DOCTORAL THESIS

Enhancing Public Employment Services with AI-enabled Virtual Competence Assistant

Markko Liutkevičius

TALLINNA TEHNIKAÜLIKOOL
TALLINN UNIVERSITY OF TECHNOLOGY
TALLINN 2024

TALLINN UNIVERSITY OF TECHNOLOGY
DOCTORAL THESIS
51/2024

Enhancing Public Employment Services with AI-enabled Virtual Competence Assistant

MARKKO LIUTKEVIČIUS

PRESS

TALLINN UNIVERSITY OF TECHNOLOGY
School of Information Technologies
Department of Software Science

The dissertation was accepted for the defence of the degree of Doctor of Philosophy (Computer Science) on 30 September 2024

Supervisor: Professor Sadok Ben Yahia,
Department of Software Science, School of Information Technologies,
Tallinn University of Technology,
Tallinn, Estonia

Co-supervisor: Associate professor Innar Liiv,
Department of Software Science, School of Information Technologies,
Tallinn University of Technology,
Tallinn, Estonia

Opponents: Professor Marissa Ponti,
University of Gothenburg,
Gothenburg, Sweden

Professor Ricardo Colomo-Palacios,
University of Universidad Politécnica de Madrid,
Madrid, Spain

Defence of the thesis: 30 September 2024, Tallinn

Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology, has not been submitted for any academic degree elsewhere.

Markko Liutkevičius ______________________

signature

ISSN 2585-6898 (publication)
ISBN 978-9916-80-204-5 (publication)
ISSN 2585-6901 (PDF)
ISBN 978-9916-80-205-2 (PDF)
DOI https://doi.org/10.23658/taltech.51/2024
Printed by Koopia Niini & Rauam

Liutkevičius, M. (2024). *Enhancing Public Employment Services with AI-enabled Virtual Competence Assistant* [TalTech Press]. https://doi.org/10.23658/taltech.51/2024

TALLINNA TEHNIKAÜLIKOOL
DOKTORITÖÖ
51/2024

Avalike tööturuteenuste parendamine tehisintellektil põhineva virtuaalse kompetentsiassistendiga

MARKKO LIUTKEVIČIUS

TALTECH
KIRJASTUS

Contents

List of Publications

The present Ph.D. thesis is based on the following publications that are referred to in the text by Roman numbers.

I M. Liutkevičius and S. B. Yahia. Research Roadmap for Designing a Virtual Competence Assistant for the European Labour Market. *Knowledge-Based and Intelligent Information & Engineering Systems: Proceedings of the 26th International Conference (KES2022), Procedia Computer Science*, 207:2404–2413, 2022

II M. Liutkevičius, M. Weck, and S. B. Yahia. Understanding the Challenges of Today's Labor Market Service Provision in the EU. *Human Factors, Business Management and Society*, 97(97), 2023

III M. Liutkevičius and R. Erlenheim. Validating the usage of Occupational Classification Systems in the Process of Creating a National Virtual Competency Assistant within the EU Labor Market. *ICEGOV '21: Proceedings of the 14th International Conference on Theory and Practice of Electronic Governance*, 7:254–259, 2022

IV M. Liutkevičius, S. Nõmmik, Piyumi, M. Weck, and S. Yahia. In Pursuit of AI Excellence in Public Employment Services: Identifying the Requirements. *TalTech Journal of European Studies*, 14, 2024

V M. Liutkevičius and S. B. Yahia. The Use of Artificial Intelligence in Job Seeking and Competence Development. *Human Factors, Business Management and Society*, 56:128–136, 2022

VI M. Liutkevičius, M. Kõosaar, and S. B. Yahia. Designing a Proof of Concept for a Virtual Competence Assistant. *Human Factors, Business Management and Society. International Conference*, 135:1–9, 2024

Author’s Contributions to the Publications

I The author of this thesis served as the lead author (first and corresponding author) of the article, playing a important role in various aspects of the research. Specifically, the author was responsible for designing the methodology, collecting and organizing interview data, conducting detailed data analysis, interpreting findings, and drafting the manuscript. The author’s contributions ensured the coherence and depth of the study, particularly in the areas of data synthesis and result interpretation.

II The author of this thesis served as the lead author (first and corresponding author) of the article, with primary responsibility for the research. This included developing the methodology, conducting seven focus group interviews across six European countries in autumn 2022, and performing thematic analysis using NVivo software. The author also triangulated findings with desk research and was instrumental in the data analysis, interpretation, and manuscript writing.

III The author of this thesis, serving as the lead author (first and corresponding author), played a crucial role in the research, which investigated the current and future states of the labor market competency domain. The author conducted a review of recent literature and developments in occupational classification and led semi-structured interviews with the Estonian Unemployment Insurance Fund (EUIF) and unemployed job seekers to gather essential data. While the author was responsible for most of the research and writing, the section on proactive services was written by coauthors.

IV The author of this thesis served as the supervisor of the second and third authors’ master thesis and as the lead author of this journal article (first author and corresponding author), taking primary responsibility for the majority of the content, including the methodology, data analysis, findings, and manuscript writing. The methodology was carefully selected to support the study’s aim. This included an online survey of job seekers and semi-structured interviews with industry experts and employers. The author combined the insights from these two approaches to produce a holistic understanding of the research subject and developed detailed requirements for AI implementation in PES services. The results were synthesized into a cohesive journal article, showcasing the author’s comprehensive approach to the research.

V The author of this thesis served as the lead author of this article (first author and corresponding author), responsible for the majority of the content, including conducting a literature survey to identify significant articles on state-of-the-art recommendation systems. The author also led the methodology, data analysis, findings, and manuscript writing.

VI The author of this thesis was the supervisor of the second author’s master thesis and served as the lead author of this article (first author and corresponding author), responsible for the majority of the content. This included data collection, methodology, data analysis, manuscript writing, and participating in the model development for the Proof of Concept (POC) of the Virtual Competence Assistant (VCA) within a simulated Estonian environment, addressing challenges related to the Estonian language as a low-resource language.

Abbreviations

AI	Artificial intelligence
ANN	Artificial neural networks
DNN	Deep neural networks
ESCO	European classification of skills/competences, qualifications and occupations
EU	European Union
ISCO	International standard classification of occupations
JP	Job posts typically advertised on PES or other labor market services
LMI	Labor market intelligence
ML	Machine learning
NLP	Natural language processing
PES	Public employment service
PoC	Proof of concept
SOTA	State of the art
VCA	Virtual competence assistant

Terms

Artificial Intelligence	Activity devoted to making machines intelligent [64]
Intelligence	Quality that enables an entity to function appropriately and with foresight in its environment [64]
Intelligent Matching	A process that leverages advanced algorithms and machine learning to connect job seekers with suitable job and training opportunities by considering their skills, experiences, and preferences to deliver personalized recommendations that closely align with the job seeker's profile.
Public Employment Service	Public services that, though structured differently in each country, facilitate the matching of supply and demand in the labor market by providing information, placement, and active support services at local, national, and European levels.
Virtual Competence Assistant	Personalized AI-enabled virtual assistant using ESCO to provide personalized recommendations on available JPs and training (Publication I)
Competence	Combination of knowledge (established facts, concepts, and theories for understanding specific subjects), skills (the ability to apply knowledge for results), and attitudes (dispositions towards ideas, people, or situations) [10]

1 Introduction

With the emergence of the fourth industrial revolution, we are getting closer to where technological progress promises to refine the scope of human achievement. Such innovation is reshaping the labor market, leading to a rising demand for new skills while traditional ones become less relevant. Additionally, recent events, including the COVID-19 pandemic, surging energy costs, and Russia's aggressive military actions against Ukraine, have intensified short-term uncertainties in the labor market and brought about fresh concerns calling for adaptability from individuals, industries, and societies to thrive in this changing environment [77].

In response to these challenges, the research focuses on harnessing AI-enabled innovations within the labor market offered by public sector organizations to enhance the adaptability and resilience of citizens. This topic aligns with EU policies that prioritize skills development as essential for maintaining competitiveness, fostering resilience, and advancing social fairness across the member states [21]. Notably, EU's member states have endorsed the EU 2030 social targets aiming for at least 60% of adults to participate in training annually to meet the employment rate target of at least 78% by 2030 [25], while the 2030 Digital Compass sets further goals that by 2030, at least 80% of all adults should possess basic digital skills [31]. Moreover, an estimation made in 2020 suggests that in the EU-28 Member States, alongside Iceland and Norway, approximately 128 million adults—or 46.1% of the adult population—have the potential to benefit from upskilling and reskilling opportunities [6]. Hence, the current demographic trends, characterized by a shrinking working-age population [71], not only emphasize the importance of unlocking the full potential of the existing labor force and investing in skills across all age groups, but also underscore the necessity of focusing efforts on integrating more individuals into the labor market due to the increasing occurrence of skill shortages [29]. This is especially important for groups that are typically underrepresented, including women, individuals with disabilities, the older workers, and youth who are not involved in education, employment, or training [65]. Consequently, this research aims to lay the next generation foundation to enhance and expand the current state of public service delivery within the labor market, ensuring a more dynamic, inclusive, and skilled citizens ready to meet future challenges.

1.1 Problem Statement

As the labor market undergoes rapid transformations due to technological advancements and shifting economic dynamics, significant challenges arise in the employment sector. In response to these changes, at the core of every country's labor market is a Public Employment Service (PES) that plays a crucial role in linking the unemployed with job and training opportunities, helping to bridge the gap between evolving job requirements and available workforce skills. In Publication I we analyzed the current state of e-services provided by the Estonian PES (the Estonian Unemployment Insurance Fund), using it as a representative example of a PES in an EU country. Based on our findings, we can summarize two critical issues that stand out in the PES sector specifically:

1. **The lack of intelligent matching between citizens' CVs and job or training advertisements.** Today, even after providing all relevant career information in the application forms of the Estonian Unemployment Insurance Fund e-service, citizens must still search through thousands of advertisements to find suitable job and training opportunities. Today there are no advanced algorithms nor machine learning methods being used, so there is no room left for citizens to not know exactly what

kind of job they should define to receive a job recommendation (see Figure 1 box "ISCO codes match?"). This shortfall results in missed opportunities for job seekers, training providers and employers, leading to inefficiencies within the labor market.

2. **Missing consideration of skills and qualifications during the matching process**. The Estonian Unemployment Insurance Fund's e-service today lack a feature that allows citizens to input specific skills they have, training providers to input specific skills they provide and job providers to input specific skills they expect. This oversight makes it harder to match citizen's skills with the actual requirements of job roles and training programs, increasing the difficulty of finding suitable employment or development opportunities.

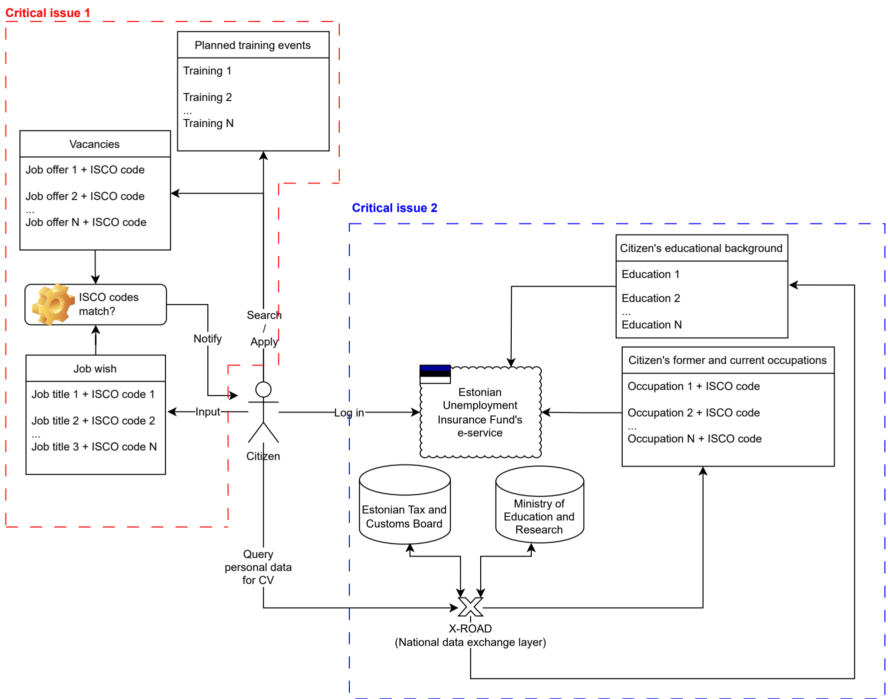

Figure 1: Citizen's activities and data related to the Estonian Unemployment Insurance Fund's e-service (Publication I).

Figure 1 concludes the main activities any citizen, both unemployed and employed in Estonia, can perform when seeking help in career advancement through the Estonian PES's e-service. The activities and findings related to issues were both validated with the representatives of the Estonian Unemployment Insurance Fund (Publication I). The figure shows that the data related to citizen's background is imported from the public registries via national data exchange layer, however, this data is not used for recommending jobs and training. The citizen must manually insert job wishes—a functionality which is rigid requiring a citizen to define specific occupation that must match with the occupation being defined by the job providers. Moreover, in order to receive a suitable job wish, selecting the suitable occupation title is often limited due to missing recently emerged occupations (such as jobs in the field of cyber security and data science) in the predefined occupations list of the e-service. Finding suitable training is even more challenging because there are no features available to receive alerts about appropriate training events. Even if a specific training is interesting for a citizen, a career counselor must manually verify its appropriateness for the citizen's profile. These issues emphasize the need for intelligent solutions that can deal with the complexities of the modern labor market, making the development of sophisticated matching systems a critical priority. In addition to the two key issues identified, a third critical aspect emerges—the need to address the gap between current and future skills. This can be achieved by focusing on exploring new ways for the government to help citizens adapt labor market changes (Publication I).

1.2 Objective and Scope

Considering the growing urgency to address skill shortages by incorporating more individuals into the labor market, especially those from underrepresented groups, the role of artificial intelligence (AI) has concurrently surged in importance. AI is now universally acknowledged as an indispensable component of modern e-services, reflecting its role in shaping the future of employment and digital services [5]. The definition of AI is constantly evolving, making it challenging to encapsulate in a static description. The OECD's definition of an AI system is being used by increasing number of sources as a reference and has just recently been revised [68]. Similarly, in 2024, the EU's final AI Act made a great effort to encapsulate all aspects of AI into one definition [28]. These definitions, however, lack explicit detail on how AI-enabled services interact with and adapt to the environments they operate in. Although, the two definitions contain "from the input it receives" and thereby hint at interaction with the environment, we need to focus more on the specific settings where AI-enabled services will be used. Within this thesis, we adopt [64] definitions, describing "AI" as an "activity devoted to making machines intelligent", and defining "intelligence" as a "quality that enables an entity to function appropriately and with foresight in its environment". The essence of "functioning appropriately and with foresight" encapsulates the need for AI-enabled services to not just process data and produce outputs but to do so in a way that is meaningful, beneficial, and contextually relevant to the specific environment.

To illustrate this principle, this research is dedicated to transforming the existing services within the EU's PES sector by implementing AI-enabled solutions. This transformation will be explored through proposing the initial concept for a Virtual Competence Assistant (VCA), specifically designed to address the challenges and enhance the capabilities of PES. The VCA is a concept for an AI-enabled assistant aimed at guiding citizens in their career journeys proactively (see Chapter 3.1). Hence, the research addresses the intersection between a citizen, regional labor market and education. The overlapping of these elements illustrate three crucial components for the VCA: (1) matching the citizen's skills with jobs, (2) matching the citizen's skills with opportunities for upskilling and reskilling, and (3) local labor market intelligence (LMI), which includes skills mismatch and future foresight (see Figure 2).

After establishing the initial concept for the VCA, the scope of the research evolved several times from the initial roadmap outlined in Publication I. It became clear that foundational research was necessary to set the stage for developing AI-enabled tools within the PES sector. Although recent reports claim that the practical use of AI in PES sector is a growing trend [66], the research about digital services using AI in PES sector is virtually non-existent [61]. Hence, we decided to establish foundational aspects before citizen-facing AI-enabled services could be built: the implementation requirements of AI-enabled services in PES sector (see Chapter 3.2).

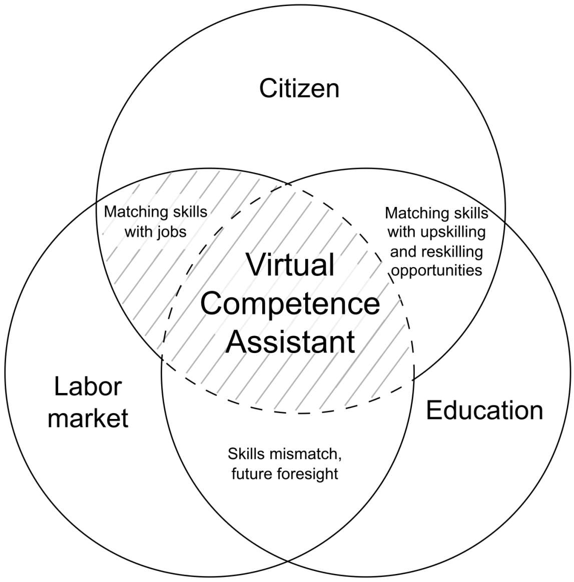

Figure 2: Intersecting fields of the virtual competence assistant. The practical scope of the research is the intersection where citizens' skills are matched with job opportunities

Later, we decided that the practical scope of the research must be limited to the first component: matching the citizen's skills with jobs (see striped area on Figure 2). The primary reason for this decision was that among the three components, job recommendation field was well-developed in scientific research, providing the building blocks necessary for the PES sector to begin experimenting with the first iteration of VCA. In contrast, the literature on training recommendation systems was sparse and did not offer a solid foundation for experimentation. Additionally, the accessibility of relevant data from the Estonian PES side on training events was initially viewable only via the web interface and then suddenly removed from the public internet entirely, additionally complicating the process. Furthermore, while the job market skills intelligence field has seen many successful trials globally, the VCA requires tailored advice at the local market level. Unfortunately, the research in this area is often a manual, one-time effort [52] [59]. However, while implementing the European Classification of Skills/Competences, Qualifications and Occupations (ESCO) as foundational classification to the VCA, it will leave the doors open for adding more functionalities, such as matching skills with training and skills intelligence tool development, in the future [22]. By focusing on the AI implementation requirements and the first component—matching skills with jobs—we effectively lay the groundwork for the subsequent developments, providing essential insights and technical details necessary for addressing the next components.

1.3 Research Questions

The thesis proposes initial concept for VCA, then focuses on the implementation requirements of AI-enabled services in PES sector in the EU and explores how to effectively match skills with job opportunities using the ESCO classification. In doing so, it establishes a robust foundation that can be expanded to include upskilling and reskilling initiatives, as well as to integrate with local LMI. Hence, the thesis addresses this topic with the following research questions:

RQ1 (Context): How can the integration of occupational classification systems into proactive services address challenges in PES service provision in the EU?
   SQ1. What are the main challenges to PES provision in the EU?
   SQ2. How can the European labor market benefit from using the occupational classification systems in proactive services?
RQ2 (Requirements): How to implement AI-enabled solutions in the Estonian PES?
   SQ1. What are the needs of external user groups for a modern PES self-service?
   SQ2. What are the internal implementation requirements to build AI-enabled solutions for PES?
RQ3 (PoC): How to create a PoC for recommending jobs to citizens based on ESCO?
   SQ1. What type of existing AI models could be usable?
   SQ2. What approach is required to train the model?

Table 1 presents how each research question is linked to the relevant publication and thesis chapter where the question is investigated and addressed.

Table 1: Mapping of research questions to relevant publications and thesis chapters

RQ	Publication	Chapter number	Core subject
Framing RQs	I	1.1	Problem
RQ1 SQ1	II	3.1	Challenges of PES in the EU
RQ1 SQ2	III	3.1	Initial concept of VCA
RQ2	IV	3.2	AI implementation requirements in PES
RQ3 SQ1	V	2.2	SOTA job recommendation methods
RQ3 SQ2	V, VI	3.3	PoC for recommending jobs to citizens

1.4 Research Methodology

To effectively explore the research questions and achieve the objectives of this study, we adopted a mixed-methods approach that integrates both qualitative and quantitative data collection techniques. As noted by [86], the synergy of these methodologies allows information systems researchers to derive conclusions that are both more accurate and insightful. The choice to employ a mixed-methods research design is fundamentally influenced by the novelty of the research field (see Chapter 2.2.2) and the complexities of implementing AI-enabled services in public sector [2] [35]. In mixed methods research, the researcher rigorously collects and analyzes both qualitative and quantitative data, integrates these data types and their results, organizes them into specific research designs that dictate the study's procedures, and situates all these processes within a theoretical and philosophical framework [11].

This research is composed of 6 original peer-reviewed research articles, including 1 journal and 5 conference papers. Figure 3 illustrates how these publications contribute to and are interconnected with the overall outcomes of this research. The overall research process can be divided into three stages: context, requirements and proof of concept (PoC) development. Publications I, II and III contribute to initial VCA concept development utilizing qualitative research methods. In Publication I we formulate the problem and validate the results with the experts working in the Estonian PES. In Publication II we analyze the overall challenges of active labor market service provision in the EU with 42

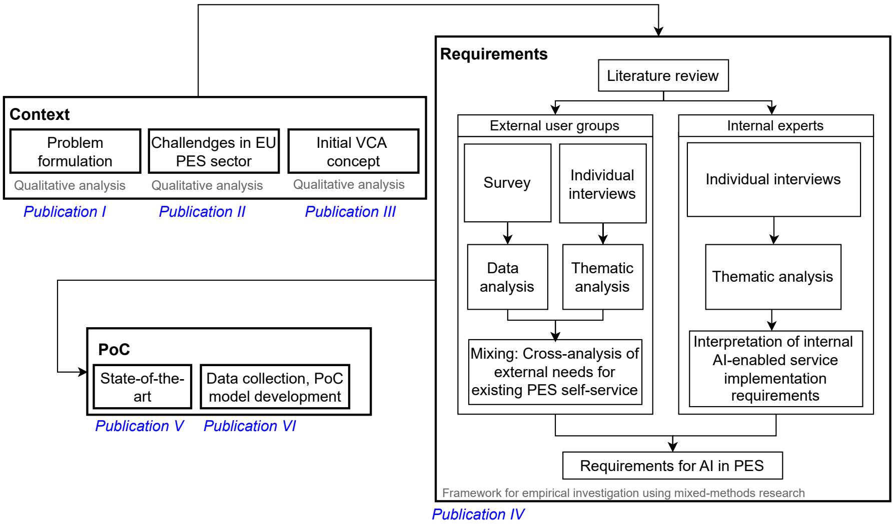

Figure 3: Research process of the research

participants from Italy, Germany, Latvia, Finland, Estonia and Norway. Publication III concentrates on proactive service delivery and recent directions of AI-enabled service developments in Estonia involving participants from the Estonian Qualifications Authority and the Estonian PES. In the second phase (Publication IV) we explore more specifically the current state of AI-enabled service delivery in the EU with literature review. Additionally we involve external user groups (job seekers and employers) to analyze the Estonian PES self-service *'e-töötukassa'* and internal experts (AI experts and scientists) to share their experience with AI-enabled service implementation in the Estonian PES. The second stage contributes with designing a methodological framework for empirical investigation that is used to identify the AI-enabled service requirements and proposes iterative requirement collection process for AI-enabled service planning and development in PES sector. Lastly, the PoC stage first analyzes the state-of-the-art (SOTA) job recommendation methods (Publication V) and proposes two models for achieving PoC for recommending jobs in a controlled environment (Publication VI).

1.4.1 Context

In the context phase, the primary methods utilized were semi-structured focus group interviews and thematic analysis. Focus groups were conducted with 43 participants across six countries, including Estonia, Finland, Latvia, Germany, Norway, and Italy, utilizing platforms like MS Teams and in-person meetings in Italy and Estonia. These discussions were analyzed using thematic analysis supported by NVivo software, which facilitated the identification of patterns and themes across different regions.

Additionally, preliminary semi-structured interviews were conducted with unemployed job seekers and stakeholders from the Estonian Unemployment Insurance Fund (EUIF) to gather direct insights into user experiences and perceptions of current labor market. These qualitative methods provided a foundational understanding for building the initial concept of VCA.

1.4.2 Requirements

The Requirements phase utilizes a combination of quantitative and qualitative methods to define specifications for AI-enabled public employment services:

1. Quantitative surveys: online surveys were conducted in English and in Estonian to gather data from Estonian job seekers and employers, focusing on demographic information, awareness, challenges, and expectations. This phase involved 176 respondents, providing a broad base of quantifiable data from PES users.
2. Qualitative interviews: semi-structured interviews were conducted with various stakeholders. Seven interviews with experts from diverse sectors such as finance, software development, and education, and eight interviews with internal AI experts, familiar with previous AI projects, provided deeper insights into both external and internal requirements for PES.

This phase integrated the quantitative survey data with qualitative interview results, using statistical analysis and thematic analysis to ensure a comprehensive understanding of user and stakeholder needs essential for developing the VCA.

1.4.3 Proof of Concept

In the PoC phase of this research, the experiments with initial VCA are executed within a simulated environment specifically designed to reflect the Estonian PES context. This phase leverages both a thorough literature survey and specialized machine learning (ML) methods to ensure the initial VCA is effectively tailored to the unique challenges presented by the Estonian context.

Literature survey: a foundational element of this phase is the literature survey, which identified the SOTA job and training recommendation systems employing AI technologies. The survey targeted publications containing specific keywords such as "recommendation system", "job", "training" and "artificial intelligence." From a broad dataset sourced from Scopus and Google Scholar, this search was refined down to 34 articles. These articles were chosen based on their explicit use of advanced AI methods like ML, artificial neural networks (ANN), and deep neural networks (DNN), and the clarity with which their datasets were described (see Section 2.2).

Simulated testing environment: addressing the practical aspect of the VCA's development, the research utilized a simulated environment tailored to overcome the specific limitations of the Estonian labor market—primarily, the challenges posed by the Estonian language, which is considered a low-resource language with limited data availability. Tools and models specifically selected for their efficacy in low-resource settings were employed to conduct PoC experiments targeting the first component of VCA: matching skills with jobs.

2 Related Work

The labor market, often called the job market, encompasses the availability of employment and the need for workers, where employees represent the supply side and employers create the demand. The classical labor market theory, with its assumptions of wage determination at equilibrium, high labor mobility, minimal government intervention, flexible wages, and the belief in the existence of full employment, presents a compelling but unrealistic illusion of labor market dynamics [46]. In 1930's these assumptions were questioned by Keynesian economics, which argued that active government intervention is necessary to address persistent unemployment and ensure economic stability [45]. Another theory, first introduced in 1970 by [19], to characterize the labor market more realistically is the Dual Labor Market (DLM) theory, which posits that the labor market is segmented into two distinct parts: the primary and secondary sectors, each with different wage levels, job stability, and working conditions. Primary jobs typically offer high wages, skill development, and career advancement, whereas secondary jobs are characterized by low wages, high turnover, limited progression, and are disproportionately filled by minority workers [74]. A study in 2023 on the US dual labor market found that secondary sector workers are six times more likely to switch labor market states and ten times more likely to be unemployed than their primary sector counterparts. Furthermore, while the secondary sector represents just 11.9% of total employment in the US, it is responsible for 61% of the economy's unemployment and almost two-thirds of the unemployment variability throughout the economic cycle [1]. In the EU, the secondary sector makes up 15.5% of the European labor market, is distinguished by "insecure employment, low incomes and a lack of job prospects" and is more likely to be on part-time jobs [79]. Furthermore, individuals employed in this segment tend to be younger, predominantly female, and concentrated in service-oriented jobs, indicating a demographic and economic segmentation in the labor market that could be critically influenced by technological advancements.

Current AI research, however, predominantly focuses on the development of AI technology itself, often overlooking the broader implications such technology may have on the actual environments in which it is deployed. This oversight highlights a gap in integrating AI developments with socio-technical system research, which considers the complex interactions between technology and society. Understanding these interactions is crucial for addressing the systemic issues in labor markets, such as those observed in the secondary sector. The integration of socio-technical perspectives could provide valuable insights into how AI can be designed and implemented to mitigate negative impacts on vulnerable labor segments and enhance overall employment quality. The concept of socio-technical systems (STS) considers integration of human, social, organizational, and technical factors within systems design, particularly emphasized in computer-based systems [36]. Initially developed during post-WWII projects by the Tavistock Institute in the British coal mining industry, STS theory has evolved to emphasize the interconnectedness of technical and social subsystems within organizations, advocating for a holistic configuration of technical, organizational, and social elements for system success [84] [4]. Recent shifts towards digital socio-technical systems highlight the transformative impact of digital technologies on organizational structures and stakeholder relationships, driven by advancements in AI, robotics, and machine learning. These technologies facilitate a new level of intelligence and decision-making autonomy in machines, marking a significant evolution from traditional socio-technical systems to dynamic, digitally interconnected frameworks [89] [14]. While focusing on the implementation of AI-technologies into organizations, we need to consider the existing interconnected elements of the environment such as existing infrasturcture, processes, stakeholders, goals of the organization, technology and culture. In socio-technical design, it is essential to recognize that organizational practices and technology are continuously co-evolving and must be constantly realigned. Moreover, before recommending the most effective strategies for deploying AI solutions and encouraging their adoption, it is crucial to first determine the areas where AI will be most influential [60]. Thereby a more holistic approach is needed to address the whole environment it is connected to. In [41] the authors have assembled a comprehensive diagram "supporting continuous and reliable functioning of AI-based socio-technical processes", outlining the tasks, actors, and interacting organizational practices typically observed in organizations that implement AI. The research has two significant outcomes. Firstly, it emphasizes the need for interdisciplinary collaboration among various social science domains and brings focus for a more participative approach, involving AI experts from all organizational levels in the conceptualization and knowledge transfer stages of research projects. Secondly, it emphasizes that implementing AI in organizations is not just a job for technical AI experts; it is a complicated, continuous process that requires involving the organization and its experts from various organizational contexts in a timely manner. The following table (Table 2) is summarizing how various studies have addressed the integration and impact of AI in public employment services.

Table 2: Related studies and reports on AI usage in PES sector

Aspect	Details
Role of AI	Despite its potential, research in AI applications within PES is limited [61]. Current AI applications in PES include profiling unemployed individuals and gathering skills intelligence [26] [17] [37].
AI implementation	Effective AI implementation in PES requires addressing predictive algorithms for profiling and matching, using data such as age, job history, and educational information to enhance service efficiency [17] [48]. The International Labour Organization highlights the need for a digital transformation strategy, skilled tech staff, robust data management, and effective cybersecurity [44].
Challenges and considerations	Integration of AI must consider data privacy, risk of discrimination, and the digital divide [85]. The success of AI tools, typically around 70% accurate, often outperforms human staff in profiling accuracy [17] [16]. However, employee acceptance and the impact on their roles are crucial factors [40].
Citizen-centric focus	AI-enabled solutions should align with citizen's needs, offering tailored recommendations [16]. However, the potential for discrimination due to biased data and the generalization of individual needs are concerns [44] [48] [85]. Citizen's acceptance and readiness for new technologies must be carefully managed.
Stakeholder Involvement	Early involvement of all stakeholders, including PES employees and clients, is recommended to ensure the effective implementation and acceptance of AI solutions in employment services [17].

Based on the available resources, only a few PESs in Europe have implemented AI technologies to directly assist citizens. Pôle Emploi in France and VDAB in Belgium utilize advanced tools, Automatic CV Analysis (AACV) and Competency-Seeker respectively, to enhance job matching by identifying unmentioned skills in citizen's profiles. AACV, based on job history and the PES taxonomy, allows caseworkers to validate or enhance a jobseeker's skill set after an interview, with a 68% user satisfaction rate [5]. Similarly, VDAB's Competency-Seeker suggests necessary skills for both jobseekers and employers, analyzing data from CVs and job ads to detect implicit skills and competencies, aiding in more accurate job placements. In addition to AACV and Competency-Seeker, VDAB offers the Jobbereik application, which assists users in exploring various job opportunities that align with their existing skills [5]. Jobbereik operates on the principle that core skills are transferable across different occupations and industries. By entering a desired job title, users receive suggestions for alternative roles that require similar skills, broadening their job search beyond their last held position. This tool not only identifies new potential career paths but also highlights the skills gaps that need to be bridged for these new roles. Consequently, Jobbereik provides insights into required additional training or education, supporting jobseekers in making informed career transitions and enhancing job mobility.

2.1 Occupational Classifications

In Publication III, various occupational classifications were analyzed and are subsequently elaborated upon in the following paragraphs. This section explores the structure, purpose, and implementation of these classifications across various contexts.

Developed by the International Labour Organization (ILO), a part of the United Nations, the International Standard Classification of Occupations (ISCO) serves as a global framework for organizing job titles and occupations. Its design categorizes jobs into a hierarchical structure, which includes 10 major groups, 40 sub-major groups, 127 minor groups, and 436 unit groups . For example, the code "2522" identifies a group called "Sytems administrators". This system is invaluable not just for categorizing occupations but also serves as a baseline for countries to adapt and expand upon for their national occupational classification systems, offering detailed descriptions for each group [43]. The most recent iteration, ISCO-08, was published in 2008 and is widely used by ministries and national statistical offices around the world for various purposes, including labor market analysis, job classification, and occupational statistics. ISCO is mostly adopted by ministries of labor or employment, ministries of education, and national statistical offices for structuring job classifications, aligning educational programs with labor market needs, and collecting labor statistics.

The European Qualifications Framework (EQF) serves as a standardized qualification system across European countries, enhancing interoperability and enabling workforce mobility within the EU. It provides a common framework based on learning outcomes—what a worker knows, understands, and can do—allowing EU countries to map their national qualification frameworks to the EQF. This creates a comprehensive qualifications map accessible through databases. The EQF categorizes qualifications into 8 levels, from basic (level 1) to advanced (level 8), with all EU member states aligning their qualifications accordingly, such as placing a "PhD degree" at level 8, despite varied national terminologies. Descriptors within the EQF, including Knowledge, Skills, Responsibility, and Autonomy, guide the alignment of national qualifications with the EQF [23]. Besides EU member states, 11 additional countries are implementing the EQF, with the latest revision by the European Commission made in 2017.

ESCO, a European Commission initiative, categorizes skills, competences, and occupations across 27 EU languages and serves as an extension to ISCO. It facilitates understanding the relationship between skills, knowledge, and specific occupations and comprises of three main components: qualifications, occupations, and skills/competences [24]. Its qualifications component aligns with the European Qualifications Framework (EQF), linking to national qualifications databases. The occupation component ties its first four levels to ISCO-08's occupational hierarchy, with ESCO-specific occupations beginning from level five. Totaling over 3000 occupations, each ESCO occupation corresponds to an ISCO unit group at level four and to skills in ESCO skills/competences pillar. The connection between ISCO, ESCO and ESCO's skills are presented in Figure 4. Each ESCO's occupation is linked to a (1) textual description of the occupation, (2) set of alternative titles of a particular occupation, (3) essential skills and competences, (4) essential knowledge, (5) optional skills and competences and (6) optional knowledge.

The skills/competences component includes over 14,000 skills, languages, knowledge, attitudes, and values, as outlined in ESCO (v1.1.2), released in 2024. ESCO offers a technical service platform and data resources, freely available for download.

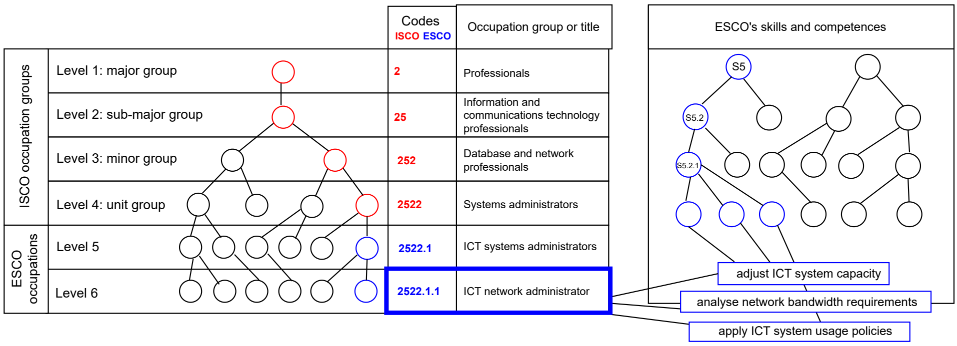

Figure 4: The link between ISCO, ESCO and skills

2.2 Job and Training Recommendation Systems

In Publication V we mapped the current state of the art job and training recommendation systems. The evolution of job recommendation systems has been significantly influenced by various approaches and technologies aimed at enhancing the effectiveness and precision of job matching. The concept of a recommendation system was pioneered by [39], who developed Tapestry, an experimental mail system, at the Xerox Palo Alto Research Center. Early foundational work in recommender systems by [75] introduced the potential of recommender systems across different domains, setting a stage for the development of specialized job recommendation systems.

Vectorization models use mathematical representations of job and candidate profiles to facilitate job matching. This approach is used for transforming qualitative attributes into quantifiable data that can be easily processed and compared [76]. Similarly, the use of embeddings, which leverages word embeddings and graph databases, effectively captures the semantic relationships between skills and job requirements, providing a nuanced understanding that surpasses simple keyword matching [38].

The significance of machine learning in refining job recommendation systems is well-documented, with various studies exploring its applications. For instance, a combined representation learning approach, which utilizes job transition and skill co-occurrence networks to recommend jobs and skills [13]. This method showcases the potential of machine learning in capturing complex patterns and relationships within job market data. Another notable application is the development of a hybrid multi-recommender system for the dual system of vocational education and training, which combines collaborative filtering and content-based filtering, which enables the adaptability of machine learning algorithms to cater to specific user needs and contexts [47]. Furthermore, the exploration of collaborative filtering techniques introduces a framework that incorporates various predictors, such as user and item interactions, highlighting the importance of leveraging collective user behavior to enhance recommendation accuracy [72].

Big data analytics have also played a crucial role in advancing job recommendation systems. For example the challenge of handling large volumes of heterogeneous and unstructured job market data is addressed by a proposed new job recommendation framework that meets the need for systems capable of effectively processing and analyzing big data to deliver accurate and relevant job recommendations [83].

Our review of the current scientific literature indicated that research on training recommendation systems and local LMI is notably scarce. Despite the growing interest in harnessing big data for employment and educational opportunities, there remains a significant gap in the dedicated studies that explore how training programs can be effectively recommended based on local market demands. This lack of research limits our understanding of how to optimally align educational offerings with the immediate and forecasted needs of local economies. Developing robust recommendation systems that factor in local labor market conditions could greatly enhance the relevance and effectiveness of training programs, ultimately contributing to a more dynamic and responsive workforce development strategy.

2.2.1 Challenges in Recommending Jobs

The literature on job recommendation systems highlights several pressing challenges that researchers and developers face. A predominant issue is information overload, where the volume of job posts and job seeker profiles makes it difficult to find relevant matches [18] [38] [83]. This is closely tied to the complexity of accurately matching candidates' desires with organizational needs, often leading to missed opportunities for qualified individuals [18]. The problems of data sparsity and the cold start phenomenon, where limited interaction data makes it challenging to provide accurate recommendations, further complicate the situation [83] [13]. Personalization emerges as a critical need, demanding systems that can tailor recommendations to individual user preferences, skills, and career aspirations [47] [51]. Addressing temporal and sequential aspects of job applications and career progressions also poses a significant challenge, as does ensuring the quality and relevance of recommendations to foster user engagement [13] [51]. Moreover, the black-box nature of some AI models raises issues of transparency and trust among users [88]. Scalability remains a concern, with systems needing to efficiently process large volumes of data while maintaining high recommendation quality [83]. These challenges show the need for careful planning to develop job recommendation systems that are both effective and user-friendly.

2.2.2 Artificial Intelligence and the European Classification of Skills / Competences, Qualifications and Occupations (ESCO)

Recent advancements in AI applied to labor market analytics and job recommendation systems have leveraged the ESCO classification to tackle challenges like skill extraction from job descriptions, job profile requirement generation, and skill classification across languages. **Key developments include:**

1. An end-to-end zero-shot system employing large language models (LLMs) for skill extraction from job posts, significantly improving skills extraction performance without human annotations [7].

2. The introduction of ESCOXLM-R, a multilingual, taxonomy-driven pre-training model, achieving state-of-the-art results in job-related tasks across multiple languages, demonstrating the model's effectiveness in the job market domain [92].

3. Utilization of neural network language models for generating up-to-date lists of job profile requirements, aimed at reducing the workload of HR specialists in recruitment, showcasing practical applications of AI and ESCO in job market operations [63].

4. Research on negative sampling strategies for skill extraction underlines the challenges and solutions in automating skill extraction from job postings, emphasizing the role of ESCO in enhancing model performance [15].

5. Fine-grained classification of skills in Danish job postings through distant supervision and transfer learning highlights the adaptability of AI methods to various languages, with ESCO providing detailed skill classifications [91].

Thereby, although ESCO classification has been available for over a decade, it is only in the last few years that research leveraging ESCO within AI frameworks, such as skill extraction, job recommendation, and multilingual job market analysis, has experienced a significant raise. Such developments in the scientific research demonstrate a growing recognition of ESCO's potential. However, the current literature does not identify any research that specifically targets the existing conditions within a particular PES service to develop a job or training recommendation system.

3 Contributions

3.1 Context (RQ1)

In Chapter 1.1 we formulated the problems associated with the Estonian PES active labor market service provision. In this chapter, we will present contributions following the research process: Context, Requirements and PoC, illustrated on Figure 3.

This section of the contributions focuses on answering RQ1 ("How can the integration of occupational classification systems into proactive services address challenges in PES service provision in the EU?"), which was the focus in Publications II, III. In the first part of this subchapter, we address the SQ1 "What are the main challenges to PES provision in the EU?)" and in the later part we address the SQ2 "How can the European labor market benefit from using the occupational classification systems in proactive services?".

Active labor market services are essential in aiding citizens to secure employment or maintain relevant skills. However, the delivery of these services faces numerous challenges, impacting their efficacy in supporting job seekers and influencing broader economic outcomes. Our research has identified significant obstacles within the EU PES sector. Key issues include inadequate focus on marginalized groups who often face the greatest barriers to employment. [80] suggest that investing in a PES's institutional capacity can significantly enhance service quality and positively affect young people's attitudes towards employment services. Additionally, a lack of effective evaluation and monitoring systems has been noted, with the European Social Fund's monitoring framework being criticized for its inability to track and assess the impact on specific target groups effectively [30]. Our findings also revealed problems with the integration of PES with other social and employment services and a general resistance to change and innovation within the sector. This resistance complicates the adoption of necessary reforms to improve service delivery and effectiveness. The high administrative burden on PESs, coupled with inadequate coordination between PESs, job providers, and job seekers, further complicates efficient service provision. The need for comprehensive reform in the European PES sector is evident. Addressing these challenges will require a collaborative effort involving governments, PES providers, job seekers, training providers, educational institutions, and employers. Implementing innovative approaches and developing robust evaluation and monitoring systems are crucial steps towards improving service delivery and ensuring that PESs remain responsive to the dynamic needs of the labor market [20] [30]. Moreover, the absence of a unified understanding of current and future job roles and skills adversely affects cross-border and regional labor migration, as well as opportunities for upskilling and retraining. Recent advances in artificial intelligence and occupational classifications offer promising solutions to these issues, providing tools that can enhance the effectiveness of PESs [69].

The European labor market could greatly benefit from the integration of occupational classification systems like ESCO into existing services, enhancing job matching and skill development. Interviews with representatives from the Estonian PES confirmed that ESCO has been a mandatory occupational classification system since August 2021, as referenced in Publication III and in [32]. However, an analysis of the current self-service *'e-töötukassa'* revealed that they have not been integrated into existing citizen facing services (see Chapter 1.1, Publication I). By integrating occupational classifications to ESCO, the existing services can be significantly improved. We discussed the nature of proactive services in the context of labor market services in Publication III. ESCO's detailed structure, regularly updated to include new and emerging occupations, provides a classification for identifying and aligning job roles with relevant skills and competences [34]. This alignment is crucial for the effectiveness of proactive services, which aim to minimize citizen interaction while ensuring they receive appropriate support and opportunities. For example, when a citizen's employment status changes, an AI-enabled service, utilizing ESCO's classifications, can automatically suggest relevant training programs or job openings that match their skills and previous job experiences. This proactive approach not only simplifies the process of finding employment or training but also enhances the precision of matching job seekers with suitable opportunities. Furthermore, ESCO's integration into labor market e-services could facilitate a better understanding of the qualifications pillar, linked to the European Qualifications Framework (EQF), thereby enhancing interoperability and data exchange among EU member states. This integration could support a more efficient public service delivery that anticipates the needs of citizens and addresses them without requiring direct action or request from the citizen [33] [34]. To summarize the analysis, we present an initial conceptual view of the Virtual Competence Assistant (VCA) as shown in Figure 5 (Publication III). This concept demonstrates how proactivity is integrated into the communication flow between individual citizens and the Estonian PES. The implementation utilizes Estonia's data exchange layer, X-Road, ensuring that all citizen data adheres to the 'once only' principle. A virtual competence assistant, enhanced by AI and utilizing ESCO, represents a concept for PES in the EU. This integration could fundamentally alter how job seekers interact with PES by proactively addressing their needs.

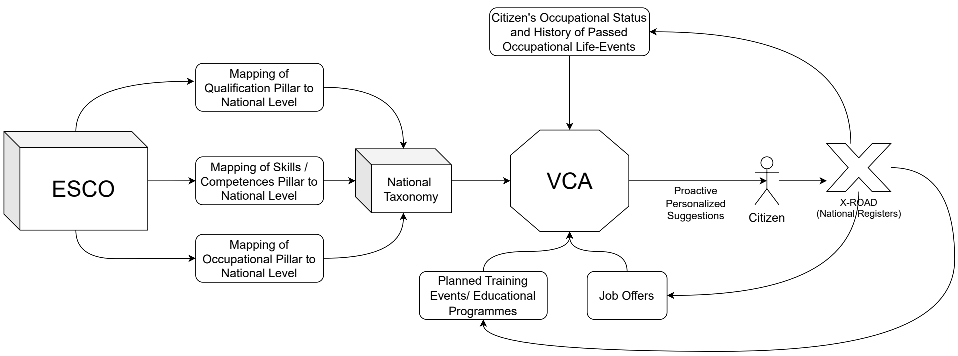

Figure 5: Initial concept of the VCA (Publication III)

Based on my publication (Publications I,II,III) findings, the main challenges in PES service provision can be addressed by taking following actions:

1. **Automated job matching and skill development:** By leveraging the ESCO classification, a VCA can automatically match citizens with opportunities that align with their skills and past work experiences. This technology not only simplifies the job-seeking process but also enhances the accuracy of matches, making the labor market more efficient and responsive.

2. **Proactive service delivery:** Rather than waiting for citizens to initiate contact or navigate complex e-services, the VCA can proactively offer support and opportunities. For example, upon changes in employment status, the system could immediately suggest relevant training programs or employment opportunities, significantly reducing the time and effort traditionally required from job seekers.

3. **Interoperability and data exchange:** Integration with ESCO facilitates a seamless exchange of information across EU member states, aligned with the European Qual-

ifications Framework (EQF). This capability supports a standardized approach to recognizing skills and qualifications across borders, promoting greater mobility within the labor market.

Integrating occupational classifications like ESCO into proactive AI-enabled services can significantly address several challenges faced by PES sector in the EU. By automating routine tasks, these proactive services reduce the administrative burden, thereby boosting service efficiency. Automation also enhances service accessibility and inclusivity, lowering barriers for marginalized groups and those in remote areas by eliminating the need for physical visits and simplifying processes. Furthermore, services such as VCA can foster lifelong learning and career development by continuously identifying upskilling and reskilling opportunities, aligning workforce development with future market demands.

3.2 Requirements (RQ2)

This section of the contributions focuses on answering RQ2 ("How to implement AI-enabled solutions in the Estonian PES?"), which was main objective of Publication IV. PES primarily serves two types of clients: job seekers and companies or employers (external users) [85]. Thereby, while specifically looking at external user needs in the context of existing e-services of the Estonian PES, we gain essential information about what are the challenges and expectations for building new services, which was the focus of the SQ1. Moreover, as the Estonian PES has already gained some specific experience in implementing AI technologies (Publication IV), our SQ2 investigates the requirements for implementing AI in PES. While implementing new technologies in PES sector, it is crucial to consider the digital readiness of the PES's staff and clients' level of technology access [85]. Understanding these aspects is crucial before initiating the developments of new AI-enabled services in PES sector.

3.2.1 External User Needs

The analysis of feedback from job seekers and employers regarding the *'e-töötukassa'* self-service platform in Estonia revealed expectations and challenges that both aligned and differed from each other. From the job seekers' perspective, derived from 176 survey responses, the predominant issue was the limited use of the platform, with nearly two-thirds having never accessed it. Among those who did, the motivation spanned from seeking new job opportunities to finding training programs for skill enhancement. However, significant concerns arose with the platform's limited range of job offerings and user experience issues, such as difficulty in navigating the platform and outdated information, which influences its effectiveness and limits regular use. Employers, on the other hand, shared concerns about the platform's functionality but focused more on its inefficiency in attracting qualified candidates and its complicated job posting process. The feedback from employers emphasized a critical gap in the platform's ability to facilitate the recruitment of skilled personnel, especially in high-demand sectors like IT, where specific skills and experience are crucial. Employers also criticized the platform's lack of visibility and popularity among potential candidates, which additionally points to concerns related to user interface and outdated job posting mechanisms. Despite these distinct points, there were notable areas of overlap, particularly regarding the platform's overall usability and the quality of its informational content. Both groups expressed a desire for improvements in language options and a more smooth user experience. Such enhancements could eliminate some of the frustrations related to navigation and accessibility that, at the time of the research, influenced both user bases. Table 3 presents the PES self-service needs of

Table 3: PES self-service needs of external-user groups (Publication IV)

	Job seekers	Employers
Technological issues	Usability concerns, session expirations and login inconveniences, demand for a mobile application	Excess manual steps, unavailability of experts, poor user experience
Workforce & skills	Limited job opportunities, insufficient training opportunities, request for more training courses and workshops	Skills shortages, need for upskilling and reskilling, demographic changes
Collaboration & integration	Desire for integration with other employment platforms	Collaboration with schools and employers, integrating with HR portals
Platform improvement	Need for functional enhancement before adding new features, improved visualization, personalized user interface, more refined search features, display of who viewed their CVs, addition of salary details in job postings, resources on CV and cover-letter crafting, introduction of an e-newsletter	Career fair representation, competitive designs and services, descriptive soft-skill analysis, extended filtering, guidance and consultancy including forecasts, personality evaluations, strong awareness campaigns
Language & translation	Language translation issues, call for broader language accessibility, more English-language content	Weaknesses in translations
Awareness level	Relatively low	Relatively low awareness, with some exposure to negative publicity.

external-user groups (Publication IV).

The introduction of AI technology into public employment services could potentially bridge these gaps. AI can automate and enhance the accuracy of matching job seekers with appropriate job vacancies, thereby increasing the platform's utility and efficiency. Research suggests that AI-driven tools can be instrumental in profiling, targeting, and matching processes in employment services, thus potentially increasing organizational efficiency [48]. However, the success of such integration relies robust data management, privacy safeguards, and the inclusion of all stakeholders in the development process to ensure that the solutions developed are tailored to the diverse needs of the platform's users.

Nevertheless, while AI presents a potential for innovation within PES, it also introduces challenges that must be considered carefully. Issues such as data security, the risk of algorithmic bias, and the potential dehumanization of personal interactions must be addressed to ensure that digital transformation enhances rather than undermines the platform's objectives [85]. According to the International Labour Organization (ILO), effective cybersecurity, skilled staff in technology, and high-level data management are critical for the successful digital transformation of public employment services [44]. Thus, while AI could significantly improve the functionality of the *'e-töötukassa'* self-service, its implementation should be approached with a detailed understanding of the specific needs and concerns of both job seekers and employers, ensuring that technology serves as an enabler rather than a disruptor [16] [8].

3.2.2 Internal Requirements for Artificial Intelligence

From the interviews with AI experts experienced with AI implementation in PES sector, several key themes were identified: infrastructure, personnel, data, legal compliance, change management, and funding—each contributing its own layer of complexity to the AI integration process.

A core concern highlighted across the interviews was the necessity for upgrading existing infrastructure to support AI capabilities effectively. This includes not only hardware and software but also comprehensive IT systems, robust data architecture, and secure data exchange mechanisms like Estonia's X-Road layer and the Estonian PES's internal data warehouse. Such upgrades are vital for enabling sophisticated data analyses essential for AI solutions. Next, the significance of having specialized personnel, particularly in data analysis, was repeatedly emphasized. The success of AI in PES hinges on the expertise of personnel who not only understand AI but can also align it with the organization's culture and goals. This expertise often goes beyond internal capabilities, requiring to collaborate with external specialists who understand well the specific needs of PES. Moreover, legal compliance, especially concerning data privacy and security, presents a notable challenge, as development often surpasses legal frameworks. For instance, compliance to GDPR within the Estonain PES involves obtaining client consent for data analysis and ensuring data is anonymized when used, which could impact the accuracy and functionality of AI tools. In addition, change management is another critical aspect, encompassing the management of stakeholder acceptance, trust in AI solutions, and organizational preparation for AI-driven transformations. Notably, the interviews confirmed that engagement of end users, particularly career counselors who are primary users of AI services in PES, in the early stages of implementation is crucial for successful adoption and utility of AI technologies. Lastly, funding for AI initiatives in the public sector is uniquely challenging due to the nature of public financing. The interviews suggest that a self-administered, long-term budget could be more effective than the fixed-term financing common in public organizations, emphasizing the need for secure and adequate funding to support the transition to AI-enabled services effectively.

Table 4: Internal AI-implementation requirements (Publication IV)

Theme	**Requirements**
Infrastructure	– Upgrade the existing infrastructure to support AI integration.
Personnel	– Engage experienced specialists, particularly in data analysis, for AI implementation. – Consider partnering with an external organization for specialist resources while ensuring that the organization understands PES culture, goals, and processes.
Data	– Ensure availability of sufficient quantities of high-quality data for AI training and implementation. – Address challenges related to limited sample sizes due to the country's small population.
Legal compliance	– Safeguard data privacy and compliance with GDPR and other relevant laws, especially when partnering with external entities. – Develop strategies to prevent potential AI-enabled discrimination due to low-quality or biased data. – Consider legal frameworks before initiating the development and deployment of AI solutions. – Make sure the activities of the Estonian PES are in accordance with laws such as the Unemployment Insurance Act and the Labor Market Services and Benefits Act.
Change management	– Manage acceptance of AI among stakeholders. – Foster trust in AI solutions among development partners and end users. – Prepare the organization for the AI-induced transformation, including potential changes in work roles and tasks.
Funding	– Secure adequate funding for the implementation of AI, keeping in mind the unique challenges of financing in the public sector.

Integrating these practical insights with existing research, it is evident that AI can transform PES by improving service delivery and operational efficiency. However, successful integration requires addressing several key factors, such as robust data management, skilled technological staff, effective cybersecurity, and comprehensive stakeholder involvement [44] [48] [85] [16] [8]. These elements are crucial not only for the functional deployment of AI but also for ensuring that these technologies are used ethically and effectively, enhancing rather than undermining the objectives of PESs. Thus, while AI presents significant opportunities for enhancing PES platforms, careful consideration of infrastructure, legal, personnel, and financial aspects is essential to harness its full potential.

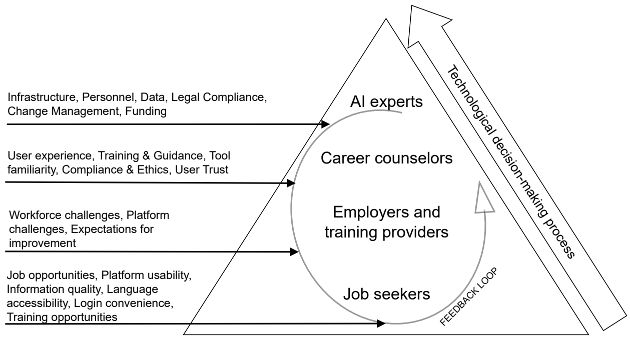

Figure 6: Pyramid of iterative requirements for building AI-enabled PES services (Publication IV)

3.2.3 Integrating Artificial Intelligence in Public Employment Services

The analysis of data gathered from job seekers, employers, and AI experts regarding existing self-service and AI-enabled services in PES reveals a complex set of requirements and challenges that underline the necessity for a nuanced integration of technology within labor markets. This understanding aligns with the socio-technical systems theory, which advocates for the integration of technological and social systems to optimize the overall functionality and responsiveness of organizations [36] [84].

Job seekers and employers present various external needs, emphasizing limitations in job opportunities, usability concerns, and informational quality on the PES platform. Both groups call for enhanced platform features, broader language accessibility, and more extensive training opportunities, highlighting these as areas where AI could significantly enhance service delivery. This intersection of needs suggests that improvements in these areas could serve to elevate the overall efficacy and user satisfaction of the PES services. Additionally, career counselors, who emerged as pivotal stakeholders during the interviews with AI experts, frequently interface with both job seekers and the PES services. Their daily experiences with the services uniquely position them to provide invaluable insights into the user challenges and requirements. Their role extends beyond users to that of vital change agents who can bridge the technological innovations with user experience, enhancing trust and acceptance among all stakeholders. The AI experts have identified several critical internal needs necessary for the successful integration of AI within PES. These include the upgrading of existing infrastructure, engagement of skilled personnel in data analysis, ensuring the availability of high-quality data, safeguarding data privacy, adherence to legal frameworks, managing organizational change, and securing adequate funding. These recommendations are rooted in the dual labor market theory and socio-technical systems theory, emphasizing that addressing these internal aspects is crucial not only for technological efficiency but also for maintaining the social integrity of the labor market [1] [79]. The feedback loop presented in the study's findings (Figure 6) encapsulates the dynamic process of continuous refinement of PES services, driven by stakeholder feedback. This model emphasizes that AI-enabled services should be developed as an ongoing, iterative process where requirements from both external and internal user groups are constantly evaluated and refined. The technological decision-making process, illustrated as an arrow in the pyramid, shows how requirements gathered from job seekers and employers are contextualized and filtered by AI experts to ensure that they align with technological capabilities and strategic goals. This holistic approach is not just about implementing new technologies but about creating a more integrated and responsive system that considers the full spectrum of user needs and system capabilities. It emphasizes the importance of interdisciplinary collaboration and participative approaches in developing AI solutions that are technologically advanced and aligned with the practical realities of the labor market, particularly those faced by individuals in the secondary sector, who may be most vulnerable to disruptions and transitions within the labor market [19] [74]. Next we will present our approach after conducting experiment in a controlled environment (Publication VI) which was based on a review made on state of the art models in job recommendation systems (Chapter 2.2, Publication V).

3.3 Approach for Developing Job Matching Proof of Concept (RQ3)

This section of the contributions summarizes the practical research conducted to develop our approach for job recommendations by specifically addressing the unique constraints and requirements of the PES in Estonia, aiming to establish a robust baseline for future enhancements and implementations. In order to answer RQ3 ("How to create a PoC for recommending jobs to citizens based on ESCO?"), first we explored what type of models from the existing literature could be usable in Chapter 2.2 (SQ1). However, since the existing models in the literature on job and training recommendation systems were not specifically usable for the Estonian language, it was also necessary to investigate models tailored to the Estonian context for more accurate and relevant application.

3.3.1 Models used in Estonian context

EstNLTK [49] is a NLP library designed specifically for the Estonian language. It offers a comprehensive set of tools and resources for analyzing Estonian text, including tasks such as tokenization, part-of-speech tagging, morphological analysis, named entity recognition, sentiment analysis, and syntactic parsing. EstNLTK is intended to assist researchers, developers, and language enthusiasts in working with Estonian text data, providing robust and efficient NLP capabilities. Its specialization in the Estonian language makes it an essential resource for projects and applications that require linguistic analysis and understanding within the Estonian context.

EstBERT [82] is a specialized variant of the BERT (Bidirectional Encoder Representations from Transformers) model, adapted and fine-tuned specifically for the Estonian language. BERT, developed by Google, is a powerful transformer-based model known for its ability to capture contextual information in text data, making it highly effective for various NLP tasks. EstBERT extends this capability by being trained on large Estonian text corpora and fine-tuned on specific Estonian language datasets. This enables EstBERT to generate accurate representations and effectively understand Estonian text, making it particularly valuable for tasks such as text classification, named entity recognition, sentiment analysis, and other NLP applications in the Estonian language domain.

SpaCy [42] is an open-source NLP library designed to be fast, efficient, and production-ready. It is widely used for a variety of NLP tasks, including tokenization, part-of-speech tagging, named entity recognition, dependency parsing, and more. Developed primarily in Python and Cython, SpaCy offers a streamlined API and pre-trained models for numerous languages, making it suitable for both research and industrial applications. However, one limitation of SpaCy has been its lack of robust support for the Estonian language, with only basic language data available and no comprehensive packages for Estonian NLP tasks, which was a drawback for this research. Fortunately, a pipeline called **EstSpaCy**[1] has been

[1] https://github.com/EstSyntax/EstSpaCy

developed and made publicly available on GitHub to address this gap. EstSpaCy provides SpaCy pipelines specifically for the Estonian language, trained on the Estonian (Universal Dependencies) UD v2.5 treebank using Python 3.6, SpaCy 3.0, and PyTorch 1.7.1. These pipelines adhere to UD tagsets for part-of-speech, morphology, and syntactic relations, making them a valuable resource for Estonian NLP tasks within the scope of this research.

prodi.gy [73] is a versatile annotation tool specifically designed to streamline the data labeling process in ML projects, particularly within the field of NLP. prodi.gy provides an intuitive and efficient platform for annotating various types of data, including text, images, and more, enabling researchers to create high-quality labeled datasets that are crucial for training and evaluating machine learning models. prodi.gy enhances the annotation workflow by offering a user-friendly interface that allows users to annotate data quickly and accurately. It features customizable annotation schemes and workflows, enabling researchers to tailor the labeling process to meet their specific research goals and dataset requirements. For instance, in an NLP project, prodi.gy can be employed to annotate text data for tasks such as text classification, named entity recognition, sentiment analysis, and more. A standout feature of prodi.gy is its active learning capabilities, which utilize machine learning algorithms to prioritize the annotation of data points that are most informative or uncertain, thereby improving model performance. This approach ensures that researchers focus their annotation efforts on the most valuable data points. Additionally, prodi.gy supports seamless integration with popular machine learning frameworks and libraries like spaCy, scikit-learn, and TensorFlow, allowing researchers to directly incorporate annotated data into their model training pipelines. In this context, prodi.gy was used to create a pattern based on the outputs of a referenced Python script, demonstrating its flexibility and effectiveness in complex machine learning workflows.

3.3.2 Model-building process

In order to answer RQ3 we next considered the models from existing literature (Chapter 2.2) and those used in the Estonian language context (Chapter 3.3.1) to conduct testing in controlled environment. This allowed us to evaluate multiple models and identify the most suitable approach for the Estonian language and PES context (SQ2). Next we describe the model-building process summarized in Table 5 and illustrated on Figure 7.

Step	Skills from Job Posts	Occupations from CVs
Data collection	Estonian PES's JP API and ESCO portal; retained relevant information from job postings for model training.	Scientific occupations from ESCO portal and CV data from Estonian university websites for testing the final model.
Data Cleaning	Removed irrelevant columns, concatenated job titles and descriptions, removed unnecessary whitespaces, commas, and non-Estonian texts.	Transformed occupation labels into tagged documents using Gensim, removed stop words, and omitted words with fewer than three characters.
Processing	JPs underwent tokenization and morphological analysis with NLP library EstNLTK for Estonian language to explore linguistic structures and extract relevant skills.	Converting texts into vectors using a Doc2Vec model to identify occupations by comparing text similarities.
Model development	Using EstSpaCy and the et_dep_ud_xlmroberta from the xlm-roberta-base transformers library, focusing on Named Entity Recognition (NER). prodi.gy tool was used to train the model, improving skill identifications.	With Gensim and Doc2Vec, employing a PV-DBOW algorithm for training. Used 'altlabels' for training and 'preferredLabel' for testing.

Table 5: Summary of steps in creating models for skill extraction from JPs and CVs (Publication VI)

The EstNLTK library was utilized for morphological analysis to investigate the linguistic structure of job postings. This was fundamental while performing the named entity recognition (NER) and morphological analysis, which were considered crucial processing steps for skill identification. Additionally, a study by [91], which focused on extracting skills from

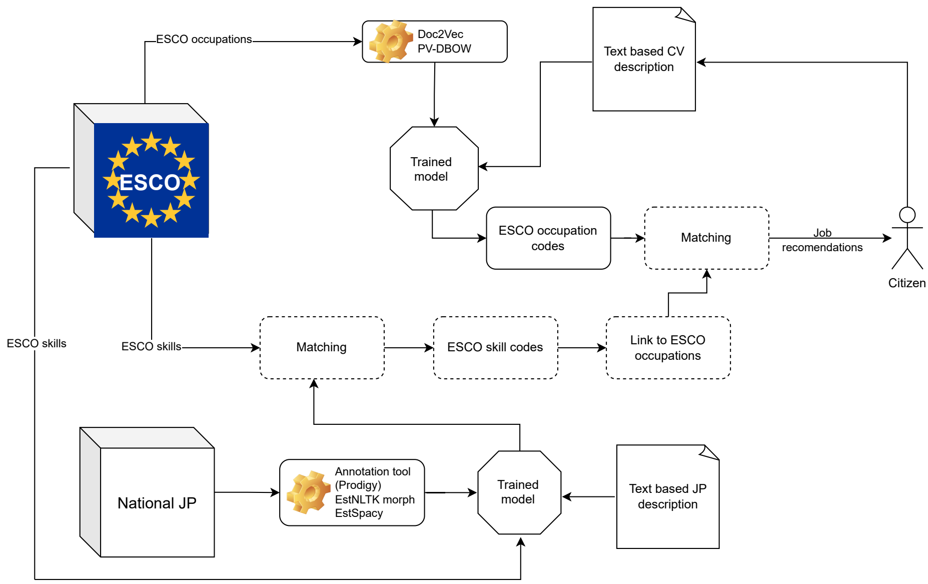

Figure 7: Job matching PoC approach for development of VCA (Publication VI)

JPs both in Danish and English, provided an example on an approach that was adapted to analyze job postings and extract preliminary skills. These researches helped in applying similar logic to extract relevant skills from JPs effectively. Additionally, an annotation tool prodi.gy played a significant role in training the model. This tool facilitated to raise the efficiency of input data annotation with active learning mechanisms, enhancing the model's accuracy. Moreover, the final model for skills identification from JPs were built using the EstSpaCy model and the `et_dep_ud_xlmroberta` based on the 'xlm-roberta-base transformers library', which provided robust platforms for developing the model [62] [9]. In preparing the data for constructing the model to identify occupations from CVs, the initial step was to convert texts into tagged documents. This process involved transforming the text into a set of words. Following that, common words and linking words were removed as stop words. Additionally, words with a length of two or fewer characters were removed. Each document required a unique tag, and for this purpose the index number of the document in the dataset was utilized as the tag. In the decision process of which ML technique to use we explored multiple options and existing models. However, considering their undeveloped capabilities in Estonian language and low reliability in providing adequate relations between input data and ESCO entities especially in Estonian language, we decided to use Gensim as a preliminary model to be used [87]. Gensim is an open-source Python library designed for natural language processing and topic modeling which is particularly well-suited for tasks involving large text corpora, document similarity analysis, and unsupervised machine learning applications [87]. The Gensim library offered the flexibility to incorporate other tags into the document. Moreover, to build the model with suitable training method for our PoC, we followed a similar approach to another research involving the assessment of commodity codes using harmonized systems' code classification [90] which is similar to ESCO and utilizes Doc2Vec model [81]. In our scenario, the ESCO code corresponding to the item description served as the second tag. During training, the distributed bag of words (PV-DBOW) was employed as the training algorithm, and the number of iterations (epochs) over the corpus was set to 40. The Doc2Vec model facilitated the discovery of the most similar documents to the original text [22]. We used 'altlabels' data for training and 'prefferdLabel' from the ESCO's dataset for testing the model. Subsequently, the closest texts were determined by assessing cosine vector similarities between the vector representation of the original text and other texts within the vocabulary.

We established an initial foundation for developing VCA in the context of Estonian PES, leveraging the mandatory classification ESCO. We described the approaches used to construct two distinct models: one for translating CV text into ESCO occupations, and another for extracting skills from job postings (JPs). However, challenges persist with the quality of text in job postings, which often lacks detailed descriptions of tasks and requirements, necessitating extensive manual data annotation—a resource-intensive process. Figure 7 describes our PoC approach for a VCA that can recommend jobs effectively, using outputs like specific ESCO concept URIs and occupational codes. We acknowledge the need for further research into specific matching techniques between these outputs, a topic not covered within the current scope of the study (represented by dotted lines in Figure 7). Moreover, as we mainly dealt with the models and data quality (conductig testing in controlled environment) in the Estonian context, we did not go into the specifics of how the citizens would actually receive these recommendations. We acknowledge that this is a critical aspect that should be researched on a wider scale within a country-specific setting, rather than being limited to a single sector such as PES. We claim that when virtual assistant such as VCA-s start emerging, they have the potential to be integrated to into a broader network of AI-enabled citizen-centered services. In Estonian case one option would be integrating the VCA into the interoperable network of chatbots called the Bürokratt [2].

[2] `https://www.kratid.ee/en/burokratt`

4 Discussion

4.1 Generalizability

A key factor in the success of a labor market is the ability to efficiently match job seekers with JPs [5]. The thesis identified deficiency in the field by analyzing current state of self-service called *'e-töötukassa'* provided by the Estonian PES. Although we did not find similar issues in related academic research, we validated the findings with the experts of Estonian PES and compared the outcome with different reports from OECD and EU to make sure these issues found in Estonian PES were representative for the whole EU's PES sector. Nevertheless, even though we validated the issues with multiple sources, the question of generalizability of the further research can be questioned —can the results of this research be applied in other countries? Firstly, to make sure our results are applicable to other EU PES, we analyzed the challenges of active labor market service provision in the EU and created an initial concept of VCA which can be scaled to other member states when the data exchange layer X-road is replaced with similar, nation-specific solution. Secondly, in further research targeting the requirements of AI-enabled PES services and the developments of PoC, we considered the context of ESCO as a main classification for occupations and skills, regardless that at the time Estonian Qualifications Authority was developing its own national skills classification tool [70]. Although, the initial concept for VCA considers the mapping of national skills to ESCO skills, based on the interviews with the representatives of Estonian Qualifications Authority, the mapping activity in Estonia was not conducted nor were the Estonian skills classification linked to the services of Estonian PES. Thereby, our approach on the PoC development directly uses ESCO data for training, which can easily be applied similarly in another country. The generalizability of the research may be somewhat limited as we used ESTNLTK, a toolkit for processing Estonian language and a NLP tool EstSpaCy, for model development which extracted skills from JPs. Both of these tools are also available in other languages and can still be applied in other EU languages. Finally, pursuing the overall research in the context of Estonia gives a good basis for transferable results because, for example, its recent second-place ranking in Europe for digital governance in the "eGovernment Benchmark" study [27] shows that the maturity to start implementing AI is most likely higher than in many other countries. Thereby, having overcome many of the basic obstacles such as data digitization and exchange between public sector organizations, the research provides valuable and practical insights for all levels of participants involved in designing and implementing AI-enabled services facing citizens in the EU's PES sector.

4.2 Novelty

While the ESCO classification system has been established for over a decade, its integration into AI-enabled service research frameworks, such as skill extraction [7] [63] [15] and multilingual job market analysis [92] [91], has only surged in recent years. This growing utilization emphasizes an increasing recognition of ESCO's potential in scientific endeavors. Notably, despite its expanded application, there remains a significant gap in the literature: no existing studies have specifically explored the unique conditions within individual PES to develop customized job or training recommendation systems. Our research directly addresses this oversight by focusing on the specific conditions of a particular PES, aiming to harness ESCO's full capabilities to enhance job matching and skill development. This approach contributes to the precision of aligning job seekers with appropriate opportunities and promotes interoperability across EU member states, thereby pioneering a targeted application of ESCO in the domain of PES. Moreover, the research proposes an initial concept of VCA demonstrating how the EU's labor market can benefit significantly from using ESCO. This concept demonstrates how proactivity is integrated into the communication flow between a citizens and the Estonian PES.

4.3 Significance

The thesis uses existing theories of dual labor market and socio-technical systems to conduct research in the specific context of PES to propose an approach of requirements collection in the sector. In the existing literature, while some researchers have explored aspects of PES e-services [12] [78] [50], from a theoretical perspective there remained a notable gap in robust methodological approaches that focus on defining the requirements for services offered by PES. In Publication IV we created a mixed-methods research design for empirical investigation specifically for the collection of requirements from external user-groups and internal experts of PES (see Requirements on Figure 3). The significance of the thesis lies in the development of a pyramid of iterative requirements for building AI-enabled services (Figure 6) that advocates for an ongoing, iterative process tailored to both internal and external user needs. This approach prioritizes continuous evaluation and refinement of user requirements, ensuring they are contextually aligned with technological capabilities and strategic objectives. It emphasizes the importance of a holistic service design that integrates and responds comprehensively to a wide range of user demands and service possibilities. The model stresses the critical role of interdisciplinary collaboration and participative methods in developing AI solutions that are technologically sophisticated while addressing to the practical challenges of the labor market.

4.4 Limitations

It is essential to recognize some limitations that might influence the scope and applicability of our research findings. While we investigated the main challenges and barriers of active labor market service provision across the EU, specifically gathering quantitative data from Italy, Germany, Estonia, Latvia, Finland, and Norway, the insights derived for the requirements are primarily reflective of the Estonian environment, concentrating specifically on external users and internal experts of the PES in Estonia. Consequently, these findings do not fully represent the diverse conditions and contexts across other EU regions.

Additionally, due to language barriers, the research concentrating the job seekers in Estonia predominantly involved participants who were proficient in Estonian or English, which may limit the diversity of perspectives captured, particularly from Russian speaking backgrounds within Estonia. This focus might have resulted in a narrower view, potentially overlooking nuanced challenges faced by those from different socio-economic backgrounds within the country.

Moreover, it is important to consider some inherent limitations in the methodological approach of our research, which focused on the development of a PoC using limited ML and NLP methods based on the ESCO classification to gather initial results. While these results were promising, they only provide preliminary insights from the narrow field of scientific occupations of ESCO classification and national JPs collected in Estonia between 2021 until 2023, emphasizing the need for including a broader scope of languages, occupations and a more detailed comparison of various ML and NLP methods to enhance accuracy and robustness. Importantly, due to the linguistic diversity within the EU, an approach that yields excellent results in one language may not perform equally well in another. This variability can significantly impact the generalizability of our findings across different linguistic contexts. Therefore, for a more comprehensive evaluation of the potential of AI-enabled services in the EU PES sector, it is recommended that future research involves collecting diverse datasets from various countries and experimenting with a range of ML techniques. Such studies would help in identifying the most effective methods that are adaptable to the linguistic and cultural nuances present across the EU. Further studies are encouraged to explore these aspects in varied EU settings to enhance the generalizability of the proposed AI-enabled service frameworks within the PES sector.

4.5 Ethical Considerations

Building AI-enabled solutions in the labor market necessitates careful consideration of ethical and privacy concerns, particularly when deploying these technologies in the PES sector. In Chapter 3.2 such concerns were shared among AI experts. AI-enabled service development poses significant ethical challenges, such as issues related to data protection and privacy, transparency and explainability of AI processes, potential biases and discrimination, and concerns regarding automated decision-making and accountability [66]. Thereby it is crucial to acknowledge the risks involved in implementing AI technologies into PES services. [85] discuss the substantial ethical and privacy challenges related to integrating digital technologies within PES, such as data protection, transparency, potential biases, and accountability in automated decision-making. In the labor market context, the ethical deployment of AI revolves around ensuring fairness and avoiding discrimination. AI services, influenced by their training data, can inadvertently reinforce existing biases, leading to discriminatory outcomes against certain groups [44]. This is particularly crucial in the labor market where AI-driven decisions can significantly affect citizens' economic opportunities. Ethical considerations must also address potential misuse of AI technologies, such as exploiting personal data without proper consent or for unintended purposes [85]. Similarly, privacy is crucial when AI systems handle sensitive personal data related to employment (see Chapter 3.2). Job seekers and employees expect their personal information, from contact details to employment history, to be handled securely and used appropriately. Ensuring data is collected, stored, and processed with robust security measures and in compliance with privacy regulations (like GDPR) is essential. Additionally, citizens should have control over their data, including the ability to understand, correct, or withdraw it. Transparency in AI involves clear communication about the operations of AI systems, the decisions they make, and the rationale behind these decisions [44]. In the labor market, this means that both job seekers and employers should understand how AI tools match candidates with jobs or predict job suitability. There should be accountability mechanisms to address any issues that arise, such as incorrect job matches or breaches of data privacy. Finally, trust in AI systems is closely tied to transparency and accountability. Trust is built when users feel confident that AI systems are working in their best interest, are fair, and do not misuse their data [44]. For AI in labor markets, building this trust is key to encouraging user engagement and acceptance. Efforts to mitigate these risks include developing measurable indicators for experts working in PES and maintaining traditional service mechanisms to support non-digital users, ensuring inclusivity and access to digital benefits.

4.6 Future Research

As stated in Chapter 1.2, the practical scope of our research was intentionally limited to the VCA's first component: matching citizens' skills with jobs. This decision was driven by the well-developed state of job recommendation systems in scientific research, which provided a robust foundation for the PES sector to experiment with the initial iteration of the VCA. In contrast, the fields of training recommendation systems and LMI, while promising, currently lack the necessary research depth and data accessibility to support immediate experimentation on a regional scale.

Future research should address the significant gap in training recommendation systems. Advanced ML and NLP techniques need to be investigated to recommend relevant training programs based on individual skill profiles and job requirements. Investigating how to integrate real-time data from various training providers will ensure that recommendations are current and tailored to the evolving job market needs. Future research should aim for stable and secure data access methods, possibly through more open collaboration with specific PES. This will ensure that vital information remains available for analysis and can be integrated into the VCA. Collaborating with PES and other stakeholders on the labor market to develop standardized data-sharing agreements could facilitate more consistent access to essential datasets.

While there have been successful trials globally, LMI requires localized, tailored advice, which today is often conducted manually. Future research should develop automated methods for generating and updating local LMI. Investigating the potential of real-time LMI and the integration with the VCA will provide ongoing, dynamic insights into local job market trends and demands.

Implementing the European Classification of Skills/Competences, Qualifications, and Occupations (ESCO) as the foundational classification system for the VCA is a significant step forward. However, the translations on the EU member state level need more effort to be usable for language-specific model training. Thereby, evaluating the effectiveness of ESCO in different contexts and refining its application to better suit the diverse needs of various EU member states will also be crucial.

We hope that future iterations of the VCA will be developed and tested in a continuous, iterative process, incorporating feedback from external user groups and stakeholders to ensure that the final citizen-facing service will be responsive to citizens' needs and evolving job market conditions. Additionally, future research should address how citizens can access these assistants, with one potential option being the integration of conversational AI to enhance accessibility and user experience. By addressing these areas in future research, we can build on the foundational work of matching skills with jobs and progressively expand the VCA's capabilities. This approach will ultimately lead to a more integrated and responsive labor market service that matches citizens with suitable jobs, guides them through relevant training opportunities and provides up-to-date LMI tailored to their local context.

5 Conclusion

The EU's labor market is currently facing significant challenges that threaten the achievement of future employment and skills development goals. These challenges include uncertainties created by rapid technological advancements in automation, various economic and social crises, and a lack of innovation in the active labor market services provided by PES. Addressing skill shortages with modern, proactive services has become increasingly critical [67] [3]. This thesis highlighted and validated two key issues in today's PES service provision while also analyzing the broader challenges in the current active labor market landscape.

To address these challenges and issues, first it was established that integrating the ESCO classification into existing services could significantly enhance job matching and skill development across the EU. The research led to the development of an initial concept for a VCA, designed with flexibility to incorporate national classification systems mapped to ESCO. The concept emphasizes the importance of proactivity, demonstrated through the example of Estonia's X-road data exchange layer, which already enables access to information regarding citizens' employment and educational activities. Secondly, the thesis integrated theories of dual labor markets and socio-technical systems to address a significant gap in the existing literature concerning PES e-services by developing a robust methodological approach for requirements collection. It proposed a model for AI-enabled services that enhances PES by instituting an ongoing, iterative process tailored to user needs, ensuring continuous alignment with technological capabilities and strategic goals. This model supports holistic service design that responds to diverse user demands and emphasizes the importance of interdisciplinary collaboration in creating sophisticated AI solutions that meet practical labor market challenges. Finally, this thesis established initial steps needed for developing a VCA for the Estonian PES, utilizing the ESCO classification. It explored the construction of two models: one converting CV text to ESCO occupations and another extracting skills from job postings, both focussing on achieving high similarity scores with occupations and skills documented in ESCO classification, despite challenges remain due to the often inadequate job descriptions requiring extensive manual annotation. The PoC for the VCA indicates effective job recommendation using ESCO URIs and codes, highlighting areas for future research in specific matching techniques, which were beyond the scope of this study.

Overall, contributions of this research highlight the potential of integrating AI and occupational classification systems into PES, which could revolutionize how citizens interact with these services by proactively addressing their needs while providing personalized service delivery. The study emphasizes the importance of a comprehensive approach that involves all stakeholders to ensure that AI solutions are effectively tailored and implemented, leading to more responsive and efficient PES services across the EU. As a final piece of this thesis, we present policy recommendations that have emerged from this investigation.

5.1 Policy Recommendations

Enhance data accessibility: Establish regulations and mechanisms that ensure consistent and secure access to necessary data across the public sector. More specifically define roles that within public organizations deal with data quality improvements (such as data managers and data analytics) ensuring that relevant data is anonymized, annotated and constantly accessible. Integrating such roles can foster dedicated actions ensuring that data can be accessed in real-time (such as active JPs, training events and anonymized CV data), thus supporting the continuous improvement and relevance of personalized recommendation systems and LMI.

Strengthen research in sparse areas: Promote academic, public and private-sector partnerships focused on developing proactive and personalized citizen-centered services. Government funding should be directed towards projects that aim to create a solid experimental foundation for developing next generation services.

Promote experimental sandboxes: Foster a regulatory sandbox environment where new technologies can be tested without the immediate constraints of existing legislation. This would allow for more innovative approaches to be experimented within the public sector, reducing resistance and increasing appetite for experimentation.

List of Figures

List of Tables

References

[1] H. J. Ahn, B. Hobijn, and A. Şahin. The dual u.s. labor market uncovered. Working Paper 31241, National Bureau of Economic Research, May 2023.

[2] J. C. W. Bernd W. Wirtz and C. Geyer. Artificial intelligence and the public sector—applications and challenges. *International Journal of Public Administration*, 42(7):596–615, 2019.

[3] M. Blank, T. Janisch, N. van der Linden, E. L. Arriëns, and P. de Bas. *Intelligent Cities - A Cities Guide to Reskilling the Local Workforce*. Publications Office of the European Union, Luxembourg, 2023. EA-04-23-099-EN-N.

[4] R. P. Bostrom and J. S. Heinen. Mis problems and failures: a socio-technical perspective, part ii: the application of socio-technical theory. *MIS quarterly*, pages 11–28, 1977.

[5] S. Broecke. Artificial intelligence and labour market matching. (284), 2023.

[6] Cedefop. *Empowering adults through upskilling and reskilling pathways: Vol. 1: adult population with potential for upskilling and reskilling*. Luxembourg: Publications Office. Cedefop reference series, 2020.

[7] B. Clavié and G. Soulié. Large language models as batteries-included zero-shot esco skills matchers. *CEUR Workshop Proceedings*, 3490, 2023. Cited by: 0.

[8] B. Cockx, M. Lechner, and J. Bollens. Priority to unemployed immigrants? A causal machine learning evaluation of training in Belgium. LIDAM Discussion Papers IRES 2020016, Université catholique de Louvain, Institut de Recherches Economiques et Sociales (IRES), May 2020.

[9] A. Conneau, K. Khandelwal, N. Goyal, V. Chaudhary, G. Wenzek, F. Guzman, E. Grave, M. Ott, L. Zettlemoyer, and V. Stoyanov. Unsupervised cross-lingual representation learning at scale. *CoRR*, abs/1911.02116, 2019.

[10] Council of the European Union. Council recommendation of 22 may 2018 on key competences for lifelong learning, 2018. Accessed: 2024-03-25.

[11] J. Creswell and V. Clark. *Designing and Conducting Mixed Methods Research*. SAGE Publications, 2017.

[12] L. Danneels and S. Viaene. How to move towards digital era governance: the case of vdab. In *Proceedings of the 16th Annual International Conference on Digital Government Research*, dg.o '15, page 29–36, New York, NY, USA, 2015. Association for Computing Machinery.

[13] V. S. Dave, M. A. Hasan, B. Zhang, K. AlJadda, and M. Korayem. A combined representation learning approach for better job and skill recommendation. *International Conference on Information and Knowledge Management*, *Proceedings*, 9:1997–2006, 10 2018.

[14] T. H. Davenport and J. Kirby. Just how smart are smart machines? *MIT Sloan Management Review*, 57(3):21, 2016.

[15] J.-J. Decorte, J. Van Hautte, J. Deleu, C. Develder, and T. Demeester. Design of negative sampling strategies for distantly supervised skill extraction. *CEUR Workshop Proceedings*, 3218, 2022. Conference name: 2nd Workshop on Recommender Systems for Human Resources, RecSys-in-HR 2022; Conference date: 18 September 2022 through 23 September 2022; Conference code: 182847.

[16] S. Desiere, K. Langenbucher, and L. Struyven. Statistical profiling in public employment services: An international comparison. OECD Social, Employment and Migration Working Papers 224, OECD Publishing, Paris, 2019.

[17] S. DESIERE and L. STRUYVEN. Using artificial intelligence to classify jobseekers: The accuracy-equity trade-off. *Journal of Social Policy*, 50(2):367–385, 2021.

[18] J. Dhameliya and N. Desai. Job recommender systems: A survey. *2019 Innovations in Power and Advanced Computing Technologies, i-PACT 2019*, 3 2019.

[19] P. B. Doeringer and M. J. Piore. *Internal Labor Markets and Manpower Analysis*. Manpower Administration, Department of Labor, United States, 1970.

[20] Estonian National Audit Office. National audit office: The unemployment insurance fund must verify which training is useful for finding a job and check the level of training courses. Audit report, Estonian National Audit Office, Tallinn, 2022. Accessed: 2024-04-22.

[21] European Commission. Questions and answers: European skills agenda for sustainable competitiveness, social fairness and resilience. Accessed July 17, 2023.

[22] European Commission. *ESCO European Classification of Skills/Competences, Qualifications and Occupations: The First Public Release*. Luxembourg, 2013. A Europe 2020 initiative. More information available on the Internet at `http://europa.eu`. Cataloguing data and an abstract can be found at the end of this publication.

[23] European Commission. Proposal for a council recommendation on the european qualifications framework for lifelong learning and repealing the recommendation of the european parliament and of the council of 23 april 2008 on the establishment of the european qualifications framework, 2016.

[24] European Commission. ESCO: improving career guidance services, 2017.

[25] European Commission. Commission welcomes member states' targets for a more social europe by 2030. Press Release, June 2022.

[26] European Commission. *Future skills, career guidance and lifelong learning in PES—Thematic paper*. Publications Office of the European Union, 2022.

[27] European Commission. Egovernment benchmark 2023—connecting digital governments, 2023.

[28] European Commission. Artificial intelligence act. `https://artificialintelligenceact.eu/ai-act-explorer/`, 2024. Accessed: 2024-03-25.

[29] European Commission. Commission sets out actions to tackle labour and skills shortages, March 2024. Accessed: 2023-05-29.

[30] European Court of Auditors. Special report no 25/2021: Long-term unemployment in the eu: Member states' use of the european social fund to support job-seekers. Special Report 25/2021, European Court of Auditors, 2021. Accessed: 2024-04-22.

[31] European Parliament and Council of the European Union. Decision (eu) 2022/2481 of the european parliament and of the council. establishing the digital decade policy programme 2030. *Official Journal of the European Union*, page L 323/4, December 2022.

[32] European Parliament and the Council of the European Union. Regulation (eu) 2016/589 of the european parliament and of the council of 13 april 2016 on a european network of employment services (eures), workers' access to mobility services and the further integration of labour markets, and amending regulations (eu) no 492/2011 and (eu) no 1296/2013, 4 2016. Text with EEA relevance.

[33] European Union. *European Skills, Competences, Qualifications and Occupations: ESCO: harnessing the power of big data analysis for a functional labour market*. Luxembourg, 2017.

[34] European Union. European skills, competences, qualifications and occupations: Esco: improving career guidance services. Europe 2020 initiative, Publications Office of the European Union, Luxembourg, 2017.

[35] S. Fatima, K. C. Desouza, and G. S. Dawson. National strategic artificial intelligence plans: A multi-dimensional analysis. *Economic Analysis and Policy*, 67:178–194, 2020.

[36] G. Fischer and T. Herrmann. Socio-technical systems: a meta-design perspective. *International Journal of Sociotechnology and Knowledge Development (IJSKD)*, 3(1):1–33, 2011.

[37] A. A. Flügge. Perspectives from practice: Algorithmic decision-making in public employment services. In *Companion Publication of the 2021 Conference on Computer Supported Cooperative Work and Social Computing*, CSCW '21 Companion, page 253–255, New York, NY, USA, 2021. Association for Computing Machinery.

[38] A. Giabelli, L. Malandri, F. Mercorio, M. Mezzanzanica, and A. Seveso. Skills2job: A recommender system that encodes job offer embeddings on graph databases. *Applied Soft Computing*, 101:107049, 2021.

[39] D. Goldberg, D. Nichols, B. M. Oki, and D. Terry. Using collaborative filtering to weave an information tapestry. *Commun. ACM*, 35(12):61–70, dec 1992.

[40] J. Grundy. Statistical profiling of the unemployed. *Studies in Political Economy*, 96(1):47–68, 2015.

[41] T. Herrmann and S. Pfeiffer. Keeping the organization in the loop: a socio-technical extension of human-centered artificial intelligence. *AI & SOCIETY*, 38(4):1523–1542, 2023.

[42] M. Honnibal and I. Montani. spacy 2: Natural language understanding with bloom embeddings, convolutional neural networks and incremental parsing. *To appear*, 2017.

[43] International Labor Office. Resolution concerning updating the international standard classification of occupations, 2007.

[44] International Labour Organization. Technology adoption in public employment services, catching up with the future: Global report. Technical report, International Labour Organization, Geneva, 2022.

[45] S. Jahan, A. S. Mahmud, and C. Papageorgiou. What is keynesian economics. *International Monetary Fund*, 51(3):53–54, 2014.

[46] J. M. Keynes. *The General Theory of Employment, Interest and Money*. Palgrave Macmillan, United Kingdom, 2007 edition, 1936.

[47] X. Kong, S. Boll, and W. Heuten. A hybrid multi-recommender system for a teaching and learning community for the dual system of vocational education and training. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 8095 LNCS:613–614, 2013.

[48] J. Körtner and G. Bonoli. Predictive algorithms in the delivery of public employment services. In D. Clegg and N. Durazzi, editors, *Handbook of Labour Market Policy in Advanced Democracies*, Chapters, chapter 27, pages 387–398. Edward Elgar Publishing, 2023.

[49] S. Laur, S. Orasmaa, D. Särg, and P. Tammo. Estnltk 1.6: Remastered estonian nlp pipeline. In *Proceedings of The 12th Language Resources and Evaluation Conference*, Marseille, France, 2020. European Language Resources Association.

[50] J. Leinberg. The improvement of a self-service process of employment mediation in estonian unemployment insurance fund, 2016.

[51] Q. Li, S. Jeon, C. Lee, and K. Kim. A study on the job recommender system using user preference information. *Journal of Information Technology Services*, 20:57–73, 2021.

[52] A. Līce and B. Sloka. The most important factors for employers in latvia in the recruitment process. *Int. J. Learning and Change*, 14(1):69, 2022.

[53] M. Liutkevičius and R. Erlenheim. Validating the usage of Occupational Classification Systems in the Process of Creating a National Virtual Competency Assistant within the EU Labor Market. *ICEGOV '21: Proceedings of the 14th International Conference on Theory and Practice of Electronic Governance*, 7:254–259, 2022.

[54] M. Liutkevičius, M. Kõosaar, and S. B. Yahia. Designing a Proof of Concept for a Virtual Competence Assistant. *Human Factors, Business Management and Society. International Conference*, 135:1–9, 2024.

[55] M. Liutkevičius, S. Nõmmik, Piyumi, M. Weck, and S. Yahia. In Pursuit of AI Excellence in Public Employment Services: Identifying the Requirements. *TalTech Journal of European Studies*, 14, 2024.

[56] M. Liutkevičius, M. Weck, and S. B. Yahia. Understanding the Challenges of Today's Labor Market Service Provision in the EU. *Human Factors, Business Management and Society*, 97(97), 2023.

[57] M. Liutkevičius and S. B. Yahia. Research Roadmap for Designing a Virtual Competence Assistant for the European Labour Market. *Knowledge-Based and Intelligent Information & Engineering Systems: Proceedings of the 26th International Conference (KES2022), Procedia Computer Science*, 207:2404–2413, 2022.

[58] M. Liutkevičius and S. B. Yahia. The Use of Artificial Intelligence in Job Seeking and Competence Development. *Human Factors, Business Management and Society*, 56:128–136, 2022.

[59] M. Mezzanzanica and F. Mercorio. Big data for labour market intelligence: An introductory guide. Report, European Training Foundation, 2019. Aimed at statisticians, researchers, policy analysts, and decision-makers in the ETF's partner countries, this paper addresses key conceptual, methodological, and organisational aspects of using Big Data for labour market intelligence. It explores how Big Data can transcend conventional labour market information systems and enhance established statistics.

[60] P. Mikalef, S. O. Fjørtoft, and H. Y. Torvatn. Artificial intelligence in the public sector: a study of challenges and opportunities for norwegian municipalities. In *Digital Transformation for a Sustainable Society in the 21st Century: 18th IFIP WG 6.11 Conference on e-Business, e-Services, and e-Society, I3E 2019, Trondheim, Norway, September 18–20, 2019, Proceedings 18*, pages 267–277. Springer, 2019.

[61] Ministry of Economic Affairs and Employment of Finland. Artificial intelligence in employment services - a mapping: Final report. Technical report, 2019. Accessed: 2024-04-23.

[62] K. Müürisep. Spacy pipelines for estonian language. `https://github.com/EstSyntax/EstSpaCy/`, 2021. Accessed: 2024-02-27.

[63] I. E. Nikolaev. An intelligent method for generating a list of job profile requirements based on neural network language models using esco taxonomy and online job corpus. *Business Informatics*, 17(2):71 – 84, 2023.

[64] N. J. Nilsson. *The quest for artificial intelligence*. Cambridge University Press, 2009.

[65] OECD. Building inclusive labour markets: Active labour market policies for the most vulnerable groups. 2021.

[66] OECD. *OECD Employment Outlook 2023. Artificial Intelligence and the Labour Market*. 2023.

[67] OECD. *OECD Skills Strategy Ireland: Assessment and Recommendations*. OECD Publishing, Paris, 2023. ISBN 978-92-64-81981-8 (pdf)
ISBN 978-92-64-62933-2 (HTML)
ISBN 978-92-64-99566-6 (epub)
ISSN 2307-8723 (print)
ISSN 2307-8731 (online).

[68] OECD. Explanatory memorandum on the updated oecd definition of an ai system. *OECD Artificial Intelligence Papers*, 2024.

[69] R. Opik, T. Kirt, and I. Liiv. Megatrend and intervention impact analyzer for jobs: A visualization method for labor market intelligence. *Journal of Official Statistics*, 34(4):961–979, 2018.

[70] OSKA. Tööelu üldoskutse klassifikatsioon: Tulevikuvajadus. OSKA Research Studies, 2023. Accessed: 2023-05-10.

[71] C.-Y. Park, K. Shin, and A. Kikkawa. Demographic change, technological advance, and growth: A cross-country analysis. *Economic Modelling*, 108(C):105742, 2022.

[72] M. Polato and F. Aiolli. A preliminary study on a recommender system for the job recommendation challenge. *Proceedings of the Recommender Systems Challenge on - RecSys Challenge '16*.

[73] Prodigy. Radically efficient machine teaching: An annotation tool powered by active learning. `https://prodi.gy/`, 2024. Accessed: 2024-02-27.

[74] M. Reich, D. M. Gordon, and R. C. Edwards. A theory of labor market segmentation. *The American Economic Review*, 63(2):359–365, 1973.

[75] P. Resnick and H. R. Varian. Recommender systems. 40(3):56–58, 1997.

[76] L. G. Rodriguez, E. P. Chavez, and C. A. Rodriguez. A vectorization model for job matching application of a government employment service office. *Proceedings of 2019 the 9th International Workshop on Computer Science and Engineering*, 9:32–36, 2019.

[77] A. Saari, M. S. Rasul, R. M. Yasin, R. Amnah, A. Rauf, Z. Hilmi, M. Ashari, and D. Pranita. Skills sets for workforce in the 4th industrial revolution: Expectation from authorities and industrial players. *Journal of Technical Education and Training*, 13:1–9, 1 2021.

[78] Y. W. Seing. When the client becomes her own caseworker: Dislocation of responsibility through digital self-support in the swedish public employment service. *Sozialer Fortschritt*, 71(6-7):405–423, 2022.

[79] H. Seo. 'dual' labour market? patterns of segmentation in european labour markets and the varieties of precariousness. *Transfer: European Review of Labour and Research*, 27(4):485–503, 2021.

[80] J. Shore and J. Tosun. Assessing youth labour market services: Young people's perceptions and evaluations of service delivery in germany. *Public Policy and Administration*, 34(1):22–41, 2019.

[81] M. Spichakova and H.-M. Haav. Using machine learning for automated assessment of misclassification of goods for fraud detection. In T. Robal, H.-M. Haav, J. Penjam, and R. Matulevičius, editors, *Databases and Information Systems*, pages 144–158, Cham, 2020. Springer International Publishing.

[82] H. Tanvir, C. Kittask, S. Eiche, and K. Sirts. EstBERT: A pretrained language-specific BERT for Estonian, 2021.

[83] P. Tripathi, R. Agarwal, and T. Vashishtha. Review of job recommender system using big data analytics. *Proceedings of the 10th INDIACom; 2016 3rd International Conference on Computing for Sustainable Global Development*, *INDIACom 2016*, pages 3773–3777, 2016.

[84] E. L. Trist. *The evolution of socio-technical systems*, volume 2. Ontario Quality of Working Life Centre Toronto, 1981.

[85] M. Urquidi and G. Ortega. Artificial intelligence for job seeking: How to enhance labor intermediation in public employment services. IDB Technical Note 1996, Inter-American Development Bank, Washington, November 2020. Viewed on 25 April 2024.

[86] V. Venkatesh, S. A. Brown, and H. Bala. Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly*, 37(1):21–54, 2013.

[87] R. Řehůřek and P. Sojka. Software framework for topic modelling with large corpora. In *Proc. LREC Workshop on New Challenges for NLP Frameworks*, Valletta, Malta, 2010.

[88] J. Wang and P. Han. Adversarial training-based mean bayesian personalized ranking for recommender system. *IEEE Access*, 8:7958–7968, 2020.

[89] S. Winby and S. A. Mohrman. Digital sociotechnical system design. *The Journal of Applied Behavioral Science*, 54(4):399–423, 2018.

[90] World Customs Organization. Nomenclature and classification of goods. `https://www.wcoomd.org/en/topics/nomenclature.aspx`, 2023. Accessed: 2023-05-29.

[91] M. Zhang, K. N. Jensen, and B. Plank. Kompetencer: Fine-grained skill classification in danish job postings via distant supervision and transfer learning. page 436 – 447. European Language Resources Association (ELRA), 2022. Conference name: 13th International Conference on Language Resources and Evaluation Conference, LREC 2022; Conference date: 20 June 2022 through 25 June 2022; Conference code: 184830.

[92] M. Zhang, R. van der Goot, and B. Plank. Escoxlm-r: Multilingual taxonomy-driven pre-training for the job market domain. *Proceedings of the Annual Meeting of the Association for Computational Linguistics*, 1:11871 – 11890, 2023. Conference name: 61st Annual Meeting of the Association for Computational Linguistics, ACL 2023; Conference date: 9 July 2023 through 14 July 2023; Conference code: 192160.

Acknowledgements

I am immensely grateful to a number of individuals whose support and guidance have been crucial throughout the course of my PhD journey. First, I would like to express my appreciation to my supervisors Sadok Ben Yahia and Innar Liiv, whose expertise and insights have been invaluable. I am also profoundly thankful for the invaluable input provided by an expert from the Estonian PES, Mari Väli. Her insights during our interviews were eye-opening and significantly enriched my understanding of the subject matter. Moreover I am grateful for the many master's and bachelor's students who were willing to explore this subject and collect data for my research. Their enthusiasm and diligence have been of crucial help to the depth and breadth of this study.

A special thanks goes to my wife, who has provided not just emotional support but also practical advice and encouragement during the most challenging times. Her belief in my abilities has been a constant source of motivation. I would also like to extend my thanks to my colleagues in the department, whose willingness to share their knowledge have greatly enriched my experience. Additionally, I am thankful for the financial support received during my research. This support has been instrumental in facilitating my work and allowing me to focus on producing quality research outputs. I must also mention our gratitude towards SpaCy's prodi.gy tool team for generously providing us with a free license. This tool has been essential in our data annotation efforts, enabling more precise and efficient research.

Each of these contributions has been vital to the completion of this dissertation, and I am deeply thankful to everyone mentioned and others unmentioned who played a role in this journey.

Abstract

Enhancing Public Employment Services with AI-enabled Virtual Competence Assistant

This dissertation explores the integration of the European Classification of Skills/ Competences, Qualifications, and Occupations (ESCO) within the Public Employment Services (PES) in Estonia, aiming to enhance job matching processes through the development of a Virtual Competence Assistant (VCA).

First, it explores the pressing issues faced by Public Employment Services (PES) in the evolving labor market, focusing on the inefficiencies of the Estonian PES's e-services. Two main problems are highlighted: the first is the lack of efficient matching process in the e-service that can effectively align citizens' CVs with appropriate job and training opportunities, forcing individuals to manually go through extensive listings, thus leading to missed opportunities and market inefficiencies. The second issue concerns the insufficient integration of skills and qualifications in the matching process, which hampers the accurate pairing of job seekers with suitable job posts and training programs. These deficiencies illustrate the urgent need for intelligent solutions to address the challenges of modern labor market and bridge the widening skills gap, thereby enhancing the functionality and impact of PES in adapting to rapid economic changes.

Second, this research identifies significant obstacles within the EU's PES sector, highlighting inadequate focus on marginalized groups, ineffective evaluation systems, resistance to change, and high administrative burdens that undermine the efficacy of services aimed at supporting job seekers and influencing broader economic outcomes. Thereby, this research introduces a novel approach by applying the established ESCO classification system specifically within the context of PESs, a focus not previously explored in academic studies. While ESCO has been utilized for skill extraction and job market analysis, this work suggests developing customized job and training recommendation systems tailored to the conditions of a PES, maximizing ESCO's capabilities to enhance job matching efficiency and foster interoperability among EU member states. Based on this, the research introduces the initial concept of VCA, which could revolutionize the interaction between citizens and PESs by embedding proactivity into their communication flows. Filling the literature gap, this approach could significantly enhance how PESs leverage technology to align job seekers with suitable opportunities and adapt to labor market changes.

Third, this research utilizes theories of dual labor markets and socio-technical systems to design a mixed-methods framework for the empirical investigation of requirements from both internal experts and external user groups of the PES. The analysis reveals a complex set of requirements and challenges that necessitate a nuanced integration of technology within labor markets. This integration aligns with the socio-technical systems theory, emphasizing the need for a collaborative approach to optimize organizational functionality and responsiveness. Job seekers and employers highlight key external needs such as improved job opportunities, platform usability, and information quality. These areas are identified as potential benefits from AI enhancements, which could significantly improve PES service delivery and user satisfaction. Meanwhile, career counselors emerge as critical stakeholders, offering unique insights that bridge user experiences with technological advancements, enhancing stakeholder trust and acceptance. Internal needs identified by AI experts—such as infrastructure upgrades, skilled personnel engagement, high-quality data availability, privacy safeguards, legal compliance, change management, and sufficient funding—emphasizes the importance of addressing both technological efficiency and the social integrity of labor markets. This holistic approach supports an iterative pro-

cess where ongoing feedback refines AI services, ensuring alignment with both technological capabilities and the practical realities of the labor market, thereby fostering more integrated and responsive service development.

Finally, this study involves describing approaches for constructing two models essential for recommending jobs: first for identifying matches between CV text and ESCO occupations and second for extracting skills from JPs. The testing was done in a controlled environment considering the context of PES and gave initial confirmation for further development. These models leverage machine learning techniques to illustrate the potential in aligning job seekers with appropriate job opportunities based on ESCO's detailed occupational classifications. However, the research identifies significant challenges, primarily due to the often generic and under-detailed job descriptions that require extensive manual data annotation. Thereby, our proof of concept is describing approaches including data annotation that could improve the data quality in a PES thereby enabling to build AI-enabled service such VCA for recommending jobs.

Kokkuvõte
Avalike tööturuteenuste parendamine tehisintellektil põhineva virtuaalse kompetentsiassistendiga

Antud väitekiri uurib, kuidas tehisintellekt saab parendada avalikke tööturuteenuseid, et lahendada tööturuga seotud probleeme, mis on põhjustatud kiiretest tehnoloogilistest muutustest ja välistest teguritest, nagu COVID-19 pandeemia ja geopoliitilised konfliktid. Traditsiooniliste oskuste hääbumine ja uute oskuste järele nõudluse kasv on pannud Euroopat seadma ambitsioonikad eesmärgid, et tagada oskustööjõu jätkusuutlikkuse ja kohaneda muutuvate oludega. Lisaks nõuavad tööjõupuudus ja demograafilised muutused, nagu vananev tööjõud, efektiivsemaid tööturuteenuseid, eriti arvestades alaesindatud sihtgruppide vajadusi. Seega keskendub väitekiri tehisintellektil põhinevatele lahendustele, et parandada avalikke tööturu teenuseid, uurides detailsemalt praegust olukorda Eesti Töötukassas kui ühte paljudest Euroopa Liidu tööturu teenuse pakkujatest. Analüüsi käigus tuuakse esile kaks tänapäeva tööturuteenuste kriitilist puudujääki: esiteks puudub intelligentne vastavuse leidmine kodanike CV-de ja töökuulutuste vahel; teiseks puudub sobitamise protsess, mille käigus võetaks arvesse kodanike oskusi. Seega peavad tänased tööotsijad töökuulutusi käsitsi läbi vaatama, kuna puuduvad kaasaegsed lahendused, mis aitaksid oskuste põhjal leida sobivaid töö- või koolitusvõimalusi. See põhjustab ebatõhusust nii tööotsijate kui ka tööandjate jaoks. Nende probleemide lahendamiseks tehakse väitekirjas ettepanek arendada Virtuaalne Kompetentsiassistent - tehisintellekti toega assistent, mis parendab töövõimaluste ja oskuste sobitamist kohaliku tööturu olukorda arvestades. Virtuaalne Kompetentsiassistendi esialgne skoop antud väitekirjas keskendub kodanike oskuste ja töövõimaluste vastavusse viimisele, kuna töösoovitussüsteemid on olemasolevates teadusuuringutes esinduslikult uuritud võrreldes vähem tähelepanu saanud koolituste soovitussüsteemide ja kohaliku tööturu analüüsisüsteemidega. Oluline aspekt uurimuses on Euroopa oskuste, pädevuste, kvalifikatsioonide ja ametite klassifikatsiooni (ESCO) integreerimine tehisintellektitoega teenustesse, et sobitada tööotsijaid töövõimalustega. Väitekiri rõhutab tehisintellekti tööriistade pideva ja iteratiivse arendamise olulisust tööturuteenustes, keskendudes kasutajate tagasisidele ja eetilisuse nõuete täitmisele. Tulevased uuringud peaksid uurima koolituste soovitussüsteeme, kohaliku tööturu analüüsisüsteeme ning tehisintellekti kasutamist mitmes erinevas keeles ja piirkonnas. Eesmärk on luua tõhusam, kaasavam ja dünaamilisem tööturg, mis sobitaks mitte ainult töötuid vaid ka kodanikke laiemalt vabade töökohtade ning koolitusvõimalustega lähtudes kohaliku tööturu kontekstist ja seal vaja minevatest oskustest.

Appendix 1

I

M. Liutkevičius and S. B. Yahia. Research Roadmap for Designing a Virtual Competence Assistant for the European Labour Market. *Knowledge-Based and Intelligent Information & Engineering Systems: Proceedings of the 26th International Conference (KES2022), Procedia Computer Science*, 207:2404–2413, 2022

Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 207 (2022) 2404–2413

Procedia Computer Science

www.elsevier.com/locate/procedia

26th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2022)

Research Roadmap for Designing a Virtual Competence Assistant for the European Labour Market

Markko Liutkevičius, Sadok Ben Yahia

Tallinn University of Technology, Akadeemia tee 15a, Tallinn, 12618, Estonia

Abstract

This research proposal explores how citizen-centered learning and career advancement can benefit from artificial intelligence, occupational classification frameworks, and the concept of proactive services. In the current literature, there are a lot of machine learning methods used in various job and training recommendation systems to tackle scientific or real-life problems. However, only a few use the existing occupational classifications to classify job and training advertisements or enable cross-regional labor mobility. Additionally, the quality of public e-services regarding labour market services in each European country varies greatly. For example, even though Estonia is typically referred to as being at the forefront of public service digitization and automation, it has not implemented machine learning methods to match job offers or training with candidates. The matching process between vacancy and job seeker is currently carried out with outdated International Standard Classification of Occupations (ISCO) codes, altered to the Estonian Unemployment Insurance Fund's needs. The ISCO code is assigned to each job vacancy by a company and job wish by a citizen manually. Such functionality is rigid and requires the users to define an accurate ISCO code. Even when the filled-in CV consists of detailed previous work experience and educational background, if the ISCO code is not accurate, the e-service will not help the citizen find a new job. Moreover, in today's public employment service portals, there is typically no option to insert specific skills that a citizen has to receive an increased number of accurate job or training recommendations. Consequently, despite many well-established frameworks dealing with competencies and occupations, citizen-centered public services supporting upskilling and finding a new job are inefficient. In this paper, we put forth a research roadmap for investigating how to enable a technical ecosystem using occupational classification frameworks so that citizens, both employed and unemployed, can receive proactive recommendations about upcoming training events and job vacancies. Such a system should be tailored to support citizen life events. For example, it could consider citizens' previous work and educational background to help with retraining, upskilling, or changing one's career path. Therefore we have initiated a project in collaboration with the Estonian Unemployment Insurance Fund, the Estonian Qualifications Authority, other Estonian public organizations, and partner universities in Latvia and Finland. The research is planned as an action design research to design an artificial intelligence-enabled Virtual Competence Assistant (VCA) for the EU labour market.

Keywords: Virtual Competence Assistant; Job Matching; Upskilling; Proactivity; AI;

1877-0509 © 2022 The Authors. Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)
Peer-review under responsibility of the scientific committee of the 26th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2022)
10.1016/j.procs.2022.09.299

1. Introduction

A recent report by International Labor Organization (ILO) revealed that in 2020 the COVID-19 pandemic caused the loss of 144 million jobs, causing a drastic shortage of employment opportunities [23]. Rapid societal changes such as a pandemic, digitization, and war in Ukraine increase the importance of government support and the role of national public employment services. Most member states in the EU have built e-services to support public employment service provision. However, it can be argued whether these portals are utilizing recent technological advancements such as machine learning and artificial intelligence to solve the problematic bottlenecks. "To take advantage of e-government services and attract a higher number of citizens, government portals should exploit intelligent techniques and deliver services in a personalized citizen-centric approach" [3]. Multiple ongoing e-Government-focused initiatives are bringing intelligent services into daylight, such as KrattAI strategy in Estonia, Virtual Finland, and Aurora AI in Finland. KrattAI strategy is mainly focused on taking existing e-services in Estonia to the intelligent level, having facilitated more than 80 AI projects in the public sector [18]. AuroraAI program is an artificial intelligence and autonomous applications network focused on creating people-oriented and proactive services based on citizens' life events and companies' business-related events [31]. Virtual Finland is a new initiative to create digital services from the public and private sectors for different target groups going to travel, work, study, or do business in Finland for companies, employees, university students, and tourists [19]. Hence governments have increased interest in artificial intelligence and proactive service provision for their citizens. However, there is still a long way to go to meet these objectives in labor market services and cross-regional labor mobility.

People tend to migrate cross-border to find better work and outcomes for themselves. The same trend is also present in the neighboring EU countries Estonia, Latvia, and Finland, as people are traveling cross-border back and forth. However, the labour market organizations of these countries are mainly focusing on cooperation in the field of passive labour market measures as communication is only related to the exchange of social security information. As a result, no tools support the citizen's cross-border movement when offering upskilling and re-training opportunities in neighboring countries.

This paper proposes a research roadmap for building a technologically universal virtual assistant based on European public sector legislation and standards. We expect that the assistant can be implemented into the existing member state employment service infrastructure while meeting certain legislative data and technological prerequisites. According to [26] "proactive services do not necessarily require a proactive government." The Virtual Competence Assistant (VCA) will use universal taxonomies to provide personalized recommendations on available job offers and training in the EU, which eventually will increase the mobility, quality, and quantity of lifelong learning. Ultimately, we argue that active labour market employment service provision can be automated with artificial intelligence and moved from reactive to proactive.

2. Research background

It was customary for a citizen to get a fundamental education, learn a profession and work for the rest of the working life, gradually increasing the skills related to the field with constant practice. However, in today's economy, we are increasingly experiencing whole sectors being closed down. E.g., in Estonia's Ida-Virumaa region, moving from fossil fuels to renewable energy sources means the closure of the oil shale sector, which will leave 8,000, household member,s into poverty [35]. On the other hand, there are new sectors constantly lacking a workforce. Hence, the mismatch between existing and future skills needs to be addressed with a focus on citizens' lifelong learning and

E-mail address: markko.liutkevicius@taltech.ee

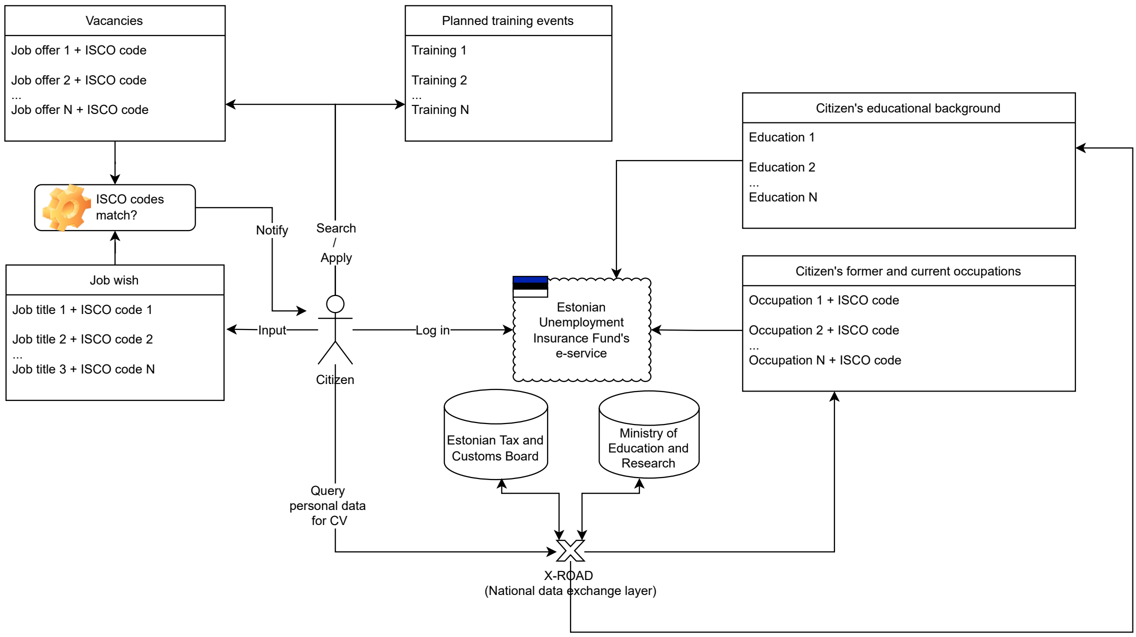

Fig. 1. Citizen's activities and data related to the Estonian Unemployment Insurance Fund's e-service

finding new ways how a government can facilitate the adoption of labor market changes. In addition to the rapid changes in the labour market, we see two significant issues: (i) the lack of intelligent matching between citizens' CVs and job or training advertisements and (ii) missing consideration of skills and qualifications during the matching process.

Today, many European public employment services, such as the Estonian Unemployment Insurance Fund, have built citizen's portals to provide support services such as applying for social security funding, finding and applying for a new job or training, etc. The functionalities of such portals vary, i.e., a citizen in Estonia has the option to request already existing personal information from other public sector organizations, i.e., educational information from the Ministry of Education and Research and previous work experience from the Tax And Customs Board. Such data exchange is made possible with the help of the national data exchange layer X-road. Fig. 1. Concludes current main activities any citizen, both employed or unemployed in Estonia, can do on such a platform when interested in finding a new job or training.

The main activities are filling in CV information, inserting job wishes, and applying for a job or training. In principle, any company can insert their job vacancy into the e-service, and any citizen can go and search from a list of vacancies or define a job wish. If the codes match, the citizen will receive an automatic notification from the e-service. Similar actions are possible with training. However, there is no functionality to insert a training wish and receive proper training notifications. The matching process between vacancy and job seeker is currently carried out with customized ISCO codes. The ISCO code is assigned to each job vacancy by a company and job wish by a citizen manually with the help of a built-in keyword algorithm. Still, such functionality is rigid and requires a citizen to define a valid ISCO code. More importantly, even when the filled-in CV consists of detailed previous work experience and educational background, if the ISCO code is not accurate, the e-service will not help the citizen find a new job. Moreover, in the latest English version of ISCO, hundreds of unit groups classify more than 7,000 job titles, so the possibility of only using ISCO codes for matching is problematic, especially with the growing number of new occupations. When it comes to labor market service provision, the situation varies in each country as all European member states have their own regional needs and requirements. However, on the European level, a European Employment Services (EURES) network facilitates the data exchange of job advertisement data among all EU countries. The network aims to empower the free movement of workers in EU-27 countries plus Switzerland, Iceland, Liechtenstein, and Norway. A single European member state and EURES are related in a data exchange partnership. The member state has implemented its e-service to supply job advertisement data to EURES automatically. Hence, any EU citizen can log into the EURES portal and search amongst all job advertisements and insert their CV. Consisting of more than 4M job advertisements brings forth a question of finding the most relevant job advertisements from the EURES portal. To date, the matching between job seekers and job advertisements on the EU and national level has been based on outdated International Standard Classification of Occupations (ISCO) [22].

Having more intelligent matching personal skills meeting the requirements of a vacancy could hugely improve today's situation. However, in today's public employment service portals, there is typically no option to insert specific skills that a citizen has to receive an increased number of accurate job or training recommendations. Moreover, new emerging occupations such as green transition and digitization need particular skillsets that can only be characterized through standardized skills, qualifications, and knowledge frameworks and tools using artificial intelligence. Hence, today the citizen must still search through thousands of advertisements to find suitable offers.

Surpassing this problem, the European Commission has released Article 19 of the EU Regulation 2016/589, requiring all member states to adopt the European classification of Skills, Competences, and Occupations (ESCO) or to map their national classification systems to ESCO [39]. The deadline is set three years from the Implementing Decisions 2018/1020, which arrived on August 2021 [40]. ESCO is a European initiative classifying skills, competencies, and occupations, forming three essential pillars of interrelated taxonomy. More importantly, the framework is translated into 27 EU member state languages enabling the potential to create interoperable services.

Based on [34], competency tools are "obsolete, and contemporary digitization requirements have not yet been incorporated into updated usable competency tools." As a result, despite many well-established competencies and occupational frameworks such as the Standard Occupational Classification (SOC), [15], ISCO, and ESCO, the existing citizen-centered services supporting upskilling and finding a new job are inefficient. Even if these classifications are effectively implemented, it requires manual resource-intensive work to get an accurate match between a citizen and a vacancy. Moreover, there are currently no recommendation services for finding appropriate training events. This has brought us to the national and cross-border opportunities we are addressing in the following years.

3. Scrutiny of the related work

The topic of job matching fostering public employment services dates back to the 1970s [30] [33] [7]. Most of the latest work in job matching is related to the improvement of CV information extraction [8] [9], classifying job vacancies [7] [6], relating vacancies to skills [29] or skills to vacancies [16] and building job matching recommender systems [24] [9] [1]. Surprisingly, many academic articles have previously covered the public sector context by addressing public employment services using artificial intelligence. E.g., predicting a citizen's probability of finding work is used to segment people into groups [11]. Because of the world's aging population, some of the focus in research related to public employment services targets older job seekers. For example, researchers have recently developed a job matching application for the elderly in Pangasinan Employment Service Office in Thailand [21].

Only a few attempts are made to create personalized virtual competence assistants, such as pedagogical recommender systems using data from university courses [38] or personal assistants for individuals to be aware of their job-related limitations and opportunities [5]. However, little focus is targeted on automating citizens' career and training advancement. Additionally, interoperability seems to be an essential issue in job-matching: "Each institution and job portal will have their data isolated, generating different information silos" [5].

There are many different standpoints on how job and training recommendation systems use AI to tackle scientific or real-life problems. One of the earliest authors targeting job recommendation with ML was in 2011 [32] where they used former job transition data of people in the US to predict their next job. Similar job transition data was used in Australia in 2014 while building a model with a cascade system combining career transitions with cosine similarity [20]. In 2018 researchers from the US were the first to adopt a representation learning framework for a job recommendation system [10]. Finally, in 2021, similar job transition data was used again in the US, proposing a two-stage embedding-based recommendation system architecture for a job to candidates matching [41].

Not all research on job recommendation systems targets was recommending jobs to people. For example, in 2011, researchers from Malaysia targeted their research to assist employers in identifying suitable soft skills for a position when preparing vacancy advertisements while developing and training a Bayesian Network Model [4]. Additionally, in 2017, research in China aimed to aid an employment network while building an online learning contextual algorithm using big data support for the job and candidate recommendation [13]. Later, in 2019, researchers from the Netherlands proposed an algorithm that matched graduating students and jobs reciprocally, allowing employers to recruit graduated students more effectively. Finally, in a recent study from 2020, researchers from Mauritius used ML techniques for building a recommendation system that can simplify the task of human resource personnel working in a company to focus on only a small selection of most promising candidates [2].

Two separate studies used occupational taxonomies such as Occupational Information Network (O*NET) [12] and the European Commission's project classifying skills, competencies, and occupations (ESCO) [17] as a supporting data set for creating vector models. However, surprisingly after 2011, when ESCO was established, there was scarce research involving the taxonomy as a data set, which can conclude that in scientific terms, there are only a few attempts made to combine ESCO with AI.

4. Proposed approach

The overall research is initiated following the Estonian Unemployment Insurance Fund's current developments and near-future needs. We explore how to enable a technical ecosystem using occupational classification frameworks so that citizens, both employed and unemployed, can receive proactive recommendations about upcoming training and personalized job recommendations. Such a system should be tailored to people's backgrounds, in which VCA supports citizen's life events, i.e., re-training or change of career path. The recommendations should not only be limited to the citizen's country of residence but also include offers to training and training courses in neighboring countries. While exploring the discovered problems in other EU countries, we discovered that the situation of labour market services offered by the public sector is similar. This is why our approach includes other countries and tries to maximize the usage of existing EU-level tools such as ESCO to enhance the data exchange and labor mobility in the EU, starting with the neighboring countries: Estonia, Latvia, and Finland. To have a more focused starting point, we begin by creating the VCA on an already existing platform. By adjusting the transnational platform from the OSIRIS Interreg BSR project (Virtual Collaborative Silver Hub), we plan to pilot the VCA on the 50+ age group in Estonia, Latvia, and Finland. By integrating our solution with the Silver Hub, we intend to improve job seekers' mobility and lifelong learning regionally for this population segment.

Consequently, our goal is to establish the VCA concept and define it as a "personalized virtual assistant to provide training and career development advice." To achieve that, we have initiated a project proposal for the Interreg's Central Baltic Program and partnered with three universities from Latvia and Finland and technical interoperability solution provider Nordic Institute for Interoperability Solutions (NIIS). Two universities from Finland: Häme University of Applied Sciences (HAMK) and Southeast Finland University of Applied Sciences (XAMK), will be covering the research in Finland, while researchers from Riga Technical University (RTU) will be conducting research in Latvia. NIIS supports and facilitates cross-border data exchange and related projects between its member countries, Estonia, Finland, and Iceland. NIIS is the software vendor of Harmony eDelivery Access, an open-source component for joining one or more eDelivery policy domains used widely in the European Union. We see that combining delivery and the ESCO framework can have tremendous potential for the future labour movement and competency development.

4.1. Research questions

Concluding the above, our research questions are:

- RQ1. How do existing occupational classification frameworks enable citizen-centered learning and career advancement automation?

  SQ1. How can the European labour market benefit from using the occupational classification systems in proactive services?

  SQ2. What existing data can be used, for what purpose, and what data needs to be created on the national level?
- RQ2. How to create a VCA based on an occupational classification framework?

SQ1. What type of existing AI models could be usable?
SQ2. What approach is required to train the model?
SQ3. How to implement VCA in the Estonian context?

- RQ3. How to scale VCA to other EU member states?
  SQ1. What adjustments are needed technically, politically, and legally?
  SQ2. How do we match data between countries to guarantee interoperability for cross-border data exchange?

RQ1 and RQ2 are formed based on the former discussion while having already conducted introductory focus group interviews and meetings with the Estonian Unemployment Insurance Fund and the Estonian Qualifications Authority. To approach RQ3, we have partnered with other universities where researchers will help conduct the research and answer the sub-questions while implementing the VCA on Silver Hub. Previously the Virtual Collaborative platform's focus was to integrate six regional clusters (Finland, Estonia, Latvian, Lithuanian, Danish, and Russian) to enhance transnational innovation and decrease the gaps in welfare, technology, and prosperity as all partners are facing the same common challenge of demographical change. The Silver Hub platform has a knowledge-sharing capacity between countries on both local and transnational levels to support cooperation and learning. It has brought together on united platform partners representing businesses, governments (public authorities), and research and development organizations who are all offering directly or indirectly services and products for the silver economy. Our research entails implementing and testing the VCA functionalities on age group 50+ and fully integrating them into Silver Hub.

4.2. Methodology

Since our research goal is creating the VCA and integrating it into the Silver Hub platform, we choose an approach that enables building an IT artifact embedded in the social environment of the organization. Hence for the fundamental research, action design research (ADR) elements are applied, mainly linked to the needs of the Estonian Unemployment Insurance Fund. the researcher will be shaping the IT artifact in collaboration with the practitioners addressing real-world problems. According to Sein et al., "ADR is a research method for generating prescriptive design knowledge through building and evaluating ensemble IT artifacts in an organizational setting" [37]. The researchers will collaborate and conduct research related to the subject of VCA, conducting semi-structured interviews and focus group discussions. Most importantly, while we deal with creating a citizen-centered VCA, the 50+ citizens in Estonia, Latvia, and Finland are interviewed, and the requirements are analyzed from the citizen's standpoint. Furthermore, to better understand national occupation and skills classification and national public employment services, other stakeholders in the public sector will be interviewed. In Estonia, this means organizations like the Statistics Estonia (maintaining national classifications such as ISCO), the Estonian Qualifications Authority (responsible for creating national skills classification system), the Estonian Tax and Customs Board (citizen's occupational data with ISCO), and Ministry of Education and Research (citizen's educational data).

International stakeholders participating in the research (NIIS, XAMK, HAMK, and RTU) participate in VCA concept validation and implementation. Additionally, we will use observation and document analysis combined with data provided by the involved stakeholders. Hence we are dividing our research into two iterations: Alpha and Beta, and four stages: (1) Problem formulation, (2) Building, intervention, and evaluation, (3) Reflection and learning, and (5) Formalization of learning.

4.2.1. Problem formulation

This stage will mainly focus on four areas. First, as we have contextual knowledge about the labour market situation in the three-member states, we must conduct a feasibility study on the 50+ population group to understand their age-specific needs and barriers in the labour market. Based on the outcomes, we will be able to gather user experience requirements for the VCA and the Silver Hub. With this information, the project partners will be able to find similarities and differences between the regions and member states and how to handle them in the VCA. For example, the Estonian Qualifications Authority is responsible for creating a national skills classification system and mapping it against the ESCO taxonomy in Estonia. We will compare similarities and differences in our partner countries at this stage. Secondly, we explore how the European labour market can benefit from using the occupational classification systems in proactive services. Such a solution must be as much automated and proactive as possible.

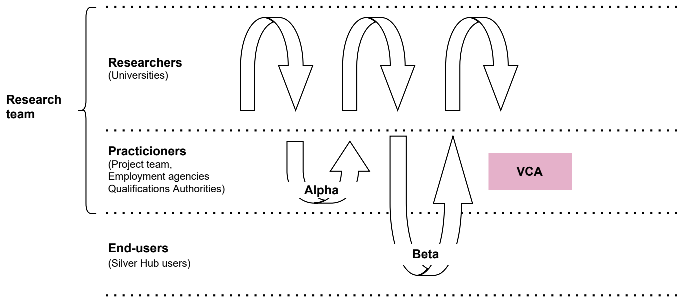

Fig. 2. Building, intervention, and evaluation scheme

The concept of proactive service is a relatively new field of research [14] [27] [25] [28] [36]. Importantly, it enables the introduction of "personalized agents" while eliminating the need for unnecessary interaction with the government. The outcome will be a conceptual model of VCA concerning the ESCO taxonomy. Thirdly, a state-of-the-art review of job and training recommendation systems will be conducted. Based on testing and data from this review, the most relevant labour market job and skills recommendation models will be selected to train the VCA model in the next stage. Lastly, a legal analysis will be conducted to understand the legislative environment, GDPR, and the current use of job/skills standards in the three countries. The result will be gathering requirements for the VCA to build the initial alpha version.

4.2.2. Building, intervention, and evaluation

The second stage composes of building the IT artifact, the intervention in the organization, and the evaluation (BIE) [37]. The study here will follow ADR's BIE scheme Fig. 2. In this stage, the system analysis will be made, incorporating the output from the feasibility study, state-of-the-art review, and the legislative environment analysis.

In the alpha cycle, the system analysis will create a conceptual design of the VCA that practitioners can use to implement the first version. Using the gained understanding, automatic job classification and training classification will be developed using the ESCO taxonomy, altering existing machine learning models and using them to design the concept of VCA for Silver Hub. In the alpha cycle, the researchers will design and iteratively evaluate the VCA's conceptual design and accuracy with partners from the Estonian Unemployment Insurance Fund and the Estonian Qualifications Authority. The partners' key role will be helping with existing public sector data such as CV-s, job vacancies, and training events. The alpha cycle will end with a pilot version of the VCA focusing on the Estonian labour market in the segment of 50+ year citizens. The output will be evaluated with Estonia's public sector organizations and partner universities.

The VCA design will be further refined in a beta cycle. Additional data is queried from Finland and Latvia to make the pilot version work in their languages. Finally, the beta cycle includes the intervention and evaluation among Silver Hub users in Estonia, Latvia, and Finland. The user feedback will be conducted as semi-structured interviews. Later the interviews will be translated and compared on a country basis. Eventually, the data from all three member states will be harmonized and implemented into Silver Hub. The interoperability issues between member states will be analyzed in collaboration with NIIS. NIIS has relevant experience in cross-border data exchange and supporting the design and implementation of data exchange platforms and ecosystems, bringing in the required expertise to make the VCA interoperable between EU member states.

4.2.3. Reflection and learning

All materials will be collected in this stage, and data triangulation will be used to identify a mismatch between theoretical literature, latest developments in ESCO occupations, skills, and qualifications to evaluate our solution and formalize VCA design principles. In addition, differences in the related countries' laws, technology, and policies will be analyzed using feedback from public sector authorities.

4.2.4. Formalization of learning

In the final stage, the concept of VCA will be formalized to characterize a general VCA for the European labour market. In this stage, we will approach Directorate-General Employment, Social Affairs and Inclusion in the European Commission, responsible for developing ESCO. We aim to conduct multiple workshops to improve the concept with revisions and receive their evaluation to derive general design principles for implementing the VCA in any European member state. ESCO will be the underlying classification for obtaining recommendations from cross-border. In this final stage, specific recommendations for improving citizen data quality will be proposed to achieve accurate job and training recommendation results.

5. Preliminary results

So far, the preparations for the research have been done, and the first stage (Problem Formulation) has been initiated. Preparations entailed mainly finding project partners and gathering a solid understanding of the Estonian and the European context. We have conducted meetings and semi-structured interviews with the Estonian Unemployment Insurance Fund and the Estonian Qualifications Authority. Additionally, we are in the process of interviewing Finnish authorities responsible for Virtual Finland and Aurora AI. In Estonia, initial interviews are pursued with the local, national-level experts accountable for implementing ESCO and creating the national skills classification. Comprehensive document analysis is sought in this activity, and actual real-life problems related to the lack of intelligent matching process and missing skill considerations are validated in collaboration with the Estonian experts. Additionally, relevant occupational and citizen-related data are currently being collected to map the existing situation and answer RQ1. Moreover, we have initiated a systematic literature review process over job and training recommendation systems. The most appropriate labour market recommendation methods will be used to train the VCA model. Our partners in Latvia and Finland have similarly started investigating the public service provision situation in their countries while contacting authorities responsible for EURES implementation and local governments dealing with skilled labour migration. To date, we have published a research paper addressing SQ1 of RQ1. Another paper addressing SQ1 of RQ2 is in the process of being published.

6. Expected Outcomes and Limitations

In this paper, we emphasized that the mismatch between existing and future skills needs to be addressed, focusing on citizens' lifelong learning and finding new ways how a government can facilitate the adoption of labor market changes. We identified and validated two significant issues: (1) the lack of intelligent matching between citizens' CVs and job or training advertisements and (2) missing consideration of skills and qualifications during the matching process. Addressing this, our goal is to create a VCA and validate how citizen-centered learning and career advancement enable automation and proactive service design. Thus, the final target is to design a VCA for 50+ citizens with the primary objective of matching employment data to actual job offers and training events. Concerning our initial model, we expect to have feedback from the Estonian Unemployment Insurance Fund, the Estonian Qualifications Authority, the Estonian Tax and Customs Board, and most importantly – the 50+ citizens registered in the Estonian Unemployment Insurance Fund. Finally, international research partners will validate the VCA concept adoption in Finnish and Latvian contexts, considering the differences in law, technology, and politics and the difference in the actual data. Like in any research, some limitations impact the current study. Most importantly, Estonia has been slowly implementing the ESCO system nationally compared to some other EU member states. Estonia is a small country and might not need such a comprehensive classification system at the national level. This, however, might not limit using ESCO for AI-enabled virtual assistants. However, it is not certain that ESCO can be used for building a VCA. For example, suppose the initial results in RQ1 show negative results (e.g., existing data is of poor quality and does not enable automating the classification of job vacancies). Other classification systems or approaches need to be considered before moving on to RQ2 and RQ3. Other constraints are related to the time and fiscal resources required to implement an actual VCA on the national level.

7. Acknowledgements

This work in the project "ICT programme" was supported by the European Union through European Social Fund. This work was supported by grants to TalTech – TalTech Industrial (H2020, grant No 952410) and Estonian Research Council (PRG1573). The authors would like to acknowledge Mrs Mari Väli from the Estonian Unemployment Insurance Fund.

References

[1] K. Appadoo, M. B. Soonnoo, and Z. Mungloo-Dilmohamud. Job recommendation system, machine learning, regression, classification, natural language processing. In *2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE)*, pages 1–6, 2020.

[2] K. Appadoo, M. B. Soonnoo, and Z. Mungloo-Dilmohamud. Job recommendation system, machine learning, regression, classification, natural language processing. *2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering, CSDE 2020*, 12 2020.

[3] R. Ayachi, I. Boukhris, S. Mellouli, N. Ben Amor, and Z. Elouedi. Proactive and reactive e-government services recommendation. *Univers. Access Inf. Soc.*, 15(4):681–697, nov 2016.

[4] A. A. Bakar and C.-Y. Ting. Soft skills recommendation systems for it jobs: A bayesian network approach. *Conference on Data Mining and Optimization*, pages 82–87, 2011.

[5] D. Baneres and J. Conesa. A life-long learning recommender system to promote employability. *International Journal of Emerging Technologies in Learning (iJET)*, 12(06):pp. 77–93, Jun. 2017.

[6] R. Boselli, M. Cesarini, F. Mercorio, and M. Mezzanzanica. Using machine learning for labour market intelligence. In *ECML/PKDD*, 2017.

[7] R. Boselli, M. Cesarini, F. Mercorio, and M. Mezzanzanica. Classifying online job advertisements through machine learning. *Future Gener. Comput. Syst.*, 86:319–328, 2018.

[8] J. Chen, C. Zhang, and Z. Niu. A two-step resume information extraction algorithm. *Mathematical Problems in Engineering*, 2018:1–8, 2018.

[9] Y.-C. Chou and H.-Y. Yu. Based on the application of ai technology in resume analysis and job recommendation. *2020 IEEE International Conference on Computational Electromagnetics (ICCEM)*, pages 291–296, 2020.

[10] V. S. Dave, M. A. Hasan, B. Zhang, K. AlJadda, and M. Korayem. A combined representation learning approach for better job and skill recommendation. *International Conference on Information and Knowledge Management, Proceedings*, 9:1997–2006, 10 2018.

[11] S. Desiere and L. Struyven. Using artificial intelligence to classify jobseekers: The accuracy-equity trade-off. *Journal of Social Policy*, 50(2):367–385, 2021. cited By 1.

[12] M. Diaby and E. Viennet. Taxonomy-based job recommender systems on facebook and linkedin profiles. *Proceedings - International Conference on Research Challenges in Information Science*, 2014.

[13] S. Dong, Z. Lei, P. Zhou, K. Bian, and G. Liu. Job and candidate recommendation with big data support: A contextual online learning approach. *2017 IEEE Global Communications Conference, GLOBECOM 2017 - Proceedings*, 2018-January:1–7, 7 2017.

[14] R. Erlenheim. Designing proactive public services. phd dissertation. Tallinn University of Technology, 2019.

[15] Executive Office of the President. Office of Management and Budget. Standard occupational classification manual, 2012.

[16] A. Giabelli, L. Malandri, F. Mercorio, M. Mezzanzanica, and A. Seveso. Skills2job: A recommender system that encodes job offer embeddings on graph databases. *Applied Soft Computing*, 101:107049, 12 2020.

[17] A. Giabelli, L. Malandri, F. Mercorio, M. Mezzanzanica, and A. Seveso. Skills2job: A recommender system that encodes job offer embeddings on graph databases. *Applied Soft Computing*, 101, 3 2021.

[18] Government CIO Office. Estonia's national artificial intelligence strategy 2022-2023, 2021.

[19] Government of Finland. Suunnitteluvaiheen raportti, 2021.

[20] B. Heap, A. Krzywicki, W. Wobcke, M. Bain, and P. Compton. Combining career progression and profile matching in a job recommender system. pages 396–408, 2014.

[21] K. Homsapaya and K. Budsara. Machine learning for older jobseeker and employment matching. In *2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, pages 427–430, 2020.

[22] International Labour Office (ILO). International standard classification of occupations. structure, group definitions and correspondence tables, 2012.

[23] International Labour Organization. World employment and social outlook: Trends 2021, 2021.

[24] M. Koh and Y. Chew. Intelligent job matching with self-learning recommendation engine. *Procedia Manufacturing*, 3:1959–1965, 12 2015.

[25] H. Kroonmäe. mplementing proactive services in estonian local governments, master thesis, tallinn. Tallinn University of Technology, 2017.

[26] P. Kuhn, M. Buchinger, and D. Balta. How to redesign government processes for proactive public services? In H. J. Scholl, J. R. Gil-Garcia, M. Janssen, E. Kalampokis, I. Lindgren, and M. P. Rodríguez Bolívar, editors, *Electronic Government*, pages 29–40, Cham, 2021. Springer International Publishing.

[27] H. Kõrge. Designing proactive business event services: a case study of the estonian company registration portal, master's thesis, tallinn. Tallinn University of Technology, 2019.

[28] D. Linders, C.-P. Liao, and C.-M. Wang. Proactive e-governance: Flipping the service delivery model from pull to push in taiwan. *Government Information Quarterly*, 35:S68–S76, 10 2018.

[29] P. G. Lovaglio, M. Cesarini, F. Mercorio, and M. Mezzanzanica. Skills in demand for ict and statistical occupations: Evidence from web-based job vacancies. *Statistical Analysis and Data Mining: The ASA Data Science Journal*, 11, 2018.

[30] R. E. Lucas and E. C. Prescott. Equilibrium search and unemployment. *Journal of Economic Theory*, 7(2):188–209, 1974.

[31] Ministry of Finance. Auroraai – towards a human-centric society. development and implementation plan 2019–2023 based on the preliminary study on the aurora national artificial intelligence programme, 2019.
[32] I. Paparrizos, B. B. Cambazoglu, and A. Gionis. Machine learned job recommendation. *RecSys'11 - Proceedings of the 5th ACM Conference on Recommender Systems*, pages 325–328, 2011.
[33] R. L. Peterson. Economics of information and job search: Another view. *The Quarterly Journal of Economics*, 86(1):127–131, 1972.
[34] F. Polo and J. Kantola. Tomorrow's digital worker: A critical review and agenda for building digital competency models. 1209 AISC:107–115, 2020.
[35] Praxis Centre for Policy Studies. Adaptation of ida-virumaa county´s economy and labor market to the reduction of oil shale industry, 2020.
[36] H. Scholta, W. Mertens, M. Kowalkiewicz, and J. Becker. From one-stop shop to no-stop shop: An e-government stage model. *Government Information Quarterly*, 36(1):11–26, 2019.
[37] M. K. Sein, O. Henfridsson, S. Purao, M. Rossi, and R. Lindgren. Action design research. *MIS Quarterly*, 35(1):37–56, 2011.
[38] W. Swartout, B. Nye, A. Hartholt, A. Reilly, A. Graesser, K. VanLehn, J. Wetzel, M. Liewer, F. Morbini, B. Morgan, L. Wang, G. Benn, and M. Rosenberg. Designing a personal assistant for life-long learning (pal3). In Z. Markov and I. Russell, editors, *Proceedings of the 29th International Florida Artificial Intelligence Research Society Conference, FLAIRS 2016*, Proceedings of the 29th International Florida Artificial Intelligence Research Society Conference, FLAIRS 2016, pages 491–496. AAAI press, 2016.
[39] The European Union. Regulation (eu) 2016/589 of the european parliament, 2016.
[40] The European Union. Commission implementing decision (eu) 2018/1020 of 18 july 2018, 2018.
[41] J. Zhao, J. Wang, M. Sigdel, B. Zhang, P. Hoang, M. Liu, and M. Korayem. Embedding-based recommender system for job to candidate matching on scale. 7 2021.

Appendix 2

II

M. Liutkevičius, M. Weck, and S. B. Yahia. Understanding the Challenges of Today's Labor Market Service Provision in the EU. *Human Factors, Business Management and Society*, 97(97), 2023

Human Factors, Business Management and Society, Vol. 97, 2023, 30–39
https://doi.org/10.54941/ahfe1003880

Understanding the Challenges of Today's Labor Market Service Provision in the EU

Markko Liutkevičius[1], Sadok Ben Yahia[1], and Marina Weck[2]

[1]Data Science Research Group, Department of Software Science, TALTECH, Estonia
[2]HAMK Smart Research Unit, Häme University of Applied Sciences, PL 230, FIN-13101, Hämeenlinna, Finland

ABSTRACT

This paper explores the challenges of today's labor market service provision in the EU, where, based on our expertise, insufficient scientific inquiry has been conducted. As there are many different focus points and factors to consider in the modern turbulent labor market, we identify the main challenges along with a list of existing scientific discussions. The central finding of the paper is that there is a lack of central collaboration between stakeholders and poor attention toward implementing changes required to meet labor market needs. We found that change management is insufficiently integrated into the service provision of the EU's public employment services. This study contributes input for building an artificial intelligence-enabled virtual assistant to help serve the needs of labor markets and citizens.

Keywords: AI, Artificial intelligence, Virtual competency assistant, Labor market

INTRODUCTION

Emerging technologies and the need for high-level skills in the labor market have caused several issues for different age groups. Despite substantial growth in employment rates of older workers in many EU countries over the past decade, the European Commission's *Joint Employment Report* (Directorate-General for Employment, 2022) highlights the potential to further increase these rates. As the population ages, the median age of the labor force has risen to 44.1 years (Eurostat, 2022a). People are staying active in their work life for longer, which in turn brings demand for the skillsets that reflect the current labor market environment. This has also brought calls to align the trainings funded by public employment services (PESs) to the current and future demands of the labor market. Furthermore, workers at the opposite end of the age spectrum tend to struggle with finding their first job. Unemployment among youth between the ages of 15 and 24 is currently 14% in the EU, which is much higher than in other age groups (Eurostat, 2022b). This highlights a crucial requirement for comprehending the most appropriate skillsets to facilitate the successful integration of younger and older individuals into the labor market, ultimately reducing the gap between the skills taught in education and the skills in high demand in the job market.

In addition to these age group-specific problems, digitalization has had a significant impact on the EU labor market. One example is seen in the ongoing anxiety over the potential for artificial intelligence (AI) to cause workers to lose jobs as workloads are automated. Emerging technologies such as ChatGPT already have the capability to significantly influence the situation in the labor market. It is clear that with ChatGPT's capabilities, some employers can reduce their number of employees but retain workers who can effectively collaborate with these systems, which requires a deep understanding of AI technologies. In addition to demographic challenges and digitalization, a recent report revealed that in 2020, the COVID-19 pandemic caused the loss of 144 million jobs, fueling a drastic shortage of employment opportunities (International Labour Organization, 2021).

Our broader research aims to build and validate an AI-enabled virtual assistant model, such as a virtual competency assistant, for the European labor market. The broader research explores the possibility of creating a scalable AI model for the EU labor market. However, in order to do so, we need to understand the existing difficulties with the PES provision. The aim of this paper is to understand the context of current challenges in today's active labor market service provision in the public sector. Accordingly, the research question is as follows: What are the main challenges to PES provision in the EU?

CHALLENGES IN THE EU PES SECTOR

In the following subsections, the challenges of existing labor market service provision by the EU's member states is presented based on the scientific literature and official sources.

Marginalized Groups

One of the major challenges facing active labor market service provision in the EU is the limited reach and accessibility for vulnerable and marginalized groups. According to Shore and Tosun (2017), investing in a PES's institutional capacity and the quality of its services can improve young people's attitudes to overcome discouragement and improve their trust in public institutions. Often the groups most in need of active labor market services "are also furthest from the labour market, thus requiring the most time and resources to help" (Bontenbal & Lillie, 2022, p. 864). For example, the COVID-19 crisis had a negative impact on labor market outcomes for marginalized groups, including women, older workers, low-skilled individuals, individuals with disabilities, rural and remote populations, the LGBTIQ community, Roma and other ethnic or racial minorities who face exclusion and discrimination, as well as those with a migrant background (European Union, 2021). When looking at general labor market age groups specifically, the participation rates of workers ages 50 to 64 in the EU labor market increased from 40% in 2001 to 64% in 2021 (OECD, 2022). At the same time, participation rates of younger worker (between the ages of 15 and 24) declined from 45% in 2001 to 39% in 2021. Integrating older workers and younger workers into the labor market for longer periods is a growing challenge in Europe. Employers generally do not seek new workers from the older population because the majority of workers beyond a certain age are unable to change their core skills. However, the lack of former work experience among younger generations (Generation Z) is not attractive to employers because of the resource-intensive skills development required for younger employees to start providing value. Generation Z has two times higher unemployment rates compared to any other age group (OECD, 2022). Notably, in 2021 in the EU, the average percentage of young people between the ages of 15 and 24 who were neither working nor studying was 10% (Eurostat, 2021).

Evaluation and Monitoring

In general, the aim of labor market evaluation and monitoring is to ensure that services are meeting the needs of employers and citizens. These components are crucial in the area of PES, as they can provide valuable information on the impact and effectiveness of these services, allowing public sector organizations to identify areas for improvement and respond to changing labor market needs. The EU provides labor market support to member states through a program called the European Social Fund (ESF). To avoid falling into long-term unemployment, offering support as early as possible, especially to marginalized groups "due to [a] complex set of issues" (European Network of Public Employment Services, 2022), is a critical component. The ESF provides measures for job search assistance, training programs, and employment promotion. However, a recent audit highlighted a persistent weakness in the ESF's monitoring and evaluation framework (European Court of Auditors, 2021). Namely, the absence of a separate category for specific target groups (such as the long-term unemployed) prevents the identification of EU funding allocations for such measures as well as the evaluation of their outcomes and impact on the target group. Similar problems appear at the EU member state level. For example, in a recent report the Estonian PES was criticized for not providing more precise targeting and evaluating the impact of training courses (Estonian National Audit Office, 2022). Specifically, the Estonian Unemployment Insurance Fund only monitored whether an individual achieved employment after graduating and training but not whether the training actually helped the individual in the new position.

Variations in Delivering PESs in the EU

Although the decentralization of PESs has been implemented in numerous countries in recent years, few studies have examined its impact. In the Italian labor market, private employment agencies and trade unions also play a role, providing employment services and representation for workers (Punta, 2019).

Similar to the Italian approach, in spring 2021, Finland also decided to transfer its employment services to local municipalities (Ministry of Economic Affairs and Employment, 2021). In Finland, these regional PESs (also referred to as Te-Palvelut, TE-Offices, or Te-Toimisto) support individuals in their job search efforts. Through these offices, individuals can register as unemployed job seekers, access vocational training programs, and receive support with finding employment.

In Germany, the Federal Employment Agency (Bundesagentur für Arbeit) is responsible for the PES. The agency operates through a network of local branches located throughout Germany, which provide access to its services and support to job seekers and employers across the country (German Federal Employment Agency, 2023). However, since 2012, Germany has had a second type of regional job center that is decentralized from the Federal Employment Agency, allowing for easier adaptation to local labor market needs. According to recent research in Germany, the decentralization of 41 federally managed job centers at the district level led to a 10% decrease in job searches within five years (Mergele & Weber, 2020).

Adapting to Changing Labor Market Needs

The labor market is constantly changing and thus requires constant reallocation of resources. One example is the gig economy and other forms of non-standard work. The gig economy is often associated with the rise of digital platforms, such as Uber and Airbnb, which facilitate the matching of workers with short-term or project-based job opportunities as opposed to permanent jobs. In the gig economy, individuals typically provide their services on a flexible, project-by-project basis and are not considered employees of the companies they work for. This model has both advantages and disadvantages, with individuals enjoying greater flexibility and control over their work schedules but often lacking access to benefits and protections typically available to employees. More importantly, it was recently established that participating in real-time ridesharing service delivery does not serve as a substitute for traditional jobs in terms of "bridging employment gaps" (Li, et al., 2019, p. 11). The gig economy has been growing rapidly in recent years and is becoming an increasingly important aspect of the labor market. However, the regulatory and legal framework for gig work is still evolving, and there is ongoing debate about how best to ensure that gig workers are protected and that the gig economy operates in a fair and sustainable way (Todolí-Signes, 2017).

Defining the Required Skills

Additional difficulties that PES face are in defining which careers have a positive outlook for the future. Combining big labor market data with AI technologies can provide some insights and reveal megatrends (Opik et al., 2018). Such megatrends affecting the job market today include automation, digitalization, globalization, and demographic changes. These trends are shaping the future of work, with far-reaching implications for businesses, workers, and the economy as a whole. There have been numerous studies on this topic, but because of limited resources, these studies have been limited to focusing on specific fields. For example, Finnish company Headai Oy launched a pilot project in 2020 with the Estonian Qualification Authority

(Kutsekoda) to conduct a skills gap analysis of Estonian job ads and specific curriculum data for mechatronics (SA Kutsekoda/OSKA, 2020). The study did not provide the expected outcomes on predicting the emerging skills, and the main weakness of the report was a limited understanding of the Estonian language because their main model only knew Finnish, Swedish, and English.

METHODOLOGY

The overall research methodology being used in our study is action design research (Sein et al., 2011) due to the nature of the research questions. In the autumn of 2022, we conducted seven semi-structured focus group interviews over a two-month period. To identify challenges in the European labor market and services such as PES, interested stakeholders, researchers, specialists, and experts were brought together to share their diverse knowledge in focus group meetings held in Italy, Estonia, and the online communication platform MS Teams. In total, there were 43 focus group participants from six different countries: Estonia, Finland, Latvia, Germany, Norway, and Italy.

To analyze the group interview data from all meetings, thematic analysis was employed, as it enables inductive and data-driven analysis. According to Braun and Clarke (2006), thematic analysis is a method that entails recognizing, analyzing, and presenting patterns or themes within data, thereby providing a detailed account of the dataset. The qualitative data analysis approach was employed with the aid of the NVivo software. This approach has become increasingly popular due to its versatility and ease of use and is often employed in the analysis of complex interview data (Braun and Clarke, 2012). The analysis process occurred in two stages. In the first stage, data were independently coded for each country to comprehend each region's specific conditions. The collected interview data were analyzed to identify individual codes. In the second stage, general themes were identified and defined using cross-country comparisons. The results were then triangulated with desk research to validate themes from the focus group interviews. For example, when a certain theme was found from the interviews related to a particular issue, a related literature research was made to gather additional information on this theme.

RESULTS

In this section, we explore the various barriers and challenges facing active labor market service provision. By understanding these challenges and barriers, we aim to highlight the importance of addressing these issues. The following challenges in labor market service provision were identified from the thematic analysis:

- Poor focus on marginalized groups;
- Lack of effective evaluation and monitoring;
- Inadequate coordination between PESs, job providers, and job seekers;
- Lack of flexibility to adapt to changing labor market needs;

- Limited integration with other social and employment services; and
- Resistance to change and to innovation in service delivery.

Poor Focus on Marginalized Groups

Participants from Estonia and Germany reported that PESs are often faced with limited resources, such as funding and personnel, which hinders their ability to effectively support marginalized and vulnerable groups in the labor market. Participants from Finland and Latvia reported that PESs often lack adequate data collection and analysis tools to effectively target their services to marginalized and vulnerable groups. Participants from Italy reported that EU PESs often face challenges in reaching out to marginalized and vulnerable groups and making their services accessible to these populations. Participants from Norway and Germany reported that EU PESs often lack coordination with other stakeholders, such as employers, trade unions, and civil society organizations, which makes it difficult for these services to effectively support marginalized and vulnerable groups.

Lack of Effective Evaluation and Monitoring

Participants from Estonia and Germany reported that PESs often lack adequate data collection and analysis tools to effectively evaluate and monitor their services and their impact on the labor market. Participants from Finland and Latvia reported that it was unclear what kind of performance indicators were used by their countries' PESs to evaluate their services and assess their effectiveness. The choice of performance indicators should depend on the specific goals and objectives of the national or regional PES and the populations they serve. Participants from Norway and Germany reported that employment services often lack meaningful engagement with stakeholders, such as trade unions, employers, and civil society organizations. This makes it difficult to assess their effectiveness from a broader perspective.

Inadequate Coordination Between PESs, Job Providers, and Job Seekers

All participants in the focus group meeting agreed that on a member state level, labor market service provisions in their country are a diverse and fragmented system, indicating coordination issues between stakeholders. According to Italian participants, the country's PES system is fragmented and divided into multiple entities with different responsibilities and areas of expertise. The national PES, Agenzia Nazionale per le Politiche Attive del Lavoro, is tasked with the development and implementation of national employment policies, while regional PESs, such as the regional employment centers, are responsible for delivering employment services, including job placement and training programs. German participants indicated that some German PES provisions overlapped, which could be confusing and ineffective for individuals in need of support.

Lack of Flexibility to Adapt to Changing Labor Market Needs

Participants from Finland and Latvia reported that forecasting future skills and jobs based on megatrends is intriguing, but there are many who are skeptical about its accuracy and usefulness. The problem is that these megatrends are usually not very relevant on a local scale (e.g., a region of a country). Conducting local skills forecasting has limitations in terms of available data. Such data must come from local industries in collaboration with labor market services. PESs can then allocate resources to providing upskilling and reskilling trainings required by the labor market. Unfortunately, the link between industries and the labor market is weak because extracting data from industries requires numerous resources from multiple stakeholders, as supported by the findings of SA Kutsekoda/OSKA (2020).

Limited Integration With Other Social and Employment Services

The majority of interviewees were particularly concerned about the limited ability of PESs. In each country, different institutions and organizations were responsible for different aspects of the activities related to labor market services. Thus, a job seeker who might be interested in a job in another region or country and needs help with relocation would have to apply for assistance through a different agency other than the PES. This is highly important issue because "being mobile is the only alternative to a decline in social status or even poverty" (Ludwig-Mayerhofer & Behrend, 2015, p. 337). In addition, to register for a training or educational program with the intention of improving their employment prospects, job seekers must turn to a specific educational agency. Such a lack of integration can lead to additional barriers for job seekers to receive the support needed to find employment. We found such integration problems in PESs in Estonia, Finland, and Germany. All participants agreed that limited integration between European member states' PESs and other social and employment services is a complex issue, especially for vulnerable and marginalized groups.

Resistance to Change and to Innovation in Service Delivery

The focus group discussions indicated that most EU member states have not yet been able to implement the European Skills, Competences, Qualifications and Occupations (ESCO) taxonomy into their existing PES platforms. One factor contributing to this slow adoption was the resistance to change and innovation in the PES sector. Hence, the lack of a unified approach has led to different interpretations and implementations of ESCO, further complicating its adoption across the EU. Participants from Estonia noticed challenges associated with integrating ESCO into existing national systems and processes, as most of the existing portals used an older classification called the International Standard Classification of Occupations. This can lead to compatibility issues with existing databases, challenges mapping national statistics or qualifications to the ESCO system, and difficulties ensuring the quality and comparability of the data collected.

CONCLUSION

Active labor market services play a crucial role in supporting citizens seeking employment or to maintain relevant skills. Despite its importance, the effective provision of these services is faced with numerous challenges that can impact the ability of service providers such as PESs to effectively support citizens in their search for relevant employment and training, leading to negative outcomes for citizens and the wider economy.

Our research has uncovered numerous significant hurdles within the European PES sector. Our findings indicate that there is a poor focus on marginalized groups, a lack of effective evaluation and monitoring systems, limited integration with other social and employment services, and a lack of flexibility to adapt to changing labor market needs. Additionally, our research found evidence of resistance to change and innovation in PES service delivery.

Importantly, there has been limited research on various aspects of European PESs. Specifically, inadequate coordination between PESs, job providers, and job seekers and a high administrative burden for PESs have not been adequately investigated. We also found that there has been limited scientific research conducted in the field of change management and innovation in the PES sector.

These findings highlight the need for a comprehensive review of the European PES sector with a focus on developing effective strategies to address these challenges. This will require a collaborative effort from all stakeholders, including governments, PES providers, job seekers, training providers, educational institutions, and employers. It will be important to develop effective evaluation and monitoring systems as well as to implement innovative approaches to service delivery. This will not only help to address the challenges facing the European PES sector but also help to improve outcomes for job seekers and ensure that the PES sector remains relevant and responsive to changing labor market needs.

Finally, the lack of a unified understanding of current and future occupations and skills is negatively affecting cross-border and regional labor migration as well as opportunities for upskilling and retraining. However, recent developments in AI have demonstrated the potential to significantly contribute to societal success by improving PESs, developing better upskilling, and matching humans with job opportunities using advanced tools to better understand and address the changing demands of the labor market.

ACKNOWLEDGMENT

This work was part of the ICT Programme project supported by the European Union through the European Social Fund. The authors would like to express their sincere appreciation to the participating specialists, researchers, and experts—Tallinn University of Technology (TalTech), Häme University of Applied Sciences (HAMK), Friedrich-Alexander University Erlangen-Nürnberg (FAU), Riga Technical University (RTU), Regional Competence Centre ICT (CeRICT), Global Universal Design Commission Europe

(GUDC-EU), Fraunhofer IIS (FIIS), and Employers' Confederation of Latvia (LDDK)—for their valuable contributions and support.

REFERENCES

Bontenbal, I. & Lillie, N., 2022. Minding the Gaps: The Role of Finnish Civil Society Organizations in the Labour Market Integration of Migrants. *Voluntas,* 333(5), pp. 862–871.

Braun, V. & Clarke, V., 2006. Using thematic analysis in psychology. *Qualitative Research in Psychology,* 3(2), pp. 77–101.

Braun, V. & Clarke, V., 2012. Thematic analysis. In: *APA handbook of research methods in psychology, Vol 2: Research designs: Quantitative, qualitative, neuropsychological, and biological.* s.l.: American Psychological Association, pp. 57–71.

Directorate-General for Employment, 2022. *Joint Employment Report 2022,* Brussels: Publications Office of the European Union.

Estonian National Audit Office, 2022. *National Audit Office: The Unemployment Insurance Fund must verify which training is useful for finding a job and check the level of training courses,* Tallinn: Estonian National Audit Office.

European Court of Auditors, 2021. *ESF support to combat long-term unemployment. Measures need to be better targeted, tailored and monitored,* Luxembourg: European Union.

European Network of Public Employment Services, 2022. *Support to vulnerable groups, Thematic paper,* Brussels: European Commission.

European Union, 2021. Commission Recommendation (EU) 2021/402 of 4 March 2021 on an effective active support to employment following the COVID-19 crisis (EASE). *Official Journal of the European Union,* Volume 64.

Eurostat, 2021. *Young people neither in employment nor in education and training (15-24 years),* s.l.: Eurostat.

Eurostat, 2022. *Most EU capital regions had fairly young populations,* s.l.: Eurostat.

Eurostat, 2022. *Youth unemployment, EU labour force survey,* Brussels: Eurostat.

German Federal Employment Agency, 2023. *German Federal Employment Agency.* [Online] Available at: https://www.arbeitsagentur.de.

Glenn, A. B., 2009. Document analysis as a qualitative research method. *Qualitative Research Journal,* 9(2), pp. 27–40.

International Labour Organization, 2021. *World employment and social outlook: trends 2021,* Geneva: International Labour Organization.

Li, L., Dillahunt, T. R. & Rosenblat, T., 2019. *Does driving as a form of "gig work" mitigate low-skilled job seekers' negative long-term unemployment effects?.* s.l., Association for Computing Machinery.

Ludwig-Mayerhofer, W. & Behrend, O., 2015. *Enforcing Mobility: Spatial Mobility under the Regime of Activation.* s.l., Routledge.

Mergele, L. & Weber, M., 2020. Decentralization, job placements, public employment services. *Journal of Public Economics,* Volume 182, pp. 104–113.

Ministry of Economic Affairs and Employment, 2021. *TE services reform 2024.* [Online] Available at: https://tem.fi/en/te-services-reform-2024.

OECD Labour Force Statistics, 2022. *OECD Labour Force Statistics 2021,* Paris: OECD Publishing.

Opik, R., Kirt, T. & Liiv, I., 2018. Megatrend and Intervention Impact Analyzer for Jobs: A Visualization Method for Labor Market Intelligence. *Journal of Official Statistics,* 34(4), pp. 961–979.

Punta, R. d., 2019. Labour market reforms and beyond: The Italian case. *International Journal of Comparative Labour Law and Industrial Relations,* 35(3), pp. 355–378.

SA Kutsekoda/OSKA, 2020. *Project report for Labor Market Analysis and Curricula Gap Assessment using Big Data in Estonia for Estonian,* Tallinn: Estonian Qualifications Authority.

Sein, M. K. et al., 2011. *Action design research*. s.l., MIS Quarterly.

Shore, J. & Tosun, J., 2017. *Assessing youth labour market services: Young people's perceptions and evaluations of service delivery in Germany.* s.l., SAGE Publications.

Todolí-Signes, A., 2017. *The 'gig economy': employee, self-employed or the need for a special employment regulation?*. s.l., SAGE Publications.

Appendix 3

III

M. Liutkevičius and R. Erlenheim. Validating the usage of Occupational Classification Systems in the Process of Creating a National Virtual Competency Assistant within the EU Labor Market. *ICEGOV '21: Proceedings of the 14th International Conference on Theory and Practice of Electronic Governance*, 7:254–259, 2022

Validating the usage of Occupational Classification Systems in the Process of Creating a National Virtual Competency Assistant within the EU Labor Market

Markko Liutkevičius
Tallinn University of Technology, Akadeemia tee 15a, 12618 Tallinn, Estonia
markko.liutkevicius@taltech.ee

Regina Erlenheim
Tallinn University of Technology, Akadeemia tee 15a, 12618 Tallinn, Estonia
regina.erlenheim@taltech.ee

ABSTRACT

Despite many national and international classification systems and organizational competency models being developed, there is still a lot of resource intensive manual workload dependent on career counselors and human resource departments. With the growing mismatch between labor market demand and supply, we aim to establish an initial concept for building a virtual competency assistant that uses European occupational taxonomy adopted on national level. Although Estonia's digital government ecosystem is widely known with its paperless management and broad use of e-services, its citizens lack proactive e-services related to career development. This paper validates current developments in the field of occupational classification systems associated to the Estonian Unemployment Insurance Fund through providing initial results gathered with qualitative methods. The results show that the existing e-service for the unemployed citizens of Estonia is not using modern automated methods that provide analysis of citizen's data and offer suitable trainings or job offers. The research offers initial findings in the process of advancing personal career developments of the EU citizens with proactive e-services while maintaining labor data interoperability across the EU.

CCS CONCEPTS

• **Information Systems**; • **Computing methodologies**; • **Artificial intelligence**; • **Distributed artificial intelligence**; • **Intelligent agents**;

KEYWORDS

Occupational Classification, Virtual Competence Assistant, Human Resource Development, Proactive Career Agent

ACM Reference Format:
Markko Liutkevičius and Regina Erlenheim. 2021. Validating the usage of Occupational Classification Systems in the Process of Creating a National Virtual Competency Assistant within the EU Labor Market. In *14th International Conference on Theory and Practice of Electronic Governance (ICEGOV 2021), October 06–08, 2021, Athens, Greece.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3494193.3494228

ICEGOV 2021, October 06–08, 2021, Athens, Greece

ACM ISBN 978-1-4503-9011-8/21/10…$15.00
https://doi.org/10.1145/3494193.3494228

1 INTRODUCTION

Through time, the labor market has evolved according to market needs. By now we have reached to a point where we can say that the near future labor market is strongly influenced by the COVID-19 pandemic and renewable energy strategies. COVID-19 crisis has changed the labor market in a way that many households have lost their income and thus increasing the unemployment rate. Additionally, switching from pollution towards renewable energy gives even more pressure to existing labor market because moving from old economy to new requires new qualifications, skillsets and knowledge. For example, while Portugal was in 2019 one of the biggest producers of clean energy in the EU, it had an unemployment rate of 6,6% while the EU average rate was 6,5% [1]. Today it is unclear to which extent the recovery from the collapse of tourism and service sector caused by COVID-19 pandemic will succeed. However, switching to renewable energy will certainly create new jobs, but also increase unemployment rates in countries that are only in the beginning of implementing renewable energy strategies. For example, according to Praxis, in Estonia's Ida-Virumaa region, where 40% of biggest companies are oil shale companies, the closure of oil shale sector will leave 8000 household members into poverty [2]. This raises massive need to retrain huge number of people on top of the currently unemployed, which is above 8% of working age citizens currently in Estonia.

As we are increasingly moving towards proactive and automated services in the process of building e-governance related solutions, the complexity related to how governments can satisfy the needs of their citizens in challenging times needs to be addressed. Thus, Estonia has been focusing on digital government ecosystems by investigating technologies that support digital transformation. That includes the understanding of architectural needs along with the requirements of the end-user. Based on over two decades of experience the most crucial parts in Estonian e-governance developments have been digital data exchange [3] and digital signing as critical step to move to paperless government [4]. In addition to state level digital transformation, the digitalization has additionally involved to the state level developments along with local governments [5] where many developments have been built upon document management systems [6]. Moreover, as part of the transition to e-government, paperless management enables creation of e-services that allow fully digitalized interaction between citizens and government entities.

Over several years, numerous integrations have been developed based on digital data exchange systems, e.g. interfaces with national registries, financial and personnel software, etc. Information management in a common system and cross-usage of data allows better monitoring of the procedural steps. Although interdisciplinarity is the main emphasis nowadays, still technological solutions are increasingly dominating factors in the move towards e-governance realizations and Estonian practice has demonstrated good evidence in that regard [7]. However, besides the high level of digitalization within government processes and public services, Estonia has taken the next generation towards automatization and use of AI within public services. In that regard, Estonia has developed a new vision Next Generation Government Architecture vision paper, where Chief Technology Officer (CTO) of Estonia with his team proposes action plan along with a new approach in a more innovative way in the area of public sector service implementation [8]. Primarily focus on updating the technology along with the domain driven design, business process modelling and related flow tools should create a new synergy within Estonian e-Governance architecture. That includes moving from monolithic applications toward an event driven microservices architecture. Besides updating monolithic applications toward an event driven microservices architecture, one important focus has taken here on use of AI in government services Estonian government by creating the chatbot proof of concept (POC) called "KrattAI" and other "Kratts" [9]. "Kratt" is a national artificial intelligence system, which is founded on a software-based algorithm. In this approach, the government decided from the beginning that whenever an AI or ML enabled decision support system would have a decision point, in accordance with the Estonian law on automation, that a human decisionmaker would be there to make the final decision [10]. These "Kratts" are developed by Nordic Institute for Interoperability Solutions (NIIS), stakeholders from the Ministry of Economic and Social Affairs of Estonia (MKM) as well as the software development company that is developing the "KrattAI" chatbot POC. Thus, the focus lies on automatization of the existing digitalized services and processes where an important aspect is data and its quality. That in turn means common standards and agreed semantics between the systems. Which helps further development of the concept of AI enabled virtual assistants to help achieve easier access to government services. In addition, the proactive service approach must be considered while setting up a proper ground for automatization of the specific service. However, the concept of proactive services and its appropriation in a society is only scarcely studied [11]. Only now the critical mass of literature on proactive services and proactive governance has started to accumulate [12] [13] [14] [15] [16] [17].

Referring to all above mentioned, the proactiveness and automatization is lacking in government decision making processes. Moreover, while human resource is one of the most valuable resource in any organization, little has achieved in automating human resource development aligned with organizational goals: "Competence management should no longer be considered as disconnected activities with few relationships with the organizational goals" [18]. Competency in scientific literature is broadly defined as work related skills, abilities and attitudes. Research, literature on human resource shows that many organizations deal with development of competency models. While competency models are often defined as collections of knowledge, skills, abilities, and other characteristics [19], surprisingly in current scientific literature little focus is targeted at implementing human resource development systems for training or re-training existing workforce. For instance, many competence models are created, but they are often theoretical and difficult to translate into measurable technical analysis approaches.

This introductory research is initiated following the current state of the art developments and near future needs of the Estonian Unemployment Insurance Fund (EUIF). Our main research question hereby is: How can the European labor market benefit from using the occupational classification systems in the field of proactive services? In general, our wider aim is to develop a framework and proof of concept for virtual competence assistant (VCA) using artificial intelligence and the concept of proactive service. Thereby, this paper deals with multidisciplinary area and focuses on data needed for the virtual assistants and what particular challenges are inherent to the general practice of using internationally accepted occupational classification type of approaches in the labor market. The paper seeks to introduce this research topic as well as formalize the research gaps involved and find preliminary results.

1.1 Research Methodology

The focus of this research is to investigate and understand the current and future states of the labor market competency domain. To understand this phenomenon case study methodology in general and qualitative research methods more specifically were used. Initially, a review of recent literature and developments in the occupational classification area served to get preliminary information in addition to the preliminary semi-structured interviews with EUIF. Also, preliminary set of unemployed job seekers were interviewed regarding their experience related to communication with career counselors in the EUIF. The interviews were pursued to form the essential requirements for the research and to establish a firm status quo. The current research is ongoing and is planned into different phases in the upcoming months. We argue that the qualitative research methods have the largest amount of flexibility. Furthermore, qualitative research methods provide a diverse and versatile set of tools to understand problems that derive from different sources and from different points of views. Furthermore, such values allow being implemented in many disciplines [20] making that approach multi-faceted.

2 STATE OF ART

2.1 Standard international classification systems/frameworks

The International Standard Classification of Occupations (ISCO) is a classification for occupations and jobs developed by International Labour Organization (ILO) as part of the United Nations. It is organizing jobs into 10 major groups based on tasks undertaken in the jobs. In total, there are four interconnected levels: 10 major groups, 40 sub-major groups, 127 minor groups and 436 unit groups [21]. The 436 unit groups classify more than 7000 job titles with 4-digit numbers, e.g. classification number "2131" is related to "Scientist, computer" and 90 other job titles. Additionally, these classifications linked to one of four ISCO skill levels, which means that by the example of "2131" with its major category of "2": "Professionals" has the highest skill level "4". Since ISCO provides descriptions to all groups, it is often used as initial classification of a country's national occupations' classification system with the possibility to extend more detailed occupations for the appropriate use [22]. ILO published the latest version, called ISCO-08, in 2008.

European Qualifications Framework (EQF) standardizes qualification across European countries so that qualification related taxonomy would be interoperable i.e. when developing systems enabling workers find work in another country in the EU. All EU countries can thereby relate to the common learning outcome based framework to be more compatible and increase mobility of their citizens. The learning outcomes indicate what a worker is able to do, what he or she understands and knows. The EU Member States can thereby reference their national qualification frameworks to the EQF and thereby a comprehensive map of qualifications is accessible through qualification databases. EQF-s main structure is divided into 8 levels (level 1: basic to level 8: advanced). In EQF, each member state has placed its occupation to one of the levels, e.g. "PhD degree" is placed to level 8 in all EU countries, regardless that there are different terminology being used for such degree (e.g., Doctoral degree in Estonia, Doctorate in Austria etc) [23]. To have better instructions for classifying the occupations, EQF has descriptors (Knowledge, Skills, Responsibility and Autonomy) which help to determine compliance between EQF and national qualifications [24]. In addition to the member states of EU, another 11 countries are implementing the EQF. Latest revision by the European Commission is made in 2017.

ESCO is a European Commission project classifying skills, competences and occupations while covering 27 languages in the EU. Moreover, it is directly related to ISCO: "ESCO has been built as an extension of the International Standard Classification of Occupations (ISCO)" [25]. ESCO is used in variety of reasons such as finding out how certain skills and knowledge relate to certain occupations; how qualifications are connected to certain competences, knowledge and skills; or how certain occupations and qualifications are interrelated [26]. Thereby ESCO is mainly consisting of three pillars: qualifications, occupations and skills/competences. The qualifications pillar of ESCO is in accordance with the EQF and thereby linked to national qualification databases. The first four levels of occupation pillar of ESCO are linked to the classification of ISCO-08 occupations hierarchy, while starting from level five ESCO occupations are located. For standardization purposes, each ESCO occupation links to one ISCO unit group on level four (unit level). In total, there are more than 4000 occupations in ESCO. The skills/competences pillar contains skills, language skills and knowledge, attitudes and values. In total, there are more than 13000 skills/competences concepts described in the latest ESCO (v1.0.8) version, which was published in 2020. ESCO offers technical service platform and many data resources that are available and free for downloading by any country or organization.

In the United States, a separate classification system is used, called the Standard Occupational Classification (SOC). In 1999, a decision was made to move on a separate way from ISCO: "The International Standard Classification of Occupations was not used because it was not flexible enough for U.S. needs" [27]. The most well-known occupational database in the U.S. is Occupational Information Network (O*NET), using the SOC as the basis of occupational classification. Last revision of O*NET-SOC taxonomy was released in 2019 containing more than 900 occupations.

2.2 Proactive services and their use – first step towards virtual agents

As Estonia is developing an innovative way of using virtual assistants to deliver government services, we are investigating the technological architectures and organizational transformation necessary for implementation and adoption. Essentially, proactive (public) e-services and e-governance are citizen-centered. Services are orchestrated so that the citizen does not need to be aware of them or navigate through extensive bureaucratic structures. It could be argued that the citizen must only act at certain access points [16]. Ideally, automated workflows take care of the sequencing of agency request and actions. Such services would be classified as proactive and automatic services. Additionally, the future role of artificial intelligence (AI) and machine learning are expected to increase drastically. Once the information to provide a specific public service exists in the state information system and it is assumed that the person would benefit or like to take advantage of the service, the organization develops a proactive service together with the authority, which is managing the database. Fundamentally, the goal of proactive services it to limit the unnecessary interaction with the citizen while making sure that the citizen gets all services and benefits they are entitled to. To some extent all services that have not explicitly stated as proactive are reactive services. Reactive in essence, as briefly discussed above, refers to something that is done in response to a situation rather than creating or controlling (proactivity) it. A limited number of academic articles on reactive-proactive services have been covered previously in the public sector context (see [28], [17]). Ayachi, et al. (2016) for instance provides a reactive and proactive recommendation engine for e-government services [28]. While the former offers e-services based on a set of interactive questions and answers, the latter suggests services without the initiation from the citizen, i.e. without any request, e.g. proactively. The reactive services are provided to citizens after request. Although the two concepts have not been discussed too broadly in the literature, this research seeks to incorporate the two concepts in a public service delivery context from a conceptual point of view. Furthermore, an initiative that can be identified as a variation of proactivity is the aforementioned "Kratt". The national artificial intelligence system is autonomous and self-learning and is assigned tasks that are traditionally done by a person. A "Kratt" expert group was brought into existence in order to research more thoroughly, how artificial intelligence could be implemented in the private sector more widely. The concept of a proactive agent is novel, as it enables the introduction of "personal assistants". As discussed briefly in the Introduction, an application, a caseworker or an artificial intelligent agent such as "Kratt" could register a life event. However, as the implementation of "Kratt's" is still underway, in this research we argue that a proactive agent could be an e-service or a physical person. It is possible to distinguish between a set of reactive and proactive characteristics in any given service ecosystem. The main difference can be observed in when government pushes out services proactively and users are reactively looking for services. The conceptual illustration below (see Figure 1) of the Reactive-Proactive conceptual space illustrates the envisioned process for the provision of proactive services while taking into consideration the potential reactive pathway in parallel.

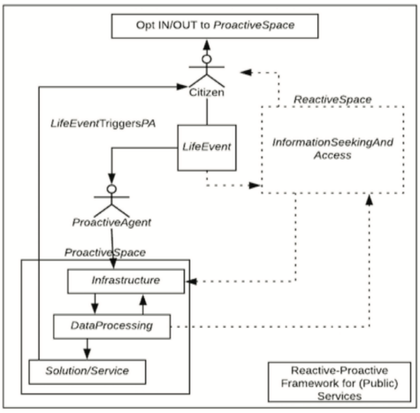

Figure 1: - Reactive-Proactive conceptual service space

It is suggested here that once a life or business event (such as a birth, marriage, starting a school, or starting a business) takes place, there could be two options: either subscribing to the ProactiveSpace or to the ReactiveSpace (see Figure 1).

In the context of our introductory research, such concept can be applied to citizen's occupational status. The life-events can be related to changes in occupational conditions, such as losing a job and thereby automatically applying for unemployment support versus having to do it manually or finding a new job proactively via automatic analysis of individual profile and matching with open positions versus spending a lot of time every day and searching manually for new vacancies. In order to have a clear target for our future research we are henceforth investigating the preliminary situation in the EUIF.

3 RESULTS

EUIF is a quasi-governmental organization that acts according to two main Estonian laws: The Unemployment Insurance Act and the Labour Market Services and Benefits Act. It is allocated in 29 different counseling centers across Estonia. The main tasks of EUIF are to organize the social insurance provisions and to support citizens who have lost their jobs find a new employment or take part in free of charge training or re-training activities. To enable easier data exchange and communication between a citizen, government and the EUIF, an online e-service called "e-töötukassa" is provided. In the e-service, a citizen can amongst other things register for unemployment, fill a personal CV, find available employment offers and seek for suitable training activities. Filling a CV is made easier because in some cases a citizen can request filling some of the fields using other Estonian government data registers via Estonian data exchange layer X-road. In case an offer or training is interesting, a citizen can apply using the e-service.

Based on preliminary interviews with the EUIF, currently standardized occupational classification ISCO-08 is being used. However starting from August 2021 ESCO will be a mandatory classification system for all Unemployment Insurance Funds in the EU member states. Currently in Estonia, mostly ISCO is used as a method for classifying occupations. The benefits for a citizen of using such a classification is seen when a citizen, seeking for a job, marks desired occupation in an e-service which in that time may not be available, however a notification is sent at once after such offer is entered by any employer to the system. In "e-töötukassa" such functionality is called job-wish. Recent efforts to modernize the fund's IT solutions is seen by its 2020 goals [29], where most important goals were: (1) Finalizing e-counseling solution for job seeker, (2) Introduce decision support model using data analytics for the fund's counselors to help the assessment of the individual long-term unemployment risks, (3) Continuation of automating processes concerning financial support payouts, (4) Deployment of transcription software on the calls of call centers.

Despite such developments are in motion, currently each job seeker and employer is advised by personal counselor. As in Estonia the unemployment rate is currently over 8% (more than 57000 unemployed citizens), contacting and keeping job seekers' efforts and progress information up to date is very resource intensive. Additionally, based on feedback by an unemployed citizen, who was laid off because of the pandemic, there are two main problems while applying to a training in the EUIF. First, a citizen can only select a training from the EUIF's official partners list, so finding the suitable training that fits to the applicant's profile is limited and the selection rules are confusing especially after one carefully selected application for training got rejected. Secondly, the counselors tend to forget information that has already been discussed in the previous contact calls.

In line with the ongoing research, the EUIF is in the near future planning to focus on 1) mapping their occupations and skills against ESCO and 2) improving the career advancement functionality, hence giving this research an academic prospect and thus validation of the need for a VCA type of solution. Such developments increase digitalization and enable building proactive e-services.

3.1 The possible usage of the VCA based on ESCO

Until now, we have analyzed the existing occupational classification systems and had preliminary view of the current situation in the Estonian state-level developments as well as the situation in the EUIF. Although there are three main occupational systems on international use: ISCO, SOC and ESCO, there are only two relevant classification systems in the European context: ISCO and ESCO. The results of our preliminary interviews with EUIF and secondary data collection confirmed that ESCO is going to be mandatory taxonomy for all EU member states starting from August, 2021. As ESCO's first pillar concerning occupations is tightly related to ISCO, there is no need to separately concentrate to ISCO per se. The two remaining pillars of ESCO are qualifications pillar, which is related to the EQF, and skills/competence pillar. The EQF is a framework for linking the European member state's national qualification frameworks (NQF) to enable data exchange and interoperability. Similar to EQF, Estonian NQF consists of 8 levels describing both formal education qualifications and occupational groups and qualifications. Skills/competences are broad description of all existing skills across

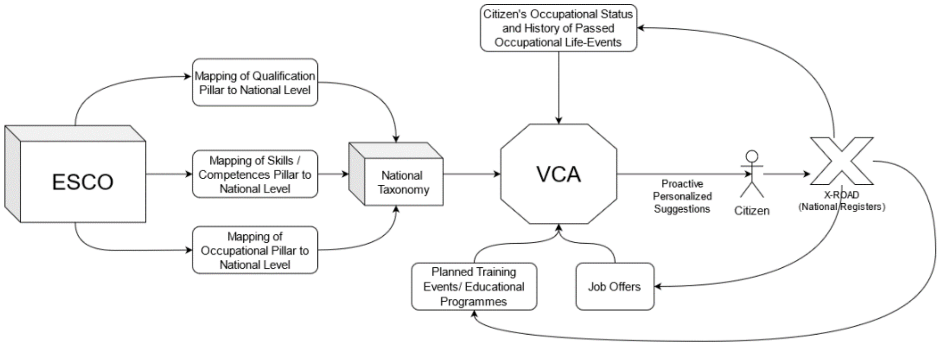

Figure 2: - Conceptual Model of Virtual Competence Assistant (VCA) Based on National Taxonomy Derived from ESCO

the EU. Based on preliminary interviews with the EUIF, out of the 13000 skills/competences Estonia only needs to define less than 1000.

Concluding the above, we construct initial conceptual view of the virtual competence assistant. The proactiveness concept in the communication flow of individual citizens and the Estonian Unemployment Insurance Fund in Figure 2 is illustrated via Estonian data exchange layer X-Road because all citizen's data is in that case following the "once only" principle. With the aid of virtual competence assistant, a citizen gets suggestions for appropriate available trainings and educational programs without having to search for them. Such suggestions may be automatically triggered for instance when a citizen's occupational status is changed to unemployed, but also while continuing to work in order to upgrade the skills related to specific occupation. Mapping national occupational classifications to ESCO rather than ISCO gives many advantages: First, since ISCO's latest update was in 2008 and having only four layers, ESCO's taxonomy is regularly updated consisting of newer occupations more specific and recently emerged occupations. Secondly, in addition to updated occupations ESCO provides additional qualifications and skills/competences pillar, which has much higher benefit in creating rules for artificial intelligence based solution. This means that knowing citizen's skills based on current and past occupations, a VCA can suggest trainings for achieving acceptance in a better job. Finally, by using similar basis for one country, the solution can be replicated more easily in another country. Of course, more research needs to be pursued.

4 DISCUSSION

One important purpose of this paper was to investigate how occupational classification systems can be used in order to automate service provision between EUIF, government and a citizen. The paper sought to establish initial ground for understanding, how we can approach the topic in order to build a digital career coach as a virtual competence assistant by using existing occupational taxonomy. The research showed that many components and building blocks are in place from the European side in order to move on with creating such a proactive service. On a national level, as discussed, the outdated ISCO is still currently in use by the EUIF. However, all EU member state unemployment insurance funds are required to implement or map their national classifications to ESCO by August 2021.

4.1 Future work

Further research still needs to focus more in detail what approaches are currently being used for existing unemployment information systems development. In addition, we need to investigate main concerns in relation to existing information systems and analyze more deeply what are main requirements for further development in order to set a foundation for VCA. Although our preliminary analysis showed a good potential, we need to investigate which components of ESCO are essential and can be used developing a proactive career agent on a national level.

5 CONCLUSION

Based on the topic of proactive services and VCA conceptual model, initial results show that it is possible to create ecosystem where ESCO could help with the classification connecting occupations to skills/competences and qualifications. Since each nation's labor market and national taxonomy is different, the main benefit of using ESCO classification is to enable interoperability between EU member states. The widely established EU-based occupational taxonomy provides agreed datsets and rules that is typically required when proactive services are built. Estonian experience shows that services can be automated and digitalized in some domains and use of "KrattAI's" is a proof of concept. Next challenges ahead are gaining data that is relevant to specific nation's labor market and classifying these according to existing taxonomy. In collaboration with EUIF, we aim to create such a service that in the future can be implemented into Estonia's government "KrattAI" ecosystem.

REFERENCES

[1] A. Pinho and R. J. Hunter, "The Portuguese Energy Sector: Its Multiple Aspects and Challenges - A Country Study," Journal of Sustainable Development Studies, vol. 12, no. 2, pp. 281-304, 2019.
[2] Praxis Centre for Policy Studies, "Adaptation of Ida-Virumaa county´s economy and labor market to the reduction of oil shale industry," Praxis Centre for Policy Studies, Tallinn, 2020.
[3] D. Draheim, K. Koosapoeg, M. Lauk, I. Pappel, I. Pappel and J. Tepandi, "The design of the Estonian governmental document exchange classification framework," in

lectronic Government and the Information Systems Perspective : 5th International Conference, EGOVIS, Porto, 2016.
[4] I. Pappel, I. Pappel, J. Tepandi and D. Draheim, "Systematic digital signing in Estonian e-government processes: influencing factors, technologies, change management.," in Transactions on Large-Scale Data- and Knowledge-Centered Systems XXXVI, Berlin, 2017.
[5] I. Pappel, V. Tsap and D. Draheim, "The e-LocGov Model for Introducing e-Governance into Local Governments: an Estonian Case Study," in IEEE Transactions on Emerging Topics in Computing, 2021.
[6] I. Pappel, V. Tsap, I. Pappel and D. Draheim, "Exploring e-services development in local government authorities by means of electronic document management systems.," in Electronic Governance and Open Society: Challenges in Eurasia : 5th International Conference, EGOSE 2018, St.Petersburg, 2018.
[7] H. Gunaratne and I. Pappel, "Enhancement of the e-invoicing systems by increasing the efficiency of workflows via disruptive technologies," in Electronic Governance and Open Society: Challenges in Eurasia : 7th International Conference, EGOSE 2020, St. Petersburg, 2020.
[8] K. Vaher, "Next Generation Digital Government Architecture," Government CIO Office, Republic of Estonia, Tallinn, 2020.
[9] Government CIO Office, Government of the Republic of Estonia, "Estonia's national artificial intelligence strategy 2019-2021," Government CIO Office, Tallinn, 2019.
[10] R. Dreyling, E. Jackson, T. Tammet, A. Labanava and I. Pappel, "Social, Legal, and Technical Considerations for Machine Learning and Artificial Intelligence Systems in Government," in International Conference on Enterprise Information Systems ICEIS 2021, Prague, 2021.
[11] R. Sirendi, A. Mendoza, M. Barrier, K. Taveter and L. Sterling, "A conceptual framework for effective appropriation of proactive public e- services," in Proceedings of the European Conference on e-Government, ECEG, 2018.
[12] R. Erlenheim, Designing Proactive Public Services, PhD Dissertation, Tallinn: Tallinn University of Technology, 2019.
[13] R. Erlenheim, D. Draheim and K. Taveter, "Identifying Design Principles for Proactive Services Through Systematically Understanding the Reactivity-Proactivity Spectrum," in ICEGOV 2020, Athens, 2020.
[14] H. Kõrge, Designing proactive business event services: a case study of the Estonian Company Registration Portal, Master's Thesis, Tallinn: Tallinn University of Technology, 2019.
[15] K. Kroonmäe, Implementing Proactive Services in Estonian Local Governments, Master thesis, Tallinn: Tallinn University of Technology, 2017.
[16] D. Linders, C. Z.-P. Liao and C.-M. Wang, "Proactive e-governance: Flipping the service delivery model from pull to push in Taiwan," Government Information Quarterly, vol. 35, no. 4, pp. S68-S76, 2015.
[17] H. Scholta, W. Mertens, M. Kowalkiewicz and J. Becker, "From one-stop shopt to no-stop shop: An e-government stage model," Government Information Quarterly, vol. 36, no. 1, pp. 11-26, 2019.
[18] R. Medina and A. Medina, "Managing competence and learning in knowledge-intensive, project-intensive organizations: A case study of a public organization," International Journal of Managing Projects in Business, vol. 10, no. 3, 2017.
[19] M. A. Campion, A. A. Fink, B. J. Ruggeberg, L. Carr, G. M. Phillips and R. B. Odman, "Doing Competencies Well: Best Practices in Competency Modeling," Personnel Psychology, vol. 64, no. N/A, pp. 225-262, 2011.
[20] R. K. Yin, Case Study Research Design and Methods (5th ed.), vol. 30, CA: Sage, 2014.
[21] International Labour Office, "International Standard Classification of Occupations. Structure, group definitions and correspondence tables," International Labour Office, Geneva, 2012.
[22] International Labor Office, "Resolution Concerning Updating the International Standard Classification of Occupations," International Labor Office, Geneva, 2007.
[23] European Union, "Europass," [Online]. Available: https://europa.eu/europass/en/compare-qualifications. [Accessed 22 04 2021].
[24] European Commission, "Proposal for a COUNCIL RECOMMENDATION on the European Qualifications Framework for lifelong learning and repealing the Recommendation of the European Parliament and of the Council of 23 April 2008 on the establishment of the European Qualifications Framew," European Commission, Brussels, 2016.
[25] European Commission, "ESCO: harnessing the power of big data analysis for a functional labour market," Luxembourg: Publications Office of the European Union, Luxembourg, 2017.
[26] European Commission, "ESCO: improving career guidance services," Luxembourg: Publications Office of the European Union, Luxembourg, 2017.
[27] C. Levine, L. Salmon and D. H. Weinberg, "Revising the Standard Occupational Classification system, Monthly Labor Review," U.S Bureu of Labor Statistics, 1999.
[28] R. Ayachi, I. Boukhris, S. Mellouli, N. Ben Amor and Z. Elouedi, "Proactive and reactive e-government services recommendation.," Universal Access in the Information Society , vol. 15 , no. 4, pp. 681-697, 2016.
[29] BDO Eesti AS , "2019 FIscal Year Report," Eesti Töötukassa, Tallinn, 2020.
[30] F. Polo and J. Kantola, "Tomorrow's Digital Worker: A Critical Review and Agenda for Building Digital Competency Models," in Proceedings of the AHFE 2020 Virtual Conferences on Human Factors, Business Management and Society, and Human Factors in Management and Leadership, N/A, 2020.

Appendix 4

IV

M. Liutkevičius, S. Nõmmik, Piyumi, M. Weck, and S. Yahia. In Pursuit of AI Excellence in Public Employment Services: Identifying the Requirements. *TalTech Journal of European Studies*, 14, 2024

In pursuit of AI excellence in public employment services: identifying the requirements

Markko Liutkevičius
Piyumi Samaranayaka
Sander Nõmmik
Sadok Ben Yahia
Department of Software Science
Tallinn University of technology
Ehitajate tee 5, Tallinn, 12611, Estonia
markko.liutkevicius@taltech.ee
piyumisamaranayaka@gmail.com
sander.nommik@eas.ee
sadok.ben@taltech.ee

Marina Weck
HAMK Smart Research Unit
Häme University of Applied Sciences
Visamäentie 35, Hämeenlinna, 13101, Finland
marina.weck@hamk.fi

Abstract: The modern labor market faces complex challenges stemming from various factors, such as demographic shifts, the far-reaching impacts of digital and technological evolution, changing job profiles, and job losses due to automation and the green-economy transition. As labor market challenges escalate, it becomes increasingly vital for public employment services (PESs) to gain a deeper understanding of their clients and the specific labor markets in which they operate. Although these services often help only unemployed people in their current form, implementing AI technologies has the potential to significantly broaden PES support for the wider public. Unfortunately, the EU's PES sector has been slow to implement AI technologies to support clients with services such as skills extraction from CVs and job offers, job-seeker matching, and recommending relevant jobs or training. This study examines the perspectives of a PES's external-user groups and internal stakeholders to establish a baseline for implementing such technologies into existing self-services. The findings emphasize that although AI has transformative potential, deploying it effectively necessitates a holistic understanding of the existing PES ecosystem and a strategic approach to requirement gathering.

Keywords: *Public employment services, Requirements gathering, AI, Public sector innovation, Digital transformation, Modern labor market*

1. Introduction

As the fourth industrial revolution (Schwab, 2023) emerges, we stand at the threshold of unprecedented technological advancements. This new era is reshaping the labor market, increasing the demand for novel skills while making traditional ones obsolete. The EU-policy level identifies skills as crucial for sustainable competitiveness and social fairness (European Commission, 2020).

Recent crises like COVID-19, high energy prices, and Russia’s aggression against Ukraine have heightened labor market uncertainty. An OECD (2022) study showed that at least one in six business-sector workers are in concentrated labor markets, limiting their negotiation power for better conditions. Despite a better-than-expected rebound from COVID-19, labor market improvements remain inconsistent, particularly challenging for low-skilled workers (Causa et al., 2022). Significantly, the member states of the EU have supported the EU 2030 social objectives, which include a goal for at least 60% of adults to engage in training each year to achieve an employment rate of no less than 78% by 2030 (European Commission, 2022-1). Additionally, the 2030 Digital Compass establishes further ambitions, aiming for at least 80% of all adults to have basic digital skills by the same year (European Commission, 2022-2). Demographic trends, like a shrinking working-age population, highlight the need to unlock the labor force's potential and invest in skills across all age groups (Park et al., 2022). In the EU-28 Member States, Iceland, and Norway, an estimated 128 million adults could benefit from upskilling and reskilling (Cedefop, 2020). Addressing skill shortages is crucial, especially for underrepresented groups like women, people with disabilities, older individuals, and youth not in education, employment, or training (Rajnai & Kocsis, 2017). Public Employment Services (PES) play a key role in connecting the unemployed with job and training opportunities, but their approaches vary widely (Łukasz Sienkiewicz, 2022).

A 2017 global report identified six obstacles to developing skills-intelligence systems in the PES sector: lack of knowledgeable human resources, funds, coordination, statistical infrastructure, policymaker support, and credibility of previous analyses (International Labour Organization, 2017). More academic research is needed on PES self-services' requirements and functionalities (Wallinder & Seing, 2022) (Danneels & Viaene, 2015) (Leinberg, 2016). The study aims to determine an approach for gathering the requirements for AI-enabled career-support services within PES, posing two research questions:

1. What are the needs of external-user groups for a modern PES self-service in Estonia?
2. What internal-implementation requirements should be considered before building AI-enabled solutions for PES in Estonia?

Estonia serves as a compelling subject for this study due to its achievements in e-governance and its high ranking in the 2022 "eGovernment Benchmark" study (European Commission, 2021). Estonia's national AI strategy, initiated in 2019, has propelled AI-enabled services in the public sector (Government CIO Office, 2019). Subsequent "Kratikava" action plans for 2019-2021, 2022-2023, and 2024-2026, developed by the Ministry of Economic Affairs and Communications, continue to direct AI adoption (Ministry of Economic Affairs and Communications (2019, 2022, 2024)). Additionally, the "Data and Artificial Intelligence White Paper 2024-2030", created by the Ministries of Economic Affairs and Communications, Justice, and Education and Research with the Government Office, outlines strategic goals for developing a data-driven governance and economy, transforming Estonia into a state empowered by AI, while emphasizing trust and human-centric approaches (Ministries of Economic Affairs and Communications, Justice, and Education and Research & Government Office (2024)). The Estonian PES has introduced new AI tools and created cooperative opportunities, enhancing internal service efficiency. However, these AI-enabled services are primarily designed for consultants, with limited direct impact on clients such as the unemployed, job seekers, employees, employers, and youth.

2. Literature review

2.1. Digital transformation and AI in the public sector

The scientific community has yet to agree on a single definition of AI. A report on a longitudinal study titled "Artificial Intelligence and Life in 2030," released by Stanford University in 2016, examined the influence of AI on diverse sectors of society. The report argued that the absence of a clear, universally-agreed-upon definition of AI might have contributed to the field's rapid expansion and progress (Stanford University, 2016). A more recent report, completed by the same standing committee and published in 2021, argued that compared to governing bodies of other countries worldwide, the EU has been the foremost governmental body in introducing specific regulatory measures for AI (Stone et al., 2022). The EU defines AI systems as "software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal" (European Commission, 2019). As this comprehensive definition indicates, the EU seeks to capture the multifaceted nature of AI, emphasizing both its data-driven decision-making processes and its overarching human-designed objectives. This underscores the EU's vision for AI and aligns with the discussion of digital transformation and its relationship with AI.

Although the private sector has shown significant progress in adopting AI and developing digital-transformation strategies, the public sector still faces challenges in this regard (Fatima et al., 2020). Thus, the adoption of AI technologies has become increasingly important for the public sector in recent years. Wirtz et al., (2019) proposed a 4-AI model that identifies the main challenges related to AI implementation; these challenges involve the main dimensions of society, technological implementation, law and regulations, and ethics. Each dimension consists of multiple subaspects of which the implementers are advised to be aware while considering the implementation of specific applications. In this regard, the implementation of AI in the public sector is a complicated issue requiring a wider understanding of the internal and external aspects of the organization. Mergel et al. (2019) conducted comprehensive research on digital transformation, stressed the importance of external drivers, and proposed a procedural pattern map. Given the emphasis on stakeholders in this research, this pattern map comprehensively addresses the nuances of the public sector. Based on this, organizations such as PESs are under pressure to undergo digital transformation to stay relevant, to be responsive to changing demands, and to respond to external pressures. Typically, the transformation involves digitizing artifacts and processes, transforming bureaucratic culture, and developing digital competencies and mindsets. Based on this, organizations such as Public Employment Services (PESs) are under pressure to undergo digital transformation to stay relevant, to be responsive to changing demands, and to respond to external pressures. The utilization of open data plays a pivotal role in these transformations, enabling the digitization of artifacts and processes, the transformation of bureaucratic culture, and the development of digital competencies. In the PES sector, a focus on data accessibility is crucial to create AI-enabled services that experiment with different models for improved service delivery. Tropp, Hoffmann, and Chochia (2022) emphasize that the strategic management of open data is essential for facilitating these changes, highlighting its impact on streamlining operations and enhancing service delivery within the public sector. Although the private sector has made significant efforts to adopt AI and implement digital-transformation plans, these efforts are not directly transferable to the public sector (Zuiderwijk et al., 2021).

According to Mikalef et al. (2019), when it comes to the implementation of AI, before suggesting the most effective methods for deploying AI solutions and facilitating their adoption, it is essential to identify the areas in which AI will play a central role. For example, a PES could implement components using AI technologies into multiple internal or external services; however, the overall service-delivery architecture might require a more centralized strategy to offer combined services that provide value to all stakeholders, such as employers seeking applicants, employees of the PES, and job seekers. Kesa and Kerikmäe (2020) highlight the inherent challenges posed by AI technologies to GDPR compliance, emphasizing the need for public employment services to consider these challenges when implementing AI-enabled services to ensure adherence to legal standards of transparency and data protection. Moreover, Chochia, Kerikmäe, and Skvarciany (2023) emphasize the integration of sustainable practices within organizational management, emphasizing the necessity for public employment services to adopt AI solutions that are not only technologically advanced but also socially responsible and environmentally sustainable.

2.2 AI in the PES sector

In recent years, there has been a growing interest in exploring the potential of AI technologies in the PES sector (Desiere & Struyven, 2021) (Flügge, 2021) (Körtner & Bonoli, 2021) (Urquidi & Ortega, 2020). According to (Broecke, 2023), the implementation of AI in job matching is still in the early stages of development, and it faces two main barriers: (1) a lack of preparedness among organizations and associated individuals to utilize these tools and (2) doubts, risks, and concerns about the technology and its potentially negative consequences. Based on the available scientific and industry resources, only a few PESs in Europe have implemented AI technologies to assist job seekers. Firstly, the *Vlaamse Dienst voor Arbeidsbemiddeling en Beroepsopleiding* (VDAB) in Flanders has integrated AI into its services with the Competency-Seeker tool, which analyzes resumes to suggest implicit skills, and the Jobbereik app, which recommends alternative jobs and required training for career moves. Secondly, France's *Pôle Emploi* has implemented the *Analyse Automatique* of CVs (AACV) tool to identify unmentioned skills on CVs based on job history, achieving a 68% satisfaction rate. Lastly, the Switch to Sweden project exemplifies a successful private-public partnership utilizing AI for efficient matchmaking between job seekers and organizations (Linköping Science Park, 2023).

2.3. The PES in Estonia

The Estonian Unemployment Insurance Fund (EUIF) is a quasi-governmental organization that provides labor market services to various segments of the Estonian population. These segments include the unemployed, job seekers, employees, employers, and youth. Though independent of the Estonian government, the EUIF operates based on the Unemployment Insurance Act (Estonian Parliament, 2002) and the Labor Market Services and Benefits Act (Estonian Parliament, 2006). These laws outline the unemployment insurance system of Estonia, employment mediation, and other related services. The EUIF's primary mission is to mitigate unemployment and its duration in Estonia, foster economic transitions, enhance the quality of the labor supply, and improve cost-effectiveness (Estonian Unemployment Insurance Fund, 2022c). It accomplishes these objectives by implementing active labor market policies, providing subsidies, and performing work-capability assessments. These three categories encapsulate a variety of services, including but not limited to employment mediation, career guidance, the provision of labor market training, and the administration of degree-study allowances, business-startup subsidies, unemployment-insurance benefits, and unemployment allowances (Estonian Unemployment Insurance Fund, 2022a).

2.3.1. AI in the EUIF

In accordance with Estonia's national AI strategy (Government CIO Office, 2019), the machine-learning-based tool OTT (Estonian abbreviation for decision support tool) was designed to assist the EUIF (E-Estonia, 2021). OTT is accessible only to consultants working in the EUIF. It predicts job-seeking individuals' likelihood of finding work and identifies factors affecting this probability. It helps EUIF consultants provide personalized recommendations to clients, streamlines workflow, and enhances overall efficiency. It categorizes clients into different groups based on risk assessments, allowing consultants to prioritize their cases and create bespoke recommendations. Utilizing AI, particularly the random forest machine-learning algorithm, OTT was developed and validated using five years' worth of unemployment data. The model takes into account 60 unique attributes and indicators to assess each job-seeking individual and compute their probability of securing new employment (Nortal, 2021). The EUIF has been involved in two other substantial AI-focused initiatives: MALLE (Estonian abbreviation for machine learning in labor economics) and MAITT (Estonian abbreviation for machine learning and AI supported services). MALLE assesses the impact of labor market services on the likelihood of reemployment among the unemployed, thereby facilitating more efficient resource allocation for such services (Estonian Unemployment Insurance Fund, 2022b). Conversely, MAITT, a project undertaken by the University of Tartu, employs machine learning and AI to calculate the risk of unemployment among those currently employed (Tartu University, 2022). Thus, it can be inferred that the EUIF's participation in the Estonian national AI strategy has augmented its AI capabilities, introduced new AI tools, and created opportunities for collaboration, enabling it to deliver services with greater efficiency. However, because these services are designed mainly for consultants, they are only remotely connected to actual clients, such as the unemployed, job seekers, employees, employers, and youth.

3. Methodology

To select appropriate data collection methods, we considered the end goal of digital transformation, which encompasses concentrating on fulfilling user needs, introducing novel modes of service delivery, and enlarging the user base (Mergel et al., 2019). When defining requirements for PESs, taking this goal into account not only establishes the need to consider both internal and external stakeholders but also sets requirements for the methods themselves, because different target groups require tailored methods of engagement for data collection; for example, conducting interviews to reach a significant number of job seekers would pose a challenge. We elaborated on how the disciplines of technology, public administration, and legal studies shape our approach, ensuring a holistic view that spans multiple disciplinary perspectives in Section 2.1. Therefore, to comprehensively address the research questions and fulfill the study's aim, we selected a mixed-methods approach that combines qualitative and quantitative data collection methods. According to (Venkatesh et al., 2013), combining these two data collection methods can enable information systems researchers to draw more precise and informed conclusions.

To fulfill the aim of this study, a literature review was undertaken to establish a theoretical framework. Given the absence of robust frameworks that focus on the requirements for PES services, this study designed a framework for empirical investigation (Figure 2).

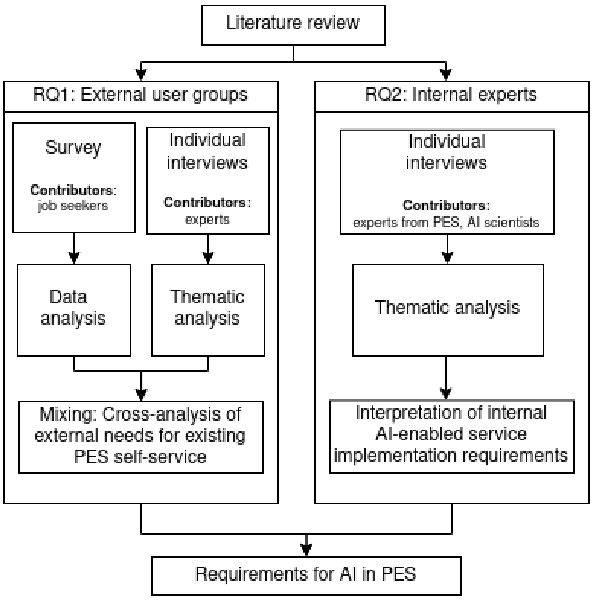

Figure 1: Mixed-methods research design for empirical investigation

To address RQ1, we used two data collection methods. In March 2023, an online survey gathered quantifiable data from job seekers, which distributed through two prominent Facebook groups widely used by locals and expatriates in Estonia. The first group, “Expats in Tallinn/Estonia”, had approximately 19,900 members and served as an active platform for sharing everyday life information. The second, “Jobs in Estonia”, included about 29,700 members and focused on the Estonian job market; it was anticipated that these groups would provide a diverse and unbiased sample of the Estonian population. In April 2023, semi-structured interviews with industry experts, higher education, and public authorities representing employers were conducted. For the interviews, experts who were well experienced and knowledgeable in the field of skills development were chosen based on their years of experience in the industry. Statistical analyses of the survey data and thematic analysis of the interviews identified six key themes: technological issues, workforce and skills, collaboration and integration, platform improvement, language and translation, and awareness level. For RQ2, in May 2023, we interviewed experts with EUIF-related AI project experience. This thematic analysis helped interpret EUIF's internal requirements for AI-enabled service implementation. In essence, the combination of these methods provided a more holistic and nuanced understanding of the research subject. This understanding benefited from the breadth of the survey data and the depth and context specificity of the interviews.

The survey, designed for job seekers, focused on modern PES services, avoiding technical AI details to ensure clarity. Conducted in both Estonian and English, it included 26 questions and gathered 176 responses from a diverse geographic distribution.

Seven individual semi-structured interviews were conducted in April 2023 with experts from different industry sectors, higher education, and public authorities, all with over 10 years of recruitment experience (Table 1).

Table 1: Main characteristics of interviewees

ID	Expert's position	Expert's organization
A	Senior manager, information security	A leading software development company, Estonia
B	Head of recruitment, career center	A leading financial organization, Estonia
C	Team manager-BI analytics team	A leading financial organization in Sweden and Baltic countries
D	Recruiter	A leading software development company, Estonia
E	Recruitment specialist	A leading software development company, Estonia
F	Associate professor	A leading university in Estonia
G	CEO and HR consultant	HR management consulting company, Estonia

In May 2023, eight AI development experts associated with the EUIF were interviewed to address RQ2. These semi-structured interviews provided detailed insights into the AI implementation requirements for PES (Table 2).

Table 2: Main characteristics of interviewees

ID	Expert's position	Expert's organization
I1	Early Stage Researcher	University
I2	Development Expert	EUIF

ID	Expert's position	Expert's organization
I3	IT Development Manager	EUIF
I4	Head Specialist	EUIF
I5	Head of Department	EUIF
I6	Analyst	AI development organization
I7	Senior Researcher	AI development organization
I8	Junior Research Fellow	AI development organization

The selection of these experts was guided by their associations with the EUIF and their contributions to various AI projects such as OTT, MAITT, and MALLE within the organization.

4. Results

4.1. External user group needs

The analysis of 176 survey responses revealed that 65.9% (116 respondents) had never used the e-Tootukassa self-service, while 34.1% (60 respondents) had used it at least once. Among users, 31 were employed and 16 were unemployed. Employed users showed interest in job finding (48.9%) and training opportunities (42.6%). Of the 60 users, 17 used the service once, and 43 used it repeatedly. Only 20 participants engaged in training programs, and 39 did not. Additionally, 32 did not submit applications, while 21 did. Half of the users regularly updated their CVs, and 21 logged in for job searches weekly or daily. Feedback highlighted several issues: limited job posting diversity, platform design and usability problems, information overload, outdated information, poor language translation, frequent session expirations, and a slow login process. Users suggested more training opportunities, better language accessibility, a mobile app, improved interface, and more personalized features.

Based on the thematic analysis of the data collected from the individual interviews with the employers, three common themes were identified: workforce challenges, PES challenges, and expectations for improving the PES. Employers face significant challenges in finding skilled candidates, especially in IT, where demand for the latest technologies is high. This issue is compounded by the influx of irrelevant applications that do not match the required qualifications or skills. To address these challenges, employers recognize the need to upskill and reskill their current workforce. The impact of demographic changes, such as an aging population and fewer young workers, further exacerbates the workforce challenges. Additionally, relocation issues due to extended visa-processing times and lack of support for families were noted. The current PES solution, e-Tootukassa, faces several issues. The job ad publication process is burdened with excessive manual steps and is time-consuming. The platform lacks headhunting capabilities and suffers from poor public awareness and limited use among HR departments. Technical issues, such as difficulties with keyword usage for CV promotion and weak translation services, were also highlighted. Employers suggested several improvements for the e-Tootukassa platform. Increasing its popularity through career fairs and collaborations with schools could help connect employers and candidates. Enhancing the platform's features, such as adding extended filtering tools, providing guidance services, and integrating with HR portals, would make it more user-friendly. Improving the design to be simple, clear, and attractive is also crucial. Public awareness campaigns and more training programs developed in collaboration with educational institutions were recommended to address skill gaps.

Table 3 - Themes from the individual interviews with the external user goups

Theme	**Details**
Workforce Challenges	Skills shortages, especially in IT (B, E, G), Need for upskilling/reskilling (A, B, F, E, G), Demographic changes impacting workforce (F)
PES Challenges	Excessive manual processes (E, F, G), Lack of headhunting support (A), Low awareness and popularity (A, C, D, E, G), Technical issues with keywords and translations (C, G, F)
Improvement Expectations	Increase platform popularity via career fairs and school collaborations (C, E, A, G), Enhanced features and better design (A, B, D, G, B, C, E, F, G), Public awareness campaigns (A, C, E), More training programs in collaboration with educational institutions (A, D, E, F)

4.2. Cross-analysis of external needs

The cross-analysis examined the current state of the PES in Estonia, focusing on the needs of job seekers and employers. Both groups provided crucial perspectives: job seekers highlighted usability, limited job opportunities, quality of information, language translation, and insufficient training. Employers pointed out skill shortages, upskilling needs, and demographic changes. The analysis identified six key overlapping themes: technological issues, workforce and skills, collaboration and integration, platform improvement, language and translation, and awareness level. Both groups emphasized platform usability, translation problems, and the need for more training opportunities. Unique concerns included job seekers' issues with login processes and lack of relevant jobs, and employers' focus on demographic changes and skill shortages. The summary of external-user-group findings is categorized and presented in Table 3.

Table 4: PES self-service needs of external-user groups

	Job seekers	**Employers**
Technological issues	Usability concerns, session expirations and login inconveniences, demand for a mobile application	Excess manual steps, unavailability of experts, poor user experience
Workforce & Skills	Limited job opportunities, insufficient training opportunities, request for more training courses and workshops	Skills shortages, need for upskilling and reskilling, demographic changes
Collaboration & Integration	Desire for integration with other employment platforms	Collaboration with schools and employers, integrating with HR portals
Platform Improvement	Need for functional enhancement before adding new features, improved visualization, personalized user interface, more refined search features, display of who viewed their CVs, addition of salary details in job postings, resources on CV and cover-letter crafting, introduction of an e-newsletter	Career fair representation, competitive designs and services, descriptive soft-skill analysis, extended filtering, guidance and consultancy including forecasts, personality evaluations, strong awareness campaigns
Language & Translation	Language translation issues, call for broader language accessibility, more English-language content	Weaknesses in translations
Awareness level	Relatively low	Negative publicity

This comprehensive understanding allows for a more nuanced, inclusive approach to designing improvements for the PES. It ensures that interventions will address the most critical and common needs reported by job seekers and employers.

4.2. Internal requirements for AI

Through deductive coding, we identified the following as the main themes of the interviews: infrastructure, personnel, data privacy and security, legal compliance, change management and funding. Upgrading existing infrastructure is crucial for AI integration, involving more than just hardware and software updates. It requires competent IT systems, well-planned data architecture, sufficient IT capabilities, effective data exchange mechanisms, backup availability, and strong relationships with hosting partners. The Estonian X-Road data exchange layer and the EUIF's data warehouse are particularly significant. Experienced personnel, especially in data analysis, are essential for AI development in PES. This includes internal team members and potential collaborations with external specialists who align with PES's culture and goals. Legal challenges include ensuring data safety and privacy compliance, especially with external developers. Development often precedes the completion of the legal framework, posing an issue. Legal compliance is imperative for the EUIF, a public sector organization. GDPR compliance, such as obtaining client consent and depersonalizing data, is necessary but may affect system accuracy. Change management involves managing AI acceptance among stakeholders, fostering trust in AI solutions, and preparing for AI-induced transformation. Involving end users, especially career counselors, early in the implementation process is crucial. This transformation requires careful planning and communication. Funding is a significant challenge, with a need for a long-term budget for the EUIF, contrasting with fixed-term public sector financing. Adequate funding is crucial for successful AI implementation. The AI-implementation requirements identified from the thematic analysis are summarized based on identified main themes in Table 5.

Table 5: AI-implementation requirements

Theme	Requirements
Infrastructure	Upgrade the existing infrastructure to support AI integration (I2, I3, I4, I5, I6).
Personnel	1. Engage experienced specialists, particularly in data analysis, for AI implementation (I1, I2, I3, I4) . 2. Consider partnering with an external organization for specialist resources while ensuring that the organization understands PES culture, goals, and processes (I1, I2, I3, I4)..
Data	1. Ensure availability of sufficient quantities of high-quality data for AI training and implementation (I3, I6). 2. Address challenges related to limited sample sizes due to the country's small population (I3, I5, I6).
Legal Compliance	1. Safeguard data privacy and compliance with GDPR and other relevant laws, especially when partnering with external entities (I1, I5, I8). 2. Develop strategies to prevent potential AI-enabled discrimination due to low-quality or biased data (I4). 3. Consider legal frameworks before initiating the development and deployment of AI solutions (I2, I3, I4, I6). 4. Make sure the activities of the Estonian PES are in accordance with laws such as the Unemployment Insurance Act and the Labor Market Services and Benefits Act (I4).
Change Management	1. Manage acceptance of AI among stakeholders (I6). 2. Foster trust in AI solutions among development partners and end users (I2, I6). 3. Prepare the organization for the AI-induced transformation, including potential changes in work roles and tasks (I1, I3, I4, I6, I7, I8).
Funding	Secure adequate funding for the implementation of AI, keeping in mind the unique challenges of financing in the public sector (I1, I2, I4, I5).

5. Discussion

In this section, we discuss the data gathered to create the requirements pyramid for AI-enabled services in the PES sector, as illustrated in Figure 3. The comprehensive analysis of job seekers, employers, and AI experts' perspectives provides a holistic view of the current state and future needs of PES. Job seekers emphasized the need for improved job opportunities, usability, information quality, language translation, enhanced features, broader language accessibility, training opportunities, and a more user-friendly interface. Employers highlighted challenges such as skills shortages, platform limitations, and expectations for improvements. Both groups converge on the critical areas of usability, information quality, and training opportunities, indicating key focus areas for AI enhancement. Career counselors emerged as pivotal users, interacting daily with PES systems and witnessing external-user challenges firsthand. Their role in collecting requirements and acting as change agents is vital for bridging technological innovation and user experience, fostering trust and acceptance among stakeholders. AI experts identified essential internal needs, including upgrading infrastructure, engaging experienced data analysts, ensuring high-quality data access, safeguarding privacy, legal compliance, managing change, and securing funding. These insights provide a strategic view that encompasses both technical and socio-organizational aspects of AI implementation.

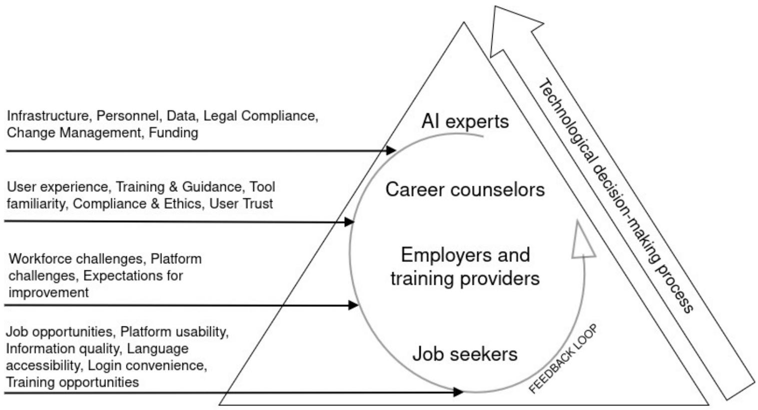

Figure 2: Pyramid of iterative requirements for building AI-enabled PES services

Figure 2 presents the requirements pyramid, illustrating the continuous refinement process of PES services. The feedback loop visualizes the dynamic nature of AI-enabled service development, where user requirements are filtered and contextualized by AI experts. This ensures that the needs are feasible and optimally addressed in the AI solutions, emphasizing the critical role of AI experts in aligning technological capabilities with user demands.

6. Conclusion

In the existing literature, while some researchers have explored aspects of PES e-services (Danneels, L., Viaene, S., 2015) (Wallinder, Y., Seing, I., 2022) (Leinberg, J., 2016), from a theoretical perspective there remained a notable gap in robust methodological approaches that focus on defining the requirements for services offered by PES. Hence, we created a mixed-methods research design for empirical investigation specifically for the collection of requirements from external user-groups and internal experts of PES (Figure 2). Our study illustrates the complex set of requirements for the successful implementation of AI-enabled services in the PES sector. Our findings underscore the importance of including a variety of stakeholders in the requirement-collection process; each stakeholder group contributes unique insights and poses different challenges. This aligns with our first contribution, where our comprehensive mixed-methods analysis integrates the perspectives of these diverse groups, providing a holistic view of the requirements for AI-enabled services in PES. Job seekers, employers, AI experts, and the overlooked stakeholders—career counselors and training providers—all play vital roles in shaping the future of AI in PESs.

Through the use of a mixed-methods methodology, this study successfully highlights the intersections and divergences among the needs of these stakeholders. The distinct needs of job seekers and employers constitute the foundation of our conceptual pyramid, which focuses on usability, language, and accessibility concerns. The insights of career counselors add a layer between AI experts and employers. This directly ties into our second contribution, emphasizing the overlooked role of career counselors as intermediaries who understand both technological and human aspects of the PES ecosystem. Further, AI experts contribute a more technical layer of requirements, ranging from infrastructure upgrades to data quality and legal compliance. This multifaceted view of the requirements for AI implementation in the PES sector, visualized as a pyramid with feedback loops, provides a roadmap for PES organizations initiating similar transformations. Our third contribution is evident here: the study promotes iterative requirement gathering and highlights the need for PES organizations to adapt continually, echoing the feedback loops in our model. By systematically addressing these requirements, PESs can maximize the potential of AI to enhance services, improve user experience, and ultimately better serve the needs of job seekers.

Although our study provides valuable insights, based on various stakeholders, into the set of requirements for building modern PES services, it is not without limitations. First, the study focuses on the Estonian PES, and although the insights obtained are valuable, they might not be wholly applicable to countries with different levels of technological maturity, different socioeconomic contexts, and different labor market conditions. To develop an EU-wide perspective, future research could include countries with varying levels of e-governance maturity. Second, we interviewed a limited number of participants, especially on the employer side. Hence, their opinions may not be fully representative of the concerns and expectations associated with the Estonian labor market. Third, during the primary data collection, it was discovered that two additional target groups should be added to the requirement-collection process: career counselors and training providers. Including their perspectives in future research and considering their perspectives will be of great benefit to the design and deployment of AI-enabled services in the PES sector.

Markko Liutkevičius has graduated from Aalborg University's Master of Science in engineering program in International Business Management with specialisation in Global Business Development in 2012 and University of Tartu's, Master of Arts program in Design and Development of Virtual Environments in 2014. He has been working as early-stage researcher in Tallinn University of Technology since 2020, where his doctoral research addresses the field of labour market service automation with AI technologies. In 2024 he started working as head of artificial intelligence in the department of Personal State at the Information System Authority, Estonia.

Sadok BEN YAHIA is Full Professor at the Southern Denmark University (SDU) at the Centre for Industrial Software (CIS) since September 2023. Before joining SDU, he was a full professor at Technology University of Tallinn (TalTech) since January 2019. He obtained his HDR in Computer Sciences from the University of Montpellier (France) in April 2009. His research interests mainly focus on data-driven approaches for near-real-time Big Data analytics, e.g., urban mobility in smart cities (e.g., information aggregation & dissemination, traffic congestion prediction), Recommendation System. and fake content fighting. Recently, his main focus is on Generative AI for building robust and resilient autonomous robots.

Marina Weck is Principal Research Scientist at the HAMK Smart Research Unit, Häme University of Applied Sciences (Finland) with more than 20 years of experience in different EU funded research and development projects. She earned a Doctor of Science (Technology) degree from the Department of Industrial Engineering and Management at Aalto University, Finland. Her current research interests include trust in the digital environment and technology, technology acceptance and uptake, smart and sustainable built environment, and circular economy business solutions.

Piyumi Samaranayaka graduated her Master of Science with a CumLaude in E-Governance Technologies and Services from Tallinn University of Technology in 2023. Piyumi is an accomplished software product owner with over seven years of experience in driving successful product development across various disciplines, including information management, finance, and e-commerce. With a proven track record of bridging the gap between technical teams and stakeholders, Piyumi has a deep understanding of user-centric design and agile methodologies. Throughout her career, Piyumi has successfully managed diverse projects, demonstrating flexibility and adaptability in dynamic environments. She excels in gathering and prioritizing product requirements, defining a clear vision and roadmap, and ensuring the timely delivery of high-quality software solutions. She has strong analytical skills which allow her to translate complex requirements into actionable tasks for cross-functional teams.

Sander Nõmmik graduated from Tallinn University of Technology with a Master of Science in Engineering in E-Governance Technologies and Services in 2023. During his studies, his research focused on AI technologies used in labor market services. In 2023, he started working as an IT Product Manager at Enterprise Estonia.

References

Broecke, S., 2023. Artificial intelligence and labour market matching. OECD Social, Employment and Migration Working Papers. OECD iLibrary. Available at: https://www.oecd-ilibrary.org/employment/artificial-intelligence-and-labour-market-matching_2b440821-en. doi: 10.1787/2b440821-en.

Causa, O., Abendschein, M., Luu, N., Soldani, E., Soriolo, C., 2022. The post-covid-19 rise in labour shortages. doi: 10.1787/e60c2d1c-en.

Cedefop, 2020. Empowering adults through upskilling and reskilling pathways: Vol. 1: adult population with potential for upskilling and reskilling. Luxembourg: Publications Office. Cedefop reference series. doi: http://data.europa.eu/doi/10.2801/691134.

Chochia, Archil, Tanel Kerikmäe, and Viktorija Skvarciany, 2023. "Global Economic Challenges for Sustainable Entrepreneurs." TalTech Journal of European Studies, vol. 13, no. 1, 2023, pp. 3-37. https://doi.org/10.2478/bjes-2023-0001.

Danneels, L., Viaene, S., 2015. How to move towards digital era governance: The case of vdab. ACM International Conference Proceeding Series 27-30-May-2015, 29–36. doi: 10.1145/2757401.

Desiere, S.A., Struyven, L., 2021. Using artificial intelligence to classify jobseekers: The accuracy-equity trade-off. Journal of Social Policy 50, 367–385. doi: 10.1017/S0047279420000203.

E-Estonia, 2021. AI to help serve the Estonian Unemployed. Available at: <https://e-estonia.com/ ai-to-help-serve-the-estonian-unemployed> [accessed 17 July 2023].

Estonian Parliament, 2002. Unemployment insurance act. Available at: https://www.riigiteataja.ee/en/eli/ee/512082020014/consolide/current [accessed 22 August 2023].

Estonian Parliament, 2006. Labour market services and benefits act. Available at: https://www.riigiteataja.ee/en/eli/ee/506062014001/consolide/current [accessed 22 August 2023].

Estonian Unemployment Insurance Fund, 2022a. Eesti töötukassa arengukava 2023-2026. Available at: https://www.tootukassa.ee/en/footer/about-tootukassa [accessed 22 August 2023].

Estonian Unemployment Insurance Fund, 2022b. Fiscal year report 2022. Available at: https://www.tootukassa.ee/en/footer/official-information/financial-information [accessed 17 July 2023].

Estonian Unemployment Insurance Fund, 2022c. Majandusaasta aruanne 2022. Available at: https://www.tootukassa.ee/en/footer/official-information/financial-information [accessed 22 August 2023].

European Commission. Questions and answers: European skills agenda for sustainable competitiveness, social fairness and resilience. Available at: https://ec.europa.eu/commission/presscorner/api/files/document/print/en/qanda_20_1197/QANDA_20_1197_EN.pdf [accessed 17 July 2023].

European Commission, 2019. A definition of AI: main capabilities and disciplines. Available at: https://ec.europa.eu/newsroom/dae/document.cfm?doc_id=56341 [accessed 22 August 2023].

European Commission, 2021. egovernment benchmark 2022. Available at: https://digital-strategy.ec.europa.eu/en/library/egovernment-benchmark-2022 [accessed 22 August 2023].

European Commission, 2022-1. *Commission welcomes Member States' targets for a more social Europe by 2030*. [Press release]. Retrieved from https://ec.europa.eu/info/strategy/priorities-2019-2024/economy-works-people/jobs-growth-and-investment/european-pillar-social-rights/european-pillar-social-rights-action-plan_en [accessed 31 August 2024]

European Commission, 2022-2. *Decision (EU) 2022/2481 of the European Parliament and of the Council of 14 December 2022 establishing the Digital Decade Policy Programme 2030 (Text with EEA relevance)*. Official Journal of the European Union. Retrieved from https://eur-lex.europa.eu/eli/dec/2022/2481/oj [accessed 31 August 2024]

Fatima, S., Desouza, K.C., Dawson, G.S., 2020. National strategic artificial intelligence plans: A multi-dimensional analysis. Economic Analysis and Policy 67, 178–194. doi: 10.1016/J.EAP.2020.07.008.

Flügge, A.A., 2021. Perspectives from practice: Algorithmic decision-making in public employment services. Proceedings of the ACM Conference on Computer Supported Cooperative Work, CSCW, 253–255, doi: 10.1145/3462204.3481787.

Government CIO Office, 2019. Estonia's national artificial intelligence strategy 2019-2021. Government CIO Office, Estonia. Available at: https://f98cc689-5814-47ec-86b3-db505a7c3978.filesusr.com/ugd/7df26f_27a618cb80a648c38be427194affa2f3.pdf [accessed 17 July 2023].

International Labour Organization (ILO), 2017. Skill needs anticipation: Systems and approaches - Analysis of stakeholder survey on skill needs assessment and anticipation. International Labour Organization.

Kesa, Aleksandr, and Tanel Kerikmäe, 2020. "Artificial Intelligence and the GDPR: Inevitable Nemeses?" *TalTech Journal of European Studies*, vol. 10, no. 3, 2020, pp. 67-90. doi.org/10.1515/bjes-2020-0022.

Körtner, J., Bonoli, G., 2021. Predictive algorithms in the delivery of public employment services. SocArXiv doi: 10.31219/OSF.IO/J7R8Y.

Leinberg, J., 2016. The improvement of a self-service process of employment mediation in Estonian Unemployment Insurance Fund.

Linköping Science Park. Switch to Sweden. Available at: https://linkopingsciencepark.se/switch-to-sweden/ [accessed 22 August 2023].

Mergel, I., Edelmann, N., Haug, N., 2019. Defining digital transformation: Results from expert interviews. Government Information Quarterly 36, 101385. doi: 10.1016/J.GIQ.2019.06.002.

Mikalef, P., Fjørtoft, S.O., Torvatn, H.Y., 2019. Artificial intelligence in the public sector: A study of challenges and opportunities for norwegian municipalities. 267-277 11701 LNCS, 267–277. doi: 10.1007/978-3-030-29374-1_22.

Ministry of Economic Affairs and Communications, 2019, 2022, 2024. Kratikava: Action Plans for the Adoption of Artificial Intelligence in Estonia. Retrieved from: 2019-2021: https://www.kratid.ee/_files/ugd/980182_d2057e15adb24de4924fc2c6f78a7649.pdf [accessed 31 August 2024], 2022-2023: https://www.kratid.ee/_files/ugd/980182_1f685990ca2e462f84c987408a816503.pdf [accessed 31 August 2024], 2024-2026: https://www.kratid.ee/_files/ugd/7df26f_21000a2dd36c4a66a30eea97563370a3.pdf [accessed 31 August 2024].

Ministries of Economic Affairs and Communications, Justice, and Education and Research & Government Office, (2024). *Data and Artificial Intelligence White Paper 2024-2030*. Available at https://mkm.ee/sites/default/files/documents/2024-02/Tehisintellekti%20ja%20andmete%20valge%20raamat%202024-2030.pdf [accessed 31 August 2024].

Nortal, 2021. OTT – an AI-powered success story in the public sector. Available at: https://nortal.com/insights/ott-an-ai-powered-success-story-in-the-public-sector/ [accessed 17 July 2023].

OECD, 2022. OECD Employment Outlook 2022. Building Back More Inclusive Labour Markets. doi: 10.1787/5bddb06a-en.

Park, C.Y., Shin, K., Kikkawa, A., 2022. Demographic change, technological advance, and growth: A cross-country analysis. Economic Modelling 108, S026499932100331X.

Rajnai, Z., Kocsis, I., 2017. Labor market risks of industry 4.0, digitization, robots and AI, in: 2017 IEEE 15th International Symposium on Intelligent Systems and Informatics (SISY), pp. 000343–000346. doi: 10.1109/SISY.2017.8080580.

Schwab, K., The fourth industrial revolution: what it means and how to respond. World Economic Forum. Available at: https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/ [accessed 17 July 2023].

Łukasz Sienkiewicz, E., 2022. Future skills, career guidance, and lifelong learning in PES. doi: 10.2767/640074.

Stanford University, 2016. 2015 study panel. "Artificial intelligence and life in 2030." One Hundred Year on Artificial Intelligence.

Stone, P., Brooks, R., Brynjolfsson, E., Calo, R., Etzioni, O., Hager, G., Hirschberg, J., Kalyanakrishnan, S., Kamar, E., Kraus, S., 2022. Artificial intelligence and life in 2030: The One Hundred Year Study on Artificial Intelligence.

Tartu University, 2022. Programmi RITA tegevuse 1 projekti Masinõppe ja AI toega teenused lõpparuanne. Tartu University.

Tropp, E.-M., Hoffmann, T., & Chochia, A. (2022). Open Data: A Stepchild in e-Estonia's Data Management Strategy? *TalTech Journal of European Studies, 12*(1), 123-134. doi: 10.2478/bjes-2022-0006

Urquidi, M., Ortega, G., 2020. Artificial intelligence for job seeking: How to enhance labor intermediation in public employment services. doi: 10.18235/0002785.

Venkatesh, V., Brown, S.A., Bala, H., 2013. Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. MIS Quarterly 37, 21–54.

Wallinder, Y., Seing, I., 2022. When the client becomes her own caseworker: Dislocation of responsibility through digital self-support in the Swedish public employment service. Sozialer Fortschritt 71, 405–423. doi: 10.3790/SFO.71.6-7.405V2.

TAL
TECH

TALLINN UNIVERSITY OF TECHNOLOGY

To Whom It May Concern

September 12, 2024
Tallinn, Estonia

Acceptance Letter

This is to confirm that article titled *“In pursuit of AI excellence in public employment services: identifying the requirements”* (authors: Markko Liutkevičius, Piyumi Samaranayaka, Sander Nõmmik, Sadok Ben Yahia, Marina Weck) has been accepted to be published in TalTech Journal of European Studies (eISSN2674-4619; ISSN2674-4600), Vol. 14 (2024), Issue 2 (40).

Sincerely,

Archil Chochia, PhD
Managing Editor
TalTech Journal of European Studies

Appendix 5

V

M. Liutkevičius and S. B. Yahia. The Use of Artificial Intelligence in Job Seeking and Competence Development. *Human Factors, Business Management and Society*, 56:128–136, 2022

Human Factors, Business Management and Society, Vol. 56, 2022, 128–136
https://doi.org/10.54941/ahfe1002260

The Use of Artificial Intelligence in Job Seeking and Competence Development

Markko Liutkevičius and Sadok Ben Yahia

Data Science Research Group Department of Software Science, Tallinn University of Technology, Tallinn, Estonia

ABSTRACT

Artificial Intelligence (AI), in the public and private sectors, creates new opportunities worldwide. One of such domains where the elements of AI play a critical role are recommendation systems related to finding a new job and offering training suggestions. Based on current literature, only a few attempts are made to implement intelligent recommendation systems in public sector environments such as employment agencies. In this regard, the existing state-of-the-art models should be explored for creating AI-enabled e-services helping unemployed citizens to find suitable jobs or to receive training suggestions based on their profiles. While job recommendation and training suggestion is still a constantly evolving area of research, the task of the current study is to support this research domain by firstly mapping the state-of-the-art AI techniques used in the current job and training recommendation system research literature. Secondly, in collaboration with multiple stakeholders in the Estonian public sector and universities from Latvia and Finland to conceptualize citizen-centered public service architecture that uses AI and is accessible to every European citizen.

Keywords: AI, Recommendation system, Virtual competency assistant, Labour market

INTRODUCTION

With the recent pandemic, many people have lost their jobs and are forced to find new career opportunities. In 2021 the global shortfall of jobs caused by the crisis was projected to stand at 75 million (International Labour Organization, 2021), which creates the need for better support by government institutions such as employment agencies. Their support to date has been built on human interaction between the citizen and career counselor and electronic tools such as portals to register for state support and search for a job. As we are increasingly moving towards proactive and automated services in building better e-governance related solutions, the complexity related to how governments can satisfy the needs of their citizens in challenging times needs addressing. As one of the pioneers in e-governance, Estonia has only recently started implementing AI technologies into public e-services using modern technological concepts such as Chatbots (Government CIO Office of Estonia, 2019). Such concepts can be implemented parallel to the already existing citizen's portals. To date, such portals' functionality is incrementally being enhanced to meet the required functionality following local legislation. However, they are currently not exploiting the benefits of the technological revolution of artificial intelligence. This research aims to establish a conceptualized view of citizen-centered service for people over 50 years old and integrate it into the already existing Virtual Collaborative platform (Silver Hub).

Based on current literature, only a few attempts are made to implement an intelligent recommendation system in a public sector agency such as employment agencies (Rodriguez, et al., 2019). In this regard, the existing state-of-the-art models should be explored for creating new AI-enabled e-services to help unemployed citizens easily find suitable jobs or get training suggestions based on their profiles. The term recommendation system in information technology literature first emerged in 1997 (Resnick & Varian, 1997) and is widely used for various purposes. However, based on (Dhameliya & Desai, 2019), a recommendation system and a job recommendation system have the following key differences: (1) increased difficulty in providing ratings to jobs, (2) the importance of timeliness as seeking jobs is time-critical and (3) compared to recommendation systems job recommendation systems need to consider the characteristics of both the candidate and job needs. Although mainly in the current literature, job and training suggestions are often handled in separate research providing models. Still, some authors, especially in the recent literature, combine job recommendation research with human skills (Dave, et al., 2018) (Giabelli, et al., 2021). However, little is researched focusing on the aspect of the AI field specifically. For example, a systematic literature review done in 2020 categorized the existing e-recruitment recommendation systems into four well-known traditional categories: Content-Based Recommendation (CBR), Collaborative Filtering Recommendation (CF), Hybrid, Knowledge-Based Recommendation (KBR), and added the fifth category called Other Techniques (OT) where all state-of-the-art AI-based recommendation system models were added, including Machine Learning (ML), Artificial Neural Networks (ANN) and Deep Neural Networks (DNN).

This paper focusses on literature where AI is used. In addition to focusing only on AI in job recommendations, the work includes the latest developments in training suggestion systems. To tackle these topics mentioned above, two research questions are formed:

RQ1. What data and models have been used in studies concerning the use of AI in job and training recommendation systems?

RQ2. How to design a new set of AI-enabled proactive solutions for supporting EU citizens with job recommendations and competence development?

METHODOLOGY

Our broader research aims to build AI-enabled public career services, such as Virtual Competency Assistants for the European labor market. Therefore, the overall research methodology is chosen as Action Research, where we aim to develop a technological artifact and intervention for the Estonian Unemployment Insurance Fund. For this research, we have been conducting a literature survey, semi-structured interviews, and workshops building upon previously validated problems and gathered data for this research.

A literature survey is conducted to answer the first research question exploring current state-of-the-art recommendation systems. For finding the most significant articles, the query was limited to: (1) Title contains "recommendation system," (2) Optional keywords in title: "job, training, artificial intelligence," (3) Time range: All. In addition, the search sources were limited to Scopus (40 matches in total) and Google Scholar (141 matches in total). Finally, we excluded all studies which did not specify the AI methods, such as ML, ANN, or DNN, used in their research and analyzed if the remaining articles had their data sets explicitly characterized. The total amount of articles left in the study after elimination was 34.

The interviews were conducted with open-ended questions to get insight into current concerns and open ends to answer the second research question. The interviewees were the representatives of Nordic Institute for Interoperability Solutions, the Estonian Unemployment Insurance Fund, Tallinn University of Technology, the Estonian Qualifications Authority, and universities from Latvia (Riga Technical University) and Finland (Häme University of Applied Sciences and South-Eastern Finland University of Applied Sciences). In addition to the interviews, in total, three workshops were conducted. The next step in broader research aims to build an AI-enabled Virtual Competency Assistant for the European labor market.

RESULTS

What Data and Models Have Been Used in Studies Concerning the use of AI in Job and Training Recommendation Systems?

The collection of data sources used in the research involved can be primarily categorized into career-related social networks such as XING (Mishra & Reddy, 2016) (Zhang & Cheng, 2016) (Polato & Aiolli, 2016) (Pacuk, et al., 2016) (Xiao, et al., 2016), LinkedIn (Diaby, et al., 2014) (Heap, et al., 2014) (Patel & Vishwakarma, 2020) and Facebook (Benabderrahmane, et al., 2018). Another major category is job portals such as CareerBuilder (Shalaby, et al., 2017) (Dave, et al., 2018) (Zhao, et al., 2021), Work4 (Diaby, et al., 2013), (Diaby, et al., 2014), (Dong, et al., 2017) (Benabderrahmane, et al., 2018), beBee (González-Briones, et al., 2019) and JobStreet (Bakar & Ting, 2011). Some researchers used historical job transitioning data to predict the next jobs. However, others included different historical activities such as user clicks (Xiao, et al., 2016) (Benabderrahmane, et al., 2018) (Shalaby, et al., 2017) (Jiang, et al., 2019), passed training records (Benabderrahmane, et al., 2018) and history of former applications (Nigam, et al., 2019). Based on the results of data sources, one singular, remarkable event stands out from another research. In the year 2016, a particular topic of Job Recommendation was co-organized by the social network XING in a yearly challenge called RecSys'16[1], held in the US, contributing six papers to improve job

[1] 10th ACM Conference on Recommender Systems, Boston, MA, USA, 15th-19th September 2016. https://recsys.acm.org/recsys16/.

recommendation with modern AI tools (Mishra & Reddy, 2016) (Zhang & Cheng, 2016) (Polato & Aiolli, 2016) (Liu, et al., 2016) (Pacuk, et al., 2016) (Xiao, et al., 2016).

Several investigated studies combine traditional recommendation system approaches (CF, CBR, KBR, and Hybrid) with new AI techniques. (Paparrizos, et al., 2011) trained a machine learning algorithm using linear Support Vector Machines (SVM) to improve the performance and results of the CBR recommendation system. Another study created a multi-agent system capable of learning through the CBR model using ML with argumentation network (González-Briones, et al., 2019). Five distinct studies improve the CF model with AI techniques:

- (Mishra & Reddy, 2016) created gradient boosting algorithm by applying linear regression and gradient boosting methods while using Random Forests for missing values.
- (Shalaby, et al., 2017) used content-based similarity measure, which is learned by the DL approach to computing the similarity scores from multiple data sources that capture users' behavior and resumes and jobs content while proposing a homogeneous graph-based recommendation architecture.
- (Hossain & Arefin, 2019) applied association rule mining to find positive frequent skill sets and train collaborative filtering model with logistic regression and linear SVM model to classify the posted jobs to positive and negative.
- (Patel & Vishwakarma, 2020) showed a concise review of CF rating prediction-based job recommendation system and their execution utilizing a tool called RapidMiner.
- (Appadoo, et al., {2020) made use of NLP and correlation between mapping user skills with the job requirements and accounts for related skills.

Three different studies used AI techniques with Hybrid models (traditional CF and CBR), combining them with: (1) Word2Vec, Latent Semantic model (LSI) (Zhang & Cheng, 2016), (2) statistical relational learning (SRL) models (Yang, et al., 2017) and (3) clustering together with text mining techniques (Tondji, 2018).

Bayesian Network Model is involved in two separate studies for (1) proposing the optimal soft skills (Bakar & Ting, 2011) and (2) for improved performance evaluation (Qin, 2017). The latter included an additional fuzzy neural network model with mathematical optimization and SVM, which is similarly used in (Diaby, et al., 2014). Model training using Cosine Similarity is explored in (Heap, et al., 2014) and (Polato & Aiolli, 2016). NLP is used in three separate studies focusing on: (1) extracting meaningful data from job postings using text-clustering methods (Mhamdi, et al., 2020), (2) in combination with correlation mapping user skills with the job requirements while considering related skills (Appadoo, et al., {2020) and (3) assigning "interaction points" with different values to the various elements in a CV (Hernández, 2016). Neural Networks are used as follows:

- RNN is used by (Liu, et al., 2016) to explore the RNNs approach to capture job-vacancy behavior patterns and by (Feng, et al., 2021) to map a student questionnaire to a weight d in combination with K-means clustering of vacancies to help students find optimal jobs collection.
- ANN is used: in combination with Logistic Regression to predict the suitable workout for each beginner in fitness using the Fitness Assistance system (Tran, et al., 2018) and for processing data from tested questionnaires to provide accurate recommendations for an internship place (Permana, 2019).

The first study using DL emerged in the field, proposing instead of the probabilistic models a DNN to predict future values of the clicks on job boards (Benabderrahmane, et al., 2018) (Benabderrahmane, et al., 2018). (Zhao, et al., 2021) construct a DL embedding model with domain-specific vocabulary to process information from CV-s and vacancies. (Nigam, et al., 2019) address an internal company-related solution and highly volatile job market while introducing a new machine learning model called Bidirectional Long Short Term Memory Networks (Bi-LSTM), which used candidate-job preference to propose future recommendations. (Shalaby, et al., 2017) use DL to compute the similarity scores from multiple data sources that capture users' behavior and CV and vacancy content.

How to Design a New Set of AI-Enabled Proactive Solutions for Supporting EU Citizens With Job Recommendations and Competence Development?

In Estonia and many other countries in the EU, a standardized occupational classification ISCO-08 is being used for multiple purposes such as its widespread acceptance, statistical simplification across organizations, etc. However, from mid-2021, another classification called ESCO[2] is strongly recommended and, to some extent, mandatory classification for EU member states. The key difference between ISCO-08 and ESCO is that there are also skills and qualifications included in addition to occupational titles. As today's employment agencies have only used ISCO codes and occupational titles, there is a lack of matching citizens' skills to specific vacancies or training for improved recommendations. According to NIIS, another EU-wide component that could assist in building EU-wide citizen-centered services is eDelivery. This set of specifications, standards, and software can enable secure data exchange between public registers, AI-enabled services, and citizen-centered platforms. Surprisingly eDelivery is already used for data exchange between employment agencies to determine the social security rights of persons in a cross-border situation. However, this solution is integrated into national social security systems and not directly related to citizen-centered services.

Interestingly, in some EU countries, including Estonia, the EU citizens can log in to the employment service with their national authentication solution, which must comply with IDentification, Authentication, and Trust Services

[2]ESCO is a European Commission project classifying skills, competences and occupations while covering 27 languages in the EU.

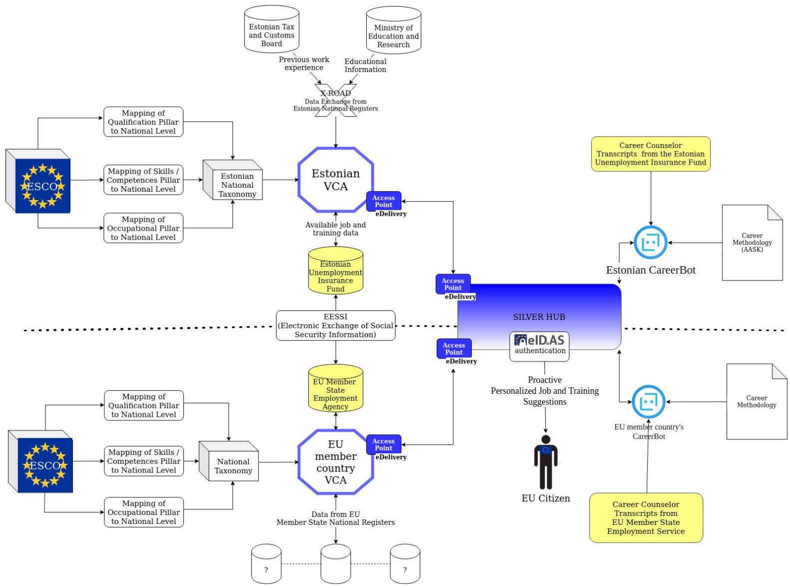

Figure 1: Conceptualized view on AI-enabled services accessible through Silver Hub.

(eIDAS) regulation and be certified by Certificate Authority. Combining such EU-wide components create the opportunity for AI-enabled service provisions and could be integrated into modern platforms. In one of the workshops with the Estonian Unemployment Insurance Fund representatives, we achieved a crucial necessity to targeting the labor market's less capable target group – the 50+ years old. After investigating this idea in a workshop with colleagues from local and international universities, we achieved the standpoint to establish a pilot version of AI-enabled competency services, integrating them to a Virtual Collaborative platform (Silver Hub). During the Interreg Baltic-Sea Region project, Tallinn University of Technology developed the platform- "OSIRIS: Supporting the Smart Specialization Approach in the Silver Economy to Increase Regional Innovation Capacity and Sustainable Growth."

DISCUSSION

In our previous research, we analyzed the current situation in the Estonian Unemployment Insurance Fund and proposed an initial model for a national VCA (Liutkevicius & Erlenheim, 2021). The main difference between Estonia and other countries in the EU is the usage of Estonian data exchange layer X-Road that is in use in Estonia for receiving citizen's data from different registers (i.e., occupational data from the Tax and Customs Board and educational data from the Ministry of Education and Research). This makes receiving the data for building AI models for VCA easier because the data already exists in a structured form. In this research, we gained initial feedback from other EU member state countries (Finland and Latvia), the Nordic

Institute of Interoperability Solutions (NIIS). Therefore, we can expand our concept to the international level (Figure 1).

CONCLUSIONS

This paper analyzed the existing research on job and training recommendation systems and conceptualized views on AI-enabled services supporting citizen-centered career services. The work is a step closer to bringing the services of employment agencies to the next level. Our objective is to target the 50+-year-old EU citizen by integrating the AI-enabled services to the already existing platform Silver Hub using the benefits of eIDAS authentication, eDelivery data exchange security, and ESCO. Besides having occupations and other essential background information about citizens, using ESCO, we additionally include skills and qualifications for improved recommendations using the new virtual assistant – Virtual Competence Assistant (VCA). In that way, if an EU citizen logs into the portal and presumes that her national employment agency has been successfully implemented, she can select the relevant skills based on the suggestions received from her background (former occupations and education from state registry) and start receiving recommendations for the next career choice. The VCA-s will proactively make personalized training and job recommendations using the citizens' personal background information. In addition, we see the opportunity to develop a national career chatbot called CareerBot for more efficient career counseling performing standardized career suitability tests, and suggesting sources of information that can help find a new career. As many employment agencies have recorded the phone calls of career counselors, they can be transcribed and used for AI model training. For that, a separate state of the art research is required, which was not in the scope of this paper. Nevertheless, such a solution can be added with similar means as VCAs. Consequently, we are creating a new set of AI-enabled solutions, which will enhance data exchange and public service provision for European citizens.

ACKNOWLEDGMENT

This work in the project "ICT programme" was supported by the European Union through European Social Fund. The authors would like to acknowledge Mr. Sander Nõmmik from the Estonian Unemployment Insurance Fund and Ms Merilin Liutkevicius from Tallinn University of Technology for their support in data collection and arranging the workshops.

REFERENCES

Appadoo, K., Soonnoo, B. M. & Mungloo-Dilmohamud, Z., {2020. *Job Recommendation System, Machine Learning, Regression, Classification, Natural Language Processing*. s.l., Institute of Electrical and Electronics Engineers Inc.

Bakar, A. A. & Ting, C.-Y., 2011. *Soft skills recommendation systems for IT jobs: A Bayesian network approach*. s.l., IEEE.

Benabderrahmane, S., Mellouli, N., Lamolle, M. & Mimouni, N., 2018. *When deep neural networks meet job offers recommendation*. s.l., IEEE Computer Society.

Benabderrahmane, S., Mellouli, N., Lamolle, M. & Mimouni, N., 2018. *When deep neural networks meet job offers recommendation.* s.l., IEEE Computer Society.

Dave, S. V. et al., 2018. *A combined representation learning approach for better job and skill recommendation.* s.l., Association for Computing Machinery.

Dhameliya, J. & Desai, N., 2019. *Job Recommender Systems: A Survey.* s.l., Institute of Electrical and Electronics Engineers Inc.

Diaby, M., Viennet, E. & Launay, T., 2013. *Toward the next generation of recruitment tools: An online social network-based job recommender system.* s.l., Association for Computing Machinery.

Diaby, M., Viennet, E. & Launay, T., 2014. *Taxonomy-based job recommender systems on Facebook and LinkedIn profiles.* s.l., IEEE Computer Society.

Dong, S. et al., 2017. *Job and candidate recommendation with big data support: A contextual online learning approach.* s.l., Institute of Electrical and Electronics Engineers Inc.

Feng, P. et al., 2021. *Job Recommendation System Based on Analytic Hierarchy Process and K-means Clustering.* s.l., Association for Computing Machinery (ACM).

Giabelli, A. et al., 2021. *Skills2Job: A recommender system that encodes job offer embeddings on graph databases.* s.l., Elsevier Ltd.

González-Briones, A. et al., 2019. *Case-Based Reasoning and Agent Based Job Offer Recommender System.* s.l., Springer Verlag.

Government CIO Office of Estonia, 2019. *Estonia's national artificial intelligence strategy 2019-2021,", Tallinn, 2019.,* Tallinn: Government of the Republic of Estonia.

Heap, B. et al., 2014. *Combining Career Progression and Profile Matching in a Job Recommender System.* s.l., Springer, Cham.

Hernández, O. F., 2016. *Resuminer – A Résumé Recommender System for Job Seekers using Cluster Analysis,* s.l.: Polytechnic University of Puerto Rico.

Hossain, M. S. & Arefin, S. M., 2019. *Development of an Intelligent Job Recommender System for Freelancers using Client's Feedback Classification and Association Rule Mining Techniques.* s.l., International Academy Publishing (IAP).

International Labour Organization, 2021. *World Employment and Social Outlook: Trends 2021,* Geneva: International Labour Organization.

Jiang, M. et al., 2019. *User click prediction for personalized job recommendation.* New York, Springer New York LLC.

Liu, K., Shi, X., Kumar, A. Z. L. & Natarajan, P., 2016. *Temporal Learning and Sequence Modeling for a Job Recommender System.* New York, USA, Proceedings of the Recommender Systems Challenge on - RecSys Challenge '16 .

Liutkevicius, M. & Erlenheim, R., 2021. *Validating the Usage of Occupational Classification Systems in the Process of Creating a National Virtual Competency Assistant within the EU Labor Market.* Athens, Greece, Association for Computing Machinery.

Mhamdi, D., Moulouki, R., El Ghoumari, M. Y. & Azzouazi, M., 2020. *Job recommendation system based on text analysis,* s.l.: Institute of Advanced Scientific Research, Inc.

Mishra, S. K. & Reddy, M., 2016. *Bottom-up approach to job recommendation system.* s.l., Association for Computing Machinery.

Nigam, A., Roy, A., Singh, H. & Waila, H., 2019. *Job recommendation through progression of job selection.* s.l., Institute of Electrical and Electronics Engineers Inc.

Pacuk, A. et al., 2016. *RecSys Challenge 2016: Job recommendations based on preselection of offers and gradient boosting.* s.l., Association for Computing Machinery.

Paparrizos, I., Cambazoglu, B. B. & Gionis, A., 2011. *Machine learned job recommendation.* s.l., ACM.

Patel, R. & Vishwakarma, K. S., 2020. *An Efficient Approach for Job Recommendation System Based on Collaborative Filtering.* s.l., Springer.

Permana, A. A. P. G. A., 2019. *Recommendation Systems for internship place using artificial intelligence based on competence.* s.l., Institute of Physics Publishing.

Polato, M. & Aiolli, F., 2016. *Proceedings of the Recommender Systems Challenge on - RecSys Challenge '16.* New York, USA, ACM Press.

Qin, W., 2017. *Application analysis of basketball training system based on personalized recommendation systems,* s.l.: Universidad Central de Venezuela.

Resnick, P. & Varian, H. R., 1997. Recommender Systems. *Communications of the ACM,* 40(3), pp. 56–58.

Rodriguez, L. G., Chavez, E. P. & Rodriguez, C. A., 2019. A Vectorization Model for Job Matching Application of a Government Employment Service Office. *Proceedings of 2019 the 9th International Workshop on Computer Science and Engineering,* 9(9), pp. 32–36.

Shalaby, W. et al., 2017. *Help me find a job: A graph-based approach for job recommendation at scale.* s.l., Institute of Electrical and Electronics Engineers Inc.

Zhang, C. & Cheng, X., 2016. *An ensemble method for job recommender systems.* s.l., Association for Computing Machinery.

Zhao, J. et al., 2021. *Embedding-based Recommender System for Job to Candidate Matching on Scale.* Georgia, USA, arXivLabs.

Tondji, N. L., 2018. *Web Recommender System for Job Seeking and Recruiting,* Dakar, Senegal: African Institute for Mathematical Sciences Senegal.

Tran, T. T. et al., 2018. *Recommender System with Artificial Intelligence for Fitness Assistance System.* s.l., Institute of Electrical and Electronics Engineers Inc.

Xiao, W. et al., 2016. *Job Recommendation with Hawkes Process An Effective Solution for Recsys Challenge 2016.* New York, ACM Press.

Yang, S., Korayem, M., AlJadda, K. & Grainger, T. N. S., 2017. *Combining content-based and collaborative filtering for job recommendation system: A cost-sensitive Statistical Relational Learning approach.* s.l., Elsevier B.V.

Appendix 6

VI

M. Liutkevičius, M. Kõosaar, and S. B. Yahia. Designing a Proof of Concept for a Virtual Competence Assistant. *Human Factors, Business Management and Society. International Conference*, 135:1–9, 2024

AHFE 2024: Vol. XX, 2024
doi: 10.54941/ahfeXXXX

.

Designing a Proof of Concept for a Virtual Competence Assistant

Markko Liutkevičius[1], Madis Kõosaar[1], Sadok Ben Yahia[1]

[1] Department of Software Science, TALTECH, Estonia

ABSTRACT

This paper addresses the critical gaps within public employment services (PES), with a particular focus on the deficiency in automation and AI-supported intelligent career recommendations. Notably, the advancements in this public sector's domain remain in their early stages, necessitating further exploration and development. The study sheds light on the underutilization and challenges faced in the PES sector, where scarcity of training data poses significant hurdles. Highlighting the potential of ESCO (European Skills, Competences, Qualifications, and Occupations) classification, the paper underscores its role in facilitating the alignment of occupations with specific skills through AI-driven approaches. By narrowing the training data to ESCO's research occupations and job posts collected from Estonian labor market, the paper lays down the preliminary foundation for constructing a digital career coach as a Virtual Competence Assistant (VCA). Ultimately, the envisioned proof of concept for an AI-based VCA holds the potential to revolutionize the delivery of PES services in the new era of efficiency and effectiveness.

Keywords: Public Employment Services, Virtual Competence Assistant, ESCO, Labor Market, AI.

INTRODUCTION

In the rapidly changing landscape of the 21st century, competency development has emerged as a fundamental element driving individual and societal progress. Technological advancements, economic shifts, and dynamic job markets necessitate a highly adaptable and skilled workforce. Unlike the past where qualifications ensured prolonged job security, the present reality emphasizes the crucial nature of competency development. This development is integral to personal growth, career advancement, economic prosperity, and social well-being. With the increasing integration of automated services, attention needs to be directed toward addressing citizens' needs during challenging times, particularly in the realm of public employment services (PES) supporting the unemployed. The EURES Regulation's Article 19 and its Implementing Decisions, endorsed by the European Commission in July 2018, introduce the use of the European Skills, Competences, and Occupations (ESCO) classification system [1]. It is crucial to highlight that ESCO serves not only as a taxonomy, formalizing hierarchical relationships among concepts and specifying terminology, but also as an ontology, identifying and distinguishing concepts based on their relationships to each other [2]. A crucial deadline of 31st of July, 2021 has been set for Member States to map their national occupational classifications or national skills classifications to ESCO, or they could choose to directly adopt ESCO for effective implementation. Many developments in the

PES sector are already promising in various aspects such as profiling jobseeker's probability of finding work [9][10] and a more general impact evaluation of active labour market measures [11]. An example of a system that aims to develop an automated skills-based matching tool is the Europass portal [23]. Member States are mandated to supply job vacancies and CVs using ESCO codes, which define occupations and skills. These developments have however little influence in making the national PES services more efficient. Moreover, certain scholars are currently directing their attention towards the potential of ESCO in the categorization of occupational postings and corresponding skill sets [12][13][14][15]. However, these developments are independent of the specific constraints and requirements set by PES. The incorporation and integration of artificial intelligence (AI) into PES activities bring forth a multitude of advantages and benefits, contributing significantly to the enhancement and optimization of various operational aspects and outcomes [8]. The European Union (EU) Commission plays a crucial role by providing guidance, coordination, and financial support to ensure that national PES activities align with broader EU employment and social policy objectives. Nevertheless, the duty of designing and executing employment services lies within the jurisdiction of national governments. Estonia has recently announced a new vision called 'Personaalne Riik' (Personal Country), where the idea is to take advantage of the latest technologies already used in the private sector and develop the public services using smart solutions to be modern, efficient and based on the needs of the user [3]. Within the Estonian Unemployment Insurance Fund (EUIF), The Estonian PES, individuals registering as unemployed are required to provide information about their job preferences through an e-service called 'e-töötukassa' [4]. Moreover, the service is accessible to all residents and citizens of Estonia. Since the service is linked to the national data exchange layer service (X-Road), the users of that service can effortlessly import data on their prior work experience and education [5]. Subsequently, individuals are assigned to a case worker consultant who personally discusses next career options. The limitation of this manual approach lies in the frequent occurrence of individuals aspiring to acquire skills diverging from their educational and experiential background. To address this issue, the development of an AI-enabled Virtual Competence Assistant (VCA) aims to facilitate citizens in effortlessly discovering suitable employment opportunities or receiving training suggestions tailored to their profile. The aim of this research is to lay down the preliminary foundation for constructing a digital career coach as a VCA for job recommendations considering the specific constraints and requirements of PES in Estonia which has been in our focus in previously published research [24][25]. Consequently, our research question is 'what approach can be used to design a proof of concept (POC) for a VCA recommending jobs for citizens in Estonia using the ESCO classification?'

METHODOLOGY

The research method employed allowed for the design of the POC for the Virtual Competence Assistant (VCA) within a simulated environment tailored to the Estonian context. Given the challenge of working with Estonian language, a low-resource language with limited available data from the labour market, the research utilized tools and models best suited to overcome this constraint and optimize the effectiveness of the POC design process.

STUDY FINDINGS

Data collection and cleaning

In the course of this investigation, obtaining an adequate volume of job advertisement data presented a challenge. Numerous websites in Estonia feature job posts (JP); nonetheless, not all are accessible to the public. Starting from 2021 we retrieved job postings through the EUIF open data API [26]. This API granted access to a significant volume of JP with daily updates. However, in November 2023, the API was unexpectedly discontinued from public access. Additionally, despite the EUIF's JavaScript Object Notation (JSON) dataset comprising 53 metadata fields, an issue was identified with respect to the linkage to specific ISCO (The International Standard Classification of Occupations) and ESCO codes. 'ESCO has been built as an extension of the International Standard Classification of Occupations (ISCO)' [7]. Having access to specific dataset linked to classification identifiers would have made the training of the data much easier. It is crucial to underscore that EURES mandates the exchange of labor information, including active job post data from EUIF, with the EU utilizing ISCO and ESCO codes [6]. This implies that information pertaining to ESCO codes linked to job posts already exists in the backend of the e-tootukassa service. The identified deficiency was communicated through meetings and correspondences with EUIF representatives already in 2021. Regrettably, the data was still not added to the public job posts. In addition to JP, we obtained the classification dataset in CSV files from the ESCO portal, selecting the Estonian language for analysis and later training of the model.

In the data cleaning phase, the primary objective was to clean and remove evidently irrelevant columns and documents from the gathered datasets. Firstly, among all the collected JP data, only the most relevant information was retained for the purpose of training models to identify skills with a clear correlation to the skills in question. The job titles and descriptions were concatenated together and in most cases, they were kept as they are. The texts were cleaned of unnecessary whitespaces and commas. Additionally, when the job description was not presented in the Estonian language it was dropped from the end document. Secondly, from the ESCO dataset, the 'preferredLabel' and 'altLabels' columns were put together as a single column. The column 'skillType' was used to filter with the value 'skill/competence' to get only skills that are relevant to this research study. Additionally, the data field 'conceptURI' was kept for later use connecting the unique skills to the ESCO data portal which encompasses further relations to specific occupations. All other columns were dropped as those were not deemed to be data fields that would have provided additional accuracy for skill classification. Thirdly, from the ESCO dataset, the fields 'prefferedLabel' and 'altlabels' were used for identifying occupations. As most of the occupations vary in the data quality we decided to narrow the identification only to scientific occupations which were well described from both 'prefferedLabel' and 'altlabels' fields. ESCO's 'researchOccupationsCollection' table consisted of 122 professions such as ‘biomedical engineer’, ‘criminologist’ linked to a comprehensive list of alternative labels. Howerer, since ‘altLabels’ were missing translation in the Estonian version. ChatGPT was used to translate the required data into Estonian from the English ESCO version. Additionally, ESCO codes, which are unique identifiers of occupations, were merged from main occupations table of ESCO as they were not present in the ‘researchOccupationsCollection’ table. During this research, specific information of CV-s obtained from the Estonian University websites, was used only to test the final model.

Data preprocessing and model development

Upon analyzing the JP data, it became apparent that frequently, job descriptions explicitly outline expectations from candidates, specifying mandatory or desirable skills. This kind of information allows for the identification of relevant skills. In line with the study conducted by Zhang, Jensen, and Plank in 2022, focusing on both Danish and English languages, similar findings were observed, enabling the application of analogous logic to extract skills and knowledge from sentences as shown on Figure 1 [13].

The job postings underwent tokenization, and EstNLTK morphological analysis was employed to examine the linguistic structure of the job postings [16]. Morphological analysis was utilized on JPs to investigate neighboring words within the participle, detecting particular word combinations such as ‘noun + noun in a partitive case’. This analysis facilitated the extraction of additional results to contribute to the input data for skill prediction models. The outcomes played a role in a subtask related to information extraction within the field of Natural Language Processing (NLP), specifically, Named Entity Recognition (NER). The primary goal of NER tagging is to identify and classify named entities within the text into predefined categories, such as individual names, organizational names, locations, and other relevant types of information. Consequently, we followed the Estonian language rules to establish a potential combination of words that is corresponding as a skill.

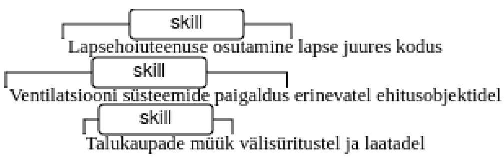

Figure 1: Skill extraction from JP by the example of Zhang, Jensen, and Plank in 2022 [13]

After preprocessing the JP data, we built patterns that could be fed into the Prodigy tool that helps to train the model using the Named Entity Recognition (NER) approach with the JP data as input so we could improve the identifications of skills [19]. The model was built using the ‘EstSpaCy’ model and the ‘et_dep_ud_xlmroberta’ based on ‘xlm-roberta-base transformers library’ [17] [18]. Finally, the model was evaluated by using a separate set of test data from job postings by validating the skills that were outputted by the model.

In preparing the data for constructing the model to identify occupations from CV-s, the initial step was to convert texts into tagged documents. This process involved transforming the text into a set of words. Following that, common words like articles and linking words were removed as stop words. Additionally, words with a length of 2 or fewer characters were omitted. Each document required a unique tag, and for this purpose, the index number of the document in the dataset was utilized as the tag. In the decision process of which ML technique to use we explored multiple options and existing models, including large language models (LLMs), JobBert [14]. However, considering their undeveloped capabilities in Estonian language and low reliability in providing adequate relations between input data and ESCO entities especially in Estonian language, we decided to use Gensim as a preliminary model to be used in the VCA [20]. Gensim is an open-source Python library designed for natural language processing and topic modeling which is particularly well-suited for tasks involving large text corpora, document similarity analysis, and unsupervised machine learning applications [20]. The Gensim library offered the flexibility to incorporate other tags into the document. To build the model, we followed a similar approach to another research involving the assessment of commodity codes using HS code classification which is similar to ESCO [21]. In our scenario, the ESCO code corresponding to the item description served as the second tag. During training, the distributed bag of words (PV-DBOW) was employed as the training algorithm, and the number of iterations (epochs) over the corpus was set to 40. The Doc2Vec model facilitated the discovery of the most similar documents to the original text [22]. We used ‘altlabels’ data for training and ’prefferdLabel’ for testing the model. If we selected the original text as ‘Kriminoloog’ and aimed to identify texts resembling it, the process involved several steps. Initially, the original text underwent preprocessing, and it was transformed into a vector using a pretrained Doc2Vec model. Subsequently, the closest texts were determined by assessing cosine vector similarities between the vector representation of the original text and other texts within the vocabulary.

DISCUSSION

Our research has previously explored the situation of PES services in the EU and how implementation of AI can be pursued in the PES based on EUIF as an example. An important purpose of this paper was to experiment how occupational classification ESCO can be used with ML technology in order to recommend relevant JP to citizens. The paper lays down the preliminary foundation for constructing a digital career coach as a VCA utilizing the compulsory occupational classification for the EU member states. Figure 2 illustrates an approach how this could be achieved taking into account the data issues presented in both the EUIF and ESCO’s Estonian version. The research shows which classification components of ESCO can be used to get started building the two separate models: 1. converting CV text into ESCO occupations and 2. identifying skills from text based JP. As scientific occupations in ESCO have the 122 occupations well described with a comprehensive list of labels, we could get high similarity scores with the chosen Doc2Vec model. The JP model’s biggest challenge was the quality of the JP text often lacking essential description of the tasks and requirements. Hence, the preprocessing needed a lot of manual data annotation help which in our case was a resource intensive task. Following the logic established in this research we propose the proof of concept of how a VCA for recommending jobs to a citizen can be achieved in Figure 2.

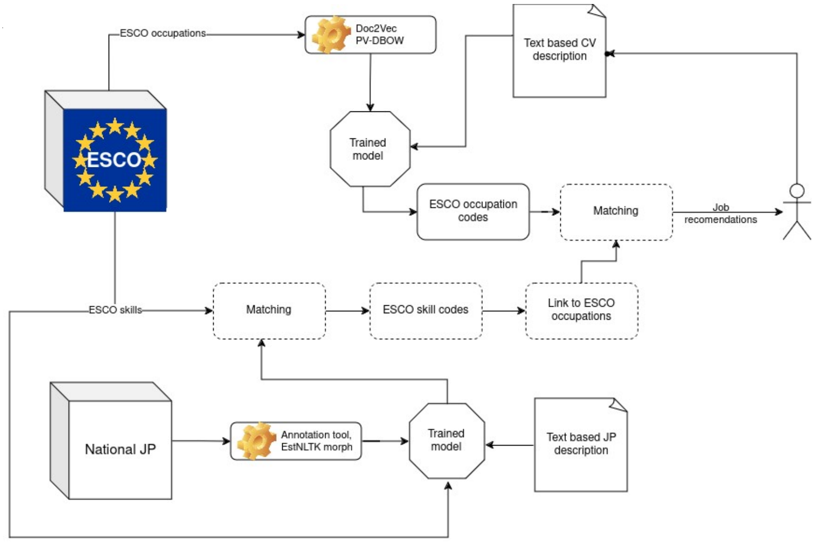

Figure 2: POC for an AI-Based VCA

The concept involves the two models outputting specific ESCO conceptURI-s and ESCO occupational codes with the limitation of describing specific techniques to match the outputs together. Specific matching techniques require further investigation which was not in the scope of this research and are illustrated as dotted-line boxes in Figure 2.

CONCLUSION

In conclusion, many developments the European PES sector are leaning towards the adoption of AI tools. However these tend to lean towards making the backend tasks more efficient and not so much designing user-friendly services. Our research lays the groundwork for a personalized recommendation tool VCA, making ESCO the default classification. Using tools like EstNLTK, Prodigy, SpaCy and Doc2Vec, show promising outcomes. However, data quality, especially in ESCO’s 'altLabels,' and JP descriptions need improvement from both the labor market and ESCO. Facilitating experimentation with such models and tools is crucial to make the services offered by governments modern, efficient and based on the needs of the citizen. However, given the closure of access to Estonian JP data by EUIF during the collection phase of this research and not making specific dataset linked to classification identifiers available for training purposes clearly illustrated room for improvement in that area. In essence, our study offers practical insights on how to initiate designing of the AI-based VCA in the evolving landscape of PES.

ACKNOWLEDGMENT

This work in the project ‘ICT programme’ was supported by the European Union through European Social Fund. This work was supported by grants to TalTech – TalTech Industrial (H2020, grant No 952410) and Estonian Research Council (PRG1573).

REFERENCES

[1] European Commission (2018), Commision implementing decision (EU) 2018/1020 of 18 July 2018 on the adoption and updating of the list of skills, competences and occupations of the European classification for the purpose of automated matching through the EURES common IT platform. Brussels: Official Journal of the European Union (2018)

[2] SkillLab. ESCO and the Creation of a Data-Rich Environment, An Opportunity for the EU Labour Market. Amsterdam, Netherlands

[3] Ministry of Economic Affairs and Communications of Estonia. Personaalne riik. 2024.

[4] Estonian Unemployment Insurance Fund (February 28, 2024). E-service "e-töötukassa". Website: https://www.tootukassa.ee/etootukassa/eng/logi-sisse

[5] e-Estonia (February 28, 2024). Interoperability services - X-Road. Website: https://e-estonia.com/solutions/interoperability-services/x-road/

[6] European Commission (February 20, 2024). How is ESCO used by Public Employment Services in Europe and in EURES? Website: https://esco.ec.europa.eu/en/node/171

[7] European Commission, ESCO: harnessing the power of big data analysis for a functional labour market, Luxembourg: Publications Office of the European Union, Luxembourg, 2017.

[8] OECD 2022. Harnessing digitalisation in Public Employment Services to connect people with jobs. Policy Brief on Active Labour Market Policies, 2022.

[9] Desiere, Sam, Struyven, Ludo. Using Artificial Intelligence to classify Jobseekers: The Accuracy-Equity Trade-off. Journal of Social Policy. 2021;50(2):367-385.

[10] Leinuste, Karina. (2021), Decision support tool „OTT“ for employment counsellors in the Estonian PES. Development, implementation and future plans, OECD.

[11] Printsmann, Piia Ereth (2023), Automated tool for impact evaluation of active labour market measures: Linking administrative data, OECD.

[12] Niittylä, Heikki (2020), Utilising artificial intelligence in the application process for ESCO competence, Job Market Finland - Current issues. Job Market Finland Website: https://tyomarkkinatori.fi/en/blogit/vieraskyna-niittyla-tekoalyn-hyodyntaminen-esco-osaamisten-haussa

[13] Zhang, Mike. Jensen, Kristian Nørgaard. Plank, Barbara (2022). Kompetencer: Fine-grained Skill Classification in Danish Job Postings via Distant Supervision and Transfer Learning. Language Resources and Evaluation Conference, LREC 2022.

[14] Zhang, Mike. Jensen, Kristian Nørgaard. Sonniks, Sif Dam. Plank, Barbara. SkillSpan: Hard and Soft Skill Extraction from English Job Postings. Association for Computational Linguistics, ACL 2022.

[15] Zhang, Mike. Jensen, Kristian Nørgaard. van der Goot, Rob. Plank. Barbara (2022). Skill Extraction from Job Postings using Weak Supervision. CEUR Workshop Proceedings 2022.

[16] Laur, Sven. Orasmaa, Siim. Särg, Dage. Tammo, Paul (2020), EstNLTK 1.6: Remastered Estonian NLP Pipeline. Proceedings of The 12th Language Resources

and Evaluation Conference. European Language Resources Association. Marseille, France.
[17] Müürisep, Kaili (2021), SpaCy pipelines for Estonian language. Website: https://github.com/EstSyntax/EstSpaCy/
[18] Conneau, Alexis. Khandelwal, Kartikay. Goyal, Naman. Chaudhary, Vishrav. Wenzek, Guillaume. Guzman, Francisco. Grave, Edouard. Ott, Myle. Zettlemoyer, Luke. Stoyanov, Veselin (2019), Unsupervised Cross-lingual Representation Learning at Scale, CoRR.
[19] Prodigy (February 27, 2024). Radically efficient machine teaching. An annotation tool powered by active learning. Website: https://prodi.gy/
[20] Řehůřek, Radim. Sojka, Petr (2010). Software framework for topic modelling with large corpora. Proc. LREC Workshop on New Challenges for NLP Frameworks. Valletta, Malta.
[21] Spichakova, Margarita, Haav, Hele-Mai. (2020). Using Machine Learning for Automated Assessment of Misclassification of Goods for Fraud Detection. In: Robal, T., Haav, HM., Penjam, J., Matulevičius, R. (eds) Databases and Information Systems. DB&IS 2020. Communications in Computer and Information Science, vol 1243. Springer
[22] Le, Q. and Mikolov, T., (2014). Distributed representations of sentences and documents. In International conference on machine learning (pp. 1188-1196). PMLR.
[23] Europass (February 27, 2024), European Union. Website: https://europa.eu/europass/en
[24] Liutkevicius, Markko; Erlenheim, Regina (2021). Validating the usage of occupational classification systems in the process of creating a national virtual competency assistant within the EU labor market. Proceedings of the 14th International Conference on Theory and Practice of Electronic Governance (ICEGOV 2021), 6 – 8 October 2021, Athens, Greece. New York: ACM Press, 254−259.
[25] Liutkevicius, Markko; Ben Yahia, Sadok (2022). Research roadmap for designing a Virtual Competence Assistant for the European labour market. Procedia Computer Science, 207, 2404−2413.
[26] Job postings API of The Estonian Unemployment Insurance Fund (27th February 2024). Website:https://www.tootukassa.ee/et/api/toopakkumised

Curriculum Vitae

1. Personal data

Name	Markko Liutkevičius
Date and place of birth	1 October 1983 Tallinn, Estonia
Nationality	Estonian

2. Contact information

Address	Tallinn University of Technology, School of Information Technologies, Department of Software Science, Ehitajate tee 5, 19086 Tallinn, Estonia

3. Education

2019–2024...	Tallinn University of Technology, School of Information Technologies, Department of Software Science, PhD studies
2012–2014	University of Tartu Design and Development of Virtual Environments, MA
2010–2012	University of Aalborg International Business Management, MSc
2002–2006	Tallinn University of Technology Information Systems and Software Engineering, BSc

4. Language competence

Estonian	native
English	fluent
German	basic
Lithuanian	basic

5. Professional employment

2024–...	Information System Authority, Head of Machine Learning and Language Technology
2014–2020	Estonian Defence League, Chief Information Security Officer, CISO
2013–2014	Estonian Defence Forces, Chief Information Officer, CIO
2012–2013	Estonian Defence Forces, IT project manager

6. Defended theses

- Merilin Liutkevicius, Master's Degree, 2023, (sup) Markko Liutkevičius, Readiness for Local and Cross-Border Intelligent Public Employment Services in the European Union, Tallinn University of Technology School of Information Technologies, Department of Software Science

- Sander Nõmmik, Master's Degree, 2023, (sup) Markko Liutkevičius, Applicability of AI-enabled Solutions in Public Employment Services by the Example of Estonia, Tallinn University of Technology, School of Information Technologies, Department of Software Science

- Ran Mohottige Piyumi Madhushik Samaranayaka, Master's Degree, 2023, (sup) Markko Liutkevičius, Towards Modern Public Employment Services: Investigating the Needs of Job Seekers and Organizations, Tallinn University of Technology, School of Information Technologies, Department of Software Science
- Serkan Ahmet Koch, Master's Degree, 2021, (sup) Eric Blake Jackson; Markko Liutkevičius, Modernization of Commodity Classification Practices in Trade for EU Customs with Machine Learning Web Solutions, Tallinn University of Technology School of Information Technologies, Department of Software Science
- Roman Rozbroj, Master's Degree, 2020, (sup) Ingrid Pappel; Markko Liutkevičius, The Upcoming EU 2021 VAT E-commerce Package from Consumer Perspective, Tallinn University of Technology School of Information Technologies, Department of Software Science

7. Scientific work
Papers

1. M. Liutkevičius and S. B. Yahia. Research Roadmap for Designing a Virtual Competence Assistant for the European Labour Market. *Knowledge-Based and Intelligent Information & Engineering Systems: Proceedings of the 26th International Conference (KES2022)*, *Procedia Computer Science*, 207:2404–2413, 2022
2. M. Liutkevičius, M. Weck, and S. B. Yahia. Understanding the Challenges of Today's Labor Market Service Provision in the EU. *Human Factors*, *Business Management and Society*, 97(97), 2023
3. M. Liutkevičius and R. Erlenheim. Validating the usage of Occupational Classification Systems in the Process of Creating a National Virtual Competency Assistant within the EU Labor Market. *ICEGOV '21: Proceedings of the 14th International Conference on Theory and Practice of Electronic Governance*, 7:254–259, 2022
4. M. Liutkevičius, S. Nõmmik, Piyumi, M. Weck, and S. Yahia. In Pursuit of AI Excellence in Public Employment Services: Identifying the Requirements. *TalTech Journal of European Studies*, 14, 2024
5. M. Liutkevičius and S. B. Yahia. The Use of Artificial Intelligence in Job Seeking and Competence Development. *Human Factors*, *Business Management and Society*, 56:128–136, 2022
6. M. Liutkevičius, M. Kõosaar, and S. B. Yahia. Designing a Proof of Concept for a Virtual Competence Assistant. *Human Factors*, *Business Management and Society. International Conference*, 135:1–9, 2024
7. M. Liutkevičius, K. I. Pappel, S. A. Butt, I. Pappel (2020). Automatization of cross–border customs declaration: Potential and challenges: A case study of the Estonian customs authority. Electronic Government: 19th IFIP WG 8.5 International Conference, EGOV 2020, Springer, 96–109.

Elulookirjeldus

1. Isikuandmed

Nimi	Markko Liutkevičius
Sünniaeg ja -koht	01.1o.1983, Tallinn, Eesti
Kodakondsus	Eesti

2. Kontaktandmed

Aadress	Tallinna Tehnikaülikool, Arvutiteaduse Instituut, Ehitajate tee 5, 19086 Tallinn, Estonia

3. Haridus

2019–2024	Tallinna Tehnikaülikool, Infotehnoloogia teaduskond, Arvutiteaduse doktoriõpingud
2012–2014	Tartu Ülikool, Virtuaalkeskkondade disain ja arendus, MA
2012–2014	Aalborgi Ülikool Rahvusvahelise tehnoloogia juhtimine, MSc
2002–2006	Tallinna Tehnikaülikool Informaatika, BSc

4. Keelteoskus

eesti keel	emakeel
inglise keel	kõrgtase
saksa keel	algtase
leedu keel	algtase

5. Teenistuskäik

2024–...	Riigi Infosüsteemi Amet, Masinõppe ja keeletehnoloogia talituse juhataja
2014–2020	Kaitseliit, Infoturbejuht
2013–2014	Kaitseväe peastaap, Infohaldusjuht
2012–2013	Kaitseväe peastaap, IT projektijuht

6. Kaitstud lõputööd

- Ran Mohottige Piyumi Madhushik Samaranayaka, Magistrikraad, 2023, (juh) Markko Liutkevičius, Avalike tööhõive teenuste moderniseerimine: tööotsijate ja tööandjate vajaduste uurimine, Tallinna Tehnikaülikool, Infotehnoloogia teaduskond, Tarkvarateaduse instituut

- Merilin Liutkevicius, magistrikraad, 2023, (juh) Markko Liutkevičius, Euroopa Liidu valmisolek intelligentseteks tööturuteenusteks kohalikul ja piiriülesel tasandil, Tallinna Tehnikaülikool, Infotehnoloogia teaduskond, Tarkvarateaduse instituut

- Sander Nõmmik, magistrikraad, 2023, (juh) Markko Liutkevičius, Tehisintellekti toega lahenduste rakendatavus tööhõiveametites Eesti näitel, Tallinna Tehnikaülikool, Infotehnoloogia teaduskond, Tarkvarateaduse instituut

- Serkan Ahmet Koch, magistrikraad, 2021, (juh) Eric Blake Jackson; Markko Liutkevičius, Masinõppel tuginevate veebilahendustega Euroopa tollinduses kauba klassifitseerimispraktikate kaasajastamine, Tallinna Tehnikaülikool, Infotehnoloogia teaduskond, Tarkvarateaduse instituut

- Roman Rozbroj, magistrikraad, 2020, (juh) Ingrid Pappel; Markko Liutkevičius, 2021. aastast jõustuv EL käibemaksu e-kaubanduse pakett tarbija seisukohast, Tallinna Tehnikaülikool, Infotehnoloogia teaduskond, Tarkvarateaduse instituut

ISSN 2585-6901 (PDF)
ISBN 978-9916-80-205-2 (PDF)