Mapping the Future Curriculum: Adopting Artificial Intelligence and Analytics in Forecasting Competence Needs

Harri Ketamo[1], Anu Moisio[3], Anu Passi-Rauste[1], and Ari Alamäki[2]
[1]Headai Ltd, Finland
[2]Haaga-Helia University of Applied Sciences, Helsinki, Finland
[3]Helsinki Metropolitan Universities of Applied Sciences, Finland
Harri.ketamo@headai.com
Anu.Moisio@haaga-helia.fi
Anu.passi-rauste@headai.com
Ari.Alamaki@haaga-helia.fi

Abstract: One of the biggest challenges in the design of a work-related curriculum is to make sure that the curriculum is up-to-date and uses the same vocabulary as the work setting. This may sound easy, but if almost any curriculum is written in an academic language and at the same time may lack terms that provide the most value to students seeking jobs. In collaboration with the Helsinki Metropolitan Area Universities of Applied Sciences (3AMK) and Headai Ltd., we are applying cognitive AI, big data and natural language processing to build real-time understanding of skills, competencies, knowledge and abilities that workplaces seek. This knowledge is visualized as maps that enable us to: i) understand what skills are needed now and in the near future, ii) guide up-to-date curriculum development, iii) advice students on their course selection and iv) gain an understanding to improve the competitive offering of universities. We are working on tools and methods using AI for labour market analysis and curriculum development, and for integrating intellectual capital in the strategic thinking of the universities of applied sciences. The very first competence maps, comparing the competence demand of the Helsinki Metropolitan area labour market with the supply of competence from the three universities of applied sciences, provided a very crucial result. The professional language - the competence definitions - of work setting differs in many respects from the wording used at universities. We need to study this gap in more detail within the fields of education the universities represent. If universities use different definitions for competences than workplaces, how can students make sense of all these definitions when seeking employment? There is a need to build ecosystems within and across different industries to initiate the discussions needed in the workplaces of today and for the future.

Keywords: Data-driven training and career development, AI-based skills maps, Curriculum development, Competence maps, Artificial Intelligence, Big data analytics

1. Introduction

Intellectual capital is, in its broad definition, knowledge that creates value for individuals and organizations (Stewart & Ruckdeschel, 1998; Edvinsson & Sullivan, 1999). Recent research of inter-organizational value creation shows that private companies are more dependent than ever on knowledge resources (Kindström, 2010). Hence, the creation of new knowledge has become a critical competitive success factor for companies across industries. Value emerges in services when individuals, customers and suppliers engage in valuable interaction and integrate their resources for co-creating value (Vargo & Lusch, 2011). This interaction involves the use of competences that individuals and groups need in co-creating value in internal and inter-organizational exchange. Higher education institutions in adopting service-dominant, value-creation logic educate individuals and groups to acquire and learn the needed competencies to successfully manage and perform expert-level work. Therefore, in this study, we contribute to the intellectual capital debate by shedding new light on the adoption of artificial intelligence and big data analytics in the competence mapping of curriculum and course planning in higher education.

In this case study, we analysed open big data by using the Headai AI platform to create information about required competencies stated in job adverts online. This study contributes to the debate on big data analytics and artificial intelligence solutions in curriculum planning and development within higher education. This study also provides new knowledge on how AI and data analytics can be used in curriculum design for higher education. The research questions were:

1. How can artificial intelligence-based data analytics be adopted for the competence mapping of open job adverts to understand the competence needs of companies?
2. How can the analytics provide value for the evaluation of a curriculum and its redesign to meet the requirements of employers and different industries?

The next section provides a review of the related literature on big data analytics. Subsequently, the case experiment and case study methodology are described. Then, the findings obtained from a case experiment are presented. In the last section, the contribution, theoretical and managerial implications and limitations of the study are discussed.

2. Related studies

Higher education institutions have traditionally created new curricula using their own personnel, professors and lecturers as domain-specific experts. They have also involved industry expertise in curriculum design. For example, institutions conduct interviews with companies in their substance domains for determining opinions and competence needs (e.g. Soitinaho & Palviainen, 2015). Thus, higher education institutions should also respond to changing competence needs as employers in companies and public organizations require that competences are aligned with changing industry demands (Chung et al. 2015; Soitinaho and Palviainen 2015; Kolmos et al. 2016).

Advanced analytics and artificial intelligence-based software provides new ways to discover competence needs in workplaces (Ketamo et al. 2018). Companies are constantly looking for new employees via digital channels, such as social media, magazines, newspapers, requirement sites and their own websites. They also produce blog articles, white papers and social media posts where they indicate their latest competence needs while presenting new products, technologies, services and customer testimonials. The textual material delivered and shared via digital channels creates huge open data sets that can be used by curriculum designers. It fulfils the typical requirements of big data. The prior research shows that big data can help companies to prepare for future trends, as it utilizes a large volume of information from which data analysts can extract patterns (Cukier & Schoenberger, 2013; Wamba et al., 2015). Higher education institutes can gain similar value in analysing open data from the future employers they serve.

The cooperation of higher education and relevant companies improves students' learning about industry-driven competences and enriches the students' learning environment (Alamäki, 2018). Thus, it is important for higher education to collaborate with employers to understand the requirements for new employees.

Companies indicate their competence needs, for example, in job adverts, social media posts, web sites and blogs. They are typical unstructured data. On average, 95% of big data is unstructured, that makes analytics more challenging than in analysing structured data. Traditionally, data that is used in creating statistics in higher education is structured data, but there is an increasing need to create insight from the unstructured data as well. Unlike data used in the administration of higher education, most data in the public domain is textual data, such as social media posts, blogs, conversations in discussion forums or communication-related information on web sites. Thus, text analytics provides important tools to convert human-generated text into useful summaries that decision makers can utilize in their business processes (Gandomi & Haider, 2015).

Practically every industry can adopt big data analytics and utilize unstructured data sources (Özköse, Ari & Gencer, 2015; Wamba et al., 2015, Ketamo et al. 2018). Big data creates new possibilities to improve business intelligence by utilizing both structured and unstructured data analytics (Chen, Chiang & Storey, 2012). It also changes traditional value chains and business ecosystems, as it provides new ways to create value (Alamäki et al. 2018). Big data is becoming a central knowledge source and asset. In industrial development, machines are also producing data, industrial processes are remotely controlled by utilizing data and new smart devices use advanced algorithms for collecting and analysing data (e.g. Lee, Kao & Yang 2014). However, there is less research about adopting big data analytics and artificial intelligence algorithms in developing administration, curriculum and education in higher education institutions. Rapidly changing industrial competences and an increasing demand to promote continuous education set new requirements for creating new understanding about competence needs and expectations of employers in higher education.

Adopting learning algorithms in analysing big data has the potential to transform educational processes and improve decision making at all levels of higher education (Ketamo et al. 2018, Wamba et al. 2015) state that a key advantage of big data analytics in organizations is that it provides real-time access to analyse various issues, and it improves information sharing. They state that organizations can utilize it in assessing strategic investments and increasing transparency and accountability. In higher education, the creation of new curricula or offering new courses is an investment that needs to support and strengthen the profile of higher education institutions. Transparency is required in creating arguments for renewing curriculum and in creating course descriptions, which support students' learning about competences that employers in private companies and public organizations are requiring.

Adopting big data analytics in an organization is a change process that requires new capabilities, process changes and new practices. Erevelles et al. (2016) show that successful adoption consists of the integration of physical, human and organizational resources. They add, that those resources require practices where consumer activities are collected and stored as big data, insight is extracted from the analysed data, and finally, insight enhances capability.

3. Case description and methodology

The goal of this case study was to test the use of AI-based big data analytics in mapping competences from job adverts and compare them to the curricula and course descriptions of higher education institutions. The higher education institutions in this experiment were three universities of applied sciences in the Helsinki Metropolitan area of Finland. The three universities combined have over 35 000 students and they employ more than 2000 teaching professionals. We will describe the experience that we gained in using the Headai artificial intelligent platform in the mapping of competences and adopting new curriculum evaluation practices in the educational organizations.

Methodologically, this research is a case study (Gummesson, 2000). It's aim was to develop new practices in adopting artificial intelligence software to analyse big data and create new understanding about demand in the job market. We also adopted an abductive qualitative research approach (Dubois and Gadde 2002) in building new practices, as it enabled the researchers to iteratively build explanations and to elaborate on a conceptual model to analyse the real-time competence needs in the job market for evaluating the current state of curricula in higher education. The abductive research approach required that we simultaneously process the prior literature and theories of higher education and information management with the analysis of the data gathered through the AI-based analytic software. Adopting this kind of iterative research process in the study allowed for the development of a deeper understanding of the empirical experiments being analysed, while simultaneously contributing to the curriculum development and management of the involved higher education institutions.

In the case experiment, we used Headai's cognitive artificial intelligence platform, that deploys natural language processing (NLP) algorithms, to build measured, micro-level understanding on competencies in real time while searching workplaces in Finland. The Headai platform generates analytic results as visualized maps, where the map topology presents in one image the fuzzy relations between single competences, how seeking is clustered and the volumes of seeking. These competence maps enabled us to:

- understand what competences were needed now and in the near future and predict changes to competences needs in general
- guide up-to-date curriculum development
- advise students on their course selection and build individual learning and career paths for students with micro-level, defined education/training suggestions
- gain an understanding to improve the competitive offerings of the universities
- enable cross-disciplinary approaches for the personnel at universities to systematically develop competences

The visualized competence maps enable different users, managers, lecturers, career coaches and students, to perform searches related to various competence needs and the available competences. The different stakeholders can utilize visualized competence maps in planning and collaboration. These maps aim to produce value in creating new insight by anticipating social changes, yet-unrecognised competence needs and competence clusters. They support the operational preconditions of industry, commerce, businesses and society.

4. Case experiment

Representing almost all fields of education in the Helsinki Metropolitan area, 3AMK, a strategic alliance of the three universities of applied sciences, was looking for new methods to foresee the competences needed from a student when graduating from any of the member universities. At the same time, Headai with its cognitive AI platform had just won the first prize of a major competition celebrating 100 years of independence for Finland, arranged by The Finnish Innovation Fund Sitra. These two parties shared a common interest – to find a match between the demand of labour in the Helsinki Metropolitan area and the supply of education provided by the three universities.

To find solutions to the challenge, two levels of data sets were needed:

1. online job adverts / job openings from various sources, covering the recruitment need in the Helsinki Metropolitan area at a given time
2. competence criteria of all curricula offered by the 3AMK universities

The job opening data set is under continuous data collection by the Headai AI platform. The data is collected from various public job opening web sites, public web services and utilizing public APIs (e.g., the Finnish Ministry of Labour's data sets). The data are used for research and modelling purposes in the same manner as a human research team would use it: data are collected; they are prepared and classified; the data are analysed; and the outcomes are reported. The only difference to manually-created research is the volume of data; in 2018, there were 122145 unique public job openings in the Helsinki metropolitan area alone. Because most of the job sites and job services are sharing others' job openings the total number of data items is more than one million. So, considering only unique job openings for an entire a year would require more than 1000 researchers to prepare and classify the data (based on the average time needed to process 500 words extrapolated to one million 500-word texts). Of course, if we didn't have AI, we'd rely on only one source and avoid this cross-checking. Naturally, this would have produced an incomplete picture. The job sites are often relatively focused on one type of work, for example, the Finnish Ministry of Labour's data consists of production and middle management job openings, while LinkedIn job openings are more related to management, leadership and specialist jobs.

The job-opening dataset consists of 13727 skill words, 11773 job-title-related words and more than 20 000 work-related words. If this text extraction had been done manually, it would have required more than 25 researchers working for a year. Natural language processing is more than a keyword search, it is dealing with the semantics and ontology of the information. The work-related semantics consisted of 1,5 million exact relations, more than 5 million general relations and more than 20 million loose relations among the skills, occupations and other relevant words. From an intellectual capital point of view, the data are the starting point, but the value that is added is in extending understanding to the dynamics of the language; most common Finnish manually-created ontologies consist of 20 000 - 80 000 words and 0,1 - 1 million relations. Still, it has taken tens of years and hundreds of work-years to build these ontologies.

Furthermore, we have to understand that up-to-date job openings represent current skills that are sought and past job openings represent past skills. We can only show historical trends and current needs. We can predict what skills or jobs are down trending, i.e. what skills and jobs are most likely to not be sought in the near future. Future forecasts, however, are very limited because of constraints in the data and changing vocabulary – we don't know future job titles, nor the names of future skills. Terminology used to describe skills is constantly changing. No one is searching for 'large-scale automated data processing', which would be appropriate in the 1980s, but the term 'big data' popularly describes that concept today.

The second data set was also publicly available. In Finnish formal education (K-12, vocational and higher education), all study module descriptions in the curricula include not only contents of the study module but more importantly the outcome of the study module – what the student can do after finishing the study module. This description is expected to be in skill details, so there should be a match between this curriculum and vocabularies in job openings.

When the first round of data set collection was finalized, two workshops for 3AMK personnel were arranged to gain user insight in the joint development project. In the two workshops, almost one hundred participants attended, including lecturers, managers at different levels, principals, educational developers and student organization representatives. The participants gained access to the AI platform and they were able to test different use cases according to their individual interests. In the qualitative feedback from the workshops, the participants stated that the rich data from the AI provided information that would otherwise not be available to them. Participants were divided into small groups to create ideas for different AI application areas. This provided ideas as building blocks for further development of AI at 3AMK in four areas:

1. Agile development of curricula to meet workplace needs, covering both degree programme and life-long learning service offerings
2. Finding cross-disciplinary competence areas to support the new growth of industries in the Helsinki Metropolitan area
3. Using AI as a career coaching tool
4. Applying AI as a competence development tool for lecturers in a world of disruption

5. Outcomes, Results and Findings

In general, if we don't know what skills are currently sought by employers, we can't adjust the curriculum to meet the workplace needs. The focus of this section is to show the possibilities of AI-generated analysis and visualisations, not to test a specific hypothesis or present a scientific proof. All data in the analysis are in Finnish.

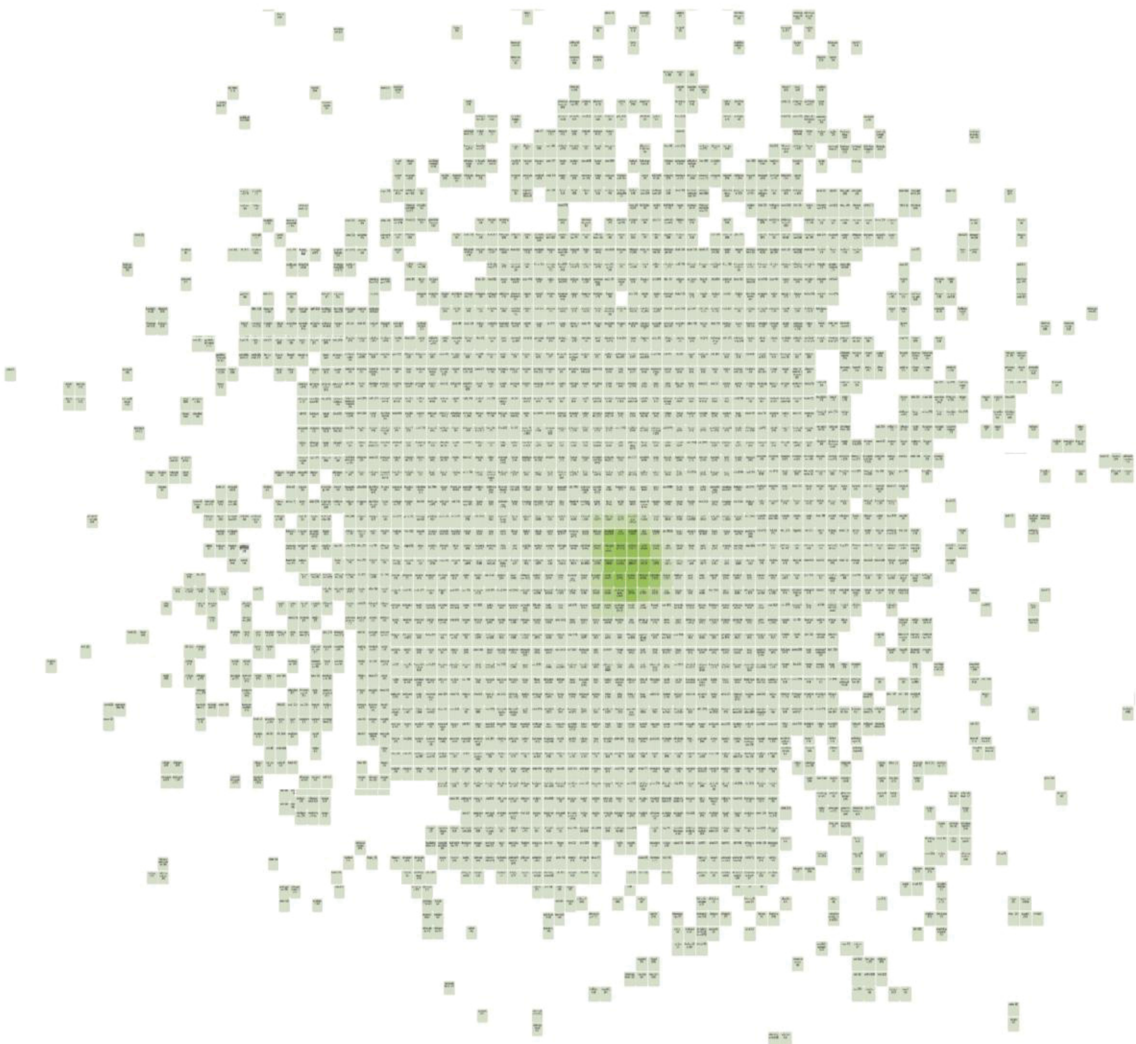

Figure 1: Overall visualization of skills sought in the Helsinki metropolitan area.

In Figure 1, the overall skills sought in the Helsinki metropolitan are visualised. The basic unit is one skill, which is represented by a block. The more a skill is sought, the deeper the green of the block becomes. The figure is clustered with an applied k-nearest clustering algorithm, i.e. the origin in the middle of the figure is the concept that has the most connections to other concepts. The next connected concept is the best fit to the k-nearest neighbours. If a fit can't be found, the concept is placed outside the current area. Because of the algorithm used, its successors can get connected back to original grid. The centre of the map represents the most connected set of skills, which can be considered as core work skills in this case. These skills include team work, self-directed behaviour, sales orientation, communication skills, etc. Furthermore, all the neighbouring skills are strongly connected each other, and areas cover common interests. These features are important to keep in mind when starting to apply this information.

When focusing on one thematic area (like healthcare) over a shorter timeframe (one month in this case), we can get more a detailed understanding on skills sought (see Figure 2). This gives teachers, education designers and administrators an immediate overview on how they use skills-words in the curriculum and education. If teachers teach all the topics, but document them in the curricula with different words, they can change the concepts or extend the descriptions.

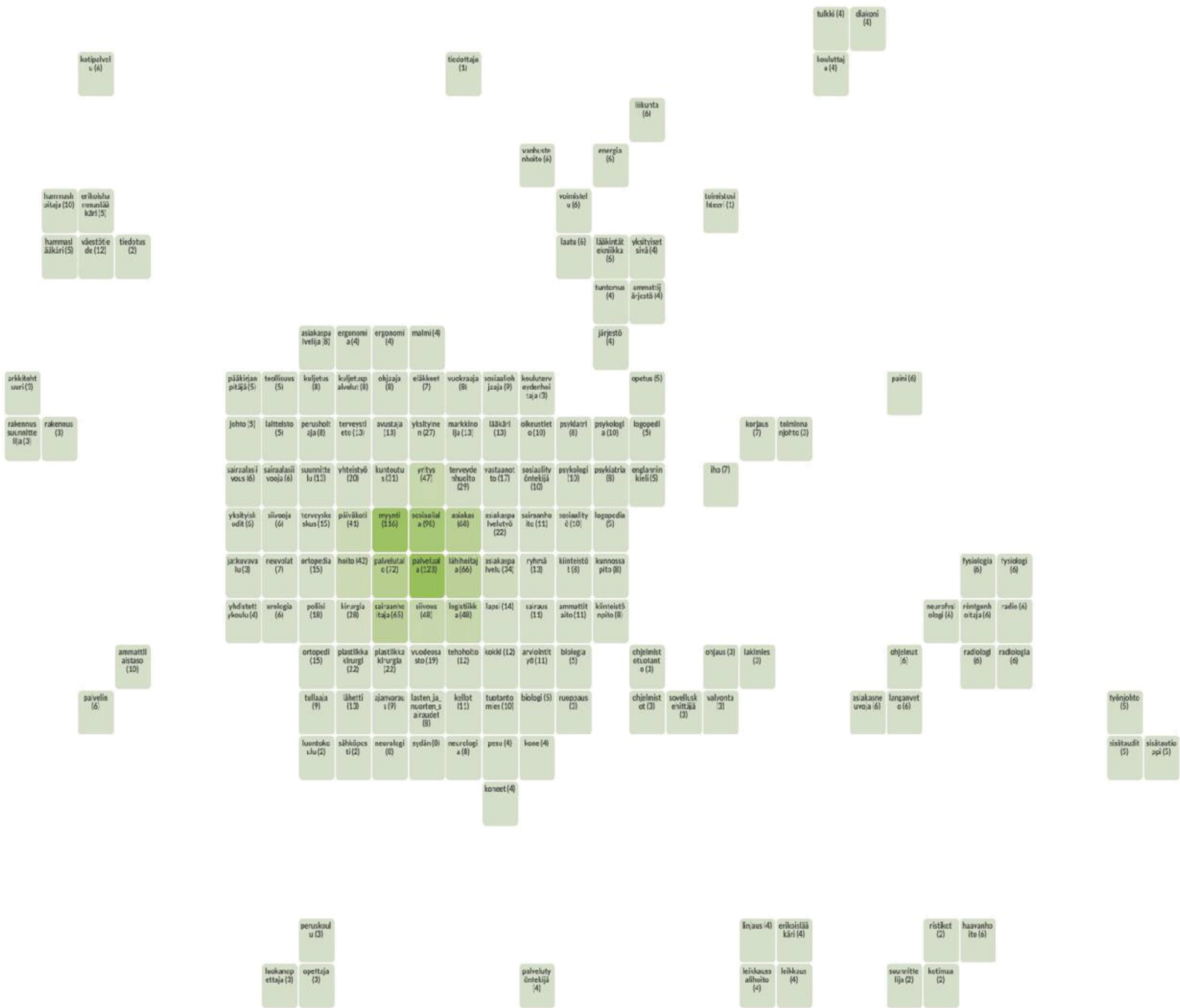

Figure 2: Health care seeking in the Helsinki metropolitan area.

Skills maps also enable real-time job seeking. In Figure 3, a map about nurse's bachelor-level curriculum is used as a semantic search definition. In this kind of search, we are no longer focusing on single keywords or single job titles. With semantic search, we are enabled to dive deeper into offerings. The jobs matching trained skills (for this purpose, existing in the curriculum is assumed to mean trained) are more versatile than just traditional job titles (like nurse in this example). There is a long list of jobs available calling for nursing skills that students don't even recognise.

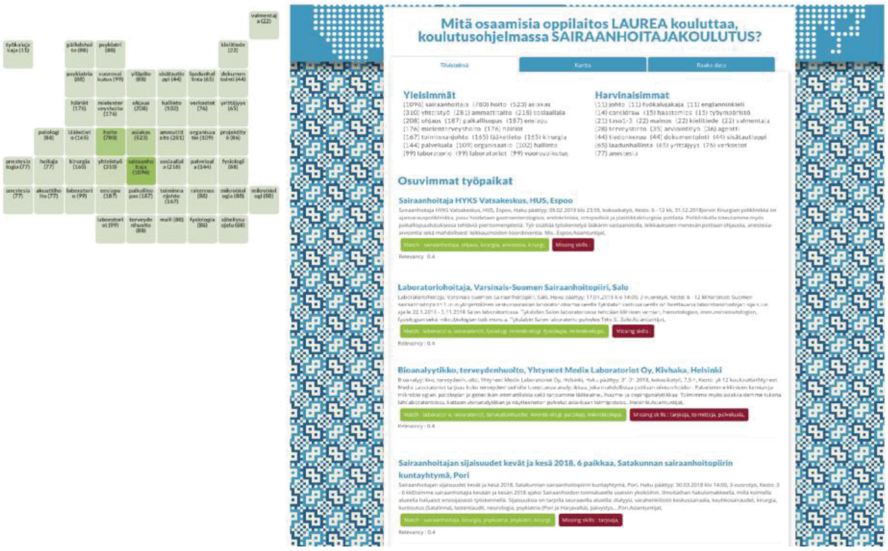

Figure 3: Jobs based on health care curriculum and current seeking

We can observe, that there are some skills that are sought, but when focusing on them in more detail, we see that they are a physician's skills, i.e. not required from a nurse. The red blocks, the skills that are educated but not sought, are obvious; not all skills are mentioned in job openings, only key skills are highlighted. Furthermore, most of the red blocks are mandatory pre-requisites or background for several required skills (yellow blocks). In other words, there couldn't be core skills without extensive skills. Also, the core skills cluster can be seen in Figure 4.

In Figure 5, a visualisation between the executive assistant's degree programme (bachelor's level) and business management programme (master's level) is provided. In this diagram, skills that are taught in both programmes are in yellow, skills that are taught only in the bachelor's programme are red blocks and skills taught only in the master's programme are green blocks. The core skills are very similar in both programmes. The only deep-red-coloured skill is a collection called assistant's skills. There are also very clear extended skills sub-clusters for both of the programmes.

Curriculum designers can use this information in order to design degree programmes that extend each other, establish collections of learning paths that can support several degree programmes and make sure that in every degree programme, students learn the core skills required in the workplace.

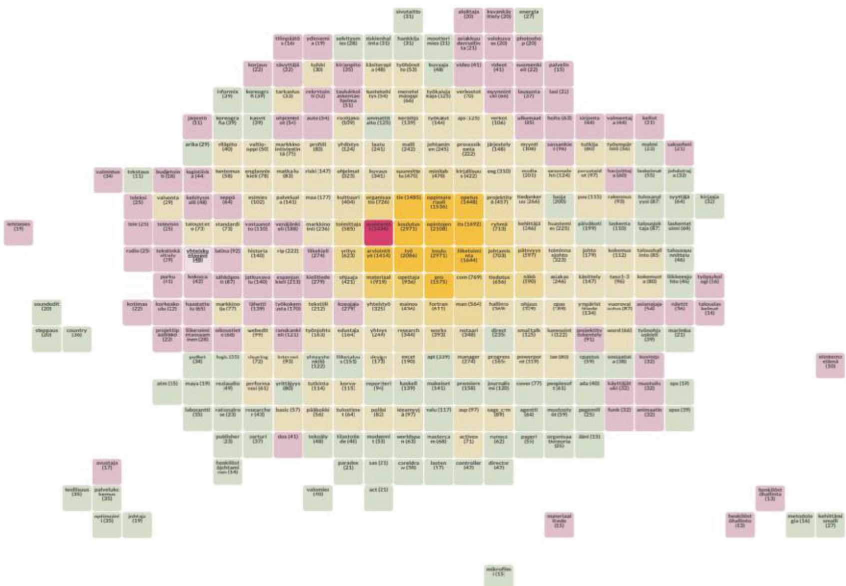

Figure 4: Skills seeking and offering/production, health care curriculum

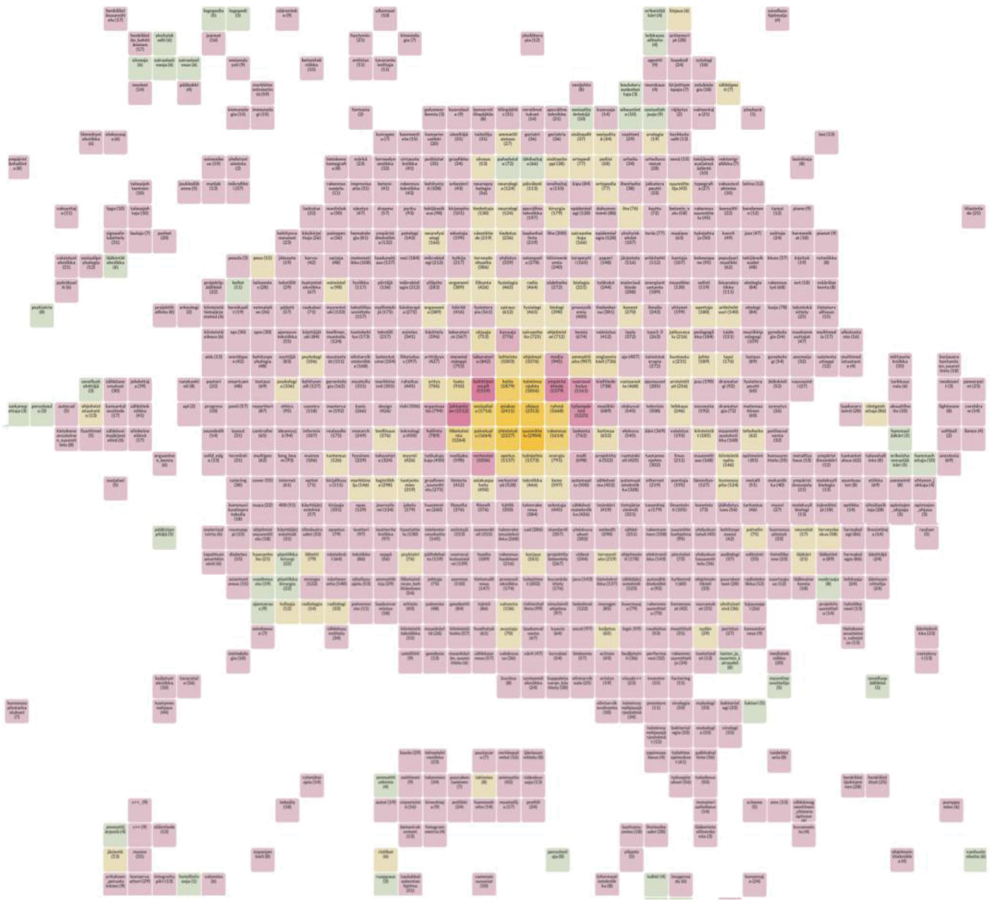

Figure 5: Making differentiating factors and overlapping themes between degree programmes visible

Curriculum designers and administrators can use skills-based information in order to determine new possible courses and/or degree programmes. In Figure 6, the Helsinki metropolitan area seeking is compared to 3AMK offerings. Skills that are required in work and taught in 3AMK are in yellow blocks; skills that are sought in work, but not taught are in green blocks; and skills that are taught but not sought are in red blocks. Core skills can be seen in deep-yellow.

When a professional is looking at this kind of map, she/he can point out areas where there is seeking without relevant offerings, but interesting existing offerings nearby, i.e. local gaps. By bringing new educational offerings and packaging them under a sub-domain relevant title, new courses and degree programmes can be designed. Finally, it must be highlighted that AI can only assist strategic planning, not actually do the necessary planning required.

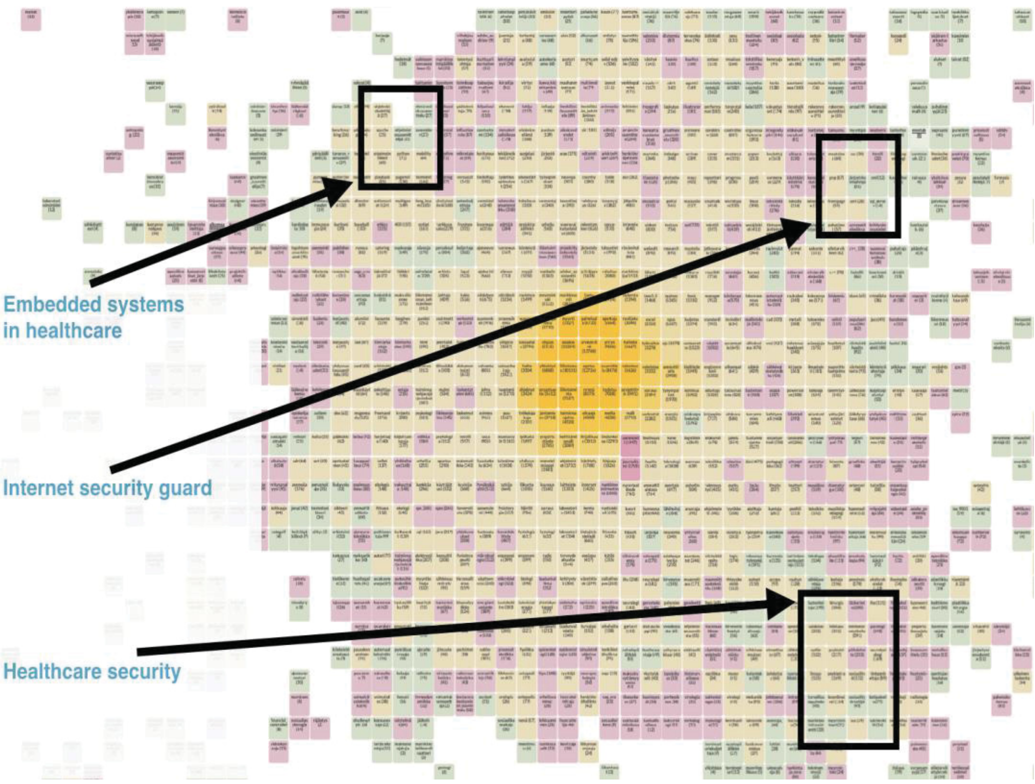

Figure 6: New courses and degree programmes based on recognised gaps in seeking and offering

6. Conclusions, limitations and future research

During the first year of collaboration between Headai and 3AMK, we have only taken the first steps of applying AI to educational development. Additional users with different backgrounds need to be involved in experimenting with the features of the platform. At the same time, we understand the need for expectation management – university professionals, with no or little prior experience in AI as a tool, could be impatient to get results for decision making more quickly. Our first steps have shown us that the grammatical cases of the Finnish language are quite challenging for natural language processing. This often results in a misinterpretation of recognized skills in the competence maps. We need to continuously monitor and refine the data we get from our sources to make it give us clearer, accurate answers.

The very first competence maps, comparing the competence demand of the Helsinki Metropolitan area labour market with the supply of competence from the three universities of applied sciences, gave us a very crucial result. The professional language - the competence definitions - of the workplace differs in many respects from the wording used at universities. We need to study this gap in more detail within the fields of education the universities represent. If universities use different definitions for competences than workplaces, how can students make sense of all these definitions when seeking employment? How can universities of applied sciences find a vocabulary that is work-related but still academic? We need to build ecosystems within and across different industries to initiate discussions needed in the workplaces of today and for the future.

A limitation of this study is that it reviews an initial experience in using artificial intelligence in analysing competence needs in the job markets. The needs portrayed in the job market vary according to the development of local and global economies, thus there are evidently changes that occur in the number of open jobs and competence needs in the long term. We could create greater insight in analysing differences between basic competences, such as social and managerial skills and rapidly developing requirements, such as technological knowledge and skills. In addition, we could also gain a more detailed picture by continuing the adoption of data analytics in analysing course implementations and competence needs in the job markets. More research is needed about the opportunities and obstacles in adopting artificial intelligence to curriculum and course development, such as mappings required and latent competences in the job markets.

Another limitation, how to enable more detailed future forecasts, also requires more research. Currently, we are studying public investment announcements and governmental foresight reports as possible data sets to help improve the quality of future forecasts. However, this is a time series study that requires further development. We plan to publish results on this dimension in 2020 at the earliest.

References

Alamäki, Ari. (2018) "A conceptual model for knowledge dimensions and processes in design and technology projects", International Journal of Technology and Design Education, Vol 28, No 3, pp 667-683.

Alamäki, Ari, Rantala, Tuija, Valkokari, Katri and Palomäki, Katariina (2018) "Business Roles in Creating Value from Data in Collaborative Networks". In Camarinha-Matos, L. M., Afsarmanesh, H. & Rezgui, Y. (eds.) Collaborative Networks of Cognitive Systems. The proceedings of the 19th IFIP/SOCOLNET Working Conference on Virtual Enterprises, Pro-Ve 2018, Cardiff, UK, September 17-19, pp 595-606.

Chen, Hsinchun, Chiang, Roger HL and Storey, Veda C. (2012) "Business intelligence and analytics: from big data to big impact", MIS Quarterly, pp 1165-1188.

Chung, Pansy, Yeh, Ron Chuen and Chen, Yi-Cheng. (2016) "Influence of problem-based learning strategy on enhancing student's industrial oriented competences learned: An action research on learning weblog analysis", International Journal of Technology and Design Education, Vol 26 No 2, pp 285-307.

Cukier, Kenneth, and Schoenberger, Viktor Mayer. (2013) "The rise of big data: How it's changing the way we think about the world", Foreign Affairs, Vol 92 No 3, pp 28-40.

Dubois, Anna and Gadde, Lars-Erik. (2002) "Systematic combining: An abductive approach to case research", Journal of Business Research, Vol 55 No 7, pp 553–560.

Edvinsson, Leif and Sullivan, Patrick. (1996) "Developing a model for managing intellectual capital", European Management Journal, Vol 14 No 4, pp 356-364.

Erevelles, Sunil, Fukawa, Nobuyuki and Swayne, Linda. (2016) "Big Data consumer analytics and the transformation of marketing", Journal of Business Research, Vol 69 No 2, pp 897-904.

Gandomi, Amir, and Haider, Murtaza. (2015) "Beyond the hype: Big data concepts, methods, and analytics", International Journal of Information Management, Vol 35 No 2, pp 137-144.

Gummesson, Evert. (2000) Qualitative Methods in Management Research (2nd ed.), Sage Publications, Thousand Oaks, CA.

Ketamo, Harri, Passi-Rauste, Anu, Vesterbacka, Peter and Vahtivuori-Hänninen, Sanna. (2018) "Accelerating the Nation: Applying AI to scout Individual and Organisational Human Capital", Proceedings of the ICIE 6th International Conference on Innovation and Entrepreneurship (ICIE 2018), pp 198-205.

Kindström, Daniel. (2010) "Towards a service-based business model–Key aspects for future competitive advantage", European Management Journal, Vol 28 No 6, pp 479-490.

Kolmos, Anette, Hadgraft, Roger G. and Holgaard, Jette Egelund. (2016) "Response strategies for curriculum change in engineering", International Journal of Technology and Design Education, Vol 26 No 3, pp 391-411.

Lee, Jay, Kao, Hung-An and Yang, Shanhu. (2014) "Service innovation and smart analytics for industry 4.0 and big data environment", Procedia CIRP, Vol 16, pp 3-8.

Soitinaho, Jouni and Palviainen, Harri. (2015) "The impact of digital revolution on the competences of business information technology students in university", INTED2015 Proceedings, pp 2374-2382.

Stewart, Thomas and Ruckdeschel, Clare. (1998) "Intellectual capital: The new wealth of organizations", Performance Improvement, Vol 37 No 7, pp. 56-59.

Vargo, Stephen L. and Lusch, Robert F. (2016) "Institutions and axioms: An extension and update of service-dominant logic", Journal of the Academy of Marketing Science, Vol 44 No 1, pp 5-23.

Wamba, Samuel Fosso, Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015) "How big data can make big impact: Findings from a systematic review and a longitudinal case study", International Journal of Production Economics, Vol 165, pp 234-246.

Özköse, Hakan, Arı, Emin Sertaç and Gencer, Cevriye. (2015) "Yesterday, today and tomorrow of big data", Procedia-Social and Behavioral Sciences, Vol 195, pp 1042-1050.