level outcomes	Reach and employment orientation are clearer than evidence of inclusion or mobility

Note. This table summarises documentary evidence and analytical interpretation from the three case profiles. It does not claim access to proprietary algorithms or user-level datasets.

4.4 Cross-case synthesis

In the three cases, workforce development with AI-based or AI-relevant platforms seems to be more than a mere technical task: it's an institutional challenge. Digital access gains meaning when coupled with affordability, digital literacy, counselling, credential recognition and earning and evidence of credibility from employers. There are lessons to be learned from Singapore, which capitalizes on the potential of coordinated lifelong learning, from Europe, which showcases the potential of multi-stakeholder coordination for digital-skills policy, and from India, which is with the challenges of enabling digital-skills policy to translate access at the national level into capability across a diverse use base.

One comparison is that governance and evidence taken as a whole are still considered to be key. Platform descriptions frequently focus on access, availability of courses, matching or skills intelligence, often without making reference to how the recommendation is generated, how the fairness of the recommendation is evaluated and/or differences between workers groups in outcomes. This poses a policy and HRD challenge – digital learning environments may be declared as inclusive if they are online despite the presence of conversion barriers. The cross-case pattern is summarized in Table 6, and a modified adaptive workforce learning ecosystem model is shown in Fig. 1, where the interpretation is provided. Figure 1 shows a reinterpretation, in terms of an adapted model for the adaptive workforce learning ecosystem, and Table 6 summarises the cross-case pattern.

Table 6
Cross-case capability conversion pattern

Conversion factor	**Why it matters for workforce development**	**Cross-case pattern**
Digital access	Createsentrytocourses,job information and platform services	Necessary in all cases but insufficient on its own
Affordability and time	Affectswhetherworkerscan	Most explicit in subsidy and public-

Digital literacy and language	**participate while managing work and household responsibilities**	**support arrangements, but relevant across all cases**
	Shapes users' ability to interpret platform information and complete digital processes	**Especiallysalientinlargeor multilingual systems, but relevant to all public platforms**
Counselling and assisted use	Helpsuserstranslateplatform information into realistic training and job decisions	Strongly important for users with weaker starting positions
Credential recognition and employer trust	Determines whether learning becomes a credible labour-market signal	Central across all cases, but public evidence of employer use remains uneven
Transparency, grievance routes and outcome evidence	Supports accountability and allows users and policymakers to evaluate whether platforms expand opportunity	Frequently under-documented in public sources, especially for algorithmic or recommendation processes

Note. The cross-case pattern is interpreted through the capability framework. It should be read as qualitative analytical evidence rather than as statistical generalisation.

Note

The model is derived from the comparative documentary analysis. It represents platform resources, capability-conversion conditions, recognised workforce capability and the feedback role of outcome evidence.

5 Discussion

The results indicated that creating workforce value with AI-enabled and AI-relevant learning ecosystems is only achieved when there are recognised skills, credible signals, and employment opportunities for gaining access to the platform. To address the first research

question, this is an interpretation that demonstrates the (contrasting) different showcases of technological form as well as the institutional support that legitimize the use of learning resources. It addresses the second research question by providing a list of affordability, digital literacy, counselling, language-sensitive design, credential recognition, employer trust, and transparency and outcome evidence as factors which keep recurring as barriers to conversions. It provides evidence and answers to the third question by revealing that information regarding algorithms and differentiated outcomes / employer use of credential is limited in public and thus use of these is limited to claims of inclusion / employability. The previous research on AI-in-L&D demonstrates the applications of AI in training systems, such as getting to know the learner, personalisation, AI analysis, assessment and feedback

(Bhatt and Muduli 2023; Pham et al. 2026; Zawacki-Richter et al. 2019). Why access to a resource is not the same as opportunities entails a call for genuine opportunities. Numberous authors have written about this, including Capability literature (Nussbaum 2011; Poquet and de Laat 2021; Robeyns 2005; and Sen 1999).

In a comparative approach to these literatures, the focus will be on how public workforce-learning Ecosystems can serve as a linking force between digital resources and workforce capability. The contribution is thus not the general principle that conversion factors count. It is the specification of learning systems in comparison to others that makes them relevant to a worker via the conversion architecture. It is also in line with the growing trend in HRD literature that makes a distinction between AI as an efficiency device and a problem of human development, where it is linked to concepts of learning readiness and the ethical caveats of designing and organising AI (Chuang et al. 2026; Ekuma 2024; Khandelwal et al. 2024; Pandya and Wang 2024; Yorks and Jester 2024). The results also provide some further clarification in the employability issues. According to the literature, employability is related to the following recognized competences, adaptive learning, social capital and credible labour

signal (Boyatzis, 2008; Fugate et al., 2004; Kato et al., 2020; McQuaid and Lindsay, 2005; Tomlinson, 2012).

The comparison makes it clear that platform-based learning could have a role to play in these conditions in combination with demand from the jobseeker, trustworthy credentials, guidance. It might be just surface data where they do not get any deeper than course availability, registrations or vacancy lists. This is especially the case for the informal sector, those living in rural areas and people whose previous qualifications are not adequately understood by employers. This is the implication of governance as well. When being a digital learning platform means categorising the user, suggesting training or matching the worker to opportunities, assessing fairness must not be based solely on the accuracy of the system or the performance of its systems. It also needs to be considered in relation to substantive opportunities the user can have to understand, use and challenge decisions made along the way through platforms (Floridi et al., 2018; Gebru et al., 2021; Jobin et al., 2019; Mitchell et al., 2019; Raji et al., 2020; Selbst et al., 2019; Veale and Binns, 2017).

In other recent research engaging with other aspects of education and human resource development, users' preparedness, ethical consciousness and responsible uses of AI in learning environments are explored (Bohara and Rana 2024; Pérez-Portabella et al. 2026). This study elaborates that focus into increasing workforce skills and public workforce delivery systems. There is an increasing shift towards jobseeker-centred and accountability-driven designs in public employment-service research, especially in countries where categorizations can have an impact on jobseeker access to training or activation support (Allhutter et al. 2020; Desiere and Struyven 2021; OECD 2024; Scott et al. 2022).

5.1 Theoretical contribution

The theoretical contribution is a capability-conversion framework for workforce learning that is relevant to AI. The model considers platforms a resource, and not an outcome. It then separates out between conversion conditions, opportunities for capabilities, realised labour-market functionings and actual outcomes of the labour-market. Governance exists as a conditioning institutional layer as it is a step determined by transparency, accountability, privacy protection, human oversight, grievance pathways and employer recognition that links to being able to transform digital resources into valued opportunities.

Based on analysis, three propositions are made that make up the study policy. First, the use of digital workforce-learning resources is more likely to be coupled with counseling, affordability and accessible design to promote capabilities. Second, for platform-based credentials to be more likely to support employability, there needs to be a involvement by employers in the definition, recognition or validation of skills. Thirdly, the capabilities and skills extensions within the framework of responsible governance of AI in workforce learning should be assessed, not just on the basis of the procedures followed or technical biases that place them. Thirdly the capability expansion of responsible AI governance of workforce learning should be targeted, not only at adherence to procedures or technical bias metrics. These propositions are hypotheses that are a result of comparative documentary evidence and must be tested in the future research.

5.2 Practical and policy implications

The tangible effects are for the actor. There are various aspects to consider when evaluating digital workforce platforms, which should not only focus on enrolments and user registrations, but on the number of available courses. The following evidence should also be disaggregated—and is complementary to these indicators—to provide evidence for worker completion, credential use, wage mobility, employer recognition and inclusion across worker groups, and job transitions. Policy design should also include the costs of offering

assisted use, multilingual access, accessibility features and support in digital literacy as part of the core infrastructure and avoid them from being added as optional extra costs (OECD 2019; UNESCO 2021; Vuorikari et al. 2022).

Businesses should engage and be involved in skills frameworks and skill validation; this would enable skills acquired via the platform to provide valid information about successful completion of the skills unit. Training providers need to link training courses to proven competencies, make assessment courses public and help students with poorer learning resources in educational and/or digital areas. Platform operators should make more transparent and publicized information on recommendations, data handled, appeals process, differences in recommendations, human review of content etc. However, the role of workforce intermediaries and counsellors is to clarify the suggestions, provide candidates with achievable options and link learning experiences with the local job market.

5.3 Limitations and future research

There were a number of limitations to this study. It is not able to verify user experiences, internal algorithms, proprietary ranking rules or causal effects on employment outcomes as it is based on information from the public secondary sources. Certain policy documents can also generate positivity bias, as it is more cognitably plain to identify policy intentions than the outcome of the policy's implementation. The inherent diversity of the cases results in a comparability boundary and was chosen for analytical contrast, not for statistically generalizable results. The three systems: SkillsFuture, the Digital Skills and Jobs Coalition, and National Career Service, are superficially similar but not intertopologically similar systems of workforce learning units. Other restrictions are in terms of temporality, language and AI attribution.

Certain AI governance aspects and features of the platforms can change over time, so it is important that they are documented. Often there are fewer numbers of English language

sources and publicly available sources which may underrepresent the local implementation realities. Most significantly, the study cannot reveal which outcomes relate specifically to AI, as there are documented systems that may represent a wider digitalisation, or changes to employment-service and/or policy coordination. This is mitigated by adopting the term AI-enabled or AI-relevant, and not claiming causal or effectiveness. Further research is warranted using longitudinal and/or mixed methods as well as in different countries/cultures to investigate user-level outcomes. Some of the questions that could be answered by collecting data from interviews with learners, employers, counsellors and platform designers would be an evaluation of how the conversion factors suggest here work in practice.

Further quantitative investigation might examine the relationship between platform participation and credential recognition variables, controlling for prior education, employment and variation in regional labour market conditions, and between participation and labour mobility/wage change variables after controlling for prior education and employment and the variation in regional labour market conditions. To build on informal labour markets, the use of digital credentials by employers, transparency of algorithms, learner agency, privacy issues, interoperability and other metrics that compare outcomes from public and private learning organizations, others also need to continue to work (International Labour Organization 2021, Kato et al. 2020, Pham et al. 2026).

6 Conclusion

The current research study investigated both the enabling and disenabling elements of learning workforce capability as the learning environment transitions from digital access to digital capabilities enabled by AI. The paper revealed that public platforms make sense of their potential development only when accessible to conversion supports which include affordability, digital literacy support, counselling, language-sensitive platform design,

recognised credential levels, employer trust, transparent governance, and outcome evidence. The overarching theoretical discovery is that workforce-learning platforms ought to be considered assets in a big scheme of things, rather than an end goal in themselves. Their value lies in how quickly they are able

to use the available courses, skills information, and employment services to create employment and learning/recognition opportunities. This framing is crucial as some of the indicators for measuring digital workforce initiatives commonly focus on platform reach, course availability, users' sign-up rates, etc. A capability perspective asks the more challenging question of how this turn into useful, believable and meaningful resources for people who have unequal means of getting to them. Even a digitised training and an enhanced matching function can't fully capture the implication of responsible AI in workforce development, as it is a bounded policy issue. Public agencies, employment as well as training and employment platform operators should develop structures accessible to all, explainable and augmented by human guidance and differentiated outcomes. The study does not measure the impact on employment at the level of individual jobs and does not test the algorithms in-house as it only uses public documentary evidence. Future studies should therefore be conducted with both user-level and employer-level and longitudinal data on his/her proposed conversion architecture. The larger contribution is to demonstrate how it is best to defend the use of AI by demonstrating the adaptability of workforce learning, especially when designed as a social and institutional ecosystem rather than just a digital service.

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Competing interests

The authors declare that they have no competing interests.

Ethics approval and consent to participate

Not applicable. The study used publicly available secondary and documentary sources and did not involve human participants, personal data collection, interviews, surveys, experiments or field observations.

Consent for publication

Not applicable. The manuscript does not contain identifiable individual data or images requiring consent for publication.

Data availability

The study is based on publicly available policy documents, institutional materials, reports and published literature cited in the manuscript. No primary dataset was generated for this study.

Author contributions

Prof. Sidharth Raja Halder: conceptualization, methodology, investigation, formal analysis, writing—original draft, supervision and project administration. Dr. Abhishek Tripathi: conceptualization, supervision and writing—review and editing. Avirup Mukherjee: methodology, formal analysis and writing—review and editing. Dr. Monika Bansal: writing—review and editing. Dr. R. Sridevi: methodology and writing—review and editing. Mr. Ravindaran Seniasamy: writing—review and editing. All authors read and approved the final manuscript.

Use of generative AI and AI-assisted technologies

Grammarly was used solely for language and grammar editing during manuscript preparation. No generative AI tools were used to create scholarly content, analyze data, generate interpretations or produce conclusions. The authors reviewed and approved the final manuscript and remain responsible for its content, citations, interpretations and conclusions.

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Figures

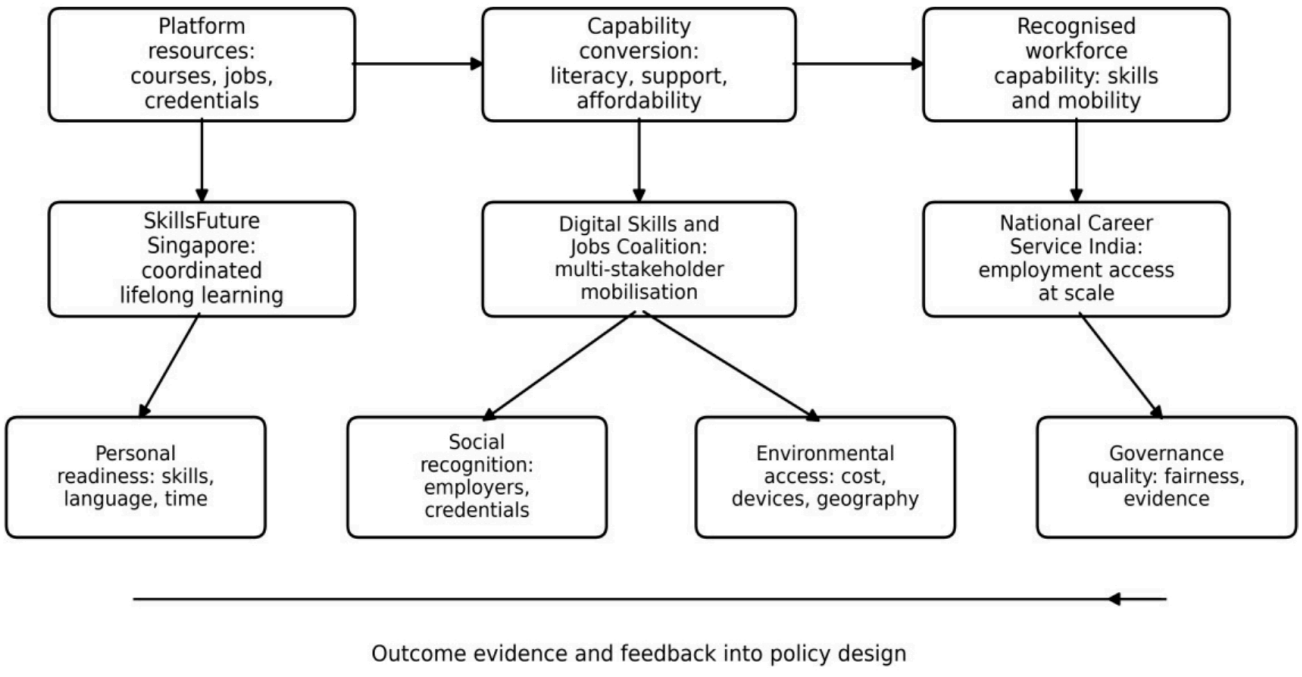


Figure 1

Adaptive workforce learning ecosystem model

Note. The model is derived from the comparative documentary analysis. It represents platform resources, capability-conversion conditions, recognised workforce capability and the feedback role of outcome

evidence.

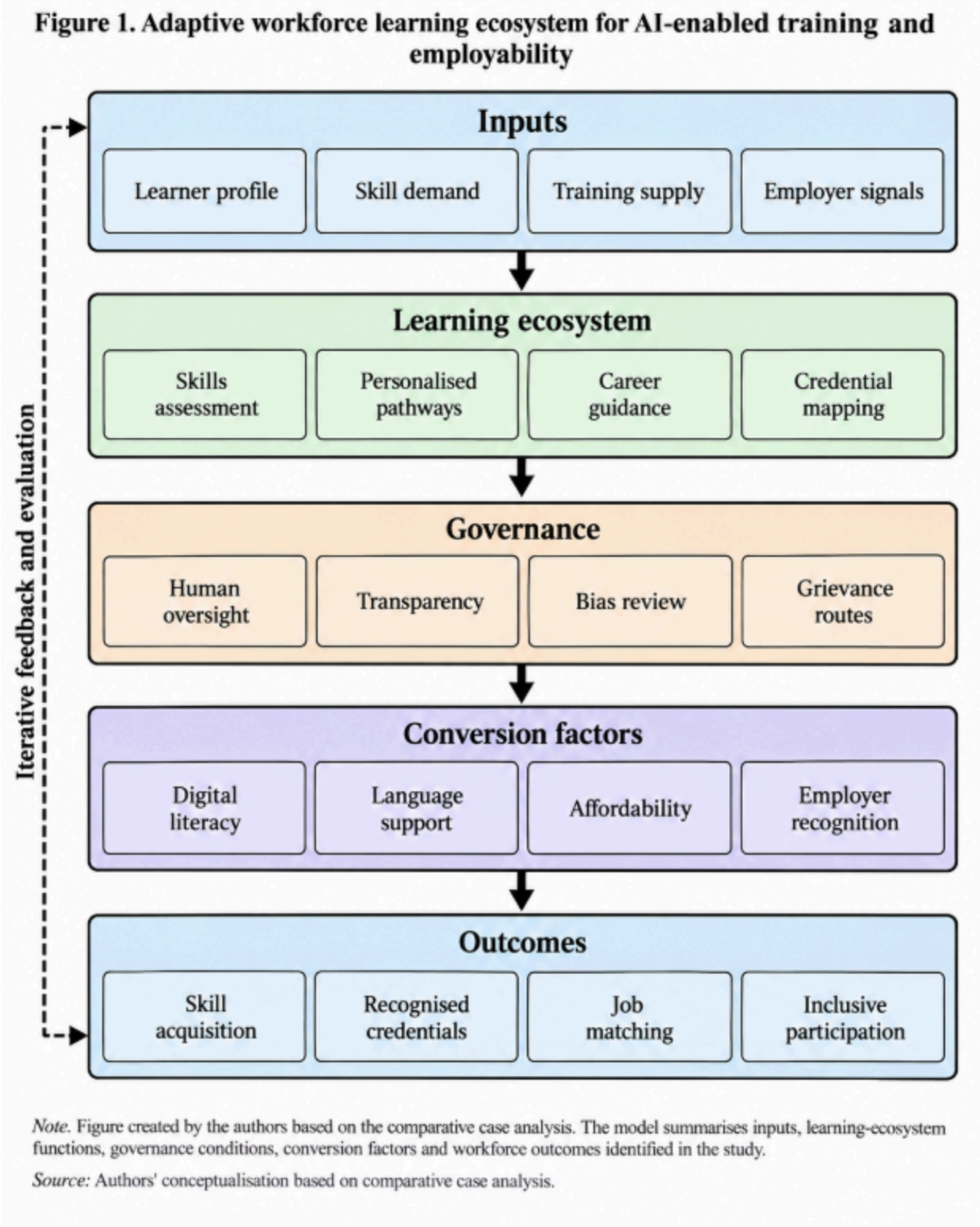


Figure 2

See image above for figure legend.

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