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The Trend of Big Data in Workforce Frameworks and Occupational Standards towards an Educational Intelligent Economy

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Abstract: The complexity of creating and updating workforce frameworks and standards is limiting the manoeuvrability of TVET educational outcomes as the world of work is constantly changing, putting stakeholders at risk of poor visibility. A literature review based on 39 documents from various types of documents including articles, conference papers, book chapters, short surveys, conference reviews and reviews within the period of 2011 to 2020 found that existing occupational taxonomies are not granular enough to support occupational classification in big data applications. On the other hand, workforce frameworks and standards although sufficient in providing detail occupational taxonomies, they are complex to develop and update thus making them inflexible to changing workforce requirements. Trend in the literature also suggests that organizations that employ occupational classification in big data applications among developed countries are in a transition from evidence-based decision making which is based on limited sampling; to a data-driven decision making which is based on the total population. This trend establishes a notion on the emergence of a data driven organization. Given evidence that support the need to improve in the flexibility of workforce frameworks and standards, and the emerging prevalence of a data driven organizations, the idea of improving workforce frameworks and occupational standards through educational intelligence is proposed to improve the manoeuvrability of TVET educational outcomes.

Keywords: Workforce frameworks, occupational standards, data driven organization, educational intelligence, technical and vocational education and training (TVET)

1. Introduction

Under the labour market mechanisms, workforce frameworks are a depiction of industry wide labour requirements (Brownie & Thomas, 2014) and occupational standards are set as the performance specification expected of competent personnel qualified for the profession (Ellis & Richardson, 2012). While workforce framework harmonizes the strategic coordination among various professions, occupational standards are set as benchmark to qualify a specific profession. Traditionally, workforce frameworks and occupational standards are instruments that are established to govern the development of workforce in support of the national social economy (Fretwell et al., 2001). These instruments play a crucial role in steering workforce development strategy through strategic coordination facilitated by the standard's organisation, government and industry. Through the lens of technical and vocational education and training (TVET) these instruments have been a source of reference in steering TVET delivery to fulfil its existential aims. Both instruments are a compilation of Labour Market Information (LMI) containing swaths of data about the job's taxonomy of mainly the competencies broken down to knowledge, skills, attitudes and abilities that are required of the worker.

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Throughout these practices, developing and updating workforce frameworks and occupational standards are limiting the manoeuvrability of TVET educational outcomes as the world of work is constantly changing, putting stakeholders at risk of poor visibility. In the interest of improving this visibility, this paper purports to assess the current state of such a data driven workforce frameworks and occupational standards mechanism related to big data in Malaysia. Section 2 presents the background on the topic, highlighting the literatures that influence and guide the research. Section 3 tells the methodology employed in this review and section 4 discusses the results before ending with a conclusion.

2. Background

In Malaysia, the development and application of occupational standards is governed through the National Skills Development Act 2006 [Act 652] also known as the National Occupational Skills Standard (NOSS). The establishment of NOSS through Act 652 has made it as a governing instrument of the skills development ecosystem in Malaysia. On the other hand, workforce frameworks are self-governed through industry participation via their representative associations with support of the government. In general, the workforce frameworks and occupational standards must reflect changing workplace realities defined by job taxonomies. They are instruments that can be used by applicants and employees to access greater career opportunities. They both contain LMI attributes that are identified through collaboration with industrial experts and practitioners. These instruments form a guide in updating skills and knowledge that has become a lifelong endeavour, causing many employers and employees to spend more effort, time, and money on education and training. Occupational standards also provide benchmarks for making education and training decisions, shaping curricula, and directing funds toward highest value education and training investments. Thus, such a mechanism that defines the job taxonomy needs to be always be relevant to requirements of its consumers.

Jobs that once were relatively simple now require high performance work processes and enhanced skills with in-depth knowledge given the rapid changes brought about by the Fourth Industrial Revolution (FIR) on the socio-economic environment affecting the nature of work and labour. In fact, the impact of the FIR has begun digitally disrupting and transforming the economy and social life at various levels in many countries (Clayton & Henry, 2011). In addition, the crisis and chaos brought about by the recent COVID-19 pandemic seem to accelerate digital disruption and transformation, thus forcing the industry (Ivanov & Dolgui, 2020) and the education (D'Orville, 2020) community to transition their activities online. The prevalence of accelerated digital disruptions and transformation towards jobs and occupations (Frey & Osborne, 2017) has evoke concerns among job prospects on the consequences to their future careers and the declining role of humans within the economy (Dwivedi et al., 2019) as they are being replaced by technology.

Specifically, for TVET as a career-oriented system, this trend has serious consequences. The digital disruptions and transformation to jobs and occupations is not reflected within the static knowledge provided in workforce frameworks and occupational standards. This is attributed to the increasing size of the industry (Mohamad et al., 2019; Chuaphun & Samanchuen, 2018), long and laborious update process (Ellis & Richardson, 2012) and the inability to timely capture evolving work context (Lester, 2014) that leads to the complex development and updates of the frameworks and standards. What this boils down to is the complexity of collecting, benchmarking, maintaining, disseminating and responding to such data in the workforce frameworks and occupational standards. It is becoming a real challenge as the world of work is constantly changing, putting the stakeholders who utilize the workforce frameworks and occupational standards at risk of poor visibility.

Among Malaysian TVET stakeholders, the risk of poor visibility demands a solution towards immunizing TVET upon the uncertainty and disruptions that is happening in the world of work. Inspired by the transition from a knowledge-based economy towards a data driven economy among the developed countries, an alternative solution is possible for TVET stakeholders to govern the complexity of such data driven mechanism in workforce frameworks and occupational standards. This inspiration is linked to the rise in capacity and capability of computers leading to breakthroughs in technology such as big data analytics in the education domain. It forms the basis for an emerging multidisciplinary area of educational intelligence which is defined as the utilization of data to assess and protect the outputs of the educational systems (Salajan & Jules, 2019). The concept of educational intelligence is core to economic intelligence which governs individual and systems level processes to harness humanities creativity and innovation potential (Salajan & Jules, 2019). In alignment to the original establishment of TVET, educational intelligence supports the aims of economic intelligence which is provided through the mastery of strategic information, thus providing economic security and establishing national influence (Revel, 2010).

To support the resolve of using educational intelligence in addressing the complexity of developing and updating workforce frameworks and occupational standards, a review of recent studies within the topic of "big data", workforce frameworks and occupational standards is conducted to answer the following questions:

i. What are the kinds of big data application that utilise workforce frameworks and occupational standards?

ii. What are the approaches in defining a job's taxanomy in big data applications?

iii. What is the motivation of utilising workforce frameworks and occupational standards data in big data applications?

3. Methodology

To answer the questions in background, an interpretive paradigm is utilised to the research so that a rather objective viewpoint amongst other researchers could be obtained through the expression of their literature in relation to the subject (Ijab et al., 2019). To start searching for the literature, a list of key words was developed containing terms such as skills standards, occupational standards, occupation standards, workforce framework, workforce standards, skills framework are being related to the term "big data". Based on the list of key words for the search, a total of 308 documents is discovered. For the literature review, reference articles were searched through the Scopus search engines. Other articles were accessed from various databases such as Scopus, IEEExplore, ScienceDirect, SpringerLink and Emerald databases. Various types of documents were included such as articles, conference papers, book chapters, short surveys, conference reviews and reviews.

The different kinds of key words for the search query was used because the terms workforce frameworks and occupational standards are problematic in that they usually reflect non-standardized and possibly loose boundaries around fiat sets of job taxonomy, which hinders their aggregation and interpretation (Gardiner et al., 2018) as many countries in world have similar labour mechanism. Therefore, to avoid possible sample bias and support face validity of this study, we restricted the search parameters to retrieve only those documents in which the keywords are paired with the term "big data" within a period of the last 10 years to gather similar literature on this already unique topic. We did not expand the search beyond the key term "big data," as doing so would have greatly increased the sample size (number of documents). Although it may sound attractive, the approach would make the sample less coarse, thereby controlling any noise that may have been introduced into the analysis resulting from a broader search. We proceeded to winnow out the relevant documents base on the inclusion and exclusion criteria of the content in the abstract. Using Mendeley as a reference manager and NVivo 12 as the computer aided qualitative data analysis software, the following are the inclusion criteria set for the study:

i. Documents that are published in English,
ii. Documents published within 2011 to 2020, and
iii. Documents that relate to the theme of career; training; education.

The following exclusion criteria are set for the study:

i. Documents not in English,
ii. Documents publish outside the period 2011 to 2020,
iii. Documents not related to the theme of interest,
iv. Duplicating documents, and
v. Non accessible documents.

Combing through the content of the literature, we ended up with 39 useable documents. The analysis of the remaining documents focused on the three (3) main questions. The first analysis is to list out the kinds of big data application that utilises workforce frameworks and occupational standards. The second analysis is to identify the different kinds of approaches in defining a job's taxonomy in big data applications. The third analysis is to identify the motivation of utilising workforce frameworks and occupational standards data in big data applications.

4. Results and Discussion

Workforce frameworks and occupational standards are instruments developed through compilation of various labour data resources from industry mainly around the themes of labour market information (LMI). The requirements of administering such swaths and variety of data demands the utilization of big data analytics. Through this literature review exercise, we observed that in general such application involving the retrieval of LMI already in the market through job portals such as JobStreet, Adnexio and LinkedIn.

4.1 What Are The Kinds of Big Data Application That Utilises Workforce Frameworks and Occupational Standards?

With regards to workforce frameworks and occupational standards, Figure 1 and Table 1 highlight a significant amount of literature contributed to the area of career (human resource) from the USA whereby a significant portion were published within period 2017 until 2018. This is followed by contribution to the knowledge management area within period of 2017 until 2020 mostly from Italy and India. Those applications were built around the concepts of job hierarchies or taxonomies.

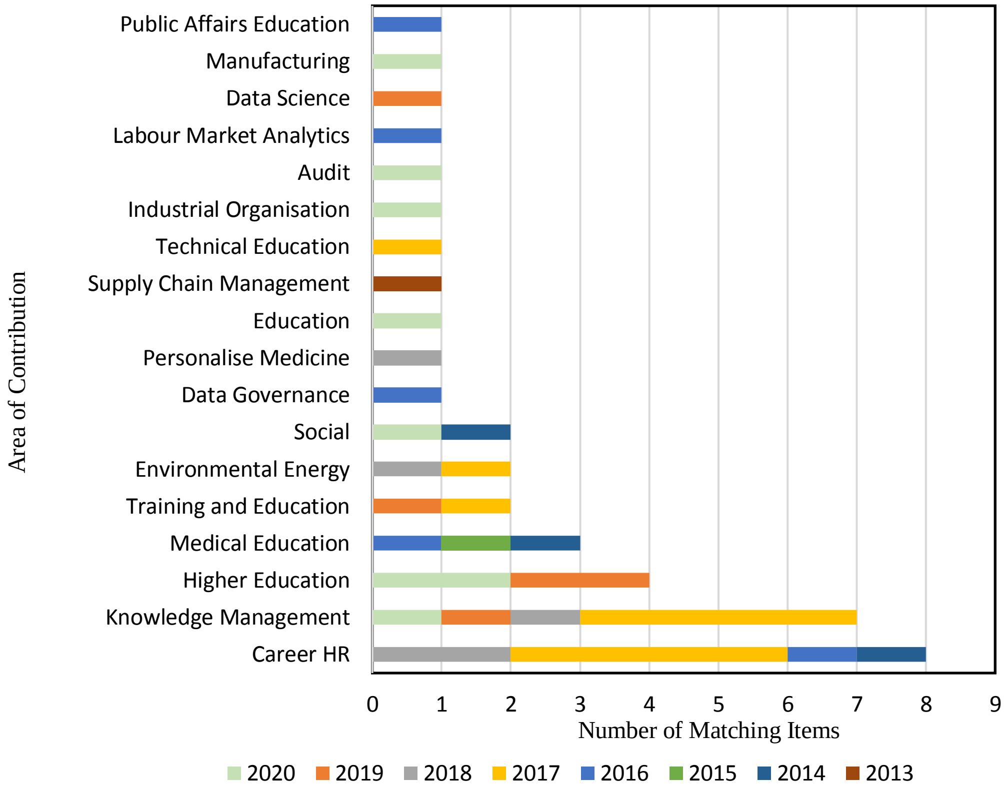

Fig. 1 - Area of contribution according to year published

More recently (2019 until 2020), a significant portion of the literature contributed within the area of higher education with half coming from Malaysia focusing on surveys and observations (Ijab et al., 2019; More & Ohatkar, 2020). This suggests that Malaysia's higher education is in transition to big data. However, from perspective of those who had implemented such mechanism, the usual motivation behind the utilization of these workforce frameworks and occupational standards in higher education was due to fact that it became a source of benchmark in the case of student's performance early warning systems (Asha et al., 2020; Zhang et al., 2020), determining career and education pathways (Abukhousa & Atif, 2014; Patel et al., 2017; Slim et al., 2019) which are features to assist the students towards educational success and more importantly is part of the concept in educational intelligence defined by Salajan (2019).

It seems that career and education are linked due to the knowledge contained within workforce frameworks and occupational standards. Mainly such knowledge management could be traced to the works of knowledge discovery (Boselli et al., 2017; Boselli et al., 2018; Denzler & Kaufmann, 2017), skill set discovery (Mandal et al., 2017; Velampalli & Eberle, 2017; Velampalli & Jonnalagedda, 2017), user oriented knowledge discovery (Muthyala et al., 2017) and organizational knowledge evaluation (Nicolaescu et al., 2020). Such references to workforce frameworks and occupational standards will enable content analysis of workforce and occupational knowledge.

Table 1 - Area of contribution based on 1st author country of origin

Area of Contribution	1st Author's Country of Origin																		
	USA	UK	Italy	Germany	Austria	Sweden	Switzerland	Netherland	Romania	Belgium	Ukraine	Russia	South Africa	India	UAE	China	Taiwan	Malaysia	Australia	Total
Career, HR	4											1		1	1	1				8
Knowledge Management	1		2				1		1					2						7
Higher Education	1															1		2		4
Medical Education	2					1														3

Table 1 - Continue

Area of Contribution	**1st Author's Country of Origin**																			
	USA	UK	Italy	Germany	Austria	Sweden	Switzerland	Netherland	Romania	Belgium	Ukraine	Russia	South Africa	India	UAE	China	Taiwan	Malaysia	Australia	Total
Training and Education							1	1												2
Environmental Energy					2															2
Social		1									1									2
Audit																			1	1
Technical Education														1						1
Supply Chain Management																	1			1
Education														1						1
Industrial Organisation														1						1
Public Affairs Education														1						1
Personalise Medicine										1										1
Data Science				1																1
Data Governance					1															1
Manufacturing													1							1
Labour Market Analytics									1											1
Total	8	1	2	1	3	1	2	1	2	1	1	1	1	7	1	2	1	2	1	39

4.2 What Are the Approaches in Defining a Job's Taxonomy in Big Data Applications?

For accurate job classification and matching such application needs to refer to existing occupational classification taxonomies which varies upon the country that the job requirement is registered. Such in case of Javed and Jacob (2016) who referred to O*NET in the development of CareerBuilder which serves job applicants in the USA. On the other hand, Boselli et al., (2017) and Boselli et al., (2018) referred to a multilingual occupational classification known as the European Skills, Competences, Qualifications and Occupations (ESCO) which is an expansion of the International Standard Classification of Occupations (ISCO). Although there were diminishing number of literature within the career domain after 2018, it does not mean that the issues have been resolved. Javed and Jacob (2016) report the issues of granularity in the taxonomy of those occupational classification potentially causing problems in classification and the ability to drill down on the level of detail expected by end users. It was reported that those taxonomies could not accommodate the emerging occupational categories as those taxonomies have long lead times for updating of about 10 years in this case.

As a way of overcoming this problem, applications which are more tailored to the needs of specific group of occupation employ taxonomies that are referred to frameworks or standards. Such was the case for Belov et al., (2017) who referred to educational standards for vocational education programs as a source of educational taxonomy and match them to the requirements of the labour market. Demchenko et al., (2017, 2019) referred to EDISON Data Science Framework (EDSF) as the primary source of taxonomy to build an educational environment system that manages competency and facilitates curriculum design for data science for an EU funded project. Chan and Sherbino (2015) mapped thier physician taxonomy at the junior level and intermediate level from the Canadian medical competency framework known as CanMEDS. This practice is based on the intuition that frameworks and standards get updated more frequently and the attributes are more detail than existing occupational classification. In Europe, Boselli et al., (2017; 2018) applications did not require matching features, rather knowledge discovery required intervention from domain experts to classify a novel skill which goes into a string similarity comparison to the ESCO.

4.3 What is the Motivation of Utilising Workforce Frameworks and Occupational Standards Data in Big Data Applications?

With workforce frameworks and occupational standards offering better granularity for occupational taxonomy, still traditional methods of developing and updating them create a problem in governance especially in terms of the complexity of collecting, benchmarking, maintaining, disseminating and responding. Granularity of classifying job taxanomy is important especially for TVET case to distinguish occupations that are associated with TVET where the types of TVET occupations have distinct types of knowledge involvement and skills content variety (Abrassart & Wolter, 2020). Such considerations need to be built into data curation capabilities of occupational taxonomies to consider the distinct attributes of knowledge and the variety of skill content specifically the differences in the involvement of physical tasks and cognitive skills (Abrassart & Wolter, 2020) that require different vocational credentials compared to occupations that require tertiary credentials (Bol & Weeden, 2015). Another motivation for granularity are in such cases of Kend and Nguyen (2020a) where practitioners refrain from fully engaging with new competency practices unless frameworks and standards setters eliminate the uncertainties around the practices which would be detrimental to the efficacy of the frameworks and standards. As stated by Kend and Nguyen (2020b), "Changing standards is understood to take time and the nature of consultations is mentioned as being 'laborious'; however, this is an aspect where the regulators and standard setters can continue to improve their own performance".

The limitation with the traditional approach of developing and updating workforce frameworks and occupational standards can be solved with a new innovation in the concept of developing and updating job taxanomy. This could be seen within the literature as there is a movement of gradual transition among organisations from knowledge-based organisation where decisions are guided by sampling of limited evidence towards a data driven organisation where decisions are guided based on the totality of the population. From Table 1, majority of the literature came from developed countries. The kind of data driven organisation feature are also commonly seen among the medical domain literature (Chan & Sherbino, 2015; Gillespie et al., 2016; Horgan, 2018; Mergel, 2016) where health practitioner skills are monitored and developed. Such practice in the medical education is required to adapt to the rapid changes happening in global healthcare that demands a flexible healthcare education system and curriculum that changes and improves medical practice standards while maintaining the strict adherence regulated through frameworks and standards of practice (Vaitsis et al., 2014). Medical education is also drawn to the perspective of accumulating immense size and variations of data as to gain a richer, longitudinal (Jorm, 2015) and epidemiological (Gillespie et al., 2016) views to support decision making.

Such accumulation of immense data among the totality of population would bring to the formation of strategies to extract the economic, social, ethical, legal and political advantage associated with the utilisation of big data (Cuquet et al., 2017). Interestingly, such practice is gradually coming into reality in non-technical topics in the form of a timeframe for the European Union (EU) to deliver social impact, skills development and standardisation (Cuquet & Fensel, 2018). A similar futuristic cyber-physical system was proposed by Hahanov et al., (2014) based on an interactive rating mechanism of competency matrix and creation of a system to govern the management of career, moral and material incentives to the individual and social level such that the algorithms replace the need for officials that are prone to biases and corruption. In contrast, Montebruno et al., (2020) look into the past from the Victorian period of British occupational survey data to discover historical employment trends through utilization of various machine learning algorithms.

5. Conclusion

Current approach of utilizing existing job taxonomies introduce problems involving low granularity leading to misclassification within applications and giving out erroneous results (Javed & Jacob, 2016). Dependence on traditional workforce frameworks and occupational standards involving long and laborious update processes by many stakeholders (regulators, standard setters, industry captains, education providers) tend to limit flexibility and often impend innovation of practices. As such, the complexity of developing and updating workforce frameworks and occupational standards is decreasing the manoeuvrability of TVET educational outcomes. Thus, regulators should take actions to improve their performance as proposed by Kend and Nguyen (2020a). In conclusion, with the emerging prevalence of data driven organizations, this review provides evidence of how educational intelligence can improve the manoeuvrability of TVET educational outcomes through improvement in workforce frameworks and occupational standards.

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