



A sociotechnical evaluation of an algorithmic service allocation tool in Helsinki Employment Services

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The objective of this thesis was to evaluate an algorithmic tool developed by Helsinki Employment Services to help allocate clients to suitable service categories. The purpose was to evaluate the effectiveness of the tool from the perspective of employment specialists, identify key limitations, and provide practical recommendations for improving its functionality in everyday workflows.

The thesis used Sociotechnical Systems (STS) theory as a framework, highlighting that both technical design and social context are important when implementing digital tools. A survey with both quantitative and qualitative questions was conducted among employment specialists.

Overall, the algorithmic tool represents a promising initiative in digitalising employment services. However, key findings showed that employment specialists were sceptical about the tool's accuracy in reflecting the labour market situations and working capacities of the clients. Main concerns included misclassification of clients, insufficient training provided, unclear logic behind the tool, and its tendency to oversimplify more complex client cases.

The results show that the algorithmic tool needs clear criteria and more transparency in how results are informed. On the organisational side, better training, clearer communication, and involving employment specialists directly in future improvements are recommended.

Keywords: algorithmic decision-making, sociotechnical systems (STS) theory, public employment services, digital transformation, service allocation

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1 Introduction

The digitalisation of public administration in Finland has been a topic of interest for several decades. There have been increasing demands to work more efficiently and deliver high-quality services in order to achieve cost-saving objectives set by the government while meeting the needs of diverse populations. According to a publication from the Prime Minister's Office by Parviainen, Kääriäinen, Honkatukia & Federley (2017, 7) digitalisation is viewed to improve efficiency and service quality, ease administrative workloads, and help control the rising costs of public spending.

In line with these digitalisation efforts, employment services in Finland have recently undergone a bigger transformation to address labour market challenges and to improve service delivery. The objective behind this reform includes the need to accelerate the employment of those seeking for employment while making sure the overall quality of services within the employment and business sector stays improved. An important part of this transformation has been the reorganisation of services, from the state's employment and economic development offices to municipalities and municipal co-management areas, uniting all employment-related support under a single entity to serve users better. Helsinki Employment Services implemented this transformation on January 1, 2025, becoming the new employment authority in Helsinki. (City of Helsinki 2025, Ministry of Economic Affairs and Employment of Finland 2025.)

Within this larger framework, the Helsinki Employment Services have developed an internal algorithmic tool designed to assess the service needs of clients and direct them to the appropriate employment specialists. The tool tries to improve the effectiveness and efficiency of employment services by allowing employment specialists to allocate resources more strategically and provide targeted support to clients. Since its broader implementation on January 1, 2025, evaluating the tool's performance and effectiveness has become increasingly important making sure it achieves its intended objectives.

The purpose of this thesis is to evaluate the performance and effectiveness of the algorithmic tool developed by Helsinki Employment Services. With an evaluation of the tool, the study assesses how well it supports employment specialists in their daily tasks, identifies any limitations or points for improvement, and offers practical suggestions for improving its functionality accordingly. The thesis is guided by the following research questions:

1. How do employment specialists perceive the effectiveness and accuracy of the algorithmic tool in allocating clients according to their employment prospects and supporting needs?

2. What are the main limitations employment specialist identify when using this algorithmic tool in their daily work?
3. Which improvements do employment specialist recommend to improve the usability and effectiveness of the tool?

This thesis examines both the tool's technical performance—such as its accuracy in assessing customer service needs—and its impact on the workflows of specialists. The scope of the study is intentionally limited to the evaluation of the tool from the perspective of its end users i.e. employment specialists. It does not discuss the technical development or coding of the algorithm itself. By narrowing the focus, the thesis provides relevant findings for improving the tool's performance and usability.

In the following chapter 2 there is a brief overview of relevant literature with key concepts as well as an introduction to the Sociotechnical Systems (STS) theory. Chapter 3 presents the algorithmic tool currently being used in Helsinki Employment Services, with some detail on its functionality and identifying initial limitations. In chapter 4 the methodology is described, including the data collection and analysis procedures used to gather the specialists' perceptions through a survey. The results, both qualitative and quantitative are presented in chapter 5 and chapter 6 offers practical recommendations for improving the usability and effectiveness of the algorithmic tool based on the survey findings. Final conclusions are made in chapter 7.

2 Literature review and theoretical framework

2.1 Relevant literature

Data-driven algorithmic tools have been introduced to public employment services in several countries, with the intention to improve efficiency, optimise decision-making, and to make sure that available resources are used more effectively. The relevant literature looks into existing research on algorithmic tools in public employment services, with attention to accuracy, fairness and user perceptions.

One of the international comparisons of algorithmic tools are described by Desiere & Struyven (2021, 368) who discuss in their article how different statistical profiling tools have been used for segmenting jobseekers based on their risk of long-term unemployment. In the United States, the Worker Profiling and Reemployment Services system was used to assign scores to jobseekers to estimate, how likely they are to use up all their unemployment benefits before finding a job. Australia used a system called the Job Seeker Classification Instrument to segment jobseekers into different service streams and in the Netherlands, they employed the

Work Profiler tool, which consists of questions related to jobseekers' skills and attitudes that help predict their likelihood of returning to work.

Flügge (2021) also looks into the global trend of incorporating algorithmic decision-making into public employment services. Their study concentrates on how these data-driven tools are being implemented to assist caseworkers in profiling jobseekers, particularly in predicting their risk of long-term unemployment. In their research, they discuss how public employment services in Denmark, Austria, and Portugal, are increasingly relying on algorithmic tools to categorise unemployed individuals and guide decision-making.

Closer to Finland, Sweden has implemented an algorithmic decision-support system within its public employment services to assist caseworkers in profiling jobseekers and guiding them toward suitable services. According to Bergman, de Fine Licht & Carlsson (2024, 4-5), the system classifies jobseekers based on their estimated likelihood of finding employment within six months, using a neural network trained on past jobseeker data. While it provides structured recommendations for service allocation, there are challenges regarding transparency and fairness. Jobseekers are only shown limited explanations for their classification and the system uses randomisation in borderline cases, which then might lead to inconsistent outcomes. Additionally, caseworkers are restricted from reinterpreting classifications, reducing their discretion in decision-making. These limitations highlight concerns about how well both caseworkers and jobseekers understand the tool's logic, as well as the potential impact on trust and perceived fairness.

From the perspective of this thesis, the studies might show that transparency and user trust are critical areas to examine in Helsinki Employment Services' algorithmic tool as well. The extent to which employment specialists understand the logic behind client classifications could directly influence their perceptions of fairness and effectiveness.

It is important that algorithmic tools are accurate when it comes to allocating services, as mistakes can result in service users being misclassified and resources being given out incorrectly. Desiere & Struyven (2021, 369) point out that while algorithmic tools can improve the accuracy of service allocation, they also carry the risk of misclassifying certain groups, particularly those who are more disadvantaged. This misclassification can lead to unequal distribution of resources, with vulnerable populations being unfairly labelled as high-risk. The authors argue that even though these tools are created to improve efficiency, they must be carefully monitored to prevent reinforcing existing biases.

Taking these factors into account, evaluating the accuracy of Helsinki Employment Services' algorithmic tool from the employment specialists' perspective becomes particularly relevant. It is important to note whether similar issues emerge in practice within Helsinki's context.

Addressing such inaccuracies could prevent potential inequalities and make sure the outcomes are fairer for clients.

Researchers who study algorithmic tools in public employment services often stress the importance to view these systems from the frontline perspective of specialists who actually use them. For instance, Allhutter et al. (2020, 12-15) point out that while algorithmic profiling can streamline the classification of job seekers, it might miss the detailed insights that caseworkers gain from personal interactions with clients, and narrowly defined categories can fail to capture an individual's unique circumstances. On the other hand, transparency and accountability in algorithmic decision-making should also be taken into consideration. According to the European Parliamentary Research (EPRS 2019, 11), the lack of transparency in algorithmic decision-making systems poses significant risks, as it makes it difficult for people to understand how decisions are generated, giving them little opportunity to question or improve them.

Concerns about bias is also commonly found in relevant literature. The Greenlining Institute (2021, 4) describes how data-driven systems can unintentionally include past discrimination in their predictions, creating new forms of inequality. Even if the algorithm tries to rank jobseekers fairly, any biased use from the historical data or assumptions can result in unfair classifications. For example, if certain groups were disadvantaged in the past, an algorithm might label them as higher risk for unemployment, even if their current situation does not support that.

To summarise on the existing research presented above, it can be said that research highlights both the potential benefits as well as the challenges with regards to algorithmic tools in public employment services. Accuracy, fairness, transparency and user trust seem to be some of the main factors that influence the successful usage of such tools. These identified factors serve as key references in evaluating the algorithmic tool used by Helsinki Employment Services. Understanding how specialists experience these aspects in practice offers valuable insights into how the tool could be further developed.

2.2 Key concepts

2.2.1 Algorithmic decision-making

An algorithm is a logical process designed to systematically solve specific challenges. It processes a given input data according to a given rule and produces an output accordingly. They can be manually written by programmers or created automatically from data. Traditionally, algorithms relied on statistical techniques, such as regression analysis, to

evaluate data and generate conclusions. (Mahmud, Islam, Ahmed & Smolander 2022, 2; EPRS 2019, 3.)

Building on this foundation, Mahmud et al. (2022, 2) describe algorithmic decision-making as the use of algorithms to assist or fully execute decision-making processes by analysing data and applying predefined rules or patterns. While some algorithms operate with pre-programmed parameters determined by humans, others – particularly those integrated with advanced technologies – can independently identify patterns in data to improve their decision-making over time. In practice, algorithmic decision-making often plays a supportive role, aiding human decision-makers in different tasks. Some examples of utilising algorithmic decision-making in public administration in Finland include processing tax-related assessments or different social benefit applications (Gröning 2023). In public employment services specifically, there are examples from Austria, Portugal and Denmark where algorithmic decision-making systems have been implemented to support caseworkers in assessing the service needs of their clients (Flügge 2021, 253-254).

2.2.2 Service needs assessment tools

Service needs assessment tools are essential for helping to identify needs and thus making sure correct services are allocated efficiently and effectively to address needs. Watkins & Kavale (2014, 20) discuss the definition of needs in their article and describe needs assessment as a process used to identify and evaluate the needs of a particular group or an organisation. They underline the importance of clearly defining what is meant by needs, as it will have an influence on the design and implementation of the assessment. Sleezer, Darlene, Russ-Eft & Gupta (2014, 1-2; 373) argue, that needs assessment often about recognising and analysing problems, opportunities, and potential solutions related to individuals, groups, organisations, or larger communities. The process consists of gathering data and working together in areas where there is need for improvement. It often relies on insider knowledge from those familiar with the context to make sure the diagnosis and actionable solutions are reliable.

When considering the tools used in needs assessment, there is a range of methods used from simple manual checklists and interviews to more advanced algorithmic models that process larger datasets. These tools generally follow a basic structure: data is collected (input), analysed or assessed, and then used to generate an output or decision. In general, these tools help in identifying service needs and determining appropriate actions. However, with the rise of digitalisation, the more traditional methods are slowly being replaced by different digital systems. Examples of these can be found in the Public Employment Service in Austria, where, in order to save money, increase efficiency and provide responsive services, an algorithmic profiling system has been implemented to classify job seekers based on their employment

prospects, or an algorithmic tool designed to support the decision-making in job placement services by assisting caseworkers in providing data-driven perspectives and recommendations in Denmark (Alhutter, Cech, Fischer, Grill & Mager 2020; Flügge, Hildebrandt & Møller 2021).

2.2.3 Accuracy in service allocation

Accuracy in service allocation is important for making sure, that services are directed to the right service users to maximise efficiency and to achieve desired outcomes. In the context of public employment services, accurate tools can help identify needs and provide tailored support. Inaccurate classifications, however, can lead to ineffective resource allocation or exclusion of those requiring assistance, which may further widen inequalities. As noted also by Briowscú, Lauringson, Saint-Martin and Xenogiani (2024, 28) achieving this level of accuracy relies on the quality of data used in service allocation tools. Public employment services must ensure that their data is reliable, consistent, and appropriately prepared for integration into AI systems. Without proper data validation and governance, inaccuracies can arise, undermining the effectiveness of these tools and the fairness of their outcomes.

It is good to keep in mind, that even with reliable data inputs, the actual outputs of such algorithmic tools may not always align with intended outcomes. For instance, the Greenlining Institute highlights in its report, that decisions based on incorrect, partial, or non-representative training data can lead algorithms to draw faulty conclusions, resulting in unfair outcomes (Greenlining Institute 2021, 8). This mismatch happens because algorithms learn from past data that might have biases, or because they focus on being efficient instead of fair, which can unintentionally harm vulnerable groups. Therefore, continuous evaluation and adjustment of these algorithmic tools accordingly is important in order to making sure they are effective and fair in service delivery.

2.2.4 The digitalisation of the public sector in Finland

Finland has been recognised as one of the top-countries promoting digital transformation within the public sector. According to a Policy Brief by the Ministry of Finance (2019, 2) the shift towards digitalisation and the adoption of new practices within the central government and the broader public sector started already in the 1990s, as advanced technologies became more widely available. This includes the development of systems such as Kanta services, which act as a nationwide digital platform for health and social care records so that both health care professionals and citizens can access relevant information (Kanta 2025). Another example of one of these systems used in the public sector is the Suomi.fi platform, offering a variety of online public services for citizens to handle their administrative tasks conveniently and securely (Suomi.fi 2025).

Despite the significant and fast progress in digitalisation, there have been challenges along the way. Protecting data privacy and concentrating on security issues are significant concerns, considering that sensitive information is increasingly stored and shared digitally. To follow the General Data Protection Regulation (GDPR), public sector organisations need to make sure that their citizen's personal data is strongly protected (European Commission 2025).

Alternatively, digitalisation can open doors to significant opportunities. It can make work processes smoother and reduce administrative tasks, allowing public sector organisations to be more efficient and focus on important areas. Additionally, as algorithmic tools become more common in public services, it is important to address potential risks like unfairness, inaccuracies and unintended discrimination. This presents an opportunity to develop policies and practices that guarantee algorithms are optimised towards equity and inclusion (Brioscú 2024, 32).

2.2.5 The Helsinki Employment Services

Public employment services have an important role in supporting jobseekers and employers by providing services aimed at improving employment outcomes. In Finland, the organisation of public employment services went through significant changes as of January 2025. According to the Ministry of Economic Affairs and Employment of Finland (2025a), the responsibility for providing these services has no longer been in the state's employment and economic development offices but at municipalities and municipal co-management areas. This restructuring has led to the formation of 45 employment areas, each of them tasked with delivering employment services, information, guidance, training, and other support measures to jobseekers and employers.

As stated in an email to the author, starting from 2025, Helsinki Employment Services have been one of the 45 employment areas responsible for providing public employment services. They focus on promoting employment in Helsinki and handle all related development and coordination tasks. Additionally, they offer services to support the integration of working-age individuals. (Rajaniemi 2025. Personal communication.)

The Helsinki Employment Services are structured according to the client's labour market position, divided into five service categories. Services are tailored to support independent job searching and quick employment. The five service categories include 1) proactive services, that gather multidisciplinary expertise and do not require employment service membership, 2) matching services that focus on job placement primarily in the open labour market, 3) pathway services for clients needing support to strengthen their labour market position, 4) employer services that manage employer-client relationships, provide employer advice, support, job postings, transition security, joint procurement training, and collaboration with

employers in the Helsinki metropolitan area, and finally 5) support services for operational success, such as communication, finance, HR, procurement, and digital/data services. (Rajaniemi 2025. Personal communication.)

2.3 Sociotechnical Systems (STS) theory

Sociotechnical systems theory (STS) was developed in the UK during the 1950's, when it was discovered that for effective operation, it was necessary to optimise both the social and technical systems. From these observations, the idea emerged that organisations should be viewed as socio-technical systems, where the interaction between people and technology influences outcomes. (Guest, Knox & Warhurst 2022, 1462.) The STS theory offers a framework for understanding how human and technological systems work together in an organisational setting, where neither the person nor the technology is sufficient alone, but it is the combination of both shaping outcomes. It is particularly useful in environments where people use technology to make important decisions or provide services, as it shows that success or failure depends on both human and technological factors. The theory is a relevant framework for studying the algorithmic tool used by Helsinki Employment services, where technology plays an important part in supporting the decision-making by employment specialists.

STS theory has been used in various contexts, including public services, to analyse the integration of new technologies. For example, Hallamaa and Kalliokoski (2023, 140-141) discuss the complexity of shared responsibility in sociotechnical systems. They emphasise that when failures occur, responsibility often cannot be traced to a single actor but is distributed across multiple parties. Similarly, Davis, Challenger, Jayewardene & Clegg (2014, 173) argue that applying STS theory requires organisations rethink ways of working and to adapt workflows, roles, and responsibilities to align with new technologies.

In public employment services, sociotechnical principles have been applied to analyse algorithmic profiling systems, such as the one used in Austria's Public Employment Service (Allhutter et al., 2020). The study demonstrates, that while algorithms can improve efficiency, their integration can create issues related with transparency, user trust, and fairness – factors that can be understood well through by applying STS theory.

This thesis uses STS framework to evaluate the algorithmic tool developed by Helsinki Employment Services, by examining both its technical and social dimensions. The technical analysis will focus on the tool's accuracy, reliability, and clarity in generating recommendations. The social analysis will explore how specialists interact with and perceive the tool's outputs, as well as how the organisational environment affects its integration into daily workflows. By combining these two perspectives, the study will offer an understanding of the tool's performance and impact. The STS framework will help finding areas where

alignment between the social and technical components could be improved, leading to actionable recommendations for optimising the tool’s effectiveness.

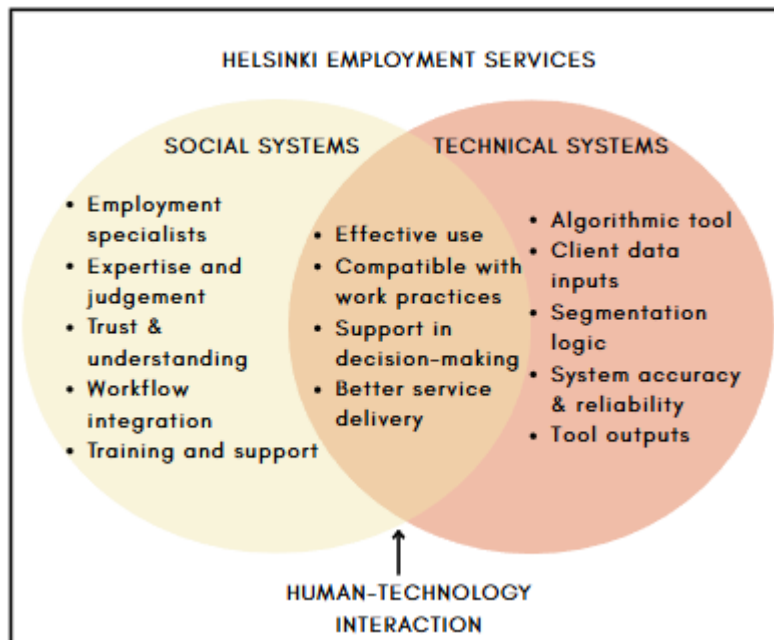


Figure 1: Sociotechnical Systems Framework (Adapted for Helsinki Employment Services)

The Figure 1 above illustrates how Helsinki Employment Services can be viewed as a sociotechnical system consisting of interacting social and technical subsystems. The social system includes employment specialists, their judgement, trust, training, and workflows, while the technical system includes the algorithmic tool itself, client data inputs, segmentation logic, tool outputs, and system reliability. The middle section highlights key outcomes that result from both elements being well integrated into the daily work. This framework is used in this thesis to evaluate the organisational alignment between the tool’s technical design and its real-world application in daily work.

3 The algorithmic tool in practice

3.1 Functionality and segmentation logic of the tool

In response to the growing demands for efficient and evidence-based public service delivery, Helsinki Employment Services has developed an algorithmic tool to better understand the labour market situations of its clients and as a result, better guide service allocation decisions. According to Rajaniemi (2025; 2025a, personal communication), the primary function of the algorithmic tool is to classify clients into one of 15 segments that represent different levels of employment prospects. The logic of the tool is based on up-to-date

information on the labour market situation of Uusimaa, added with the professional code of each client as well as their need for employment support.

As clarified by Paanala (2025, personal communication), the labour market data used by the tool is based on data from KEHA's (the joint development and administration centre for employment services). Specifically, it is based on KEHA's monthly updated "Labour Availability and Matching" dataset, which applies Beveridge curve calculations—a recognised method for examining labour market mismatch by comparing the number of jobseekers to the number of open vacancies in different occupational sectors. Despite a standard two-month delay in data updates, this dataset is considered one of the most accurate currently available for regional labour market assessment.

This combination helps to pinpoint both the availability of jobs in given fields as well as possible challenges clients might face while trying to become employed. The tool only uses so called hard variables as data and it has been upgraded from P15 dataset to a newer and more complete P17 dataset, allowing it to perform more complex analyses. (Rajaniemi 2025; Rajaniemi 2025a. Personal communication.)

The algorithmic tool segments clients into different employment categories with the help of a two-phase process. Figure 2 provides an overview of how the segmentation unfolds, beginning with an initial classification based on professional codes and labour market conditions, followed by adjustments that take into account employment support needs.

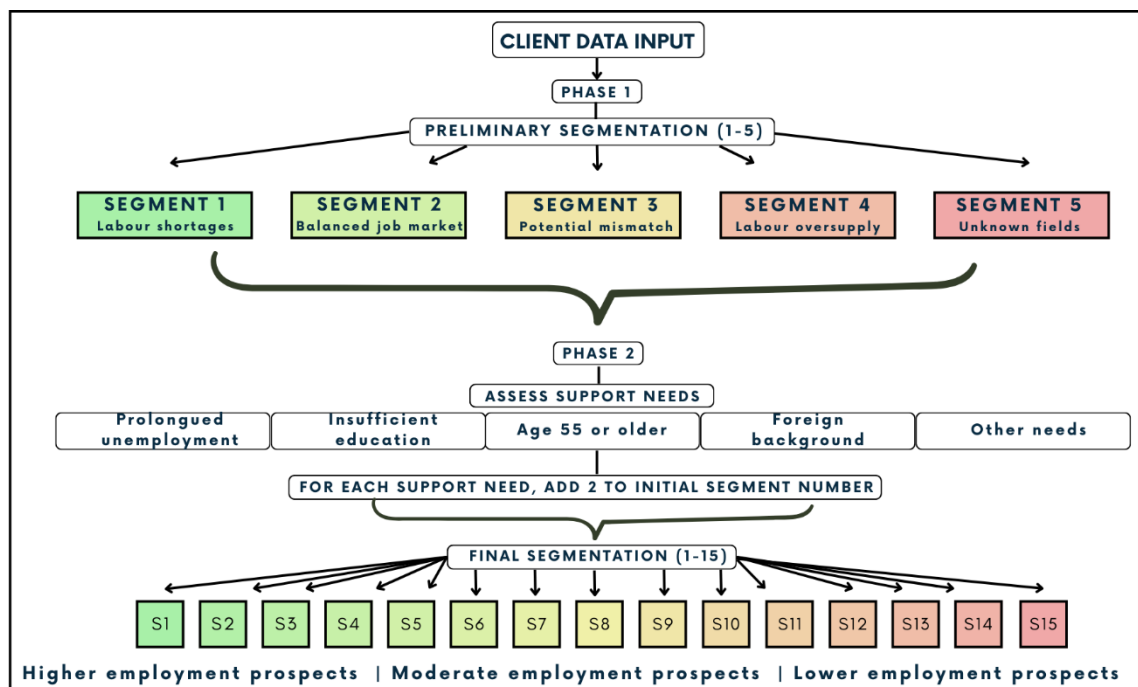


Figure 2: Segmentation process for employment assessment and service allocation

As seen in Figure 2, the tool operates in two distinct phases. According to Rajaniemi (2025, personal communication), in the first phase, each client is assigned to one of five preliminary segments, that are based on the client's professional code and the current labour market conditions in Uusimaa. The professional code refers to the occupation registered in the URA (the national client information system previously used by TE Offices) or A-TMT (the employment services' new client information system used by municipalities) systems and is interpreted as the client's primary field of work (Paanala 2025, personal communication).

Segment 1 represents professionals in fields experiencing labour shortages. Segment 2 is for professionals in fields that are balanced in the job market, meaning there is an even match between the number of available jobs and the number of people looking for work. Segment 3 groups those in fields where there is a potential mismatch between supply and demand while Segment 4 is for professionals with an oversupply of labour. Finally, Segment 5 includes those who are in unknown or unclassified professions.

While the segments are numbered sequentially, they do not represent a simple linear scale of employment status. Instead, they represent different probabilities of getting employment. Moving from one segment to another one can expect to see apparent differences in the likelihood of employment. (Rajaniemi 2025. Personal communication.)

In the second phase, the tool adjusts the initial groups by adding information about the client's need for support for employment. Rajaniemi (2025, personal communication) explains, that five risk factors that are currently included: prolonged unemployment (unemployment, that has lasts for over 365 days), insufficient education for the profession they have, age 55 or older, having a foreign background (defined by a nationality code other than 246), and health-related risks affecting the ability to work (evidenced by a recoded diagnosis).

Foreign background is identified using nationality code 246, which is the ISO country code for Finland. According to Paanala (2025, personal communication), while it would be technically possible to create a more detailed classification—such as for instance separating European and non-European countries—this would require strong justification. In the current model, the simplest available rule was intentionally chosen to support clarity, transparency, and ease of implementation within the algorithm.

Regarding health-related risks, the system uses structured diagnosis data fields from the URA system. Paanala (2025, personal communication) points out, that the presence of a main diagnosis—recorded in structured health fields by a professional—is used as an indicator. Although not all diagnoses are up to date, this field was found to be the most reliable and feasible option for modelling this risk factor within the available data structure. The tool operates under the assumption that professionals maintain client data frequently enough to

ensure its relevance. However, this assumption may be too optimistic. Still, in the absence of other data sources, it allows the system to function with a practical level of accuracy – as long as users are aware that these outputs should not be trusted blindly but interpreted with professional judgment.

The risk factors in Figure 2 are named support needs. For each separate need for support the client might have, the algorithmic tool adds a fixed amount of 2 to the existing segment number from the first phase. Those who do not have any support needs stay in their original segment from the first phase. For example, if a client has one type of support need, their final segment will be the initial segment number from the first phase (from 1-5) plus an addition of 2, moving them to a higher segment in phase two. As a result, the final segmentation does not only reflect on the client's current occupational situation but also models potential disadvantages related with their need for support, giving a more accurate picture of the job market. (Rajaniemi 2025, personal communication; Paanala 2025, personal communication.)

The main goal of this two-phase process is to show how complicated the job market is, and the real-life challenges related with job hunting. By considering both the overall job market and individual challenges clients face, the algorithmic tool aims to give a clearer picture of clients' opportunities of finding a job. The segments show that clients without support needs are usually in a better position (segments 1-4), while those with one or more support needs move to higher segments, which means a lower chance of successful employment. (Rajaniemi 2025. Personal communication.)

3.2 Operational workflow and practical use

In addition to understanding how the tool segments clients, it is important to explore how the tool is actually used in the daily work of Helsinki Employment Services. Beyond the segmentation process described in previous chapter, the overall system also includes another operational process which is specifically focused on the reassignment of already existing clients in the Employment Services. In this process, additional variables such as integration status, language proficiency, age, and educational background are taken into account to allocate clients into appropriate teams within the organisation.

According to Paanala (2025, personal communication), this reassignment process was introduced due to a number of operational challenges that emerged during the transition from the state-run Employment and Economic Development Offices (TE Offices) to municipal Employment Services, as introduced earlier in this thesis. For example, many clients' service needs could not be identified clearly from existing records, and their earlier team assignments were used to infer their probable needs. While this helped maintain continuity, it also created a circular logic, where the team assignment itself became evidence of the

client's needs. Furthermore, technical limitations restricted access to some fields for former TE Office clients, forcing reliance on incomplete data. Finally, because the new team structure did not line up directly with the previous one, some interpretive decisions had to be made when reallocating clients to the updated organisational model. (Paanala 2025, personal communication.)

At the time of writing, the tool is used in a manual format through Power BI, without saving client data into the system itself. Client information is entered manually into the tool by members of the TNO team (short for Työllisyyden neuvonta ja ohjaus, or Employment guidance and support team), who then use the resulting segmentation to allocate the client to the appropriate service team. This team then begins the client's service process. While the segmentation result is not currently visible to individual employment specialists, it indirectly guides team allocations. According to Paanala (2025, personal communication), making the results more transparent to specialists is considered a future development priority, as it could improve alignment between the tool's outputs and the professionals' decision-making. The team assignment process relies on both the A-TMT case management system and the Power BI environment where the segmentation tool is currently at.

3.3 Limitations and areas for improvement

Although the algorithmic tool has been designed to improve the effectiveness and efficiency within Helsinki Employment Services, some limitations and improvement needs have been identified during its early use.

Firstly, the segmentation process relies exclusively on structured, so-called "hard" variables such as unemployment duration, education, age, nationality code, and diagnosis data. While this ensures consistency and transparency, it also limits the tool's ability to recognise some of the more complex individual factors that employment specialists often consider in real-life client interactions. As noted earlier, assumptions such as up-to-date and comprehensive client information may not always be true. For instance, if diagnosis fields or education data are outdated or incomplete, the segmentation results may not fully reflect the client's actual support needs (Paanala 2025, personal communication).

Secondly, the current implementation of the tool is manual and does not store any client data. This makes the process dependent on the capacity and availability of the TNO team members responsible for entering and interpreting the data. While this setup enables flexibility during the initial stages, it also limits scalability and consistency in the long term. Plans to automate the tool exist but face technical challenges, especially related to system integration and data flow (Paanala 2025, personal communication).

Another issue arose from how the tool's outputs are communicated within the organisation. In early 2025, a change in how clients were routed into pathway services caused confusion among some professionals. The tool began assigning a high number of clients to the "TYM-arviointi" (working capacity assessment) segment due to the consolidation of entry points into these services. As a result, even young clients without apparent need for this assessment were temporarily routed through this process, creating a mismatch between service need and workflow. Importantly, this issue was not caused by the tool's logic itself, but more because of how the results were interpreted and presented within the routing framework. The problem has since been recognised and is currently being resolved. (Paanala 2025, personal communication.)

Lastly, the segmentation result is not yet visible to individual employment specialists. While it guides client-team assignments behind the scenes, professionals do not currently have access to the actual output of the segmentation. According to Paanala (2025, personal communication), making these results transparent is considered a beneficial change. Allowing specialists to view and reflect on the tool's recommendations could help adjust its use more closely with professional judgment and strengthen trust in its functioning.

These limitations reflect a common challenge in sociotechnical systems: success depends not only on the quality of the technical solution, but also on how well it is embedded into workflows, understood by its users, and aligned with organisational practices. Addressing these gaps will be essential for optimising the tool's role in decision-making and ensuring its long-term impact.

4 Methodology

4.1 Research design

To evaluate the algorithmic tool developed by Helsinki Employment services, a survey-based research design was used to assess the tool's usability, perceived accuracy, and its impact on the workflow of employment specialists. Moreover, the STS framework was used to guide the research design. The primary data collection method was a survey targeted at employment specialists who use or whose direct work is affected by the algorithmic tool in their daily work. A survey was chosen as the most practical method due to the size of the target group as well as the need to collect responses efficiently. It allowed the participation of a wide range of employment specialists while making sure it was an anonymous process, which in itself might also promote a more open and honest feedback compared to face-to-face interviews.

To gain different kinds of information, it is important to use different research methods (Moilanen, Ojalaso & Ritalahti 2022, chap. 2.2). Therefore, the survey included both structured (quantitative) and open-ended (qualitative) questions. The structured questions focused on the perceived accuracy, reliability, and clarity of the tool's outputs, while the open-ended questions allowed respondents to share personal experiences, challenges, and suggestions for improvement.

The qualitative data from open-ended responses was analysed using thematic analysis to find frequently discussed themes and patterns in the data. Descriptive statistics were used to summarise the quantitative responses, identifying general trends and variation in the views of the participants. Although the initial research plan included the potential use of secondary data (such as possible internal performance metrics), no such data was available for this study. The analysis relied therefore only on the survey responses provided by specialists.

The evaluation criteria were grounded in the STS framework and focused on both technical and social dimensions. The technical aspects included perceived accuracy, reliability, and clarity of the tool, while the social aspects focused on trust, workflow integration and organisational support. This dual focus allowed the study to explore not only how the tool functions technically but also how it is experienced and used within its organisational context.

4.2 Data collection

The data for this research was obtained through an online survey, which participants completed independently using Microsoft Forms. The survey targeted all employment specialists working at Helsinki Employment Services, who benefit from the algorithmic tool in their daily work. An estimated 500 employment specialists were invited to participate.

The survey link, along with an information letter explaining the purpose of the study, anonymity, voluntary participation, and contact details of the researcher was sent via internal email to the employment specialists. Additionally, the survey and the information letter were published on the organisation's intranet by the communications team of the Helsinki Employment Services. Participation was completely anonymous, and no personally identifiable information was collected.

The survey remained open for two weeks between March and April 2025. In total, 58 responses were received. The survey consisted of 11 questions, divided into five thematic sections: familiarity with the tool, technical aspects (such as perceived accuracy, reliability, and clarity), influence on daily work and service processes, organisational support and training, and development suggestions. The structure included both closed-ended questions

(using Likert scales and multiple choice) and open-ended prompts, allowing respondents to discuss on their experiences in their own words.

The information letter sent to participants is provided in Appendix 1 and the full questionnaire can be found in Appendix 2. The sample size and response rate are discussed in more detail in chapter 5, where results are analysed.

4.3 Data analysis procedures

The collected data was analysed using a mixed-method approach, combining both qualitative and quantitative analysis techniques. The analysis was conducted with the goal of making sense of how the algorithmic tool performed in practice, focusing on both its technical functionality and how it fits into daily work. It also helped provide a more complete understanding of how the algorithmic tool is experienced in everyday work by employment specialists.

The responses from structured questions were exported from Microsoft Forms into Microsoft Excel and examined using descriptive statistics. According to Lazar, Feng & Hochheiser (2017, 129) descriptive statistics help organise and present data in a clear way, making it easier to interpret. This approach helped identify how respondents perceived the tool's accuracy, reliability, and clarity.

The qualitative data from the open-ended responses was examined using thematic analysis, which allowed for identifying recurring themes, experiences, and suggestions expressed by the respondents. According to Moilanen, Ojasalo & Ritalahti (2022, chap 4.2) the process of the analysis begins with reviewing the data to gain familiarity on it, which follows by linking it to relevant theoretical concepts and finally organising the content based on different thematic categories. Since the open-ended responses were written in Finnish, the selected quotes included in this thesis were translated into English by the author. Care was taken to ensure that the original meaning and tone were kept with the translated versions.

4.4 Ethical considerations and data security

This study followed ethical research principles, particularly in relation to informed consent, voluntary participation, data protection and transparency. A research permit was obtained from Helsinki Employment Services before the survey was conducted, in accordance with their guidelines.

Participation in the survey was entirely voluntary and anonymous. An information letter (Appendix 1) was provided together with the link to the survey, explaining the purpose of the study and how the responses would be used. The letter also stated that no personal or identifiable data would be collected, and that participants could withdraw at any time from

participating in the survey. Before accessing the actual survey questions, participants were presented with the same content as in the information letter outlining the study's purpose, anonymity, voluntary participation, and data handling practices. The first item in the survey required participants to confirm that they had read and understood this information. Only after selecting "Yes" to this question were the rest of the survey questions displayed. This approach ensured that informed consent was obtained before any data was collected.

No identifiable data (such as names, email addresses, or IP addresses) were collected. The survey platform, Microsoft Forms, was set up to allow anonymity. Responses were stored securely and were only accessible to the author. The data was stored only for the duration of the analysis process. Once the thesis has been submitted and accepted, all collected material will be securely deleted to provide full confidentiality of the participants.

To minimise bias, the survey questions were written in a neutral and balanced way, encouraging honest feedback about the algorithmic tool. It was clearly communicated that the results were only to be used for the purpose of this study and the possible further development of the algorithmic tool. Nevertheless, some response bias might still exist. Similarly, during qualitative analysis, the researcher was aware of potential interpretive bias. To address this, a systematic thematic analysis approach was used to guarantee consistency and transparency in coding and interpretation of the data.

4.5 Validity and reliability

The validity and reliability of this study has been a priority throughout the research process. Validity refers to how accurately the study measures what it intends to measure, while reliability is about the consistency and repeatability of the findings (Saunders, Lewis & Thornhill 2015, 202).

Validity was supported by designing the survey questions around the main themes being studied such as the algorithmic tool's accuracy, reliability, clarity and impact on workflow. While usability was not addressed through a single direct question, it was approached indirectly through questions related to training, organisational support, and workflow. Moreover, open-ended questions allowed additional comments. The questions were based on both the theoretical framework of sociotechnical systems as well as on some of the discussions and insights from the internal experts of Helsinki Employment Services.

As Dawadi, Shrestha & Giri (2021, 27) point out, that when mixed-methods research is combined, it allows the study to present more measurable results, and that the triangulation of data can compensate for limitations in any single approach. This can be particularly useful in contexts where a more comprehensive understanding is essential, such as in the public sector or organisational research.

Reliability was promoted by using the same approach for gathering the data. All respondents received the same information letter and questionnaire, and the survey was administered using a standardised online form from Microsoft Forms. Using descriptive statistics allowed for standardised response analysis among participants. The thematic analysis of open-ended responses followed a structured process.

While the response rate was relatively modest, with approximately 12% of employment specialists responding to the survey, this is not uncommon in public sector research, especially when participation is voluntary, and subject to time constraints. Similar response rates have been reported in organisational and healthcare studies (e.g. Naday, Kaihlanen, Kujala, Keskimäki, Viitanen, Salovaara, Saukkonen, Vänskä, Vehko & Heponiemi 2024; Havaei, Ji & Boamah 2022). Despite this, the inclusion of open-ended questions strengthened the study's credibility by providing deeper insights and highlighting recurring themes across multiple responses.

Overall, the study followed established research practices to make sure that the results are both trustworthy and useful. Although certain limitations remain – particularly in terms of how widely results can be generalised – the data still provides important insights into how the algorithmic tool is perceived in everyday work.

5 Results and evaluation

5.1 Presentation of quantitative data

This chapter introduces the results from the quantitative questions, which were used to assess the employment specialists' views on the algorithmic tool. The aim was to understand how the tool is perceived in terms of accuracy, reliability and usefulness, as well as how well specialist feel they understand the logic of how the tool works. The closed-ended questions focused on a few key-areas: familiarity with the tool's classification logic, perceived accuracy in describing both the clients labour market situation and actual working capacity, general reliability of the tool, trust in the tool's classifications compared to their professional judgement, adequacy of training or guidance received, and the general attitude toward the tool within the organisation.

A total of 58 specialists responded to the survey, which corresponds to an approximate response rate of 12% of the total target group. While the response rate is modest, it is not unusual for voluntary online surveys conducted within large organisations, especially when participation is not tied to work obligations. These results in this chapter should in any case be interpreted as indicative rather than fully representative of all employment specialist working at Helsinki Employment Services. The responses still offer valuable insights into how

the algorithmic tool is perceived by a group of professionals, who are familiar with its use, and recurring themes within the answers can point towards shared experiences among the employment specialists. The data from these questions is presented below, using both numerical summaries and visualisations to provide an overview of how the tool is currently experienced by its users. The following paragraphs examine each survey question in turn, beginning with how well the respondents feel they understand the principles on which the tool’s classification is based.

5.1.1 Understanding the tool’s logic

The distribution of responses to fit the first survey question on understanding the tool’s logic (N=58) is seen in Figure 3 below. The first question asked how well the respondents understand the basic logic of the algorithmic tool - i.e., on what basis the classification is formed.

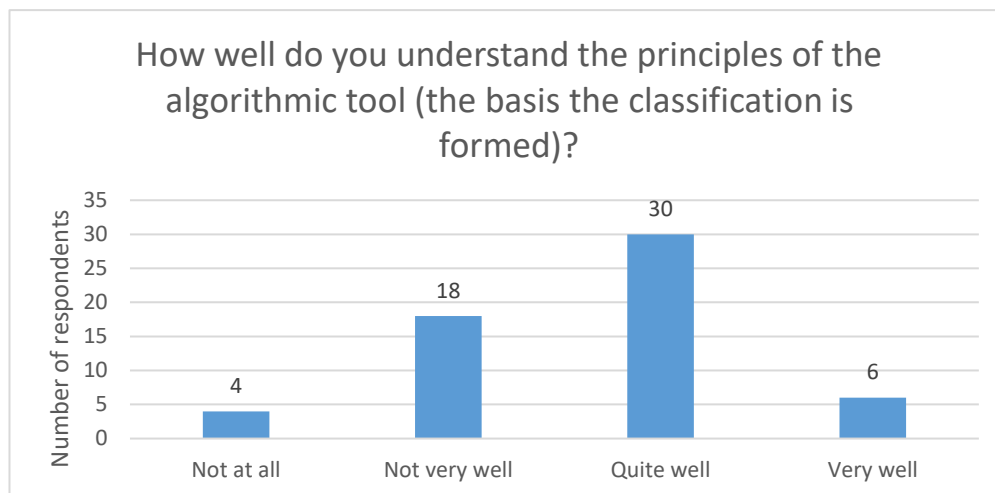


Figure 3: Understanding of the algorithmic tool’s classification logic

Respondents selected their answers from four-point scale between “Not at all” to “Very well”. As shown in Figure 3, the majority of respondents indicated a relatively strong understanding of the tool’s underlying logic. “Quite well” was the most common response, selected by 30 out of 58 respondents (about 52%). An additional 6 respondents (around 10%) reported that they understand the tool “Very well”. In contrast, 18 respondents (31%) said they do not understand the tool’s logic very well and a small minority of 4 respondents (7%) reported understanding it “Not at all”. This distribution of answers could suggest that while most employment specialists have a good grasp of the algorithmic tool’s basic principles, there remains a notable minority with only limited understanding of how the tool’s classification is formed. Such a finding may indicate the need for additional training or communication to make sure that all staff members develop a sufficient familiarity with the tool’s logic.

5.1.2 Accuracy in reflecting labour market situation

The second survey question focused on how well the algorithmic tool is perceived to describe the client’s labour market situation. Respondents were asked to assess the accuracy of the classifications using a six-point scale ranging from “Very inaccurate” to “Very accurate”, with a neutral option also included.

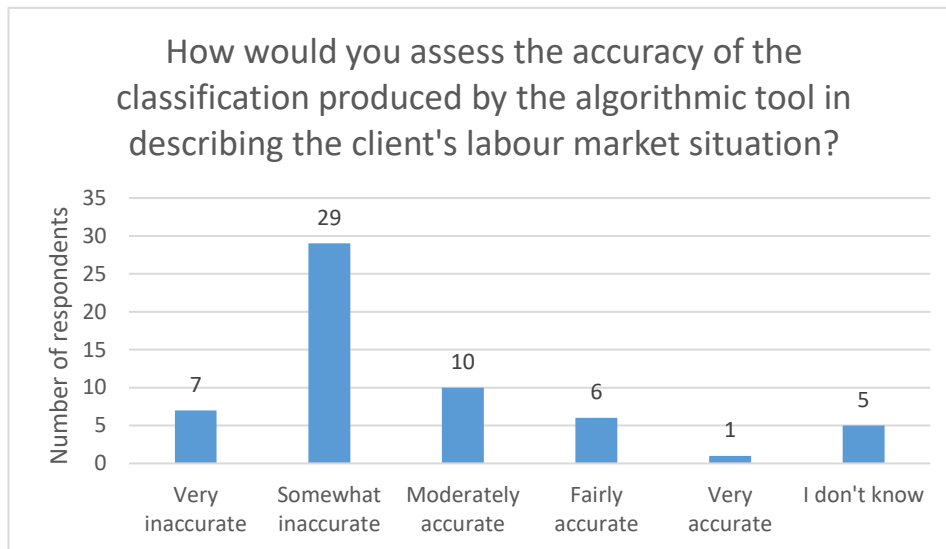


Figure 4: Accuracy of classification in describing clients’ labour market situation

As seen in Figure 4, the most common response was “Somewhat inaccurate”, selected by 29 respondents, representing exactly 50% of the total. This suggests that half of the specialists felt the classifications produced by the tool do not accurately reflect the actual labour market situation of their clients. An additional 7 respondents rated the tool as “Very inaccurate”, further underscoring concerns about the tool’s descriptive power. In contrast, more positive assessments were less frequent: only 6 respondents chose “Fairly accurate” and just 1 selected “Very accurate.” A group of 10 participants opted for “Moderately accurate”, possibly indicating a more neutral or case-dependent experience. A group of 5 respondents chose “I don’t know”, indicating uncertainty about the accuracy of the tool’s outputs.

This distribution suggests a general scepticism among specialists regarding how accurately the tool reflects labour market realities. While a few viewed the tool as relatively accurate, the majority leaned toward the lower end of the scale. These results may reflect either a mismatch between the tool’s classifications and real-life cases or a lack of clarity in how the classifications are formed and communicated. This could point to a need for further transparency about how labour market data feeds into the algorithm, or for additional training to help specialists better interpret the results.

5.1.3 Accuracy in describing working capacity

The next question examined how accurately respondents felt the tool reflected the client’s actual working capacity rather than just their labour market positioning. The results are presented in Figure 5 below. As shown, the majority of responses were again at the lower end of the scale: 24 respondents (41%) selected “Somewhat inaccurate,” while 18 respondents (31%) chose “Very inaccurate.” These results reflect a widespread concern that the tool fails to capture the complexity of the clients’ working capacity, which may be a more complex and context-specific dimension than labour market fit.

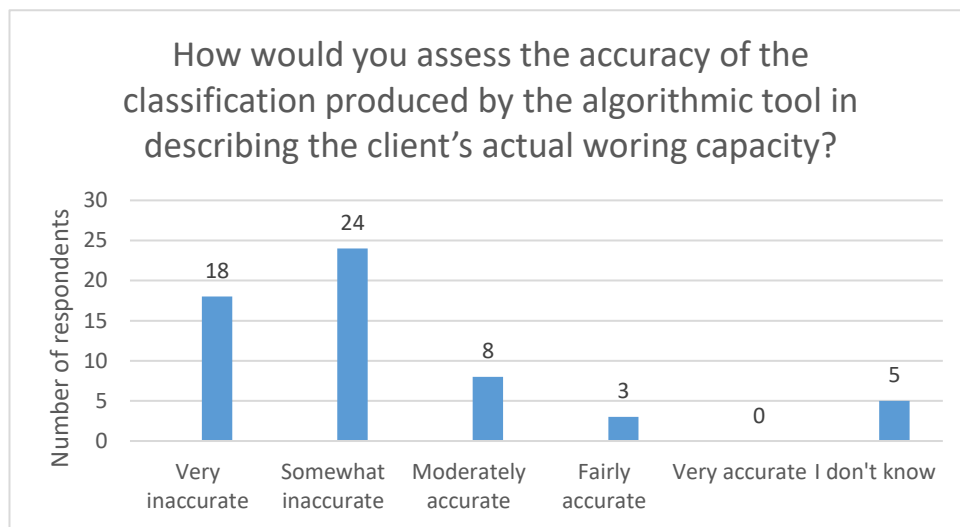


Figure 5: Assessment of the tool’s accuracy in describing clients’ actual working capacity

Only a small number of participants provided more favourable evaluations: 8 respondents (14%) considered the classification “Moderately accurate,” and 3 (5%) viewed it as “Fairly accurate.” No respondents rated the classification as “Very accurate.” Additionally, 5 respondents (9%) selected “I don’t know,” which may reflect uncertainty or lack of familiarity with how this aspect of the classification is determined. Overall, the results suggest that many specialists perceive a mismatch between the tool’s outputs and clients’ real-life working capacity, which may indicate a need for reviewing the input data or providing clearer guidance on how such classifications should be interpreted.

5.1.4 General reliability of the tool

The following question asked respondents to evaluate the general reliability of the algorithmic tool. As shown in Figure 6, the responses were again primarily critical. “Somewhat unreliable” was by far the most common answer, chosen by 30 respondents (52%), and another 8 participants (14%) considered the tool “Very unreliable.” This means that roughly two-thirds of the respondents expressed doubt about the tool’s overall reliability.

Only 6 respondents (10%) considered the tool “Somewhat reliable,” while no respondents selected “Very reliable.” A larger group of respondents (13, or 22%) chose “Neutral,” and 3 respondents (5%) answered “I don’t know.”

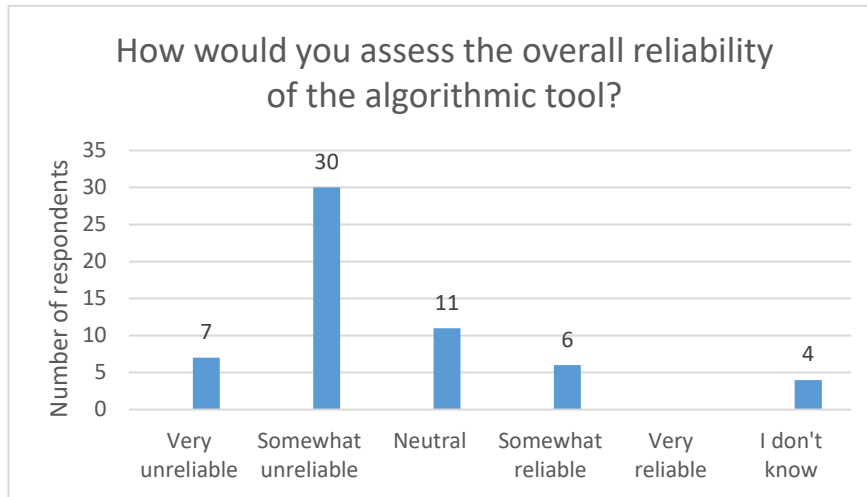


Figure 6: Respondents’ assessment of the overall reliability of the algorithmic tool

These results show a similar trend as earlier responses: specialists generally remain cautious or sceptical about the tool’s dependability. The lack of “Very reliable” responses, combined with the dominance of the “Somewhat unreliable” category, suggests that concerns about the consistency or trustworthiness of the tool are common. This highlights the need to investigate whether these views are based on actual tool errors, communication gaps, or the nature of the tool’s use in practice.

5.1.5 Trust in the tool vs. professional judgment

The sixth question asked respondents how much they trust the classifications provided by the algorithmic tool in comparison to their own professional assessment. As shown in Figure 7, a strong pattern of scepticism was again present. Most respondents (31/58) answered that they “trust it very little,” while 9 participants indicated that they “do not trust it at all.” This means that almost 70% of respondents expressed a low level of trust in the tool relative to their own judgement.

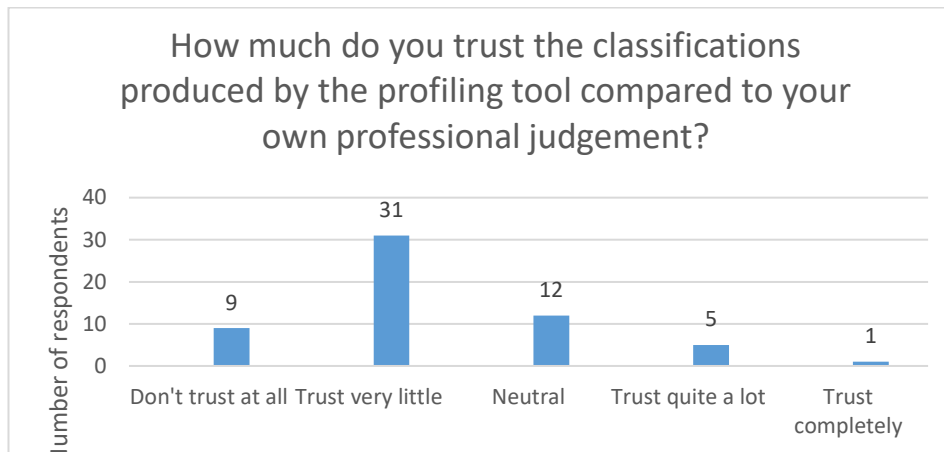


Figure 7: Trust in the algorithmic tool's classifications vs. professional judgement

Only 5 respondents reported trusting the classifications “quite a lot,” and just one participant indicated full trust in the tool. A group of 11 respondents selected “Neutral,” suggesting some uncertainty or a case-by-case perspective in balancing their own judgment with the tool's output.

5.1.6 Training and guidance

This question focused on support and attitudes within the organisation. As shown in Figure 8, most respondents (31 out of 58) felt they had only partially received sufficient training or guidance on the tool. An additional 17 respondents stated that they had not received adequate training, while only 10 specialists felt the training provided had been sufficient. This indicates a clear need for continued or better training to make sure there is consistent understanding and of the algorithmic tool.

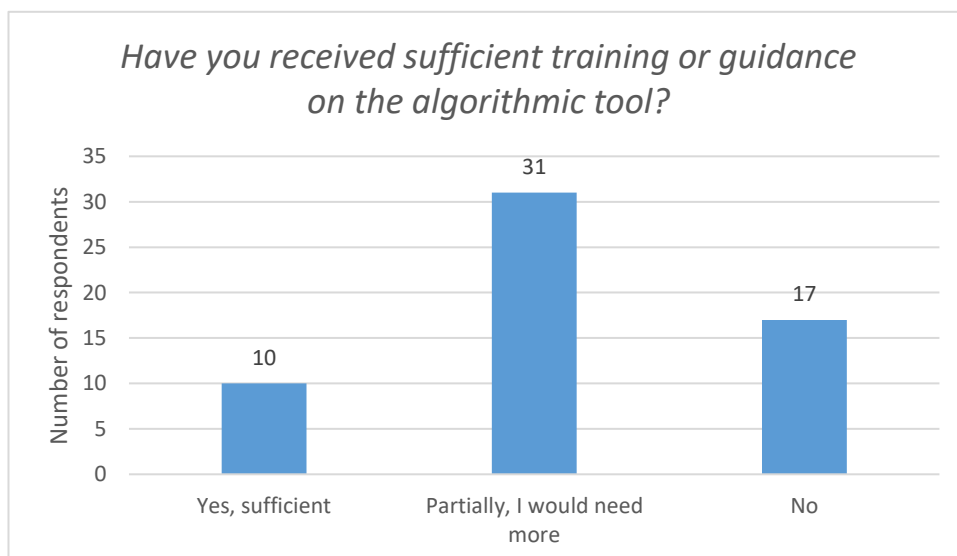


Figure 8: Sufficiency of training and guidance on the algorithmic tool

5.1.7 Organisational attitude toward the tool

The final closed-ended question was about the attitudes toward the tool. Figure 9 presents responses regarding the general attitude toward the algorithmic tool within the organisation. Most respondents described the overall perception as either “Somewhat negative” (30) or “Very negative” (9). Fourteen respondents selected “Neutral”, and only a small minority perceived the general attitude as “Somewhat positive” (4) or “Very positive” (1). These results point to a rather critical organisational climate around the use of the algorithmic tool, which may influence both how the tool is applied and how its results are interpreted in practice.

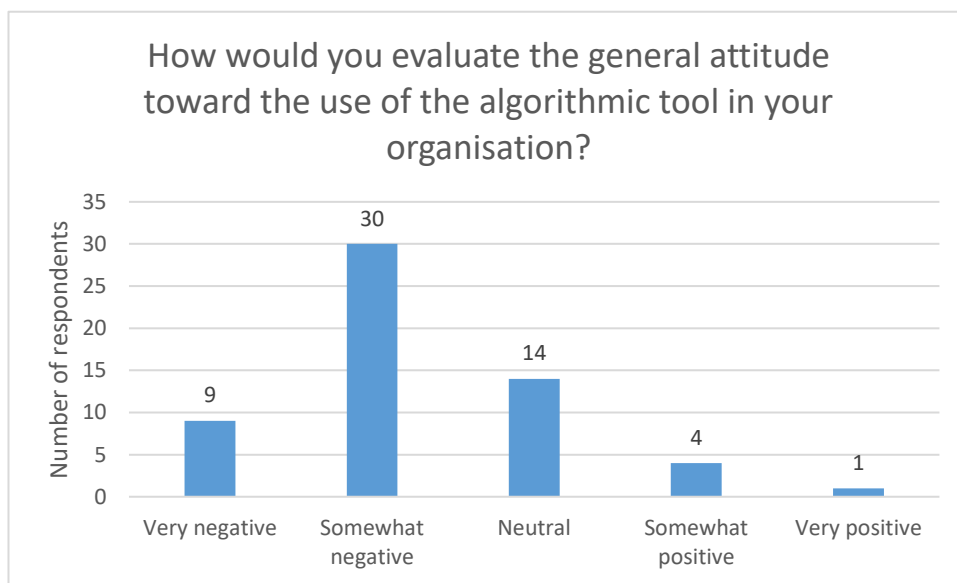


Figure 9: General organisational attitude toward the algorithmic tool

Together, these two final survey question results may suggest, that making the tool work well in practice is not only about how it functions technically, but also relies on how well staff members are trained and involved.

5.2 Thematic analysis of qualitative data

This chapter presents findings from the open-ended survey questions, which offered employment specialists the opportunity to share their views regarding the algorithmic tool. Thematic analysis was used to organise the responses into broader categories, helping to identify patterns in how the tool is experienced in practice. Responses were first reviewed and colour-coded in Excel, after which similar issues were grouped under shared themes.

5.2.1 Recurring problems or errors

Employment specialists were asked about their experiences on recurring problems or errors using the algorithmic tool. This question received a total of 58 responses and four central themes were identified, each reflecting common experiences or concerns expressed by the respondents.

The first theme, **limited familiarity or exposure**, brings together responses indicating that specialists lacked sufficient training or experience with the tool. Specialists pointed out a potential communication gap between different groups in the organisation, particularly those transitioning from state employment services.

“I have never used the algorithmic tool. There has been no encouragement to use it, and we, who came from the state, have not been informed about it.”

The second theme, **lack of trust in the tool’s outputs and contextual understanding**, captures critical views on the tool’s accuracy and perceived failure to understand individual client situations. Several respondents questioned whether a technical system could reflect the realities faced by clients or replace professional experience in decision-making.

“Clients are human beings, and this kind of tool cannot interpret their complex situations.”

Several respondents also raised reliability concerns, noting earlier errors, which had been reportedly fixed but continued to affect their trust in the tool.

The third theme, **misclassification and incorrect team placement**, describes frustrations with how the tool assigned clients to service categories. Specialists noted inconsistencies in outcomes, even for clients with similar profiles, which raised fairness concerns. Respondents indicated confusion around the parameters used by the tool, leading to perceptions of randomness in client assignments.

“Clients are in completely wrong service categories. With the completely same profile clients are both found in pathway services and matching services.”

Several specialists added that the lack of transparency in how these classifications are made contributes significantly to their scepticism and confusion about the tool’s decision-making.

Finally, the fourth identified theme, **oversimplification of complex client situations**, highlights broader concerns to how the algorithmic tool fails to capture the diversity of client’s backgrounds and challenges including education, health, and immigrant backgrounds.

Specialists argued that subjective assessments were overemphasised, potentially reinforcing biases or generalisations rather than accurately representing individual client situations.

“The client’s own judgment of their working capacity is highlighted too much. Subjective assessment is usually not a very good indicator on its own. Immigrant background is also overemphasised. Although there may be a risk that unemployment will be prolonged, this is not the case for everyone. Pathway services are flooded with clients whose only risk of prolonged unemployment is their immigrant background.”

The findings suggest that limited familiarity and trust have an impact on training, communication, and organisational transitions. Addressing these issues will help improving the integration of the tool into the workflows of the employment specialists.

5.2.2 Classification mismatches with actual needs

The next open-ended question was about whether employment specialists had noticed classification mismatches between the tool-generated classifications and the actual needs of the clients, but the majority however generated rich examples. Again, four central themes emerged from the responses.

The primary theme, **mismatch between output of the algorithmic tool and client reality**, was the most commonly raised concern. Many specialists described how the client’s actual support needs did not match with the automated classification they received. Specialists explained how initial client data collected during registration often lacked accuracy, leading to incorrect classifications and inefficient support paths.

“When a client registers as a job seeker, the information is often incomplete and with this incomplete information the client is transferred to a certain service (matching services, pathway services, etc.). Once the client has been transferred somewhere, they cannot be transferred to where they really belong, even if new information is discovered during the initial assessment/interview.”

Respondents also emphasised the tool’s rigidity and inflexibility, describing situations where clients were locked into inappropriate categories despite later discovery of new information.

The second theme, **limitations in recognising complex or evolving situations**, was also commonly mentioned. Respondents felt that the algorithm was not well equipped to reflect the full spectrum of barriers and strengths clients might have and advocated strongly for integrating human judgement to balance algorithmic limitations.

“The algorithmic tool does not take into account anything about the real situation, human or other, so quite often the truth is different compared to the tool's result.”

Thirdly, specialists highlighted **background-related bias or failure**, particularly concerning immigrant background and language proficiency. Several respondents indicated the algorithm seemed overly reliant on single characteristics, potentially leading to unfair assumptions or stereotypical views on job eligibility.

“In addition, if the client's native language is other than Finnish or Swedish, the client seems to be directed to pathway services, even if their Finnish language skills are at native level and the customer has a highly employable education and no problems with their ability to work.”

Lastly, the theme of **lack of transparency and information at client registration** touches on the initial encounter between the client and the system. Several responses noted that clients often do not fully understand what the survey or classification process include and are not guided on how their answers will affect the outcome. Specialists felt subjective self-assessments were ineffective without proper context.

“The customer is also not advised when registering as a job seeker how the working capacity scale works or why it is asked and why it is important information.”

The responses point to both system's framework and communication gaps as key contributors to classification inaccuracies. Addressing these through improved data, adaptability, and transparency could make the tool more effective in meeting real client needs.

5.2.3 Suggestions for improving the tool

In the third open-ended question employment specialist were asked for suggestions to improve the algorithmic tool. This open-ended question received 40 responses, and though not compulsory, many employment specialists took the opportunity to offer detailed

suggestions for improvement. After careful thematic analysis, four central themes emerged from their recommendations.

First, specialists recommended **increasing training and awareness**, highlighting the importance of a more thorough introduction to the tool's features and purpose. Respondents found current training inadequate, wishing for more transparency and deeper insights into criteria weighting.

“To receive information about it which is shared more broadly through some kind of training, emphasising that it must now be used and explaining the reasons behind it—rather than just a Teams message, where some start using it and others don't.”

Specialists further suggested providing clear explanations of assessment categories and decision-making criteria, reducing confusion and uncertainty.

Second, respondents suggested **clarifying and updating criteria and variables** within the algorithm, calling for more precise criteria to reduce inefficient transfers between service categories. Specific suggestions included reviewing unemployment duration, education levels, and job-search activities more closely.

Third, specialists strongly emphasised **strengthening human involvement and professional judgement**, arguing that algorithmic classifications should complement—not replace—human expertise. They proposed that employment specialists should be more actively involved in the tool's ongoing development and adjustments.

“The algorithmic tool is probably a good tool, but it should not be trusted blindly. Experts are able to see the client's overall situation better, and an electronic tool should not be valued higher than this.”

Lastly, the theme of increasing flexibility and responsiveness focused on the tool's ability to better handle those more dynamic and complex client cases. Specialists proposed integrating qualitative factors, such as motivational and mental health considerations, to ensure more holistic client assessments.

The proposed improvements stress that development of the tool must include not only technical optimisations but also organisational planning that supports continuous specialist engagement and better flexibility to address real-world complexities.

5.2.4 Broader reflections and organisational impact

Responses to the final open-ended question resulted in four main themes (27 responses), often reinforcing earlier points but also offering broader organisational reflections. Specialists were asked if they wanted to add anything else to how the algorithmic tool functioned or impacted their work.

First, specialists expressed continued frustration over the **perceived misplacement of clients**, emphasising ongoing inefficiencies and confusion due to frequent mismatches in classification outcomes. These issues were seen as weakening both the effectiveness and suitability of the assistance provided to clients.

Second, respondents pointed out issues with clarity and communication, emphasising the need for better explanations and more structured organisational messaging about the tool's purpose, functionality, and role in daily workflows. They stressed that transparency builds trust and makes adoption easier.

Third, specialists raised concerns about inefficiencies that added to their workload and frustration, particularly when handling misclassifications and strict client placements. This issue repeatedly surfaced as a factor affecting both efficiency and overall job satisfaction.

“The mistakes it makes increase my own work, as I have to check each client individually.”

Finally, respondents cautiously reflected on the **tool's potential value and future improvements**, recognising its potential while highlighting the need for well-planned improvements. They remained hopeful that improvements in design and structure could bring it closer to fulfilling its purpose.

These final thoughts underline the importance between tool functionality, clear organisational communication, and appropriate workload management. Addressing these elements is crucial to achieving meaningful improvements.

5.3 Evaluation of the algorithmic tool's performance in practice

This chapter brings together the main findings from both the quantitative and qualitative results, evaluating the performance of the algorithmic tool from the perspective of the employment specialists. The evaluation is guided by the STS framework introduced earlier in this thesis, focusing on two central dimensions: the technical functionality of the tool and its social integration within the organisational context of Helsinki Employment Services. The aim

is to assess how well the tool supports specialists in their daily work, identify areas where alignment between technical systems and social practices could be improved, and prepare the ground for the practical recommendations presented in chapter 6.

From a technical perspective, the survey results suggest that the algorithmic tool is not yet perceived as reliable or accurate enough to fully support service classification decisions. As shown in chapter 5.1, most specialists assessed the tool as somewhat or very inaccurate in describing both the clients' labour market situations and their actual working capacity. Concerns were raised particularly around the limited and outdated nature of some input variables, and the perceived mismatch between classification outputs and real client needs. Additionally, the tool was seen by many as lacking flexibility and producing results that could not always be trusted without further human judgement. While some specialists recognised the tool's potential, the quantitative data confirms that trust in its current performance remains low.

On the social side, the results indicate broader challenges with integration into daily workflows and organisational communication. Many respondents reported having received only limited training or guidance on the tool's purpose, logic, and use. This uneven introduction appears to have led to inconsistent adoption and varying levels of understanding across the organisation. The qualitative responses also highlighted a lack of transparency in how client classifications are formed and how the results influence service category decisions. This was further underlined in the perceptions of organisational attitude, which was mostly described as somewhat or very negative. The thematic analysis suggests that some of these challenges are not only about the technical logic of the tool, but about how well the tool is embedded in existing structures, routines, and support systems.

When viewed through the STS framework, it seems to be that the tool's current performance is affected by a mismatch between its technical functionality and the social systems in which it operates. Success with digital tools requires more than technical excellence – it depends on ongoing adaptation and meaningful user involvement. Likewise, staff can maximise their benefits from digital support when they are informed and engaged in the development process.

These findings reflect the previously recognised limitations identified in chapter 3.3, where issues such as the use of narrow input variables, manual processes, and lack of transparency were raised. The survey responses confirm that these technical features have more broader social implications, in particular for trust, workflow efficiency and perceived fairness.

The following chapter will present concrete and targeted suggestions to strengthen both the technical and organisational dimensions of the tool.

The findings indicate that strengthening the tool's effectiveness will require changes on both fronts. On the technical side, efforts could focus on improving the clarity and reliability of classifications by reviewing criteria and input variables, and by increasing transparency in how outcomes are formed. On the organisational side, increasing training, support, and professional involvement in future updates could improve adoption and rebuild trust. Addressing these areas could help assure that the tool functions not only as a classification mechanism but also as a supportive system that fits into the everyday practices of employment specialists.

These findings also reinforce the initial limitations identified earlier in chapter 3.3, where concerns were raised about the tool's reliance on structured "hard" variables, the manual nature of its implementation, and the lack of transparency in segmentation results. At the time, these issues were based primarily on internal observations and technical insights. The survey responses now confirm that these limitations are not only technical in nature, but also have clear implications for user trust, workflow efficiency, and the perceived fairness of the tool. This overlap between earlier internal assessments and user experiences highlights the importance of addressing both the design and implementation of the tool in future development efforts.

6 Recommendations

This chapter provides concrete, practice-oriented recommendations based on the findings presented in chapters 5.1, 5.2, and 5.3. It examines the main results through the research objectives, considers their relevance for policy and practice within Helsinki Employment Services, and concludes with study limitations and suggestions for future research.

The analysis of both quantitative and qualitative survey data shows that while the algorithmic tool developed by Helsinki Employment Services is a promising initiative, its current implementation shows room for improvement. The tool's technical strengths lie in its use of consistent, structured labour market data and its potential for scalable client segmentation. However, results show that many employment specialists do not yet view the tool as accurate, reliable, or sufficiently supportive in daily decision-making.

The low levels of trust expressed by employment specialists appear to arise from two main issues. First, the tool's technical limitations – including outdated or overly simplified input variables and inflexible classification logic - reduce its ability to reflect real client situations. Second, insufficient training and a lack of transparency in the tool's functionality add to inconsistent use while reinforcing scepticism. These challenges are worsened by the fact that

the segmentation results are not visible to most end users, limiting their ability to evaluate or contextualise outcomes.

Viewed through the STS framework, these issues reflect a mismatch between the technical system (the algorithm) and the social system (the organisation and its users). The findings suggest that for the tool to effectively support employment specialists, improvements must be made to both its technical logic and its integration into everyday practice. This means not only refining the algorithm's classification rules, but also strengthening communication, training, and opportunities for end-user involvement.

To support the ongoing development of the algorithmic tool and support it better meets the needs of its users, the following recommendations are proposed. These have been grouped according to whether they primarily address technical improvements or organisational and social integration. A summary is presented in Table 1 below:

Area of improvement	Recommendation	Description
Technical	Review and refine classification criteria	Reassess input variables to make sure they reflect relevant up-to-date factors, including more holistic and diverse indicators (e.g. educational history, current language proficiency, evolving health data).
Technical	Increase transparency of the tool's logic	Make sure the algorithm's decision rules are accessible to employment specialist so they can better understand how classifications are formed.
Technical	Improve segmentation output visibility	Make sure that segmentation results are made visible in the case management system (A-TMT) to support the judgement of the employment specialist.
Technical	Automate and streamline the tool	Move beyond manual data entry by integrating the tool directly with client data systems to strengthen productivity and reduce reliance on individual team members.

Organisational	Offer extensive training	Develop organisation-wide training covering tool logic, variable weighting, and practical usage scenarios.
Organisational	Clarify the purpose and use of the tool	Strengthen internal communication to make sure all employment specialists understand how the tool supports, rather than replaces, their expertise.
Organisational	Involve employment specialist in future development	Create channels for feedback and participation in the design and testing of future updates.
Organisational	Address trust and workload concerns	Acknowledge concerns raised by employment specialist and identify strategies to reduce perceived burden, making sure reassessments and adjustments are more transparent and efficient.

Table 1: Recommendations for improving the algorithmic tool

These recommendations are intended to support both short-term adjustments and longer-term strategic development of the algorithmic tool. Together, they aim to improve the alignment between the tool’s technical logic and the daily needs and practices of its users, ultimately supporting the broader goals of service quality and efficiency in employment services.

While this study brings attention to the practical use and perceived performance of the algorithmic tool, it is important to note that it also has some limitations. The response rate for the survey was modest with only 12% of respondents, and although the results offer important indications, they may not fully represent the views of all employment specialists in the organisation. Additionally, the study focused exclusively on the end-user perspective (employment specialists) and did not include external validation data to assess the accuracy or outcomes of the tool from a client-level perspective.

Another limitation concerns the dynamic nature of the algorithmic tool itself. As it is still under development and refinement, some of the concerns raised by employment specialists may already be in the process of being addressed. However, this also highlights the importance of ongoing evaluation as the system further develops.

Future research could explore several directions. First, a follow-up evaluation could be conducted after future updates to assess whether the proposed improvements have been implemented and how they have affected user perceptions and outcomes. Second, future studies could include a comparative analysis of client outcomes between classifications generated by the algorithm and those based solely on human judgement. Finally, future studies could take a more technical approach by analysing the algorithmic logic, accuracy of its classification model, or how different machine learning techniques or data inputs could improve predictive performance. This would deepen understanding of how technical improvements support real-world service needs.

7 Conclusion

This thesis set out to evaluate the algorithmic tool developed by Helsinki Employment Services, focusing on how it performs in practice from the perspective of its end users – the employment specialists. The study combined both quantitative and qualitative data to assess the tool’s perceived accuracy, reliability, and usefulness, as well as how it is integrated into daily work processes. Guided by the sociotechnical systems (STS) framework, the analysis considered both the technical and organisational aspects that shape the tool’s real-world performance.

The results indicate that while the algorithmic tool represents a promising step in the digitalisation of public employment services, there are still outstanding challenges in how it is experienced and used in practice. From a technical point of view, employment specialists reported concerns regarding the relevance of the input variables, the inflexibility of the classification logic, and the overall transparency of the system. At the same time, the social context in which the tool is introduced plays an equally important role. A lack of sufficient training, uneven communication, and limited end-user involvement have led to varying levels of trust and understanding between employment specialists.

Some of these concerns, as raised in the survey, are similar to the limitations previously identified by one of the internal experts during the development of the tool. For instance, frustrations around misclassifications were pointed out by expert discussions, noting that the tool relies on structured data that may sometimes be outdated or incomplete. Similarly, the confusion of the employment specialists on how results are formed can be partly explained by the current invisibility of segmentation outcomes in the client information management system. These findings show, that perceptions of inaccuracy are not necessarily due to the algorithm’s logic alone, but also in surrounding practices and communication gaps.

The evaluation also showed that some of the frustrations reported by the employment specialists, such as large numbers of clients being assessed for the wrong service categories, were not caused by the algorithm itself, but by parallel changes in organisational process. This distinction is important, as it suggests that part of the perceived inaccuracy might be addressed by clarifying internal procedures and improving transparency in how the tool's outputs are interpreted and applied.

As a whole, the results indicate a gap between the tool's technical design and its actual integration into employment specialist workflows. This reflects a wider challenge often encountered in IT-driven public sector initiatives – that even well-designed tools may not deliver intended benefits if users are not sufficiently engaged with the process. Strengthening the link between how systems are built and what users need helps digital tools better support professionals.

Although the focus of this thesis was not on the algorithm's development from a technical or coding perspective, it contributes to the broader field of applied information technology by presenting findings into how data-driven systems are experienced by their intended users. In doing so, it provides useful input for future IT-driven service development, particularly in contexts where human decision-making and algorithmic classifications overlap.

The study underlines, that the success of algorithmic tools in public services depends not just on their design but also on their introduction, explanation, and integration into the broader service ecosystem. Maintaining open communication between developers and users, while emphasising clarity, transparency, and professional expertise, is crucial for making digital tools as effective as possible in public employment services.

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Appendix 1: Survey information letter

Arvoisa Helsingin työllisyyspalveluiden asiantuntija,

Teen opinnäytetyötä Helsingin työllisyyspalveluissa käyttöön otetun kartoitustyökalun toimivuudesta ja sen vaikutuksista asiantuntijoiden päivittäiseen työhön. Kyselyn avulla kerätään arvokasta tietoa työkalun käytettävyydestä sekä mahdollisista kehittämistarpeista. Vastauksesi ovat erittäin tärkeitä sekä työkalun että asiakaspalveluprosessien kehittämisessä.

Kysely on lyhyt, ja sen täyttämiseen kuluu noin 5-10 minuuttia.

Kyselyyn vastaaminen tapahtuu täysin nimettömästi, eikä mitään henkilötietoja (esim. nimi, sähköpostiosoite tai IP-osoite) tallenneta. Kyselyyn osallistuminen on vapaaehtoista, ja voit milloin tahansa keskeyttää osallistumisesi ilman seurauksia. Pyydän sinua vastaamaan kyselyyn mahdollisimman pian, kuitenkin viimeistään 8.4.2025 mennessä.

Jos sinulla on kysyttävää tutkimuksesta tai tarvitset lisätietoja, voit olla yhteydessä minuun.

Jatkamalla eteenpäin kyselyyn, annat suostumuksesi edellä kuvattuihin ehtoihin. Linkki kyselyyn: <https://forms.office.com/e/iTKQpFn547>

Parhain terveisin,

Anna Paraczký
Laurea-ammattikorkeakoulu
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Appendix 2: Survey questionnaire

Kartoitustyökalun tuntemus

1. Kuinka hyvin tunnet kartoitustyökalun peruseriaatteet (millä perusteella luokitus muodostuu?)
 - Erittäin hyvin
 - Melko hyvin
 - En kovin hyvin
 - En lainkaan

Työkalun tekninen ulottuvuus (tarkkuus, selkeys, luotettavuus)

2. Miten arvioisit kartoitustyökalun tuottaman luokituksen tarkkuutta **asiakkaan työmarkkinatilanteen** kuvaamisessa?
 - 1= Erittäin epätarkka
 - 2= Melko epätarkka
 - 3= Kohtalaisen tarkka
 - 4= Melko tarkka
 - 5= Erittäin tarkka
 - 6= En osaa sanoa
3. Miten arvioisit kartoitustyökalun tuottaman luokituksen tarkkuutta **asiakkaan todellisen työkyvyn** kuvaamisessa?
 - 1= Erittäin epätarkka
 - 2= Melko epätarkka
 - 3= Kohtalaisen tarkka
 - 4= Melko tarkka
 - 5= Erittäin tarkka
 - 6= En osaa sanoa

4. Miten arvioisit kartoitustyökalun luotettavuutta yleisesti?
 - 1= Erittäin epäluotettava
 - 2= Melko epäluotettava
 - 3= Neutraali
 - 4= Melko luotettava
 - 5= Erittäin luotettava
 - 6= En osaa sanoa

5. Oletko havainnut kartoitustyökaluun liittyviä toistuvia ongelmia tai virheitä? Kuvaile lyhyesti.

Vaikutus työskentelyyn ja asiakasprosesseihin

6. Kuinka paljon luotat kartoitustyökalun antamiin luokituksiin verrattuna omaan asiantuntija-arvioosi?
 - 1= En luota lainkaan
 - 2= Luotan hyvin vähän
 - 3= Neutraali
 - 4= Luotan melko paljon
 - 5= Luotan täysin

7. Oletko huomannut tilanteita, joissa kartoitustyökalun antama asiakasluokittelu ei vastannut asiakkaan todellista palveluntarvetta? Kuvaile esimerkin avulla.

Organisaation tuki ja koulutus

8. Oletko saanut riittävästi koulutusta tai ohjeistusta kartoitustyökalusta
 - Kyllä, riittävästi
 - Osittain, kaipaisin lisää
 - En ole saanut riittävästi koulutusta

9. Miten arvioisit yleistä suhtautumista kartoitustyökalun käyttöön organisaatiossa?
 - 1= Erittäin kielteistä
 - 2= Melko kielteistä

- 3= Neutraalia
- 4= Melko myönteistä
- 5= Erittäin myönteistä

Kehittäminen ja loppukommentit

10. Mitä parannuksia sinulla on kartoitustyökalun kehittämiseksi?

11. Onko jotain muuta, mitä haluaisit kertoa kartoitustyökalun toimivuudesta tai sen vaikutuksesta työhösi?