Will a Skills Passport ever get me through the lifelong learning border?

Two critical challenges facing personalised user models for lifelong learning

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ABSTRACT

Lifelong personalised learning is often described as the holy grail of the educational data sciences, but work on the topic is sporadic and we are yet to achieve this goal in a meaningful form. In the wake of the skills shortages arising from national responses to COVID-19 this problem has again become a topic of interest. A number of proposals have emerged that some sort of a *skills passport* would help individuals, educational institutions, and employers to identify training and recruitment needs according to identified skills gaps. And yet, we are a long way from achieving a skills passport that could support lifelong learning despite more than 25 years of work on the topic. This paper draws attention to two of the critical *socio-technical* challenges facing skills passports, and lifelong learner models in general. This leads to a proposal for how we might move towards a *useful* skills passport that can cross the "skills sector border".

CCS CONCEPTS

• Information systems → Personalization; **• Applied computing → Education**; **• Security and privacy → Social aspects of security and privacy**.

KEYWORDS

lifelong learning, personal user model, skills, data portability, contextualisation

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1 INTRODUCTION

The modern conceptualisation of employment is rapidly shifting. While our parents planned to work for the same company for life, our children can expect to change career many times [2]. Rather than completing a set amount of schooling early in life to achieve a qualification, the 4th industrial revolution [3] means that people will increasingly need to return to the education sector: for further training, to gain new skills as their position is disrupted by technology, or to re-skill so that they might transition into new careers as positions traditionally deemed safe are automated. This collection of challenges is often framed in terms of lifelong learning, and it appeared in the literature more than 50 years ago (see Friesen and Anderson [21] for an overview of this history).

One suggestion that has recently been gaining in popularity is that a *skills passport* could somehow provide a general representation of a learner's knowledge, skills and competencies across a lifetime of learning. But while skills passports have been discussed at periodic intervals since at least 1997 [1], they are yet to gain traction as a useful technology solution. We need to ask ourselves why. This question has become more urgent in the wake of the COVID-19 crisis. Many economies are now facing a skills shortage due to the border lockdowns that they implemented to protect their citizens, which means that skills passports, and lifelong learning in general, are again rising in prominence. Various governments, corporations, and professional associations have all created what they call a skills passport, however, this paper will argue that none of the current solutions would support lifelong learning in its true complexity. It will start by exploring the history of lifelong, and introducing the Personal User Model for Life-long, Life-wide Learners (PUML) framework that has been developed by Kay and Kummerfeld [30]. It will then use two challenges identified for PUMLs to explore some of the reasons behind the failure of skills passports to achieve a status that could actually be used to help a learner move through what I will identify as the "skills sector border". We will see that the problem is *socio-technical*, but that much of the research completed to date has tended to focus on the technical aspects of this problem alone. I will conclude with a proposal for how we might incrementally work towards building up the socio-technical infrastructure required to achieve the vision of a universal skills based PUML that could support lifelong learning across global contexts and specifically, through the skills sector border.

2 BACKGROUND

Narratives around lifelong learning have subtly evolved over the decades. It is currently portrayed as a largely positive feature of modern education that would enable participation and support across all stages of a person's lifetime of learning and work. However, this has not always been the case. Field [18] sketches out a history of the concept which draws attention to a series of epochs

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where different narratives prevailed, often driven by very different stakeholders.

2.1 The contested history of lifelong learning

The fourth United Nations' Sustainable Development Goal is to "Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all", but we might ask what precisely this vision entails. There have been many different versions of lifelong learning discussed over the last 50 years [7, 18]. In the 1970s UNESCO[1] championed a number of policy driven attempts to generate stronger social outcomes for people who were failing to benefit from the "front loaded" K-16 educational model. However, by the 1990s the emphasis had shifted to an approach more focused upon the up-skilling of individuals in order to support the development of a competitive economy. Thus, the narrative of this topic has shifted from personal actualisation and development to one that emphasises how we might create flexible workers who can innovate and respond to change, so supporting the modern economy. This has led to some criticism. For example, in 1998 Tight [45] argued that the economic perspective can lead to a form of entrapment, where highly stressed and already busy workers are still expected to up-skill but provided with very little space to do so. Similarly, Borg and Mayo [9] argued that the concept is tied to a neo-liberal agenda for welfare reform. These early debates were not resolved, but have now been largely forgotten. However, this ambiguity about the overarching purpose of lifelong learning has not prevented a rise in popularity of the concept itself.

In the wake of the skills shortages that emerged in many countries both during the COVID-19 crisis [41], and in the ongoing recovery phase [13, 38] there is a renewed surge in interest in lifelong learning, retraining, and skills. This trend was already present before the COVID-19 crisis, with many organisations calling attention to the workforce adjustments that will be required by responses to climate change, automation, and artificial intelligence (AI) (see e.g. the WEF future of jobs report from 2018 [37]). Educational institutions have responded, with an increasing shift to models of learning that are flexible, support the recognition of prior learning (RPL), and encourage workers towards an ongoing program of part time study. This trend has been reflected in their strategy documentation. For example, in 2018 Kinash and Judd [32] found that 20 of 41 Australian universities had identified lifelong learning within their strategic plans. There is no doubt this number reflects a global trend, and has grown since then. As various economies increasingly face a shortage in skilled workers [5], we see educational institutions, companies, and a wide range of venture capital firms, all rushing towards provisioning what is at best a rather nebulous concept.

However, despite this long-term interest in supporting lifelong learning, our tools and data services are far from mature. While there is ongoing interest in generating learner profiles and models [15, 19] and even in lifelong lifewide personal user models [30], we are a long way from achieving a useful lifelong learner model. Indeed, the challenges associated with generating distributed user profiles have been known for a long time [6, 28]. Why are we still so far away from achieving a useful lifelong learning profile?

[1]The United Nations Educational, Social and Cultural Organisation (UNESCO)

2.2 What is different in Lifelong Learning?

It remarkable how many early papers make use of a compelling anecdote about how useful some sort of a portable learner model could be to a person in the lifelong learning context [21, 26, 28]. If the use case is so obvious then why are we so far away from achieving it? This paper will explore two critical challenges that are holding back progress, using them to focus attention on the problems associated with creating a useful skills passport as a case study.

2.2.1 Challenge 1: Lifelong Learning requires data from many different systems. Lifelong Learning requires a significant shift in thinking from the norm. Instead of providing stand alone solutions *within* a specific Educational Technology (EdTech) product we need to think about how a learner might be supported across the *many* different learning environments that they interface with across a lifetime. Ideally, a lifelong learner model would help people to understand how they learn, and what they need to learn, supporting them in setting and then achieving goals that could be very long term. Importantly, learners should be supported through the many different transitions that they undergo throughout their lifetime: from school to university, to the workplace, and back to further education and professional development [40], helping them to re-frame their thinking about themselves along the way [10].

Kay [28] presented a vision for lifelong learning as early as 2008, when she proposed that we need to put people in control of rich and scrutable lifelong user models which would help them learn how to learn. Key to this proposal, was the argument that user models should be elevated to the status of a *first-class citizen*, meaning that they should have "intrinsic value independent of any one application". The paper reviews a number of prototype scrutable user models demonstrating how they can help a learner to understand their own learning process. A more recent update [30] revisits this grand challenge, introducing a notion of a Personal User Model for Life-long Life-wide Learners (PUMLs), and reviews an ongoing program of research on the topic. Importantly, this paper presents a clear conceptual model of how the various user models intersect, and points to the distinction that a PUML is a *personal model for one user*. However, the way we could gather data generated by a learner over their lifetime was given less attention in these papers.

This is by no means an easy challenge to solve, but a PUML will require precisely this type of advance. This is because learning occurs across formal and informal educational contexts, in a wide array of different environments. People do not just stay within an institutionally authorised Learning Management System (LMS) and its associated supported tools. They can learn anywhere and everywhere, and are becoming increasingly "non-compliant" learners [23]. People use a range of social media to communicate with one another, sometimes supported the workplace, but sometimes not. They make use of sites like StackExchange and Youtube to find answers to challenges they face, enrol in microcredentials and Massive Open Online Courses (MOOCs), interact with coaches and more senior colleagues over coffee to resolve challenges that they are facing, and increasingly turn to ChatGPT to answer questions on the fly. This learning that occurs "in the wild" [33] presents a problem for those who would build lifelong learner models [15].

We need to be able to gather data from multiple places, and it often comes in a wide array of formats.

Comprehensive and scalable solutions for dealing with data from multiple sources have yet to be implemented. Educational data standards are often proposed as a method for delivering data interoperability at the point of data emission, but the process is fraught and adoption has been sporadic at best. Early standards like SCORM[2], and now the two more modern updates, Experience API (xAPI)[3], and IMS Caliper[4], all attempt to harmonise educational data at its original source using one pre-defined format, but to date they have largely failed [24, 36]. Why the ongoing failure? One explanation is proposed by Feldstein [17], who notes that specifications tend to produce compromises that few people are thrilled with, and often leads to them striking out with their own solutions. Similarly, Stringer et al. [44] have highlighted the social problems facing standards adoption, pointing to: the slowness of the standards development process; researcher resistance; diversity in tools; institutional issues; and a lack of vendor cooperation. Thus, achieving data interoperability is much more of a socio-technical problem than a straight technical one. And yet the bulk of the data standards work in this space has tended to focus upon technical issues alone. An alternative approach involves trying to harmonise data at point of capture [33, 34], while encouraging vendors and large organisations to work towards a more uniform emission of learning data [36]. In this scenario great care must be taken to ensure that the data captured is mapped into educationally meaningful constructs [29], as this helps to ensure that the data is actually useful in a learner model [36]. While such hybrid socio-technical models show promise, they are yet to be implemented at scale across a lifelong learning context. The social barrier remains a difficult one to overcome.

2.2.2 Challenge 2: Lifelong learning requires portable learner models. Even if we could aggregate data from a wide array of learning environments in a meaningful sense, another problem remains. We must also be able to move the resulting learner model between different learning systems. Baker et al. [8] identified this problem as a key grand challenge, calling it the problem of *transferability*, or the learning systems wall. Critically, each time a learner interfaces with a new learning environment they must endure a cold start as the system knows nothing about them and has to build up a new learner model. Valdés Aguirre et al. [46] suggest that this problem arises because user models in learning environments tend to be more heterogeneous and complex than the models traditionally used in recommender systems (RecSys). For example, while a RecSys would typically contain some basic user information (e.g. location, browser, language) coupled with information like click through rate to other pages, time spent looking at items etc., learner models often contain far more complex constructs such as emotional state and affect, knowledge models, social dynamics etc., which are more difficult to represent across different systems. Furthermore, as machine learning is often used to extract models about these complex constructs, the resulting models are rarely portable to other environments.

While attempts to move learner models and competencies between educational domains have existed for decades (see e.g. [6, 27, 28] for some early attempts) this problem remains largely unsolved. Multiple reasons lie behind this failure, and in fact the problem could again be considered socio-technical. For example, there is a tendency for most groups to work upon improving the learner model in *their* system rather than working on porting that model to other systems. This is an understandable omission as the models are often remarkably different. Desmarais and Baker [15] provide a comprehensive review of learner and skills-based models, calling attention to the issues associated with aligning ontologies between different models in a long term learner model. This lack of semantic interoperability [11] between different learner models is a key unresolved challenge. Even if this problem could be resolved, where precisely the learner model would be stored, and in what technology stack, remains an open question. While many different proposals have been made [14, 39], the lack of convergence upon one solution is concerning.

3 CASE STUDY: THE STALLED SKILLS PASSPORT

We are now ready to ground our discussion of the above two challenges using an explicit case study, which springs from the concept of a skills passport as a potential solution for supporting lifelong learners. It is claimed that such a tool would provide learners with a way to construct a skills profile by claiming skills from experiences in their past, identifying career goals, and then finding training pathways that might help them to fill gaps in their skills profile.

One example of a current flurry of interest around this concept can be found in Australia, where entities like the Business Council of Australia (BCA) have argued that long term growth of the future workforce will need a "skills passport" that recognises short courses and micro-credentials and somehow works like a digital CV[5]. In 2023 this lobbying resulted in the Federal government budgeting AU$9.1 million to develop a business case exploring the utility of such a tool.[6] It is important to realise that the skills passport idea advocated by the BCA is not new [20]. Skills passports have been periodically discussed in Australia at least as far back as 1997 [1], but despite wide-ranging attempts to use them, they are yet to gain widespread uptake as either valid indicators of capability, or as useful tools for identifying recommended training pathways. Again we come to the question we asked of PUMLs: if the tool is so useful then why has it yet to emerge as a viable aid to support lifelong learning in Australia? Other examples of skills passports at various levels of implementation around the world include:

Europass (https://europa.eu/europass/en) is set of online tools that were created to promote transparency and mobility in the European job market. It enables people to create a profile of their skills, qualifications, and experiences in one location, along with information about their digital capabilities, languages spoken, past volunteering, reference letters etc. This profile can then lead to suggestions about possible jobs and courses to study, and can even be shared with employers,

[2]https://www.adlnet.gov/research/scorm/
[3]https://www.adlnet.gov/research/performance-tracking-analysis/experience-api
[4]https://www.imsglobal.org/activity/caliper
[5]https://www.bca.com.au/setting_up_long_term_growth_not_a_short_term_comeback
[6]https://www.education.gov.au/national-skills-passport-consultation/resources/national-skills-passport-consultation-paper

recruiters and guidance counsellors. It is possible to create a number of alternative CVs which can then be shared with different employers. However, just like a standard CV, none of the information stored in a Europass profile is currently verified, which limits its utility as a trusted store of information about what a person can actually do.

MySKILLSfuture (https://www.myskillsfuture.gov.sg/) is an ongoing initiative in Singapore, which is using a mix of skills profiling technology, government subsidies for learners, and prioritised courses, to encourage a country wide transition to a culture of lifelong learning [31]. One component of this initiative includes a skills passport which enables people to view and manage their skills, certificates, and licenses. In contrast to Europass, this tool links through to verified certificates (OpenCerts) offered through the general initiative.

MYPASS Global™ (https://www.mypassglobal.com/) is a form of workforce compliance management software that helps employers in high risk industries to track employee compliance with nominated training and to reduce risk. Employees can create and manage their own MyPass Skills Passport, which ensures a certain amount of portability if their next employer is using the same system, but this is not often the case.

SkyHive (https://www.skillpassport.org) has developed what it terms a Skills Passport Ecosystem™, which connects workers to potential employers, while also offering real-time labour market data to governments which it claims can help them to develop rapid responses to shifts in economic circumstances. People can upload their CV to a tool that uses Natural Language Processing (NLP) to extract their likely technical skills, soft skills, tools, and technologies from identified work experience, education history, credentials, and hobbies. They can then see recommended jobs based on their history as well as training that might help to fill any identified skills gaps. This is one of the most advanced systems currently in circulation, however, SkyHive's closed skill knowledge graph means that their passports are not currently portable to any other system. This restricts the use of the resulting passports outside of the context in which they were generated.

Without verification of training, and a fine grained representation of skills and capabilities, many of these tools sound remarkably similar to a standard ePortfolio solution. For example, while Europass does support some diagnostic tools, as well as translation between European languages and alternative CVs for different contexts, its base functionality is markedly similar to that provided by a LinkedIn profile. In fact it is possible to import a LinkedIn portfolio to Europass, which raises questions about why precisely we need them both. While it is likely that many of these tools will move towards verification of trusted credentials, a basic problem persists: multiple different skills passports now exist, often defined for specific geopolitical contexts, or as proprietary tools. This brings us to a crucial point in this paper: for a skills passport to be "useful" it would have to be a form of PUML, and yet we know that these models face two critical challenges. How does this impact upon the dream of a useful skills passport?

3.1 The skills sector border

To be useful over a lifetime of learning, a learner needs their skills passport to make sense across a wide range of geographical, political and organisational domains. The concept is illustrated in Figure 1, where we see a lifelong learner attempting to use the same skills passport across three different organisations, all of which have adopted a different technology stack to support skills passports. Thus, our learner's skills passport might have been initially created at Organisation 1, a University which perhaps uses the Australian Skills Classification[7] (ASC), and the CREDNet[8] credentialling platform. Upon graduation they might decide to go and work for a period in Europe, where their workplace is using a mix of Europass coupled with skills diagnostics that link to the European Skills, Competences, and Occupations[9] (ESCO) classification. Moving again to a new location, our learner finds themselves in the USA, working for Organisation 3 which uses the SkyHive platform. How can we create a situation where this person does not have to create a new skill passport every time they cross these *skills sector borders*? We will see that substantial improvement is required in both syntactic and semantic data interoperability as well as the portability of the resulting user models. Let us explore this problem in more detail.

3.2 Challenge 1: Skills passports need to aggregate data from multiple locations

Skills passports provide a simplified version of a PUML as they focus upon collecting a restricted subset of information about a lifelong learner: their skills, capabilities, and sometimes a record of courses, micro-credentials and other qualifications that learners have accrued. As such, many of the issues besetting the collection of interoperable learning data across multiple EdTech tools and environments are removed in this scenario. And yet Challenge 1 still remains a considerable issue. For example, what representation of skills, capabilities and learning experiences should we store in a skills passport? To be useful a skills passport must aggregate skills and credentials from multiple sources, at organisations which are frequently on different sides of the skills sector border. This means that each of these sources may use very different representations of skills and capabilities. We need sophisticated methods to translate between these representations. Three examples will help to illustrate this problem in more depth.

3.2.1 Different socio-geographical sectors use markedly different data and metadata. Core to the challenge facing skills passports is the wildly varying data that they will have to aggregate from various socio-geographical sectors, in the form of skills taxonomies, ontologies, graphs, capability frameworks, course information and learning experience data. How will this data make sense as someone crosses the skills sector border depicted in Figure 1? Let us assume that our learner starts in Australia, which appears to be heading towards broadscale adoption of the ASC across the higher and vocational education sectors. As of the December 2023 release, the ASC features three types of skills for 1575 occupations, coming to combinations of: 1686 specialist tasks, 94 technology tools and 10

[7] https://www.jobsandskills.gov.au/australian-skills-classification
[8] https://www.uac.edu.au/about/business-solutions/products-services/crednet
[9] https://esco.ec.europa.eu/en

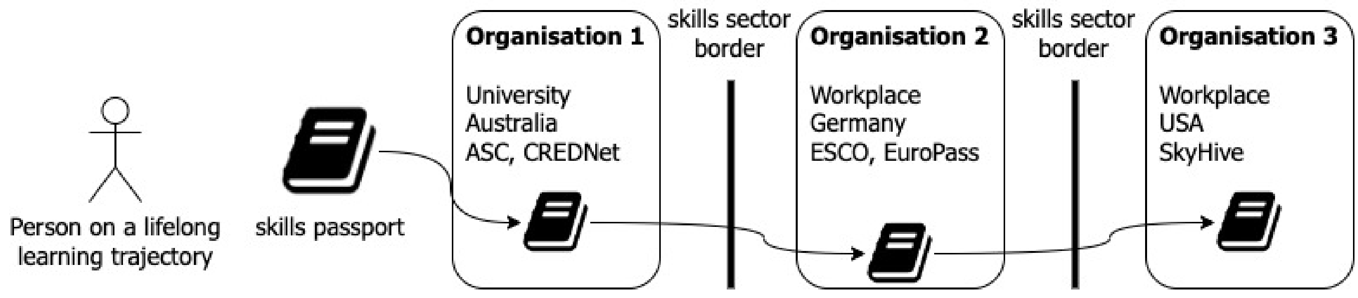

Figure 1: Each time a person crosses a "skills sector border" there is a risk that the data in their skills passport will cease to make sense.

core competencies. Assume further that our learner interfaces with a tool to claim 5 skills in the ASC along with a related occupation, say the new *Data Scientist* (ANZSCO 224115) occupation. The resulting simplified "skills passport" is listed in the first two columns of Table 1. However, the claimed strength of a skills passport does not lie in this simple representation of our learner's skills. Rather, a skills passport becomes useful because of its ability to support someone who is not in their desired occupation to see what skills they need to get there, and what training pathway they might take to reach that goal. Thus, using the same ASC representation of skills, a *Policy Analyst* might be able to see that they could reach their dream job of *Data Scientist* by acquiring the skills required for a *Data Analyst* and then perhaps taking some more advanced training while working in that job for a period. (See the last two columns of Table 1.)

But what happens if our user attempts to move from the Australian context across to a a job in Germany? Perhaps they saw an advertisement that requires applications using a CV generated in the Europass system. At this point we start to see where the skills sector border becomes a serious issue to contend with. We can quickly see the complexity of this problem thinking about how skills would be represented in Europass. It is likely that this skills sector would use the multilingual ESCO taxonomy. Version v1.1.1 of this taxonomy stores information about 3007 occupations, over 13,890 skills and qualifications submitted from contributing countries that span 28 European languages. Completed qualifications can be tagged by contributing institutions with ESCO skills, and displayed in a learner's Europass.[10] However, there are currently no cross-walks between ESCO and the ASC.[11] This means that the only way our learner could currently apply for their job in Germany is by undergoing a cold start and creating a new skills passport with this new data format; there are no tools to help our learner cross the skills sector border. This has quickly become a problem of user model portability, so we will return to this problem in Section 3.3 when we discuss Challenge 2.

3.2.2 The skills passport would need to interface with a broad array of systems. Our learner will also have to interface with a variety of learning environments, each of which is likely to both consume and produce data in different formats. This brings both a challenge of integrating with the many different learning environments, as well as the problems of data interoperability, at both the syntactic and the semantic levels. The difficulty of doing this well can be seen in the Europass ecosystem. While participating countries can add their qualifications to Europass, and can even label their level according to the European Qualifications Framework[12] (EQF), mapping between these awards remains a difficult challenge. This is exemplified by the need for Europass Mobility templates[13] and Certificate Supplements.[14] The existence of these templates demonstrates that actually integrating the data supplied by different European countries remains a manual task that is very difficult to resolve. For a skills passport to be genuinely useful it would have to represent both formal and informal learning across the domain where it is widely used, but the challenges associated with doing this in Europass should give us reason to pause — integrating with IT systems representing curriculum is no easy task, and there is no one system available to make this integration easier. Moreover, any skills passport would likely experience a phasing in period before it became a universal representation of a learner's capabilities. This means that along the way the tool would likely need to integrate with a wide range of existing Portfolios (e.g. LinkedIn) as well as numerous Human Resources (HR) systems used by companies that had yet to adopt the skills passport as a representation of capability. Our learner is now likely to be in a situation where they have built up a skill profile representing their data science capability in two government frameworks and numerous private environments, undergoing a cold start at each step along the way.

3.2.3 Skills and capabilities are contextually dependent on where they are demonstrated. One final problem of data interoperability remains to be explored. This one arises from the frequently made claim that a skills passport could help a learner to identify training pathways to change their career. Thus, in the December 2023 version of the ASC, a *Policy Analyst* has a specialist task (i.e. a skill) named "Analyse data to identify trends or relationships among variables", which is shared by 38 other job roles, including *Data Scientist* and *Neuroscientist*. While it is quite likely that this specialist task is in fact performed by each of these occupations, it is equally probable that each of these occupations performs this task at a very

[10]See https://esco.ec.europa.eu/en/classification/qualifications, although the search available does not appear to link through directly to ESCO skills as of January 2024.
[11]See https://esco.ec.europa.eu/en/use-esco/other-crosswalks (January 2024).
[12]See https://europa.eu/europass/en/compare-qualifications for a comparison of qualifications across participating countries.
[13]https://europa.eu/europass/en/work-europe/mobility
[14]https://europa.eu/europass/en/learn-europe/certificate-supplement

Technical Skill	Data Scientist	Data Analyst	Policy Analyst
Analyse data to identify trends or relationships among variables	X	X	
Apply new technologies to improve work processes	X		
Prepare graphics or other visual representations of information	X	X	
Advise others on business or operational matters	X		X
Prepare data for analysis	X	X	

Table 1: A subset of the Technical Skills available in the ASC mapped to three of the occupations in the same taxonomy.

different level of capability. Thus, an "advanced" capability in this skill for the *Policy Analyst* is unlikely to be considered "advanced" for a *Data Scientist*. This makes the unambiguous collection of data from people working in the two different occupations a difficult problem to solve. Some work has been completed by ESCO in using context to restrict occupation suggestions [4], but this is a research problem that requires far more work. Even if we can account for the contextuality of skills within one specific framework or ontology, we would still need to be able to port those skills to highly similar skills described in other skills representations. This returns us to a consideration of Challenge 2.

3.3 Challenge 2: The model of competency needs to be portable across multiple locations and contexts

The most critical problem for a skills passport centres around the second challenge identified above for PUMLs. Specifically, for a skills passport to be useful, we need the information stored in it (i.e. it's user model) to be portable across the skills sector border. This is problematic because at present there is no one global representation of skills, competencies and qualifications. Let us explore this challenge by continuing the discussion from the example above, where our lifelong learner attempts to move from Australia to Germany as a *Data Scientist*. This move requires a skills passport that can somehow translate between the ASC and the ESCO representations. In essence, our user needs a way of porting their learner model of skills and capabilities from the ASC to ESCO. Even though the two frameworks share many characteristics, this is not a trivial exercise. This problem becomes even more pronounced if we continue to stage 3 of our scenario, with the learner attempting to travel to the USA, where their skills and competencies are represented using SkyHive, a proprietary skills framework with no public mapping tools that would enable portability and no public description of the skills it associates with the *Data Scientist* occupation.

These three representations of skills are by no means the only ones (see for example Siekmann and Fowler [42] for a comprehensive discussion). In the USA the O*Net-SOC taxonomy[15] provides an open skills framework built up from the answers provided to surveys about the abilities and skills possessed by a random sample of workers in identified occupations. Then, we also have the International Standard Classification of Occupations (ISCO)[16] which is maintained by the United Nations. Why do so many skills taxonomies even exist? The claim is often made that occupation descriptions need to be tuned to the specifics of a geographical location, but it seems unlikely that occupations are that specialised from country to country. Indeed, job specialisation is more likely to occur in specific regions than nation states. For example, we might find that the skills required by a *civil engineer* in a mining town are somewhat different from those required of a *civil engineer* working in a city. It could perhaps be claimed that these different taxonomies spring more from socio-political considerations and historical inertia, than from any real technical necessity.

Government taxonomies are generally publicly available and so could be used by anyone attempting to create a useful skills passport. However, they have a number of shortcomings which are stalling their widespread adoption. First, they are generally updated slowly, often by committee, or using human oversight and input, which means that they usually lag behind shifts in the workforce, e.g. they can take a long time to incorporate new skills and occupations as they emerge (all of which are problems highly reminiscent of the challenges besetting data standards that were introduced above [44]). It can also be difficult to track updates across versions, as the changes are rarely documented in a format that could be looked up by an online application. Second, they are often seen as too general, or not representative enough of specific sectors, which leads to the emergence of discipline specific taxonomies and knowledge representations [43]. While this can facilitate the representation of a learner's skills to a domain in which they are easier to track and compare, it restricts the utility of skills passports if people need to transition to new sectors. For example the Australian Public Sector (APS) has created a Careers Pathfinder tool[17] that utilises the Skills for the Information Age[18] (SFIA) framework and a specialised APS Data Capability Framework[19] (DCA) to represent the capabilities of its Information Technology (IT) workers. Interestingly, the Australian Computing Society (ACS) also uses the SFIA framework, which suggests a clear place where a skills passport might fruitfully be developed to facilitate sector mobility. However, for true mobility this passport would need to enable the representation of a broader range of skills than just IT ones. At present an *Accountant* who wanted to become a *Cyber Security Analyst* would be forced to undergo a cold start when they started using SFIA. An obvious contender for this broader range of skills in the Australian context is the ASC, but as there is no cross-walk between the two frameworks this is not a trivial undertaking. Table 2 lists a selection of

[15]https://www.onetcenter.org/taxonomy.html
[16]https://www.ilo.org/public/english/bureau/stat/isco/
[17]https://www.digitalprofession.gov.au/career-development/aps-career-pathfinder-tool
[18]https://sfia-online.org/en
[19]https://www.apsc.gov.au/publication/aps-data-capability-framework/aps-data-capability-framework-user-guide

the skills frameworks that are currently available, along with an overview of their features and relationships.

A lack of satisfaction with existing frameworks has led to a number of attempts to build taxonomies, ontologies, and knowledge graphs by applying Machine Learning (ML) and Natural Language Processing (NLP) methods over job advertisements. This approach is claimed to enable the identification of emerging skills and occupations faster, and has been used to more rapidly update some of the above taxonomies, such as ESCO[20] and the ASC.[21] However, this space is also an area of extreme competition in the private sector where a number of companies are moving very fast to claim a market advantage in workforce re-training and upskilling. Examples in this domain include solutions provided by Lightcast[22] (which formed from the merger of Burning Glass and Emsi), SkyHive[23], LinkedIn [24], Gloat[25], and IBM's Talent Framework[26]. Claims are often made that these "skills-first" commercial solutions to identifying and retaining talent are more comprehensive, better representative of current workforce trends, and more up to date. And yet, while methods relying upon NLP are becoming very common, they also face a number of different issues. First their dependency upon input job advertisements data can bias the resulting skills and occupations to ones that are advertised in online job boards. It also fails to recognise that the workers actually employed are not necessarily a perfect fit for the job ads that they responded to. As such, while these methods are faster to update, the claim that they are a better representation of the skills required by various teams and occupations is somewhat optimistic. It is likely that a mix of automated NLP coupled with human oversight will provide a better long term solution for a skills passport, and indeed most of the best solutions in both commercial and government categories utilise this approach. However, this brings us to the crux of the problem facing this challenge: which representation should we use?

3.4 There will never be "the one" skills taxonomy (or ontology, or graph)

At this point we can see the dilemma that comes from hoping for a convergence towards one universal description of skills across the entire workforce. Too much work has been invested already in various descriptions across a range of different sectors and geographical domains. Even if an alignment could be reached among the various government based frameworks, the environment created by numerous companies and start-ups attempting to claim the skills-first HR training space suggests that competition in this space will become the norm. The problem of achieving a skills passport that could move across the skills sector border is as much a social one as it is a technical one. How can we make it easier to encourage "good citizenship" where a skills passport becomes seen as a public good for society rather than a competitive advantage to be gained by a subset of competitors?

3.5 A proposed solution: local skills with a global lookup

A certain amount of oversight and coordination will be required for skills passports to become capable of usefully supporting lifelong learners. The ongoing failure of this agenda to deliver a viable tool suggests that an incremental approach is necessary, where good citizenship is encouraged through the provisioning of locally relevant tools and services that are designed to eventually link up. Government bodies provide good candidates for leading work in this area due to their generally neutral position across the sector. Their published open skills taxonomies are good starting points, but much more work is required to link between existing work, which has generally tended to focus upon one geographical domain or sector. Critically, we need leadership that provides tools and services to support the translation of skills and occupation data between the already published skills taxonomies. As Table 2 demonstrates there are a range of different agencies maintaining their own skills taxonomies and competency frameworks. However, there are also many other more proprietary skills taxonomies, ontologies and graphs available, some of which are open, some behind paywalls, and some that are used largely internally as business intelligence. It appears that a race is currently on to claim a competitive advantage in what is rapidly becoming a very crowded domain. Both technical and social solutions are required to navigate the problems introduced in this paper. Specifically, while there is very little hope for a single dominant skills taxonomy emerging, it is possible to leverage the considerable amount of work already completed through some careful policy development and the creation of support services that encourage good citizenship.

The first step in this process would involve the designation by various governments of a set of open and preferred *core taxonomies* that would be recognised by their local skills passport. This would encourage the development and refinement of these core taxonomies and so work to focus efforts. If these preferred taxonomies could be found via some sort of a look up service (e.g. a semantic web service) then it would in principle be possible to create a set of NLP services and cross-walks that could port data between geographical locations and other sub-domains. However, it will be necessary to fill in numerous research gaps and answer some thorny policy problems in order to achieve this kind of end state. What work would need to be completed?

3.5.1 Trustworthy cross-walks between the core taxonomies. First, a substantial gap exists in the technology available to map between skills taxonomies. Table 2 lists likely candidates for core taxonomies with a "Government" label, and looking down the "Cross-walks" column we see that almost none of them have been mapped to each other. For example, there is currently no way for a person to move a skills passport from Australia to Europe, the USA or to Singapore. The only geographical transition that is currently facilitated is between Europe and the USA (or vice versa). While this is a significant advance, and covers millions of potential users, a skills passport or EdTech provider that takes advantage of this

[20]See the pages on how data science is increasingly being used with ESCO here: https://esco.ec.europa.eu/en/about-esco/data-science-and-esco
[21]https://www.jobsandskills.gov.au/sites/default/files/2023-12/Australian%20Skills%20Classification%20Methodology.docx
[22]https://lightcast.io/
[23]https://www.skyhive.ai/
[24]https://linkedin.github.io/future-of-skills/
[25]https://gloat.com/
[26]https://github.com/watson-talent-services/developer-documents/blob/master/developer-guide/v1-talent-frameworks-guide.md

Taxonomy	Form	Sub-sector	Cross-walks and Other relationships
ASC	Government	Australia	ANZSCO Occupations
ESCO	Government	Europe	O*Net-SOC Occupations
SkillsFutureSG	Government	Singapore	None
O*Net-SOC	Government	USA	ESCO Occupations, Lightcast
ISCO	United Nations		ESCO
SFIA	Competency	IT	
DCA	Competency	Data	
Lightcast	Commercial		O*Net-SOC
SkyHive	Commercial		
LinkedIn	Commercial		
Gloat	Commercial		
IBM	Commercial		

Table 2: A selection of the different English language taxonomies describing skills and occupations, and their relationships.

technological development is yet to emerge — supporting the claim that the problem is *socio*-technical.

It is interesting how few cross-walks have been constructed between *any* skills frameworks and taxonomies. This problem has likely arisen because cross-walks were traditionally created by hand, which meant that they required a substantial labour investment with very little potential reward. However, the emergence of a general drive towards lifelong learning facilitated by global skills passports provides the potential "killer app" on the horizon that could encourage more work in this domain. One early cross-walk was created by Burning Glass (now Lightcast), whose proprietary ontology originally had a mapping to O*Net-SOC and to ANZSCO. The Lightcast "Open Skills" taxonomy[27] now maps to O*Net-SOC, however, the ANZSCO cross-walk appears to be depreciated by changes in the taxonomy post merger. However, more open approaches are emerging. For example, a 2022 Masters thesis by Guru Rao [25], used XLNet to map between ESCO and O*Net-SOC with a 69% accuracy over a sample of 200 human labelled occupations. This work also investigated ways in which this matching process might be improved by incorporating domain specific knowledge to bridge between the two ontologies (accuracy 34%), or extending XLNet's vocabulary with domain knowledge (accuracy: 59%), claiming that the relatively small size of the hand labelled validation set led to poorer performance in this case. Even more positive, at a similar point in time, the above mentioned Europe-USA cross-walk was created when the European Commission mapped ESCO into O*Net-SOC using a ML model based upon BERT to speed up matching with human oversight and correction.[28] The same methodology could be used to create a similar set of cross-walks between other taxonomies in future work.

Some research has been published which demonstrates how these more global cross-walks might be mapped to geographically local representations of skills and occupations. For example, Dörpinghaus et al. [16] discuss a process by which they constructed a German labour market ontology which takes ISCO occupations as its top level and also maps to ESCO by design. This approach guarantees a cross-walk between three important taxonomies and so is a sound one for supporting both local contextualisation of skills and occupations while retaining the data portability that a skills passport requires. Taking a more automated approach based on word embeddings constructed from a corpus combining both ESCO and the Italian occupation taxonomy, Giabelli et al. [22] mapped the Italian labour market taxonomy into ESCO using FastText, which is an extension of word2vec. This approach did not require the pre-existing mappings between ISCO and the local country specific ontology that was utilised by the previous approach [16], but it also suffered a loss of accuracy as a result which suggests that some human oversight would still be required.

This is because accurate cross-walks between core taxonomies are an essential requirement for a globally useful skills passport. While NLP may go some way towards speeding up the creation of the cross-walks, it seems unlikely that this process will be fully automatable. Restricting the number of core taxonomies used would reduce the amount of work that would need to be performed by humans to ensure that the mappings were trustworthy, which is the underlying reason behind the suggestion that only some skills taxonomies should be approved as core. An ongoing lack of validated publicly available crosswalks will hold back the emergence of a genuinely useful skills passport, and will also encourage the ongoing proliferation of alternative skills taxonomies, private ontologies and graphs. In short, we will see companies, governments and researchers all creating new skills and competency frameworks while it is easier to create a new ontology than it is to map into an existing one. In order to make progress we require national skills bodies to focus more upon this critical enabling infrastructure.

3.5.2 Publicly available NLP tools to support mapping into core taxonomies. This approach would also require the public release of tools to encourage good citizenship across the skills ecosystem. For example, tools that support the mapping of *other* skills taxonomies and descriptors into those that are designated as core would make it possible for individuals to port their skills passport to core taxonomies in other domains, irrespective of how much work their provider had completed on data portability. While this approach

[27] https://lightcast.io/open-skills
[28] See https://esco.ec.europa.eu/en/about-esco/data-science-and-esco/crosswalk-between-esco-and-onet for an explanation of the methodology used over the 2021-2022 period.

would not guarantee trusted mappings, it would encourage the emergence of tools to support people in moving their passports as required while waiting for improvements in technology, so helping to ensure that individuals are not "trapped" in one skills sector. Individual users, or perhaps even a set of validation services would likely be required to approve the resulting mappings. At UTS, we are investigating the possibility of constructing models that can rapidly map between any two skills taxonomies or capability frameworks. Our solution uses GPT to generate lists of skills that are representative of a given skill or capability. These are then compared using cosine similarity over bags of skills to return a ranked list of likely matches in the second taxonomy.

Similarly, educational institutions would benefit from tools that support the tagging of their curriculum descriptions into core skills taxonomies. These tools could be semi-automated using NLP (e.g. the skills extraction tool released by Singapore[29]) or require human input to select skills against a defined taxonomy (which would enable instructors to maintain some control over how their subjects are represented in a taxonomy). In both cases human oversight would again be required to approve suggested skills tags or make decisions based upon the resulting analytics. For example, our early work on using NLP tools provided by BG took its skills taxonomy as a controlled vocabulary for automating the Recognition of Prior Learning (RPL) [35], and demonstrated that out of the box NLP tools could be used to build up more extensive services that would help to encourage good citizenship in this space.

3.5.3 A global look up service. For this solution to work it would be necessary to store the information in a skills passport with contextual information designating which taxonomy its skills originated from. Named graphs [12] could perform this role, providing a mechanism for contextualising a skill or occupation listed in a skills passport to a specific taxonomy. However, other approaches are no doubt possible. Government agencies could take on this governance role, signing taxonomies that they had chosen to warrant as core to authorise their use in skills passports they consider valid in their domain. These agencies could then also become responsible for maintaining mapping tools to support translation to other core taxonomies. This brings us to the final critical element for a useful skills passport.

3.5.4 Governance. The above proposal is designed to be localisable to a specific jurisdiction during an initial set up phase. This makes it possible for one domain to start developing a skills passport within their own border, but to plan for eventual user model portability to other domains. However, ensuring that a skills passport could function across all skills-sector boundaries would likely require substantial governance and oversight. It is likely that some sort of governing or standards body would need to be created to manage communication between the different local authorities, and to approve the designation of new taxonomies as core. A set of expectations are likely to be necessary to elevate a taxonomy to core status. Some criteria that seem likely to form an initial minimal set could include:

(1) A core skills taxonomy MUST describe each skill it lists with an id, a name, and a brief description for use in NLP.
(2) The server for the taxonomy MUST provide at least one cross-walk of its skills to another core taxonomy.
(3) The service SHOULD provide cross-walks to all other core taxonomies.
(4) A set of public APIs SHOULD be made available to facilitate other mappings and services.

[29] https://www.tpgateway.gov.sg/plan-courses/skills-extraction-algorithm

Components of this ecosystem already exist. In particular, ESCO is a fully defined ontology that contains ids, names and a description of each entity, and as previously discussed, a cross-walk has been created between ESCO and O*Net-SOC. As such, ESCO is largely in compliance with the above compulsory requirements. Note however, that the ESCO-O*Net-SOC cross-walk concerns only occupations, and that no further NLP services or APIs currently exist. More work is required to achieve all requirements and to map occupations to skills claims in a passport, but this is in principle possible.

3.5.5 An embryonic user model for a portable skills passport. It seems that the technology for creating a minimal viable product (MVP) that could cross one skills sector border (Europe to the USA) is within reach. A skills passport provider that used ESCO (e.g. Europass) should in principle be able to translate any claims that a user made in their passport about previous occupations that they had worked in to the US occupations listed in O*Net-SOC. Furthermore, each of those occupation claims could be linked to the skills listed in both taxonomies right now, which would yield an embryonic skills profile capable of crossing the skills sector border.

Mapping skills across both taxonomies would potentially also help to identify equivalences between the skills listed in each occupation and so support the creation of skills cross-walks between ESCO and O*Net-SOC. This would be an important step for the user model to move beyond a situation where only occupations could be ported between the two geographical domains. Indeed, the entire point of a skills passport is to disaggregate the coarse-grained representation of courses and occupations down to a finer grained skills based user model that would be more suitable for personalisation. Hence this problem of mapping between *skills* taxonomies remains a critical enabling step.

Such mappings would bring other benefits as well. For example, mapping from occupations to skills in the ESCO-O*Net-SOC cross-walk may also enable the identification of possibilities for contextualising skills with a level designation (e.g. introductory, intermediate and advanced), if certain occupations could be identified as requiring more advanced capabilities. This would assist with the personalisation of training pathways between job roles that shared similar skills but at different levels of capability. An extension of this user model could eventually include the ability for individuals to rate their competency (or not) in a given skill, as well as to claim new skills. Note that this program of work makes the creation of a genuine skills cross-walk more urgent.

More work remains to be completed. However, the lack of progress toward an MVP of this form comes from *social* factors as much as technical ones, with research teams, commercial providers, and government agencies all tending to work in their own local domains and failing to support the broader global context. If a MVP were to emerge that provided this first simple skills based user model then perhaps more sectors would see benefit in working towards convergence. Thus, an MVP could encourage the mapping of more taxonomies into the already declared core ones, so helping us to develop a socio-technical infrastructure that could in fact cross the skills sector border.

4 CONCLUSIONS

Despite decades of work attempting to personalise lifelong learning, we are still a long way from achieving a viable PUML. This paper has explored two challenges that are holding back progress in this critical domain: (i) collecting data from diverse learning environments; and, (ii) porting learner models across those environments. Using the widely discussed (but yet to be usefully realised) concept of a skills passport as a restricted case study to illustrate these challenges, we have seen how many of the issues holding back lifelong learning are socio-technical. And yet the bulk of the work in this space has been technical in nature, which perhaps helps to explain the ongoing lack of progress. Enabling learners to use their skills passports to cross the various skills sector borders now in existence will require substantial work towards convergence. This paper has made a modest suggestion about how this could be facilitated by the various national skills bodies already in existence. A proposal for achieving a MVP has been presented, along with ideas for where further substantive work is required. Helping people to learn for a lifetime is within reach, but achieving this end point requires a focus upon more than just technological solutions alone.

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