OULUN AMMATTIKORKEAKOULU

FROM EARLY STAGES TO INFINITE POTENTIAL

Predictive HR analytics use cases in wellbeing services counties

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ABSTRACT

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The thesis delves into the transformative power of predictive HR analytics, uncovering its potential through compelling case studies within the theoretical framework. The study illuminates customer needs related to predictive HR analytics within the wellbeing services counties through thematic interviews, providing valuable insights for future innovations.

This thesis was conducted for the product development team within a global IT and consulting company. The product development team specializes in providing reporting and analytics services to its clients. The thesis aims to explore expectations and experiences regarding the utilization and potential of predictive HR analytics. The study investigates whether customer needs are common and general or if they, along with models of predictive HR analytics, are always dependent on specific contexts and the organization's characteristics. The former studies in the theoretical part act as examples of different use cases of how to use machine learning in predictive HR analytics.

The research was a qualitative study. The data was collected through thematic interviews. For the research, two wellbeing services counties were interviewed, with a total of eight interviewees. The interviews were conducted as individual interviews via Microsoft Teams. The data was analyzed using thematic analysis.

According to the results, the utilization of predictive HR analytics is still in its early stages in both of the interviewed organizations. The interviewees' opinions on the current situation varied within the same wellbeing services county, but there were also organization-specific differences. The interviews revealed 45 different development suggestions, the need for which has been addressed in each theme. Finally, the development suggestions were prioritized based on how many interviews mentioned each suggestion.

Keywords: HR analytics, talent analytics, human capital analytics, people analytics, workforce analytics, predictive HR analytics, artificial intelligence, machine learning

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1 INTRODUCTION

Anticipating personnel resourcing is essential for ensuring that the right resources are available at the right time, reducing reliance on urgent and costly temporary labor. Effective workforce planning minimizes the risks of both overloading and under-resourcing, enhancing work efficiency and productivity. Moreover, it supports employee well-being and engagement, which can lower turnover rates and related costs. By preventing excessive workloads, organizations can reduce the amount of sick leaves, leading to direct cost savings. In Finland, municipalities and wellbeing services counties face significant cost-cutting pressures, making proactive personnel management increasingly critical for maintaining operational efficiency and financial sustainability. Additionally, businesses that successfully adapt to changing market conditions by optimizing their workforce can strengthen their competitive position and improve long-term profitability.

1.1 Background

The thesis author works as a Business Intelligence Consultant in CGI in a People Analytics product development team. The features of the business intelligence tool, CGI People Analytics, include extensive descriptive analytics and a touch of predictive analytics. In addition to the present data, the users, who are typically managers and HR professionals, need to explore data more deeply and understand what led to the present state, and what will happen next.

It has been recognized that the product should include more reports and visualizations concerning forecasting such as risks of well-being, occupational health, turnover, and productivity monitoring. For example, predictive analytics can be explored regarding employee turnover and sick leaves. One use case has already been identified: absences during vacations affect the availability of personnel. Until now, the customers have done the work manually with Excel. Customers need to predict the need for human resources in the organization.

CGI People Analytics reporting and analysis tool focuses on HR analytics, so also in this thesis, the focus is on researching HR analytics. The interviews were conducted with wellbeing services counties, as they are under significant pressure to achieve cost savings, and their operations are a topic of public discussion in Finnish society.

1.2 Objectives, research questions, and delimitations

The goal of the thesis is to identify use cases in predictive HR analytics. The thesis discusses whether it is possible to create general predictive HR analytics models for all customers or whether predictive analytics is always dependent on specific contexts and the organization's characteristics.

The research questions for this thesis are as follows:

1. What kind of customer needs do the wellbeing services counties have for predictive HR analytics?
2. Is it possible to create common and general models, or are the models always dependent on the organization?
3. How can machine learning and predictive HR analytics models help fulfill customer needs?

The thesis is written from a non-technical perspective, particularly from the viewpoints of business stakeholders and end-users. The thesis focuses on researching the topic and mapping customer needs. Implementation of the actual predictive models and machine learning algorithms is limited outside this thesis.

1.3 Structure of the thesis

The content of the thesis is described in this paragraph. The structure of the thesis is presented in Figure 1.

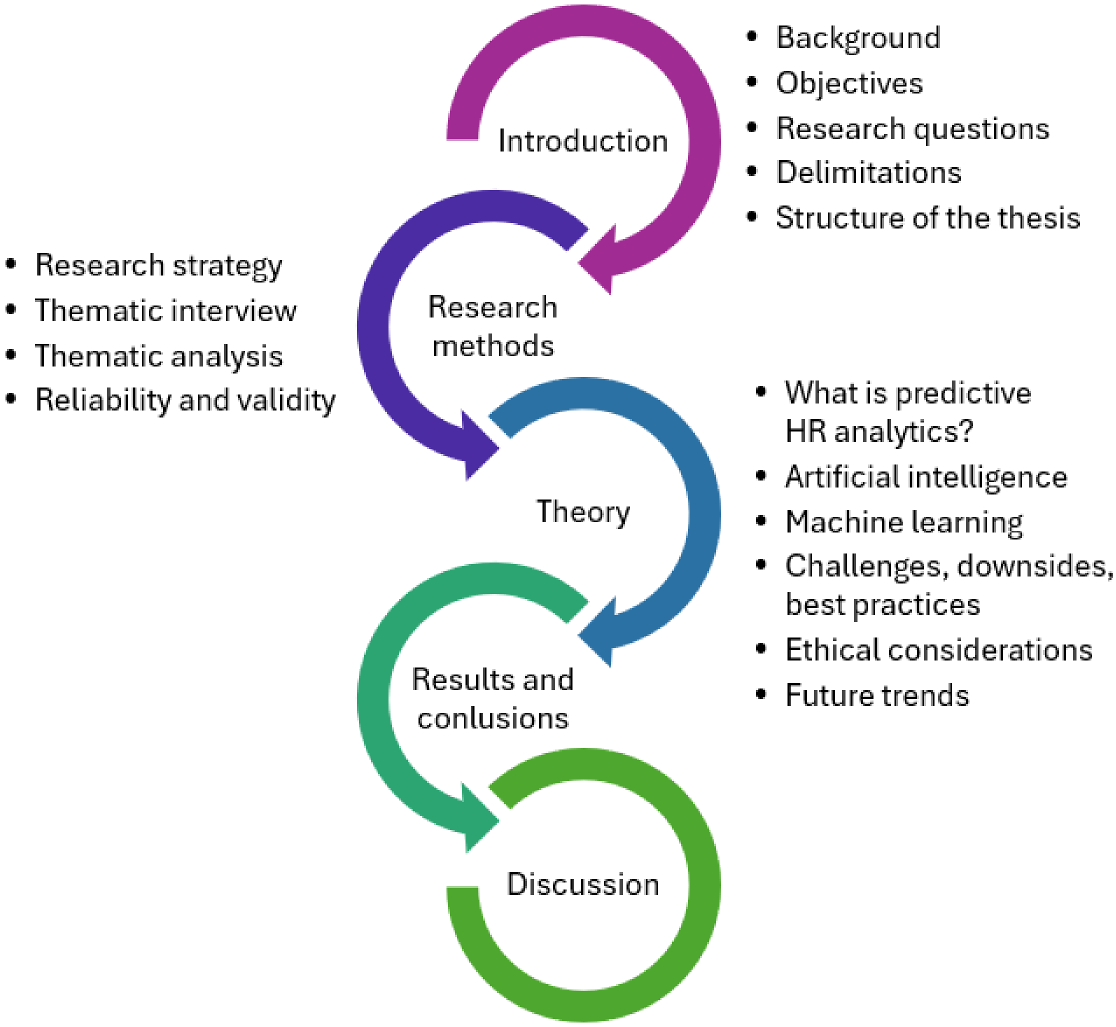

FIGURE 1. Structure of the thesis.

The first chapter covers the introduction. The subject, the starting point, and the meaning of the thesis are presented. The introduction explains to the reader why the topic is important and worthy of research. The chapter covers the background, objectives, research questions, delimitations, and structure of the thesis.

The second chapter addresses research methods. The subchapters examine qualitative research as a research strategy. The thematic interview is explained as a qualitative research method and thematic analysis discusses how research data was being analyzed. To ensure the reliability and validity of the study, these concepts are examined at the end of the chapter.

The third chapter focuses on the theoretical framework which includes the basics of HR and predictive HR analytics such as talent management, employee engagement, performance, well-being, AI and machine learning. Challenges, downsides, and best practices as well as ethical considerations and future trends are part of the theoretical framework. Up-to-date research information has been searched for in each subject area. The research materials and articles are international since there is no research data on this topic concerning Finnish organizations, especially the wellbeing services counties. Using research articles, case examples of studies that have applied predictive HR analytics are presented.

Chapter four discusses the results of the thematic interviews on the research topic. Each theme based on the thematic analysis is presented in its subchapter. The development suggestions that emerged in the interviews have been presented in each subchapter. Additionally, the most essential development suggestions have been highlighted in their own subchapter to emphasize their importance.

In chapter five, there is a summary of the main results of the thesis. The results are compared to previous research on the topic. Considerations are made on how the subject area could be studied further in the future. The chapter includes ethical considerations on the use of predictive HR analytics and personal reflections on the research experience. The chapter summarizes the key customer needs and development suggestions for predictive HR analytics.

2 RESEARCH METHODS

The research was executed as a qualitative study, focusing on gaining in-depth insights into the research subject. Data collection was carried out through thematic interviews, which allowed for a comprehensive understanding of participants' perspectives and experiences. These interviews provided rich, detailed data that was subsequently analyzed using thematic analysis. This method enabled the identification of key themes and patterns within the data, offering valuable insights and a deeper understanding of the research topic.

In this thesis, OpenAI's ChatGPT, Microsoft's Copilot, and Grammarly AI have been used to support and assist in text editing, such as language corrections, translations, alternative linguistic expressions, and improving text fluency. OpenAI's ChatGPT and Microsoft's Copilot AI were also utilized for brainstorming and the planning of topics and visualizations.

2.1 Research strategy

The research was conducted using qualitative research methods. The features of qualitative data analysis are presented in Figure 2. According to Cresswell, Kananen, and Leavy, a qualitative research approach emphasizes the depth of meaning, interpretations of the data and the interviewee's subjective experiences. This enables a deep comprehension and strong understanding of the topic. Qualitative approaches are usually used in exploratory or descriptive studies. (Cresswell 2014, 4,18; Kananen 2017, 33, 35; Leavy 2017, 124.) The analysis of qualitative data aims to uncover meaningful insights from the data and interpret the meanings through words rather than numerical data. The richness of interpretations enables researchers to explore deeper into the phenomenon under investigation and gain a more comprehensive understanding of it. (Creswell 2014, 185-186; Omeihe & Harrison 2024, 192-193.)

In qualitative research, the goal is to get a deep insight into the phenomenon and to explain in more detail the phenomenon, of which there is still not much information (Kananen 2017 32-33). Previous research on how wellbeing services counties utilize predictive HR analytics does not exist. Therefore, qualitative research was a justified choice as a research method.

Features	Qualitative Data Analysis	Quantitative Data Analysis
Nature of data	Non-numerical, descriptive and subjective	Numerical, measurable and objective
Sample size	Smaller, often focuses on in-depth analysis of a few cases.	Larger, typically representative of a population
Data collection methods	Interviews, observations, focus groups	Surveys, experiments, measurements
Data analysis approaches	Inductive, interpretive and exploratory	Deductive, statistical and confirmatory
Data representation	Textual, narrative and visual depictions	Numerical tables, charts and graphs
Generalisability	Findings are context-specific, limited generalisability	Findings can be generalised to a larger population
Subjectivity	Relies on the researcher's interpretation and judgement	Strives for objectivity and minimising researcher bias
Time and resources	Time-consuming and resource intensive	Efficient and less resource demanding
Depth of understanding	Provides rich, in-depth insights and detailed explanations	Provides a broad overview and statistical patterns
Research questions	Typically, open-minded and exploratory	Typically, closed-ended and hypothesis-driven

FIGURE 2. Features of qualitative data analysis (Omeihe & Harrison 2024, 194).

2.2 Thematic interview

A thematic interview is based on addressing key, pre-selected themes, and related clarifying questions. The questions can be refined and deepened during the thematic interview according to the interview situation. (Hirsjärvi & Hurme 2008, 47-48; Kananen & Jyväskylä University of Applied Sciences 2015, 149-150; Kananen 2017, 89-90; Tuomi & Sarajärvi 2018, 87-88.)

The interviews were conducted as thematic interviews in an individual format. The thematic interview was chosen as a survey method for this research since the focus is on the depth and versatility of the research subject. The purpose of the interviews was to understand organizations' current state, experiences, perceptions, and insights regarding the use of predictive analytics in HR. Thematic interviews, as a data collection method, provide a comprehensive understanding of customers' perspectives on the research subject.

For this study, there were eight thematic interviews. The organizations participating in the interviews included two wellbeing services counties. Both organizations are clients of CGI and one of them uses CGI People Analytics reporting and analytics tool. The number of interviewees by wellbeing services county is represented in Table 1.

TABLE 1. The number of interviewees by organization

Organization	The number of interviewees
Wellbeing services county 1	4
Wellbeing services county 2	4
Total	8

The questions for the interviews were selected so that they cover the basic areas of predictive HR analytics which are often monitored using various tools. The themes selected for the interview are those that can be implemented with the CGI People Analytics product and are part of its present roadmap. The preliminary thematic interview framework was provided to the interviewees in advance so that they had time to prepare for the interview. The interviews were conducted in Finnish. The thematic interview framework in Finnish is presented in Appendix 1, and the thematic interview framework in English is presented in Appendix 2.

From both organizations, a person who works with HR analytics or has experience utilizing it was interviewed. The interviewees were selected based on their roles within HR experience and expertise within the organization. They represented diverse roles and perspectives, ensuring a comprehensive understanding of the phenomenon under study. Exceptions to this were the themes of competence management, training planning and career development, and work shift planning and personnel needs, which would have required a deeper review, as the individuals participating in the interview did not have a thorough understanding of the topic. The selection process aimed to include individuals with relevant experience to address the research questions effectively. Participation was voluntary. The interviewees were informed about the purpose of the study, and confidentiality was guaranteed.

At the beginning of each interview, the GDPR Privacy Notice of the study was reviewed. Its purpose was to inform the participant clearly and understandably about how their personal data will be used and processed. In each interview there was a review of the interviewee's background information to establish context and gain an understanding of their role and experience in the organization. The role and significance of predictive HR analytics covered the use of predictive HR analytics, its perceived benefits, and challenges in its implementation or utilization. When examining data sources, tools, and data management, an overall picture of the current HR system architecture emerged, along with how data reliability is ensured and how employees respond to the use of their data in analytics. After this, the interview delved into the main thematic part which covered skills, competencies, employee engagement, well-being, and performance in predictive HR analytics. At the end of the interview future expectations and prospects were covered as well as how AI is or could be used in predictive HR analytics.

From both organizations, four persons were interviewed via Microsoft Teams, resulting in a total of eight interviews. The interviews were held between 21 October and 27 November 2024 (Figure 3). The duration of the interviews varied from one hour to two hours. The total duration of the interviews was 11 hours, and the transcribed data amounted to 151 pages. The interviews were transcribed using Microsoft Word after each interview and before the next one.

Wellbeing services county 1	21.10.	5.11.	14.11.	22.11.
Wellbeing services county 2	7.11.	8.11.	21.11.	27.11.

FIGURE 3. Schedule of the interviews.

2.3 Thematic analysis

Thematic analysis is a qualitative data analysis process covering identifying, analyzing, and interpreting patterns or themes in the dataset through a systematic and iterative process of coding and theme development. (Braun & Clarke 2022, 4; Omeihe & Harrison 2024, 202). The thematic analysis in this study was executed according to the ADEPT Method by Omeihe & Harrison. The method is presented in Figure 4. It has four phases: Analysis, Data Exploration, Pattern Identification, and Theme Development (Omeihe & Harrison 2024, 203-204).

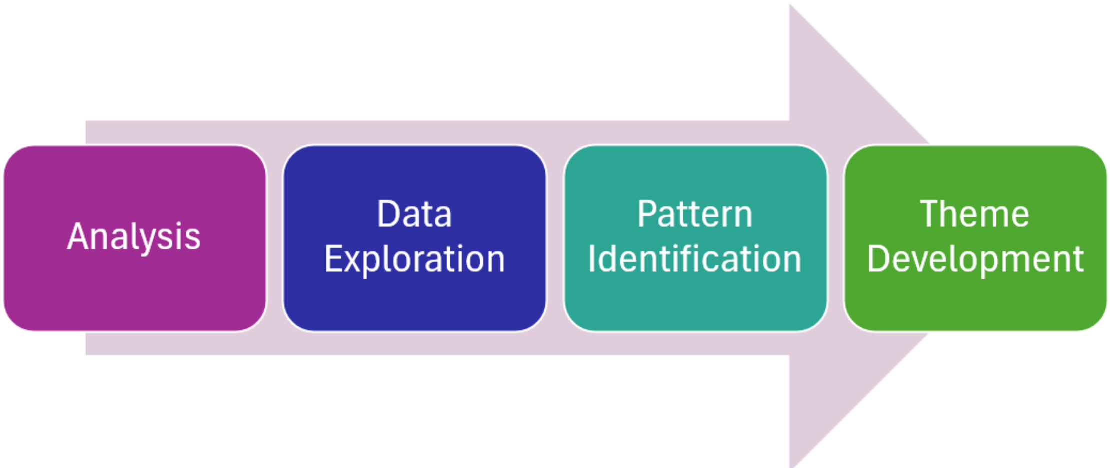

FIGURE 4. The ADEPT Method.

In this study, the coding was done using Microsoft Word and Excel, using techniques such as highlighting, underlining, and using different colors. In the first phase, Analysis, the researcher delves into the dataset and gains a deep understanding of its content and context by conducting initial readings and noting key concepts, ideas, and patterns from the data (Omeihe & Harrison 2024, 203-204).

In the second phase, Data Exploration, the researcher reviews and examines the dataset by identifying relevant segments. The researcher organizes and categorizes the data based on its terms, codes, concepts, and patterns. The researcher focuses on the third phase, Pattern Identification, identifying patterns within the coded data by analyzing the relationships, comparisons, connections, and variations between the data segments In the final phase, Theme Development, the researcher develops final themes based on the patterns identified earlier and analyzes and interprets the data segments within each segment. Themes are refined, merged, or split if needed to ensure they capture the complexity and richness so that the outcome reflects the essence of the data set. (Omeihe & Harrison 2024, 203-204.)

2.4 Reliability and validity

Validity refers to whether the research results represent accurately the phenomenon being studied. Reliability aims to ensure that the research results are repeatable. In qualitative research, validity and reliability are difficult to assess, as these concepts are primarily applicable to quantitative research. (Creswell 2014, 201; Kananen 2017, 175; Tuomi & Sarajärvi 2018, 160; Omeihe & Harrison 2024, 219.) The results of a qualitative study are only valid for the study in question and the phenomenon being studied (Kananen 2017, 33).

As stated by Cresswell (2014, 201-202) there are eight validity strategies in a qualitative study:

1. Triangulation
2. Member checking
3. Rich descriptions
4. Bias clarification
5. Presenting negative or discrepant information
6. Spending prolonged time in the field
7. Peer debriefing
8. Use of an external auditor

Hirsjärvi & Hurme (2008, 189) state that the aforementioned strategies are a part of Bloor's (1997) studies in terms of triangulation and Janesick's (1994) studies in terms of member checking.

In qualitative research, the researcher must have sufficient time to conduct the study, which enhances reliability and validity. The transparency of the research process is also considered to improve reliability and validity, as the researcher provides a detailed report on the situation, peers evaluate the process, and the study’s informants assess the applicability of the results and conclusions to the research topic. (Tuomi & Sarajärvi 2018, 165-166.)

In this study, validity was ensured through triangulation, as the interview included participants working in different roles. This helped to build a consistent justification for themes, and enriched and diversified the exploration of the topics. The study used rich descriptions to convey the findings to the reader. This facilitated the presentation of versatile perspectives on a theme, leading to more realistic and richer findings. The study also presented some negative or discrepant information between interviewees' opinions. Presenting contradictory information and considering possible root causes is important from the perspective of transparency and honesty in research. Highlighting negative results helped create a comprehensive understanding of the subject being studied.

Creswell (2014, 203) presents Gibbs’s (2007) four strategies for the assessment of the reliability of qualitative study:

1. Checking the transcriptions
2. Consistency of the codes
3. Communication among other researchers in team studies
4. Cross-checking the codes by different researchers in team studies

The reliability of this study was ensured by checking the transcriptions so that they were clear and flawless. Also, the consistency of the codes was applied so that the data was compared with the codes to ensure that the meaning of the codes did not change during the process of coding.

3 TOWARDS PREDICTIVE HR ANALYTICS

In the emerging era of big data when every aspect of our lives - including preferences, decisions, geolocation, habits, personality traits, social interactions, and behaviors – is being collected, encoded, and transformed into data, encompassing both professional and personal domains. This improves product quality, service quality, innovation, and productivity. Human activities are transformed into data so that everything can be tracked, analyzed, optimized, personalized, and monetized. (Falletta 2024, chapter 2, The Datafication of Everything.)

3.1 Introduction to analytics

Analytics is becoming part of everyday operations and a competitive advantage in organizations. Corporations are constantly searching for exploring innovative methods to speed up launching new services and continuously enhancing customer experience to maintain a competitive edge. Analytics is one of the key components to better comprehend the business and the customers so that changes are relevant and made efficiently. (Ali 2024, chapter 1, Different Types of Data Analytics.)

Analytics is a combination of applying statistics, data mining, and technology to use data for insights and actionable information. Analytics involves data analysis and visualization along with mathematics or statistics and machine learning. Analytics assists effective decision-making by observing patterns of variations. Examining the patterns helps the organizations understand and predict uncertainties related to their business. (Roy, Srivastava, Jat &. Karaca 2022, 16.)

All stages of data analytics assist organizations in making efficient decisions and supporting strategic business management (Sharma et al. 2022, 12). According to Isson & Harriott and Ali analytics is divided into four categories (Figure 5): descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics (Isson & Harriott 2016, 83; Ali 2024, chapter 1, Different Types of Data Analytics). Organizations are at different stages in their analytics journey.

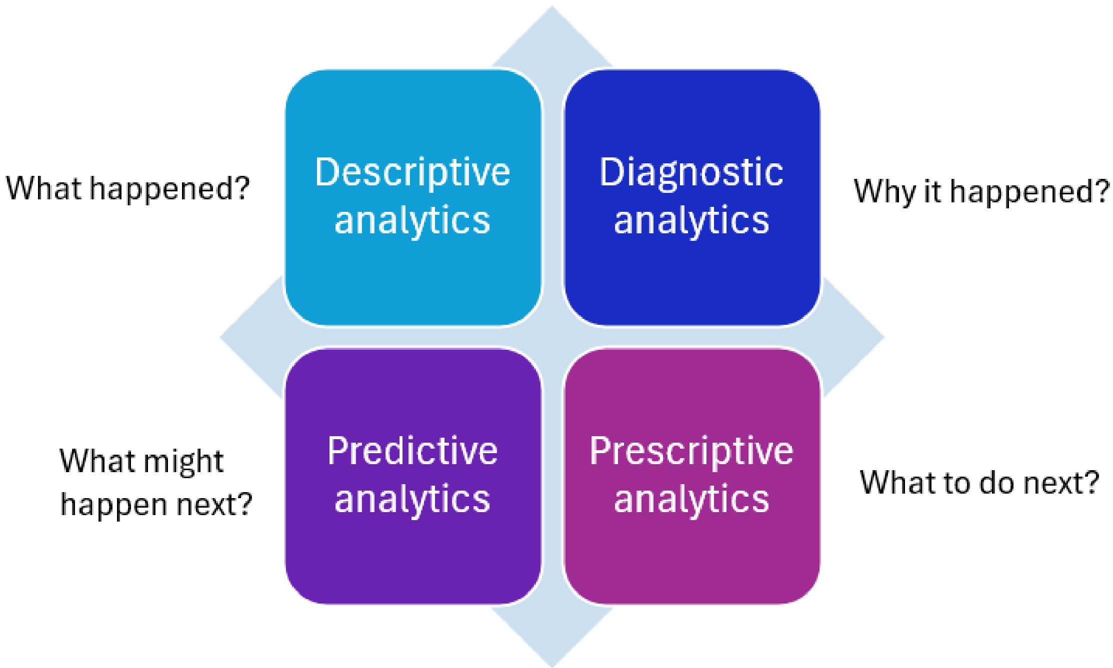

FIGURE 5. Different categories of analytics.

There are also different perspectives regarding the levels of analytics. Some researchers state that analytics is divided into three levels instead of four levels: descriptive, predictive, and prescriptive analytics (Fitz-enz & Mattox 2014, 2-3; Eubanks 2019, 25; Roy et al. 2022, 17; Sharma et al. 2022, 4; De Vos, De Smedt, Verbruggen & Verbeke 2024, 2). Fitz-enz & Mattox (2014, 2-3) note that diagnostic analytics is a part of predictive analytics.

The levels of analytics have traditionally been viewed as steps on a ladder. Saramies & Törnroos describe the levels of analytics as pieces of a puzzle. They think that analytics does not progress step by step from the bottom up, but from one level to another, because each level complements the previous one. In their model, each organization has different cultural, strategic, and technical capabilities that influence the level of analytics applied. (Saramies & Törnroos 2021, 176-179.)

Descriptive analytics

Descriptive analytics analyses historical and current data to understand the relationships and trends, and guide to understanding what has happened (Fitz-enz & Mattox 2014, 3; Isson & Harriott 2016, 83; Sharma et al. 2022, 5: Ali 2024, chapter

1, Different Types of Data Analytics). Therefore, descriptive analytics provides historical context, demonstrates how present processes function, helps to assess the business goals, and provides a holistic approach. Recognizing trends and visualizing patterns highlights the organization's strengths and weaknesses, and offers a historical summary to support function more optimally in the future. (Sharma et al. 2022, 7.)

Descriptive analytics contains HR metrics and key performance indicators such as turnover rate, recruitment duration, cost of hire, and the number of hired and trained persons. Dashboards, scorecards, workforce segmentation, summary statistics, regression analysis, and periodic reports are typically part of descriptive analytics. (Fitz-enz & Mattox 2014, 3; Sharma et al. 2022, 6.)

Data aggregation and mining are critical components of descriptive analytics. Aggregation is the first step, where data is collected and organized to enable efficient management of datasets. After data aggregation, data mining involves extracting relevant information by identifying and interpreting patterns using advanced analytical methods. Once the data has been transformed, sorted, and analyzed, visual representation becomes essential for clarifying the insights. Descriptive analytics, therefore, plays a key role in establishing key performance indicators and aligning them with business objectives to assess the current state of the business based on past activities. (Sharma et al. 2022, 5.)

Cayrat & Boxall studied challenges, risks, and impacts of HR analytics in 40 large companies by interviewing HR managers and specialists in Canada, France, New Zealand, and Switzerland. Half of the organizations in the survey reported that they use real-time alerts and automated calculation of HR metrics in descriptive analytics. In this way, HR experts can help a manager in a situation where it is observed that the employee is frequently absent due to illness on Fridays. Two-thirds of the organizations investigated the statistical relationships of HR variables, such as factors related to a higher level of turnover. A little more than half focused on HR and performance variables. (Cayrat & Boxall 2022, 581-582.)

Diagnostic analytics

Diagnostic analytics is utilized to gain deeper insights into the underlying reasons behind an event. The analysis can be executed as root cause analysis, and it aims to understand the relationships between variables and trends to show correlation and causation. (Isson & Harriott 2016, 83; Ali 2024, chapter 1, Different Types of Data Analytics.)

Predictive analytics

Predictive analytics utilizes historical and current data to predict future events with machine learning and AI. The predictions can be simple (if something happens) or more complex (for instance who are at a higher risk of developing certain diseases). Predictive analysis can be done by analyzing data manually using predictive data modeling and machine learning. The objective is to leverage data to gain a deeper understanding of the business and generate practical insights that pave the way for prescriptive analytics. (Fitz-enz & Mattox 2014, 3; Isson & Harriott 2016, 83; Roy et al. 2022, 20, 24-25; Sharma et al. 2022, 8; Ali 2024, chapter 1, Different Types of Data Analytics.) Predictive analytics is used to decrease risks, enhance operations, and increase revenue. It can also resolve complex problems and reveal new business opportunities (Sharma et al. 2022, 5).

Prescriptive analytics

Prescriptive analytics extends predictive analytics with actionable decision options and strategies for optimizing the outcome. It leverages complex data analysis to forecast results, proposes choices, and illustrates potential impacts on the business. This stage helps to determine what is the optimal next step by evaluating multiple variables. Prescriptive analytics can be conducted manually with analytical tools or it can automated with algorithms. (Fitz-enz & Mattox 2014, 3; Isson & Harriott 2016, 83; Sharma et al. 2022, 10; Ali 2024, chapter 1, Different Types of Data Analytics.) Prescriptive analytics goes beyond merely forecasting future outcomes; it also recommends actions based on predictions, illustrating the consequences of each choice for the decision-makers. It not only predicts what will happen and why, but also when it will happen. (Sharma et al. 2022, 10.)

Prescriptive analytics is commonly regarded as the most advanced level of data analytics. It utilizes optimization techniques to identify the most effective approach for achieving the desired goal, whether it involves reducing or increasing a specific outcome. The process relies on predictive modeling, actionable data, and a feedback system that monitors the results of implemented actions. (Sharma et al. 2022, 10.)

In Cayrat & Boxall's research, only 5% of organizations used prescriptive analytics by running simulations and what-if scenarios. Approximately 25% of organizations deployed machine-learning models to identify patterns and relationships between variables. (Cayrat & Boxall 2022, 581-582.)

Prescriptive analytics can be valuable to healthcare strategic planning by leveraging the operational and usage data combined with aspects such as demographic trends, financial data, and health trends to more precise plans for future capital investments like new facilities and equipment. To create and implement an effective prescriptive analytics strategy, an organization must have an information management plan that incorporates both internal and external data, as well as structured and unstructured data. Additionally, it requires a technology strategy and a data science strategy. (Sharma et al. 2022, 11.)

Roy et al. divide analytics into three steps: obtaining, organizing, and observing (Figure 6). Obtaining means gathering or collecting data, which is the most crucial part of the process. Data collection depends on the problem statement. Organizing the data makes it more compatible for analysis. Data should be arranged to extract as many insights as possible. Observing is the last step after the data is structured and organized. Through analysis, relationships, patterns, and trends are observed, enabling the prediction of future outcomes. (Roy et al. 2022, 15-16.)

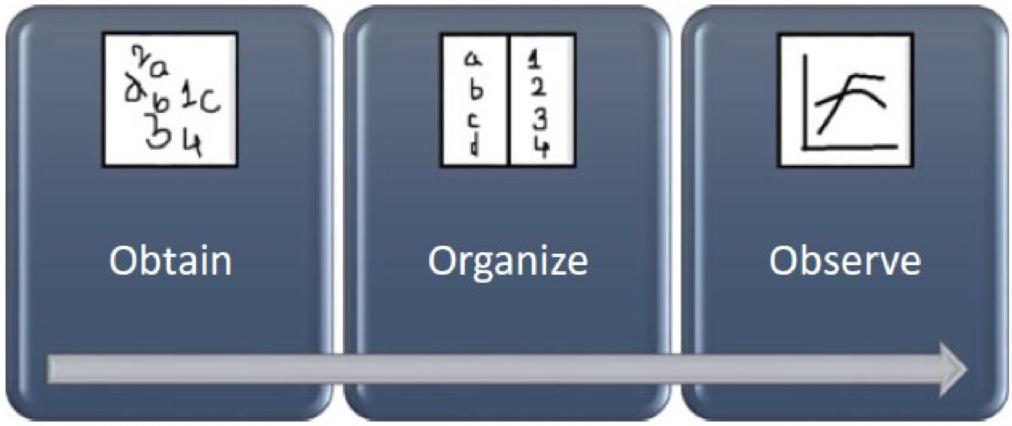

FIGURE 6. Three steps of analytics (Roy et al. 2022, 16).

3.1.1 HR analytics

There are several synonyms for HR analytics such as HR talent analytics, human capital analytics, people analytics, and workforce analytics. Each synonym reflects its purpose, history, values, expertise, resources, structure, and placement in the organization in terms of ownership, leadership, and accountability. In HR analytics, the importance of evidence-based management, the broad role of HR research and experimentation, ethical perspectives and the role of HR analytics in strategy and implementation are emphasized. (Falletta 2024, chapter 1, Multiple Monikers.)

In Cayrat & Boxall's research organizations and individuals used the terms people analytics, HR analytics, workforce planning and reporting, and workforce analytics to describe similar functions, but the choice of terminology emphasized slightly different perspectives or areas of focus. (Cayrat & Boxall (2022, 572, 576, 578-579.) This indicates that there is no single established term in the field; instead, the terminology is used in part according to the organization and from different viewpoints.

In KIRD's (2021) survey, over 7000 HR professionals from 35 countries responded to the survey, and 55% of respondents stated they needed help with the implementation of HR analytics. Cho, Choi & Choi (2023, 1-2) state this is caused by the fact that the tools are still new to organizations. Poor data quality and finding suitable business cases for implementation also increase challenges.

Marler & Boudreau point out that although HR analytics is widely popular, there is a significant lack of high-quality, evidence-based scientific research on the subject. They find it contradictory that existing studies frequently highlight positive outcomes achieved by HR analytics in organizations. (Marler & Boudreau 2017, 22.) This could be a result of the limited research available on the subject. Kravariti & Johnston (2019, 1, 5) emphasize that for instance a significant portion of public sector talent management research originates from consultancy reports, which provide recommendations based on private sector practices.

Hyytiäinen investigated the current state of HR analytics in Finnish public and private organizations. Based on the research, descriptive analytics is used the most in organizations, and 69% of the respondents use often or always descriptive analytics, which focuses on reporting in the past. 52% of respondents said they do not use predictive analytics. Due to the small sample of the study, the public and private sectors cannot be examined separately in the results. (Hyytiäinen 2019, 52-53, 70-74.)

Cho et al. see that even though data technology has advanced HR analytics and organizations nowadays use more and more algorithm-based predictive tools in decision-making, the utilization rate, especially in the public sector, remains low. They explored concepts and key practices of HR analytics through a thematic review and proposed a five-step process (define, collect, analyze, share, and reflect) for assisting the implementation. The study found examples for areas such as workforce planning, recruitment, HR development, and performance management. (Cho et al. 2023, 1.)

Arora, Prakash, Mittal & Singh investigated the factors that facilitate or prevent the use of HR analytics among HR professionals in the banking, financial services, and insurance sectors in India. The results showed that behavioral intention was positively influenced by data availability, hedonic motivation, and performance expectancy, while effort expectancy, social influence, and habit had no significant impact. Together, facilitating conditions, habits, and behavioral intentions explained 60% of the variance in HR analytics usage. Actual usage of HR analytics was drastically influenced by both facilitating conditions and behavioral intention. (Arora et al. 2024, 432.)

Beyond traditional HR metric reporting and ad hoc querying, HR analytics encompasses a broader scope, providing deeper insights, and advanced capabilities. With HR analytics organizations can make data-driven decisions by using the best available scientific evidence and organizational facts with evidence-based HR which impacts business success. (Bandari 2019, 15-16; Falletta 2024, chapter 1, The Meaning of HR Analytics.) HR analytics must be based on key business questions and objectives (Isson & Harriott 2016, 32).

Companies gain a deeper understanding of their workforce by analyzing employee data, and they consequently gain insights into behaviors, patterns, and trends uncovering key factors and variables (Bandari 2019, 15-16; Falletta 2024, chapter 1, The Meaning of HR Analytics.) Data-driven insights lead to evidence-based decisions, when the factors affecting employee performance and productivity are better understood. Analytics assists organizations in optimizing their recruitment and retention strategies, designing employee training programs, boosting employee engagement and satisfaction clarifying decisions regarding promotion at the optimum time, appraisal-related decisions, role changes, reasons for absences, and activities related to onboarding and offboarding. (Bandari 2019, 15-16; Chatterjee, Chaudhuri, Vrontis & Siachou 2022, 52.) Optimization, what-if-scenarios and cause-and-effect relationships influence crucial business results and decision-making (Falletta 2024, chapter 1, The Meaning of HR Analytics).

Strategically supported HR analytics projects with active HR research and experimentation to collect new data and test exclusive hypotheses play a fundamental role in qualifying strategy and decision-making. An organization’s HR analytics capabilities and priorities should not be limited to a few projects that prioritize the interests of influential stakeholders. Projects should be innovative with the potential for significant disruption, utilizing evidence-based data and resources, such as scientific research findings. Most of all, the ethical implications of HR analytics must be considered, and HR strategy and workforce decisions should be guided by insights generated through comprehensive HR research and analytical methodologies. (Falletta 2024, chapter 1, Defining HR Analytics.)

HR analytics is being used to improve the efficiency and effectiveness of HR processes and their contribution to operational outcomes. For example, reducing the time to fill vacancies and reducing costs while improving the volume and quality of candidates improves the recruitment process. (Cayrat & Boxall 2022, 583.) Important contextual elements, like a candidate's cultural fit within the organization or ability to collaborate in the team, impact HR decisions. Decision-making requires qualitative data, such as emotional intelligence and performance-related aspects. It also needs quantitative data from predictive models for support. (S & Dulloo 2023, 830.) Relying solely on predictive models without human judgment and interpretation can lead to limited assessments and flawed decisions.

HR analytics helps organizations identify what, why, and how redesigning HR activities improves HR outcomes, such as employee engagement, performance, and retention. These improvements, in turn, affect targeted indicators of operational performance, such as productivity, service quality, and innovation. (Cayrat & Boxall 2022, 58.)

Employee engagement

Employee engagement affects employee satisfaction, productivity, and retention. It can be studied by analyzing employee survey responses to identify the factors to improve engagement and the work environment. By mitigating risks through tracking HR metrics such as employee turnover, absences, and engagement, organizations can identify potential concerns and take action before situations escalate into problems. Additionally, by reducing the costs of employee turnover, organizations can minimize the risk of legal action and create a more stable and productive workforce. (Bandari 2019, 19-20.)

IoT (Internet of Things) devices can be used in employee monitoring by tracking physical movements, location, conditions, and social interactions. Employee performance, collaboration, and productivity can be analyzed by utilizing the data. This helps organizations detect incompetence in workflows, which increases productivity and cost savings. The sensors help to identify potential hazards and to mitigate them. By using IoT devices to monitor work environment conditions, employers ensure compliance with safety regulations, avoid fines and legal penalties for non-compliance. (Bandari 2019, 16-17.)

Talent management

Talent management gathers data on employees' skills, experiences, and preferences, enabling organizations to identify high-potential individuals. By analyzing data on employees' work history and job preferences, employers can create personalized career paths that are tailored to their employees' individual needs and interests. Additionally, IoT devices can help monitor employees’ experiences and preferences in real time. When employees work in roles they prefer, employee engagement and job satisfaction increase, as well as overall organizational performance improves when employees are working in roles that are well-suited to their skills and interests. (Bandari 2019, 17.)

Piwowar-Sulej, Blštáková, Ližbetinová & Zagorsek studied if employee-oriented digitalization positively impacts employees’ future competencies. The results show that human resource development (HRD) has a significant impact on the skills and competencies employees are likely to have in the future. Training, providing learning opportunities, and a culture that supports learning create the foundation for the skills that employees need to succeed in their jobs. The study hypothesized that investing in HRD would amplify the effect of digitalization on employee skills; however, this was not observed. (Piwowar-Sulej et al. 2024, 39, 44-47.) One possible explanation is that HRD and digitalization initiatives are not yet sufficiently integrated within organizations, or that organizations have not yet learned to leverage HRD effectively to enhance the impact of digitalization. It is also possible that employees' skills develop through unstructured learning and learning-by-doing processes.

Workforce planning

By predicting employee attendance, absence rates, and utilization and optimizing workforce planning and scheduling, organizations ensure that the optimal number of employees is maintained to meet the demands while reducing costs and enhancing efficiency. Insufficient or excessive personnel levels can be reduced by having a more versatile understanding of attendance patterns which enables more efficient planning of work shifts. By tracking the number of absences, the organization can provide additional support or resources to departments in need.

The root causes of absences are important to address since the analysis can help employers reduce the effect of absences on productivity and customer service. (Bandari 2019, 18.)

Deloitte's report emphasizes the importance of leveraging new data sources and technology to enhance transparency and build workforce trust. By using predictive HR analytics, companies can not only monitor but also anticipate workforce needs, such as skills gaps, well-being risks, and overall performance. (Deloitte 2024, 35.) Optimizing workforce utilization by analyzing data on how employees are allocating their working hours gives employers information about extra training, support, or reallocation of resources. Cost reductions can lead to improvements in organizational performance. (Bandari 2019, 18.)

Tucker studied the importance of strategic workforce planning in the research by the American Productivity and Quality Center. The study, conducted with 236 organizations from various industries and regions, found that 46 respondents excel in optimizing talent. These organizations leverage technology, varied work arrangements, and employee development. They have standardized workforce planning processes across the organization and use software from external vendors to provide up-to-date and accurate data. Additionally, they invest in training participants and collaborate closely with the business. By using timely indicators and shorter planning horizons, they can respond quickly to changes. (Tucker 2022, 14-18.)

3.1.2 Predictive HR analytics

Predictive HR analytics leverages data, statistical algorithms, and machine learning to forecast future workforce trends, supporting informed decision-making in HR management. By analyzing historical data, organizations can predict employee performance, retention, and engagement, enabling more effective workforce planning and talent management. Research has shown that predictive analytics significantly enhances HR practices by providing insights into recruitment, performance management, and employee engagement. By optimizing these processes, HR analytics not only improves organizational performance but also strengthens competitive advantage in the market. (Bandari 2019, 23; S & Dulloo 2023, 833.) Isson & Harriott (2016, 32) assess that HR analytics is most useful when it focuses on a predictive view and is forward-looking instead of looking at the past.

Roy et al. state that there are two types of predictive models: classification models and regression models (Figure 7). Classification models predict labels such as whether the match will happen or not, or whether someone is likely to leave the organization. Classification models include methods such as decision tree, logistic regression, random forest, and gradient-boosted tree. Regression models predict a quantifiable variable. This predictive modeling technique helps examine the relationship between a dependent variable and an independent variable such as how much revenue a company will generate next year or the employee turnover rate for next year. (Roy et al. 2022, 22.)

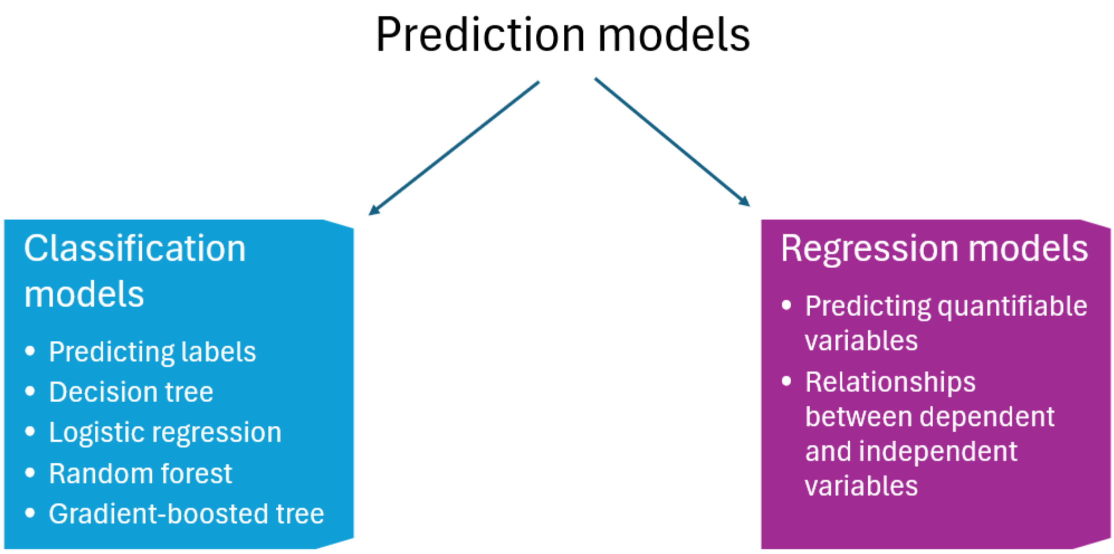

FIGURE 7. Categories of prediction models.

Lee & Song developed a conceptual model of positive employee experience using sentiment analysis as a text-mining technique within algorithm-based HR strategies to assess employee reviews and extract positive experience factors. The study collected data from the Job Planet website during March and April 2022. The dataset consisted of 62,594 reviews from the top 10 companies within each industry group. Utilizing sentiment analysis, 135 keywords were identified and categorized into four clusters impacting employee experience: work, relationships, organizational system, and organizational culture. The tone of employee experience keywords was evaluated with an accuracy of approximately 94.8%. (Lee & Song 2024, 1, 5, 7.) The clusters and the scientific frameworks applicable to them are presented in Figure 8.

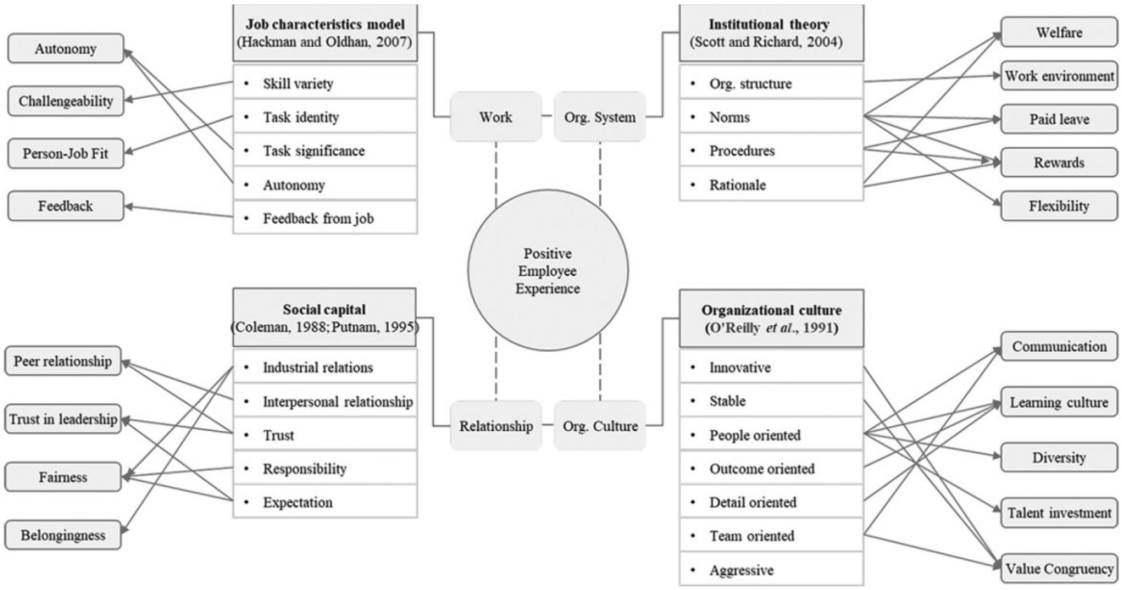

FIGURE 8. A cluster model of positive employee experience (Lee & Song 2024, 8).

There is diverse research data available on the utilization rate of predictive HR analytics. Cayrat & Boxall's findings indicate that predictive HR analytics is widely used. Approximately 70% of organizations reported analyzing trends to forecast their progression over time, such as predicting turnover-related reasons for retirements and departures and assessing their impact on personnel. (Cayrat & Boxall 2022, 581.) Instead, in Hyytiäinen's (2019, 52-53, 70-74) research 52% of respondents said they do not use predictive analytics.

S & Dulloo (2023, 824) note that predictive HR analytics provides five key advantages: better hiring decisions, tailored learning and development, optimized workforce planning, reduced costs, and higher employee retention. Key areas with benefits are represented in Figure 9.

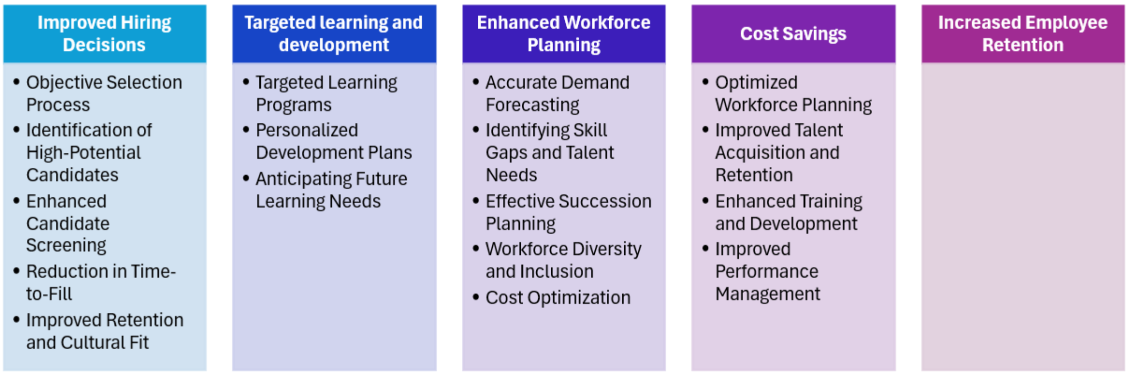

FIGURE 9. Five key areas and their benefits of using predictive HR Analytics.

Improved hiring decisions

AI can lead to enhanced HR practices and increased productivity and accuracy as repetitive tasks are being automated. AI-powered candidate screening, resume parsing and performance appraisal free HR professionals' time for strategic initiatives like talent development and organizational growth. AI assists in predicting employee turnover and spotting high-potential individuals. AI-powered candidate screening streamlines the preliminary evaluation of candidates with job requirements. (Madanchian, Hamed & Mohamed 2023, 368-369; S & Dulloo 2023, 825-826; Savolainen & Alma Insights. 2024, 199.) Video interviews with facial analysis provide delicate insights for assessing applicants' capability by interpreting non-verbal signals (Madanchian, Hamed & Mohamed 2023, 369).

Automated resume parsing utilizes Natural Language Processing (NLP) as a subline of machine learning to extract data from resumes to identify the best applicants (Madanchian, Hamed & Mohamed 2023, 369.) Jagwani, Meghani, Pai & Dhage studied automating the resume rating process with NLP. They found that their model improved the accuracy of resume evaluation to 82%. (Jagwani et al. s.a.) According to Ali, Mughal, Khan, Ahmed & Mujtaba's NLP-related study the classification algorithms achieved more than 96% accuracy on the training and test data, which provides insights into the importance of the research findings.

(Ali et al. 2022). The power of NLP is remarkable for instance within chatbots powered by NLP because employee queries and sentiment analysis support understanding employees' emotions (Madanchian, Hamed & Mohamed 2023, 368).

AI is set to transform and redefine the limits of the HR function. Deloitte's study highlights that at IBM new AI tools helped managers to make better decisions and spot issues like turnover risks, and suggested a salary increase. AI estimated performance, market pay gaps, internal turnover by employee skills, and current and future external demand for each employee's skills. (Deloitte 2024, 99.)

Targeted learning and development

Predictive HR analytics is often employed to forecast employee performance and turnover, develop retention strategies, and match employees with suitable jobs (De Vos et al. 2024, 2). Internal mobility frequently relies on forecasting future job satisfaction. Forecasts of future employee satisfaction are used in the planning of internal transfers or promotions. Companies assess how satisfied employees are likely to be in different positions so that they can make decisions that increase employee comfort and engagement. The goal is to place employees in positions where they are comfortable in the long term. (Bossi et al. 2022, 2.)

Trivedi, Srivastava, Patra, Singh & Jena developed an explainable machine learning model to predict employee satisfaction with the fairness of the reward and recognition systems in a large public sector company. The study applied text-mining techniques to validate the findings from the machine learning model and it identified transparency, recognition, unbiasedness, appreciation, and timeliness in reward as key factors influencing employee satisfaction. (Trivedi et al. 2024, 1, 12-18.)

De Vos et al. studied internal employee mobility. The research focused on predicting job matching after hiring, viewing careers from a process-based perspective instead of prescribing specific steps. The study introduced a data-driven approach to support internal mobility by recommending job matches within organizations. The authors developed a recommender system that enhanced traditional collaborative filtering by adding similarity regularization. This regularization included personal employee data, helping to address challenges like the cold start problem, which occurs with new or short-tenure employees due to limited data. The approach was evaluated on three real-life datasets, demonstrating competitive performance compared to existing methods. The method outperformed traditional systems by improving prediction accuracy and internal job-matching performance. (De Vos et al. 2024, 1, 9.)

Enhanced workforce planning

Workforce planning aligns with business objectives and expectations, and it is an essential aspect of strategic human resources management (S & Dulloo 2023, 827-828). Forecasting workforce demand by analyzing historical data, market trends, and business strategies helps to optimize personnel levels, reduces labor costs, and improves overall operational efficiency. By analyzing data on employee competencies, certifications, career ambitions, and identifying key leadership aspirations, organizations can identify skill gaps, anticipate talent needs, and do effective succession planning. Effective workforce planning relies heavily on targeted development programs and maintaining a ready pool of talent to seamlessly fill key positions when necessary. (Bandari 2019, 21; S & Dulloo 2023, 827-828.)

Employee demographics, representation across different groups, and identifying potential biases in hiring and promotion processes help organizations establish strategies to cultivate a diverse and inclusive workforce. Adjusting workforce supply with demand optimizes labor costs. Precise predictions of talent need and analyzing workforce data, support organizations to make decisions about hiring, onboarding, training, and workforce structure. (S & Dulloo 2023, 828.)

Ozkan-Ozen & Kazancoglu researched workforce development challenges and relationships between them during the era of Industry 4.0, which refers to the Fourth Industrial Revolution, a time when intelligent digital technologies merged with physical machines and production processes. They constructed a structural model to classify these challenges and provide recommendations for managers to enhance HR practices and improve organizational performance. (Ozkan-Ozen & Kazancoglu 2022, 310.)

Ozkan-Ozen & Kazancoglu’s study found that a lack of IT or digital skills significantly impacts workforce development. A matrix organizational structure enhances multidisciplinary management, efficiency, and digitalization, addressing challenges like the lack of digital culture and decentralized decision-making. The recruitment process, supported by technologies like big data and AI, is crucial for meeting Industry 4.0 needs and overcoming skill gaps, learning readiness, and resistance to change. Orientation programs and regular training reduce learning time and improve analytical thinking and human-machine interaction. Enhancing stakeholder and supply chain management strengthens system and interdisciplinary thinking. Workforce development also requires policy recommendations, such as education policies and employment strategies, to promote analytical thinking and digital skills. New employment strategies and specialized training programs are needed to balance labor market and industry needs. The challenges are listed in Figure 10. (Ozkan-Ozen & Kazancoglu (2022, 310, 324-327.)

Tailoring training programs to address critical skill gaps fosters employee growth and development while reducing costs by directing resources toward initiatives with the greatest impact. Maximizing employee productivity and efficiency improves performance management processes and reduces costs. Performance data analysis helps organizations spot patterns and trends that illustrate strengths and weaknesses. AI can help eliminate biases in the performance management process. Human biases can affect performance evaluations and lead to unfair treatment of employees. (S & Dulloo 2023, 829.)

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FIGURE 10. Workforce development challenges.

Maintaining a productive and engaged workforce requires actions for employee retention by exploring the contributing factors of turnover. For instance, employees in specific roles may be more likely to resign. The first warning signals of turnover can be identified from employee engagement data, performance assessments, compensation, and demographic information. Retaining valuable talent in the organization is more likely to occur by enhancing employee satisfaction and providing development opportunities. (S & Dulloo 2023, 829.)

Hastuti & Timming studied how the HR department can screen and predict mental health crises by recognizing employees at risk of suicide and providing preventive mental health support. This research data consisted of open access dataset from the National Survey on Drug Use and Health. The dataset contains information on substance use and mental health in the United States for the year 2019. The study used multivariate binary logistic regression analysis for model estimation. Three dependent variables that were predicted were suicidal ideation, suicidal planning, and suicide attempts. The results show that periods of unemployment, the total number of sick leave and unauthorized absences during the last 12 months demonstrate a significant correlation while taking into consideration essential psychosocial factors such as age, gender, sexual identity, income, education, US armed forces history, body mass index, mental illness history, and psychological distress level. The results also indicate that employee assistance programs reduce the likelihood of suicidal ideation. (Hastuti & Timming 2023, 1728, 1731-1740.)

Collecting the data described in Hastuti & Timming’s study would be prohibited because processing it could create substantial risks to the fundamental rights and freedom of the individual and acting against GDPR. According to the Office of the Data Protection Ombudsman (s.a.), it is prohibited to collect data that reveals the person’s racial or ethnic origin, political opinions, religion, philosophical beliefs, trade union membership, health data, sexual orientation or activity, and genetic and biometric data. This would mean that in reality the HR department would not be able to collect information about the person's sexual identity, body mass index, mental illness history, or psychological distress level – at least not in the EU.

3.2 Artificial intelligence

Artificial intelligence (AI) is a general domain that encompasses machine learning and deep learning (Figure 11). AI seeks to automate human intellectual activities. Machines can derive patterns and insights from data through machine learning algorithms, eliminating the need for explicit programming. Image recognition, NLP, and predictive modeling are typical tasks for machine learning. Deep learning is a subbranch of machine learning. It employs neural networks to mimic the human brain's structure and function. By learning from unstructured data, neural networks are highly effective at solving complex problems such as image and speech recognition, and autonomous vehicles. (Eubanks 2019, 28-29, 31-32, 4-35; Chollet 2021, 1.1.1 Artificial intelligence; Chollet 2021 1.1.2 Machine learning; Chollet 2021 1.1.4 The “deep” in “deep learning; Sharifani & Amini 2023, 3897, 3900.)

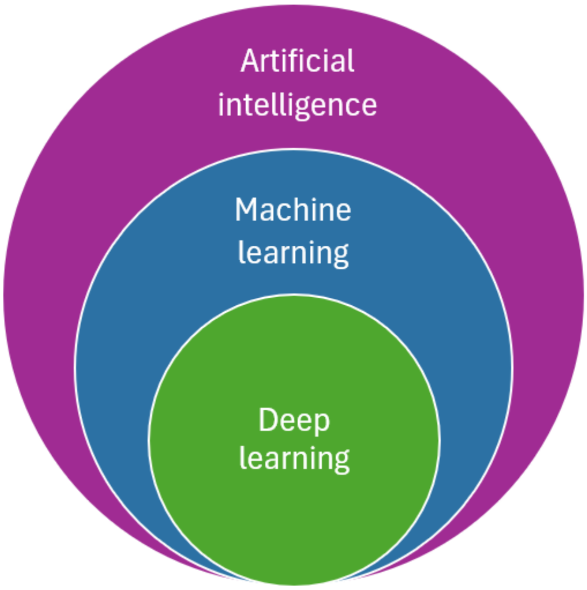

FIGURE 11. AI, machine learning, and deep learning.

AI helps spot the best candidates, automate the resume screening process, and make predictions about employee performance and retention. AI facilitates bias identification and mitigates the critical recruitment and performance management processes. Objective data analysis ensures that candidates and their performance are evaluated fairly, based on qualifications rather than demographic information, while also providing HR professionals with insights into employee engagement and areas for improvement. (Bandari 2019, 15, 19-20.)

Performance management improves employee performance and business outcomes. AI can analyze and make predictions about employee performance and help managers know which employees need additional support or development. AI can identify areas where employees need improvement and suggest targeted training, helping organizations enhance employee performance and satisfaction. (Bandari 2019, 19.) The US Air Force employed augmented and virtual reality for pilot and maintenance crew training and reskilling, resulting in a 46% increase in safety and faster training completion. This program also offered personalized prompts tailored to each employee's learning style. (Deloitte 2024, 71.)

AI can enable personalized learning paths and realistic simulations for effective onboarding and training by analyzing employee profiles and former knowledge to deliver training modules that match their skills and learning pace. Real-time feedback benefits performance management enhances performance assessment and fosters a culture of continuous improvement. Analysis of feedback and suggestions for tailored career path impact on employee engagement and retention strategies. (Madanchian, Hamed & Nachaat 2023, 368-369; S & Dulloo 2023, 826-827.)

In Deloitte's study, an organization used AI and algorithms to analyze and search employee profiles, utilizing machine learning to identify pathways related to employees' skill development. This tripled the size of the talent pool. After hiring workers with related skills, the company trained them in machine learning, and it now has technology that helps workers compare their skills to different jobs and identify areas for development. (Deloitte 2024, 71.)

3.2.1 Black box AI

AI-powered platforms use a patent algorithm and an unexplainable black box, which refers to an AI system which methods and processes are not transparent to the end user (Falletta 2024, chapter 2, Black Box AI and Algorithms; Savolainen & Alma Insights 2024, 118-119). Black box AI is marketed as a procedure to eliminate human bias in workforce decision-making. Training data for AI models or machine learning algorithms can introduce bias into the system if certain groups - based on gender, race, age, sexual orientation, or disability - are overrepresented or underrepresented, regardless of whether the data is real or synthetic. This can lead to inaccurate predictions and skewed workforce decisions. (Falletta 2024, chapter 2, Black Box AI and Algorithms.) Clark & Garbis's (2022) research refutes the recent claim that the most accurate models must be complex and unexplainable, rather than interpretable.

Narayanan (2021) claims that a lot of what is currently promoted as AI is more hype than substance and that there are many flawed AI claims. Also, Chollet (2021 1.1.7 Don’t believe the short-term hype) points out that it is important to approach AI critically, but optimistically.

3.2.2 White box AI

White box AI, which is considered explainable and ethical, has been supported by the General Data Protection Regulation in the European Union, the EU AI Act, and the California Consumer Privacy Act. Compared to black box AI, white box AI utilizes the organization’s internal data and simpler linear models, which can mitigate potential bias, and improve validity and reliability. There is no difference in accuracy between black box AI and white box AI. It is good to stay vigilant toward companies that do not want to provide transparency into their black box AI. To ensure ethical practices, organizations must demand transparent AI and challenge the science behind the measurements, algorithms, claims, and predictions. (Falletta 2024, chapter 2, Black Box AI and Algorithms.; Falletta 2024, chapter 2, The Ends Justifies the Meanness.)

3.2.3 Machine learning in predictive analytics

Machine learning imitates the process of learning and improving. In machine learning, algorithms are trained to make predictions. (Ali 2024, chapter 1, Different Types of Data Analytics.) Machine learning accelerates predictive HR analytics, assists in turnover prediction, workforce planning, and identifies talented employees (Madanchian, Hamed & Mohamed 2023, 368).

Ali (2024, chapter 1, Different Types of Data Analytics) divides machine learning into four categories: supervised, unsupervised, semi-supervised, and reinforcement machine learning (Figure 12). Kananen & Puolitaival (2019, 45) instead argue that machine learning can be divided into three categories: supervised, unsupervised, and reinforcement machine learning.

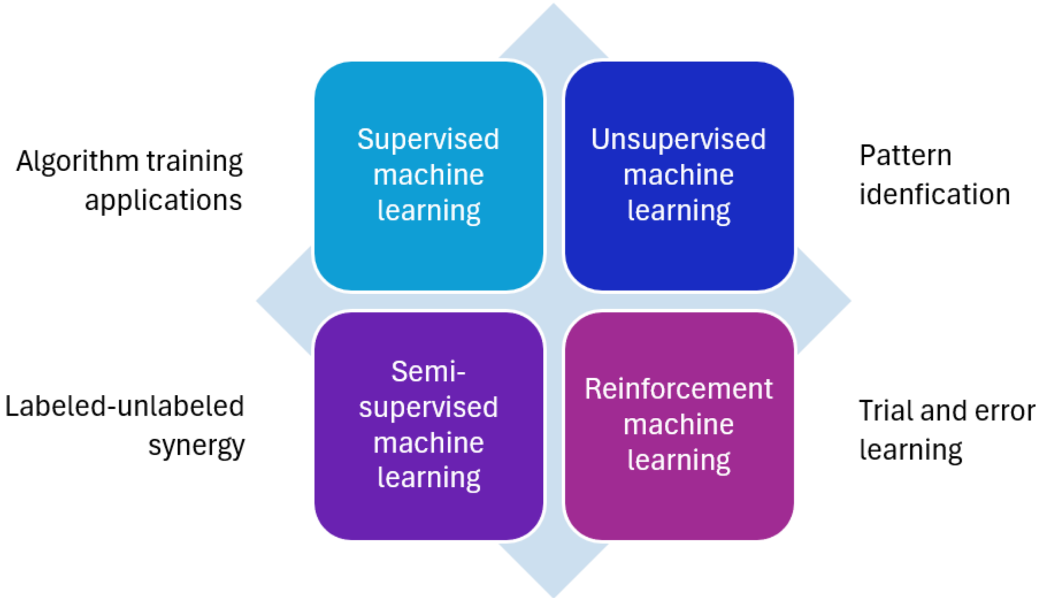

FIGURE 12. Categories of machine learning.

Supervised machine learning

In supervised machine learning an algorithm is trained with training data to make predictions. The decision process itself makes predictions, the error function defines the accuracy of the forecast and how successful the forecast was compared to the actual values and finally the optimization function modifies the prediction model so that the prediction is as accurate as possible, given the actual and predicted values. (Ali 2024, chapter 1, Different Types of Data Analytics.) Kananen & Puolitaival observe that in business, supervised learning is the most popular form of machine learning. Supervised learning is used, for example, in image recognition, medical statements, quality control, temperature predictions, various recommendation engines and pricing. (Kananen & Puolitaival 2019, 50.)

Unsupervised machine learning

In unsupervised machine learning an algorithm identifies relationships and patterns in the data without any external help such as historical data or user input (Ali 2024, chapter 1, Different Types of Data Analytics). In unsupervised learning, the algorithm is provided only with raw data and tasked with identifying patterns or regularities within it. The aim is for the machine to organize the data on its own. One advantage of unsupervised learning is that it does not require labeling every specific case in the data, as the algorithm can detect exceptions by itself. The primary objective is to classify patterns in values and the structure of objects based on their similarities and differences. In unsupervised learning, the algorithm seeks out shared characteristics within the data. The model can be fine-tuned so that the algorithm focuses on certain features, emphasizes specific aspects, or completely ignores others. This allows the search to highlight perspectives relevant to the business and to identify specific cases, such as extreme examples or outliers, as needed. Unsupervised learning can identify consistent patterns within the data that might be challenging for humans to detect. (Kananen & Puolitaival 2019, 50-52.)

Semi-supervised machine learning

In semi-supervised machine learning a small amount of labeled data is used with a much larger set of unlabeled data during training. The algorithm learns to label the unlabeled data and after that, produce predictions. Ali (2024, chapter 1, Different Types of Data Analytics.)

Reinforcement machine learning

In reinforcement machine learning the algorithm learns through trial and error without using any labeled data. The model is being rewarded for successful outcomes and punished to minimize failures. The algorithm learns from its own experiences and adapts its actions based on the feedback it receives from the environment. (Kananen & Puolitaival 2019, 158; Ali 2024, chapter 1, Different Types of Data Analytics.)

Bossi et al. compared how well traditional Structural Equation Modeling and machine learning algorithms (Lasso and Bagging meta-model with the k-nearest neighbors (KNN)) to predict job satisfaction for employees participating in internal mobility programs. KNN, as a classification algorithm, operates on the idea that data points that are close to one another are likely to share similar characteristics and can therefore be placed in the same category. In the study job satisfaction was predicted based on the available variables such as individual differences in personality, motivation, and change resistance. The research confirmed the belief that employees transitioning to new roles should be trained to reduce their resistance to change, promote their resilience, and improve their social skills. Study showed that AI algorithms can help in selecting employees who are more willing to be relocated to a new job position. Comparing different methods is important because of their applicability and performance. (Bossi et al. 2022, 1-x.)

Artar, Balcioglu & Erdil developed a machine learning model to predict a candidate’s potential contribution to the organization to improve more informed and accurate hiring decisions. The model was applied to the IT department of a Turkish state bank, enhancing the quality of hires by identifying candidates with high potential. The model provided an analysis by utilizing K-Nearest Neighbors algorithm to cluster candidates based on their attributes and questions of the interview. In addition to qualifications and experience the model also predicted potential performance and candidate’s fit within the organization. (Artar et al. 2024, 1, 8-9.) The article did not present concrete metrics for reviewing the success of recruitment. To support further development, it would be beneficial to examine employee turnover, job satisfaction, and performance. This would allow for a more precise measurement of improvements in the quality of recruitment.

Lata & Garg developed a model to predict non-violent work behaviour among employees using four machine learning techniques: Naïve Bayes, decision tree, logistic regression, and ensemble learning. Workplace violence includes physical, psychological, and sexual violence as well as harassment and bullying. The sample of the study consisted of 412 employees employed in various organizations in India. The data was collected using a structured questionnaire including demographic variables like gender, age, work experience, income level, marital status, personality type (introvert or extrovert), and education level. The questionnaire also collected organizational data, including sector (public or private, manufacturing or service), turnover, and organization size. The model using random forest as an ensemble learning technique was identified as the best prediction model because the model achieved the highest rates for both True Positive Rate (TPR) and True Negative Rate (TNR). In this context, TPR represents employees who may potentially be violent and are correctly predicted as such, while. TNR represents employees who may potentially be violent but are not predicted as such. (Lata & Garg 2023, 931, 935, 938-939.)

3.3 Challenges, downsides, and best practices

S & Dulloo (2023, 829-830) point out that incomplete, subjective, or outdated data with errors, can lead to inaccurate forecasts and flawed decision-making. If the predictive model relies merely on historical data, the sudden changes in the present state are overlooked. This impairs decision-making and may lead to excessive personnel levels and increased costs.

HR data is frequently incomplete, outdated, or inconsistent, which makes it difficult to make reliable insights (Mishra & Mishra 2023, 1748; S & Dulloo 2023, 821, 830). Data standard definition, cleaning, regular validation, and integrating data into a centralized data repository or data warehouse as a part of data governance practices ensure data quality, reliability, and accessibility (S & Dulloo 2023, 830-831).

Quality is also affected by the calculation methods of individual metrics, which may vary in different units within the organization (Cayrat & Boxall 2022, 582). For example, if the headcount is calculated differently in different units of the organization, the results may be contradictory, which weakens the comparability of the data and the reliability of the information that is the basis of decision-making.

Data is often scattered across different HR systems, making data difficult to access and consolidate for analysis (S & Dulloo (2023, 830). Integration of data from various sources requires intricate data management and analysis techniques (Mishra & Mishra 2023, 1748).

The adoption of analytics is a cultural change in the organization to data-driven decision-making. Resistance and lack of trust hinder the acceptance and adoption of predictive HR analytics. Resisting the change leads to slower adoption. Change can be seen as a fear and a threat to employees' autonomy, privacy, or job security. (Mishra & Mishra 2023, 1748; S & Dulloo 2023, 830.)

Angrave, Charlwood, Kirkpatrick, Lawrence & Stuart state that organizational silos prevent the combination of HR data with productivity and performance data. This hinders the building of analytical models and examination of HR-related factors and other relevant factors. They emphasize that analytics software needs to have the capability to build long-term, multidimensional models and to conduct end-to-end analytics. (Angrave et al. 2016, 4, 8.)

Best practices

S & Dulloo see change management and adoption as a part of the successful implementation of predictive HR analytics. When the inclusion of key stakeholders such as HR professionals, managers, and employees, real-life examples, and success stories are part of the implementation, the organization's culture truly adopts data-driven decision-making and highlights the value of analytics in HR practices. (S & Dulloo 2023, 831.)

In Deloitte's Global Human Capital Trend study, 65% of respondents thought that HR analytics in their organization gained no commercial benefit for their organization during the previous year. Merely 24% of executives agreed that HR is evaluated using the same business metrics as other operational departments. Organizations should ensure that managers have access to the data and information they need to assess performance. For instance, VW Australia generated an integration platform that combined customer and employee experience data for access by local managers. This change led to sales growth and improved retention rates and workforce experience scores. (Deloitte 2024, 99.)

Organizations need skilled personnel who can design, implement, and understand AI systems (Bandari 2019, 26). According to S & Dulloo, investing in upskilling HR professionals and data analysts, and collaborating with external consultants or experts bridge skill gaps and provide guidance. It is important that HR professionals conduct analyses and interpret results as effectively as possible. (S & Dulloo 2023, 831.) HR analytics requires effective use of data analysis, statistics, and data visualization (Mishra & Mishra 2023, 1748).

From a HR analytics professional's point of view keeping up with analytical development and technological change is challenging. Nowadays Business Intelligence platforms such as Power BI and statistical tools such as SPSS and R are commonly used in diagnostic analytics, and predictive models are based on data science tools and machine-learning frameworks. Data standardization is challenging when organizations have different systems, for example for specific HR practices such as recruitment and performance review, in addition to HR analytics and Human Capital Management software. (Cayrat & Boxall 2022, 582.)

3.4 Ethical considerations

Consideration of the ethical perspective can be ensured by several practical measures. For example, an internal ethical guideline can serve as a reference framework and communication tool, which strengthens employees' trust in data confidentiality, anonymity, and privacy. Checklists, encryption, and data aggregation can be used as practical measures, which prevent further data protection. Personal data is processed under strict supervision, and personnel is trained and informed on the subject. Building trust is the key. It is important that the organization only collects necessary data, and analyses are only performed when there is sufficient justification for them. A risk analysis performed before the implementation of the model ensures that all ethical aspects have been taken into account. (Cayrat & Boxall 2022, 583.)

SaaS-based and AI-powered platforms that measure, analyze, monitor, track, screen, select, listen, sense, quantify, manage, shape, nudge, engage, coach, and retain employees raise ethical concerns because of the potential abuse and bias (Falletta 2024, chapter 2, Black Box AI and Algorithms). Bandari points out the ethical use of AI since HR data contains sensitive information. The accuracy and fairness of AI models must be monitored and adjusted. AI has a lot of potential to transform HR analytics, but caution, transparency, and commitment to ethical use must be considered within the use of it. (Bandari 2019, 26.)

Quantified employee agenda refers to situations where employees are being monitored and tracked with always-on listening and sensing platforms and devices. This brings up potential privacy and ethical risks even though the method has clear benefits for an organization such as increased employee accountability, productivity, and retention. An organization must be open about the tangible and intangible benefits of a quantified workforce to foster trust and transparency. (Falletta 2024, chapter 2, The Quantified Employee Agenda.)

Employee privacy rights are nowadays very protected and unauthorized access to data is prevented by legal and ethical regulations and policies such as GDPR (General Data Protection Regulation) (Cayrat & Boxall 2022, 582; Mishra & Mishra 2023, 1748; S & Dulloo 2023, 830-831). Data privacy and security protocols work as a part of the solution. Transparent communication about data usage, security measurements, and employees' rights to their personal information is important. (S & Dulloo 2023, 830-831.) The use of employee data for analytics requires securing employees' consent before collecting any data (Mishra & Mishra 2023, 1748).

There are challenges in the decision-making framework to balance the optimal mix of human and machine involvement. Data privacy, biases in AI algorithms, and the reduction of human elements in HR processes must be considered so that these concerns do not affect the fairness of hiring. (Madanchian, Hamed & Mohamed 2023, 368.) S & Dulloo classify bias as a drawback and challenge. Predictive HR analytics models may conserve biases from historical data, leading to prejudiced consequences. For instance, earlier favored demographics in recruitment decisions might lead to a prediction model that ensures that similar applicants are recruited in the future. (S & Dulloo 2023, 829.)

Chatterjee et al. studied the negative consequences of HR analytics applications. They developed a theoretical model based on existing literature and privacy calculus theory. (Chatterjee et al. 2022, 52.) According to the privacy calculus theory individuals always rationally weigh the potential benefits and potential risks before disclosing personal information. Emotions, current mood, need for cognition or faith in intuition, the framing of a message, status quo bias, anchoring effect, positivity bias, or peer pressure affect individuals and therefore may lead to irrational data disclosure decisions. (Mini 2017.)

Chatterjee et al. study demonstrates that employees' privacy concerns influence their perception of privacy risks, and their concerns about data security also shape how they perceive privacy risks. When developing HR analytics applications, the designers and developers must follow policies and regulations so that employees' privacy is fully guaranteed, and their data is not misused. The HR managers must be vigilant that the right policies and regulations are being applied. The misuse of HR analytics applications might impact the organization's reputation and lower employees' morale. The results show that employee privacy is at risk if users have unauthorized access to employee data. Uncontrolled use of the applications is a security concern, and tracking employees without their approval increases the risk. The study recommends appropriate regulation for using HR analytics applications. (Chatterjee et al. 2022, 52, 66.)

3.5 Future trends

Some organizations have expanded their HR research and analytics practices to include a wider range of data sources and approaches besides metrics, score-cards, and reporting. Some dispute that this may lead to a lack of strategic focus, because the organization focuses too much on data mining instead of model building and testing. Generating new data and deeper insights that support the business strategy and implementation might mitigate this problem. (Falletta 2024, chapter 1, Defining HR Analytics.)

Data-driven leadership, data science, and the future of work have leveraged the human capital management technology industry. Technological tools and trends like SaaS-based platforms, data aggregation and visualization tools, apps, chat-bots, and AI, as well as deep and machine learning capabilities will reshape the methodologies utilized in HR analytics and the competencies required for future applications. (Falletta 2024, chapter 1, Revolutionary or Evolutionary Capability?) However, technology alone is not the miracle worker that solves all business problems of the organization (Falletta 2024, chapter 2, HR's Inescapable Attraction to Shiny Gadgets).

Falletta (2024, chapter 2, The Ends Justifies the Meanness) emphasizes that HR managers need to collaborate with the IT department. S & Dulloo point out that collaboration is needed across different departments and teams. They see a fos-tered culture of collaboration with cross-functional teams and data governance committees and data sharing across departments as a key element in implemen-tation. (S & Dulloo 2023, 831-832).

S & Dulloo (2023, 832-833) recognize that the future implications of predictive HR analytics are expected to be transformational when technology progresses and data becomes more accessible. The six potential future implications of predictive analytics are (Figure 13):

1. improved talent acquisition and retention
2. personalized employee development
3. proactive workforce planning
4. enhanced employee experience and well-being
5. ethical and inclusive decision-making
6. strategic workforce analytics.

Talent acquisition and retention improves as identifying potential candidates becomes more accurate and machine learning models can handle extensive amounts of data to calculate the likelihood of success and cultural fit. This enables organizations to attract and retain skilled professionals, which improves performance and reduces turnover. Predictive models consider external factors like economic conditions, industry trends, and technological progress to forecast skill needs. Utilizing predictive models requires anticipating workforce needs, identifying skill gaps, and assessing the impact of different workforce scenarios in various business contexts. Strategic workforce analytics allows organizations to align their HR strategies with overall business objectives, increase agility, and achieve a competitive edge in the market. (Bandari 2019, 21; S & Dulloo 2023, 832.)

FIGURE 13. The potential future implications of predictive HR analytics.

Fallucchi, Coladangelo, Giuliano & De Luca explored which factors influence employee turnover. The analysis used a heatmap of 35 features to identify the characteristics that show strong correlations with the factors influencing why employees leave the organization. Out of the 35 features mentioned below, five features with the highest correlation coefficients were taken into the final analysis. These features were employee's income, age, workplace distance, work experience in the company, and whether the employee worked overtime (Figure 14). The resignations progressively increased for lower salaries. As employees aged, their likelihood of leaving the company decreased. The distance between home and office also impacted turnover, with employees living closer to the workplace being more likely to resign. Additionally, those with fewer years of experience in the organization were more prone to leaving. Overtime also played a role in turnover, as one-third of employees working overtime left the company in this case study. (Fallucchi et al. 2020, 1-2, 5, 7-12.)

Also, Mozaffari, Rahimi, Yazdani & Sohrabi studied turnover, and which factors affect it in the HR department of a pharmaceutical company in Iran. They developed a model for predicting employees at high risk of turnover, which uses the gradient boosting machine algorithm. The model achieved 89% accuracy. (Mozaffari et al. 2023, 4140.)

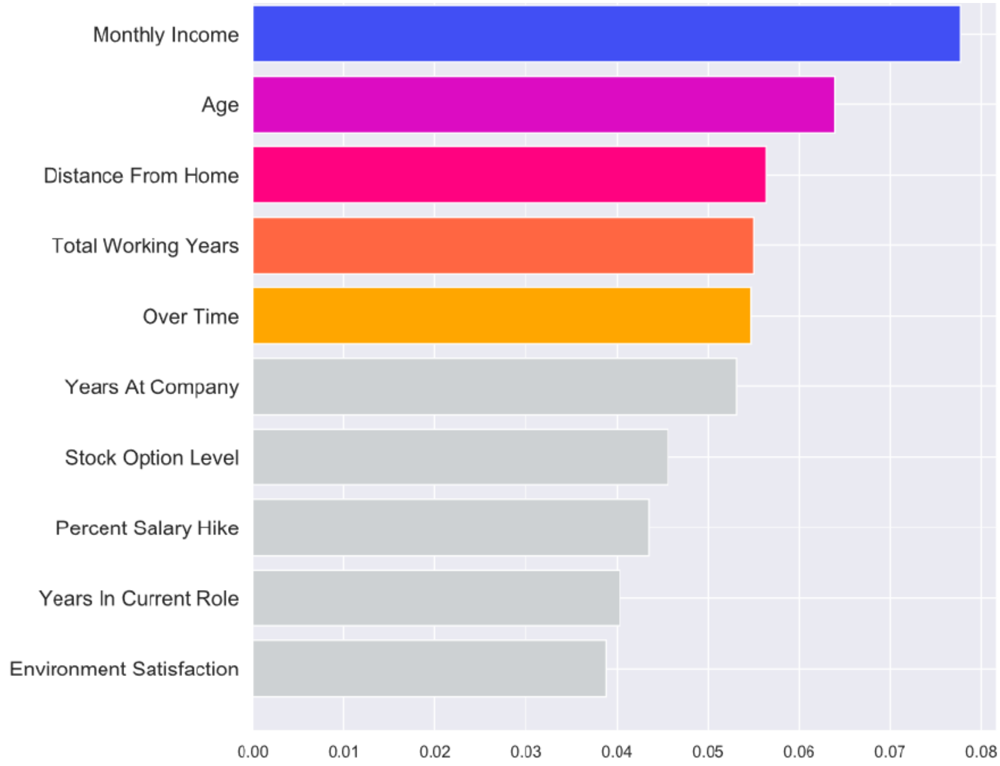

FIGURE 14. Features that affect turnover (Fallucchi et al. Luca 2020, 7).

Bandari's study recommends that organizations invest in IoT, AI, and cloud computing technologies to increase their competitiveness and to respond to the current and changing demands of working life (Bandari 2019, 15). A new mindset into a more boundaryless world with qualified procedures, measures, and technologies helps HR to metamorphose itself from a focused role solely managing workforce responsibilities into a collaborative approach that is co-created and connected with employees, businesses, and the whole community. This approach helps organizations to develop cross-functional solutions to tackle progressively more complex challenges. Solutions are possible by focusing on shared outcomes, such as agility, customer satisfaction, employee performance and multiple data sources combining analytics. (Deloitte 2024, 7, 99.)

Transparent communication, inclusive decision-making and recommendations for the use of predictive HR analytics will be crucial to building trust and maintaining ethical practices. Organizations need to pay attention to biases in historical data and make sure that algorithms ensure fair and unbiased results. Transparent communication and guidelines for using predictive HR analytics will be fundamental to building trust and preserving ethical procedures. (S & Dulloo 2023, 832.)

Integrating analytics into strategic business management reduces operational risks by enabling the identification of opportunities and threats in advance. Through broader integration, an AI-based system can provide solutions that support critical decision-making. Examining factors beyond organizational boundaries helps in designing a comprehensive business model. (Sharma et al. 2022, 13.)

4 RESULTS AND CONCLUSIONS

The interview results are presented in the following subchapters, and they are addressed according to the themes. A direct quote that best describes each theme has been highlighted in the subheading of each theme. The original translations of direct quotations in the citations can be found in Appendix 3.

The coverage of themes varied depending on the interviewee's background and job role, which sometimes resulted in a more superficial treatment of certain themes. Each theme was covered sufficiently to provide insights into the researched topic. Wellbeing services counties are large organizations, and job descriptions within them can differ significantly.

A comprehensive dataset was collected through interviews, covering various customer needs and development suggestions. The most significant and most voted customer needs of the interviews are compiled into their subchapter as a final subchapter. Presenting development suggestions in a separate subchapter improves clarity and readability, as the reader can easily find them in one place. The development suggestions are arranged from most to least frequent based on how often they were mentioned in the interviews. This arrangement also provides an indication of which proposals have the highest demand. It helps to form an overall picture, identify connections, and compare suggestions on different themes.

In the interviewees' organizations, predictive HR analytics is not yet systematically applied; instead, the main focus is at the moment on descriptive analytics, which concentrates on examining the past and present state. The interviews highlighted that predictive HR analytics is scarcely utilized in wellbeing services counties, whose operational activities have continued for just over two years. All interviewees viewed predictive HR analytics as being full of potential and it was delightful to hear that the subject of the research was considered as engaging and valuable.

As the mapping of customer needs indicates, some needs were common to the two wellbeing services counties under review, while other needs differed among the interviewed organizations. The interviews also highlighted the need for customer-specific changes and customizations, suggesting that the basic structure and functionality of certain features could be uniform, while other functionalities might differ based on customer requirements. However, the comparability of data between wellbeing services counties should be considered. As the interviews revealed, there are currently variations in the metrics and data calculation and processing methods of the wellbeing services counties, which affect the comparability of the data.

Machine learning and predictive HR analytics models can address customer needs for example by forecasting turnover, optimizing workforce planning, and identifying personnel requirements and talented employees. Nevertheless, interviewees found the practical assessment and application of AI capabilities to be challenging. As evidenced by the studies within the theoretical framework machine learning and predictive HR analytics models can be implemented in various ways to suit different scenarios and business cases.

4.1 *"Looking ahead with everyday risk management"* - The meaning and significance

For all eight interviewees, predictive HR analytics meant, as the name suggests, focusing on the future rather than looking at the past. The need for this varies according to the situation and may extend into the coming months, for example, in terms of contracts signed, so that it is known with certainty what the personnel costs will be. In other situations, long-term predictions, such as five or ten years, are important when addressing financial challenges, or looking at retirements or job profiles.

Simply reporting actual data is not enough, and all eight interviewees considered predictive HR analytics to play a significant role. All interviewees felt that the use of deeper HR analytics as part of business operations is still incomplete or in its infancy. Interviewees attributed this to factors such as the fact that the wellbeing services counties have only been in operation for just over two years.

Demand for predictive HR analytics is constant and is requested several times a year. In the case of the wellbeing services counties, the information is needed by the regional government, the organization's management and managers. One interviewee assessed that predictive analytics will increase in wellbeing services counties in the future, not only for HR data but also for examining health indices or migration situations.

Since the beginning of their operations, the wellbeing services counties have been under financial pressure. According to Yle, the wellbeing services counties have faced significant financial challenges because their costs were often estimated based on incomplete data before operations began. Contributing factors included differences in municipal accounting practices, the impact of inflation, wage agreements, and the atypical baseline conditions during the COVID years. Additionally, cost allocation and service need coefficients varied considerably. (Yle 14.11.2024.)

Half of the interviewees highlighted the role of finance and how predictive HR analytics is used to address financial challenges and assess, for example, the adequacy of resources and personnel costs against the budget. In this context, for example, the retirement forecast becomes important if the organization launches financial adjustment measures such as cooperation negotiations.

4.2 "*Window to the future*" - Utilization and expected benefits

The most frequently mentioned themes regarding utilization and benefits were financial benefits, resource management, and decision-making. Predictive HR analytics was also seen to have potential, and it was considered to foster employee well-being, engagement, operational planning, and organizational efficiency. Additionally, individual themes that emerged included better service delivery to target groups and responding to future needs. A word cloud presented in Figure 15 has been created from the interview responses concerning the utilization and expected benefits of predictive HR analytics, where the frequency of topics is reflected in the size of the words. The more mentionings a word has, the larger its font size.

FIGURE 15. Word cloud of utilization and expected benefits of predictive HR analytics.

The experiences of interviewees working in the same wellbeing service county differed somewhat in their current use of predictive HR analytics. One interviewee mentioned that predictive HR analytics is already a part of everyday operations in the organization, while another interviewee felt it should become more integrated into everyday practices. The third interviewee from the same organization felt that predictive HR analytics is currently not used much in the organization. The differing opinions could be explained by the fact that wellbeing services counties are large organizations, and the tasks of the individuals naturally differ to some extent. Some roles may have a wider visibility of the use cases and development needs of predictive HR analytics and the role itself may have a different perspective on the use of predictive HR analytics, as not everyone can be involved in everything.

The importance of financial monitoring was emphasized in the interviews, as the biggest expenditure item in the wellbeing services counties is the personnel and the budget strongly influences the planning of activities. Predictive HR analytics was seen to increase cost-effectiveness, as analytics provides support and a backbone to focus on the right things. One interviewee stated that, instead of large and costly projects for the coming years, the focus should be on proactive planning and risk management. This will help to assess where the wellbeing service county is heading and ensure that resources are not invested in projects that turn out to be unnecessary.

Half of the interviewees mentioned that predictive HR analytics is used in the organization to support decision-making in action planning. This is done by evaluating the current direction, assessing the correctness of choices, and using data to provide a variety of options and comprehensive information on the topic. If it turns out that choices have been wrong, it is necessary to consider what steps should be taken to remedy the situation. As money was perceived to be a major driver of activity and resources in the wellbeing services counties, predictive HR analytics can provide guidance and support for action planning.

Three interviewees highlighted the usefulness of predictive HR analytics in aligning workforce competency requirements. The organization needs to know what kind of competence the organization will need in the future. Work methods and care methods are changing a lot, which will also reflect in future competence requirements. Interviewees thought that AI solutions will bring new opportunities and at the same time challenge the skills of human resources, for which readiness must also be ensured. According to the interviewees, predictive HR analytics helps to ensure that the right people are placed in the right roles, thereby increasing employee engagement and job satisfaction. This contributes to their professional development and to updating their skills through continuous training. Optimizing the roles and tasks of employees and allocating internal human resources where they are needed also improves organizational efficiency and productivity.

Supporting managers in decision-making and analyzing information is also important, for example in terms of forecasting workload and personnel budgets, to ensure that the organization continues to have well-performing and engaged employees in the future. Two of the interviewees mentioned that there could be some kind of thresholds or alerts in the tools for users to see the cumulative situation and if the figures are starting to be higher than planned or they have exceeded last year's corresponding values. However, this would require inputting estimated figures into the system in the same manner as the budget is entered into financial tools, with the budget being tracked accordingly. Alerts, when sick leave rates surpass a predefined threshold, enable timely and effective actions to address potential concerns.

Two interviewees mentioned that the costs of employees' unused annual holidays are reflected in the personnel budget and holiday pay expence. Unused annual holidays should be monitored in real-time to minimize surprises at the end of the holiday credit year when employees still have a significant amount of annual holiday remaining. According to one interviewee, the forecast for the holiday pay expence is used to adjust the budget if necessary, as changes impact the personnel expense budget. Failure to take leave within the specified time can lead to employee overwork, decreased productivity, and increased sick leave. Additionally, organizational resource planning may suffer, causing budget deviations and disruptions in operational activities. Neglecting employment terms can also pose legal and reputational risks.

Two interviewees reported that predictive HR analytics is part of an organization’s risk management, for example to prepare for surprises and disruptions that affect service delivery. Predictive HR analytics is about removing uncertainty and chaos from issues related to different stages of the employment lifecycle. One interviewee highlighted that predictive models, risk analyses, and risk management can refine resources to a high level of quality, enabling the organization to produce more precisely and effectively for target groups through its services.

As the wellbeing service counties continue to operate, the availability of long-term data also improves forecasting. One interviewee emphasized the importance of anticipation, particularly from the point of view of decision-makers, who want to look at the data regularly and anticipate possible actions or changes to react to situations as early as possible.

One interviewee emphasized that the effective integration of HR data with financial figures, performance metrics, and changes in the operating environment is a key factor in future success. The more comprehensively and extensively HR data is connected to other critical organizational information, the greater its value in decision-making. In this context, individual predictive models, such as forecasting turnover, are not sufficient as decisive factors. Instead, the focus lies on how these models can be integrated into a broader knowledge base and utilized holistically in decision-making that guides the organization's operations.

4.3 *"Sometimes we have had to learn these things the hard way"* - Challenges in implementation or use

According to the interviewees, the implementation of predictive HR analytics in wellbeing services counties has encountered several challenges related to technical, procedural, and human factors. A word cloud presented in Figure 16 was created from the interview responses concerning challenges in the implementation or use of predictive HR analytics, where the frequency of topics is reflected in the size of the words. The more mentionings a word has, the larger its font size.

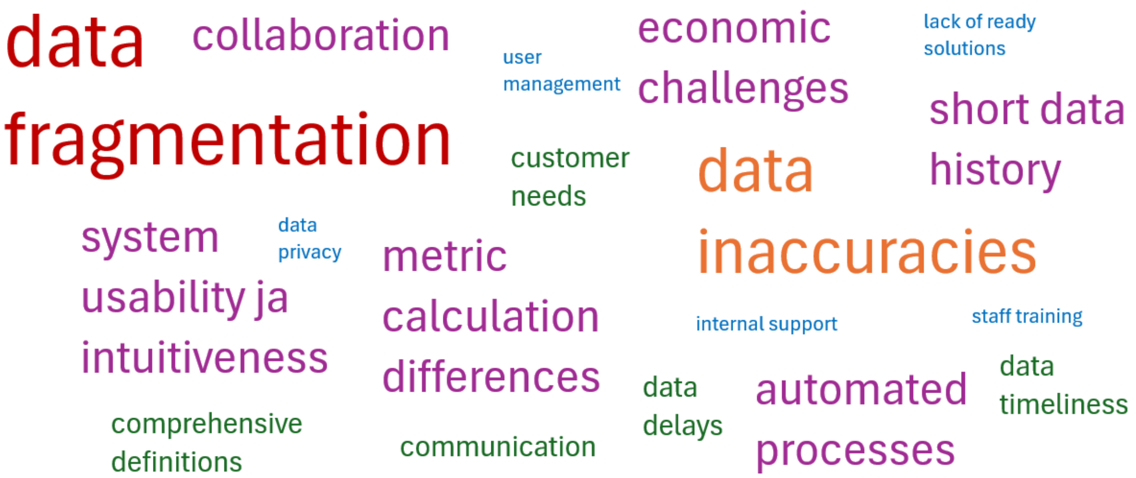

FIGURE 16. Word cloud of challenges in implementation or use of predictive HR analytics.

The fragmentation of data and the need to integrate it from multiple source systems pose significant challenges, impacting data reliability and timeliness. Interviewees expect seamless integration, especially when the systems involved are provided by the same vendor. According to the interviewees, data should be integrated smoothly across various sources such as financial and personnel data. Manual data integration is time-consuming, prone to errors, and reduces data quality. It also burdens employees and is inefficient when handling large data volumes. One interviewee emphasized the need to improve both the source systems and the integration to address and resolve these issues. Integrating data from the work shift planning system was considered important for enabling a more comprehensive analysis of actual working hours, such as comparing the number of patients to the number of headcount, as highlighted by one interviewee.

The importance of collaboration was highlighted by three interviewees in the context of working with system providers, internal cooperation, and cooperation with other wellbeing services counties. Two interviewees mentioned that when data is integrated from various source systems, collaboration with system providers plays a crucial role. The work and various contracts form an essential framework that must be incorporated for schedules, resource utilization, costs, and other factors influencing the overall process.

One interviewee highlighted that collaboration between wellbeing services counties lays the foundation for uniform reporting methods and metrics, which improve the clarity and consistency of reporting. Currently, practices and calculation methods are not uniform across wellbeing services counties, making it difficult to compare data. Uniform practices also facilitate authorities' ability to understand how reports are prepared, what information they contain, and what is feasible in terms of data collection and reporting. Consistent practices also reduce the risk of errors, streamline the reporting process, and strengthen trust between parties. Similarly, uniform reporting methods are followed in the financial reporting of wellbeing services counties (Ministry of Finance s.a).

Collaboration between system providers and wellbeing services counties is important, as is peer support and cooperation between different wellbeing services counties. One interviewee mentioned that cooperation between wellbeing services counties is conducted in terms of data-driven management, for example, under the leadership of KT. In the future, there is a need for continued cooperation, especially for deepening collaboration and exchanging experiences and ideas. When wellbeing services counties review their development areas together from a peer support perspective, they can share best practices, identify common challenges, and develop scalable solutions. Collaboration accelerates learning, promotes networking, and creates opportunities to leverage others' experiences to improve their operations. Additionally, peer support increases motivation, brings new perspectives, and strengthens inter-organizational cooperation, helping to find innovative and effective solutions.

In times of financial constraint, organizations often cut costs in areas where benefits are not immediately apparent, or where the activity is not legally required or mandatory. One interviewee emphasized that financial savings should not hinder development. The importance of strengthening internal collaboration, particularly with the ICT department, was highlighted.

Systems should be user-friendly and intuitive, as their usability directly influences data quality and, consequently, its reliability. It is also beneficial for source systems to have built-in functionalities that ensure and support data accuracy such as allowing the input of personal identification numbers only in the correct format. If systems are difficult to use or leave too much room for interpretation, users may make incorrect choices, thereby diminishing the accuracy and utility of the final data. One interviewee highlighted that not all supervisors possess the necessary technical skills to use the systems, as their strengths may lie more in managing nursing work than in system administration.

Data inaccuracy affects the reliability of forecasts, decision-making quality, inter-team collaboration, customer and stakeholder relationships, as well as the development of innovations and strategies. Incorrect data may result from incomplete integration, ambiguity, or unclear guidelines. To address these issues, systems should be user-friendly and include functionalities that support data accuracy. According to the interviewees, data quality, reliability, and timeliness are ensured through comprehensive guidelines and the functionality of basic processes.

In two interviews, language versions of user interfaces were highlighted as a need arising from increasingly and altering diverse labor markets, where the workforce includes non-native Finnish speakers alongside native Finnish employees. This development impacts the quality of guidance and, consequently, the accuracy, timeliness, and reliability of the data.

As one interviewee mentioned, the wellbeing service county plays an important role in data processing, even though there may be third-party providers involved in building the tool. However, the wellbeing service county knows their operations best, so, naturally, the wellbeing service county plays a key role in further processing the data and information.

Differences in the calculation methods of metrics and key performance indicators across source systems and reporting tools complicate data comparability both within wellbeing services counties and between systems. Additionally, these delays in data processing limit the usefulness of up-to-date information, slowing down and complicating decision-making.

The short operational history of wellbeing services counties undermines the reliability of predictive models, as there is insufficient historical data available to support high-quality analyses. One interviewee noted that the operations in wellbeing services counties have primarily focused on addressing daily urgent matters and ensuring basic operational conditions, rather than directing resources towards long-term development and strategic actions. Additionally, integrating previous data from before the wellbeing services counties started operating is practically impossible, as the previous organizations had different reporting practices, and data stored in old systems is no longer accessible.

One interviewee highlighted the idea of having all information accessible from one place as a development concept. The concern was about the reliability of a fragmented system, which complicates data accessibility and reliability. Such a solution could be implemented through centralized dashboards or reporting tools that consolidate key HR data on a single platform tailored to user needs. This would enhance data accessibility and usability without requiring all information to be physically stored in one system. Additionally, it is important to recognize that HR data needs vary depending on the user’s role: for example, the information needs of managers, HR specialists, and executives may differ significantly.

Effective and well-integrated communication is essential for the success of predictive HR analytics. Wellbeing services counties must stay informed about changes made in the tools so they can report to their users and implement necessary actions. Transparent communication is particularly important in the case of errors. Additionally, organizations' varying starting points and client-specific needs require attention. Adapting to these needs calls for flexibility in software solutions and fine-tuning of configurations. To ensure effective utilization of analytics, it is important to design and implement comprehensive training programs that enhance users' understanding and capabilities.

Software development does not always offer ready-made solutions for all needs, forcing users to build and adapt systems themselves. One interviewee noted that this consumes resources and creates an additional workload for wellbeing services counties. Furthermore, user management solutions pose challenges, particularly in handling parallel employment relationships common in the public sector. Product configurations should be flexible and adaptable to organizational practices to ensure solutions are sustainable and fit for purpose.

4.4 “*Numerous systems on use*” - Data sources and tools

The interviewees reported that their organizations utilize various data sources, depending on the use case. These data sources are presented in Figure 17, where their frequency in the interviews is illustrated using a word cloud. The frequency of the data source is reflected in the size of the words. The more mentionings a word has, the larger its font size.

FIGURE 17. Word cloud of challenges in implementation or use of predictive HR analytics.

The interviews revealed that different HR systems are commonly used as data sources. All eight interviewees identified payroll systems and workforce scheduling software as key data sources. Additionally, data lakes, recruitment systems, competence management systems and reporting systems for near-miss incidents and safety alerts were frequently mentioned in several interviews.

The QWL (Quality of Work Life) metric system emerged as a prominent data tool specifically in the responses of interviewees whose organization utilizes this system. According to Kesti, there are three wellbeing services counties which use the production function for human resources that he developed. Employee experience is measured using the QWL index, which transforms workplace well-being into a clear performance indicator. The index enables the organization to identify four types of employee risks: absenteeism risk, burnout risk, turnover risk, and disability risk. (Kesti 3.12.2024.)

In the interviews of participants whose organization does not utilize the QWL system or any similar tools, Excel was identified as the primary tool used for predictive HR analytics which means that forecasts are created manually by experts. Interviewees noted a demand for predictive HR analytics, highlighting that existing tools are predominantly focused on analyzing historical data. An interviewee from this organization highlighted the need for use of mood indicators as tools for assessing employee opinions, experiences, and satisfaction. In addition to traditional, comprehensive employee surveys, the implementation of a lighter mood indicator could be considered to monitor employees' current mood and emotional states. While mood indicators facilitate quick and continuous feedback, employee surveys provide a more extensive and in-depth analysis of the organization's overall state.

Regarding the system for competence management, the insights of the interviewees within the same organization differed on the use of tools. One interviewee mentioned that their organization uses digital tools for mapping competencies, while another interviewee from the same organization stated that such tools are not available. This observation indicates potential differences in internal communication within the organization, the level of tool adoption across departments, or individual perspectives on the existence and use of competence management tools.

Data sources mentioned only in a few individual interviews included occupational accident insurance records, Keva's retirement forecast data, exit surveys, and national data sources produced by authorities such as the Ministry of Economic Affairs and Employment (TEM), the Finnish Institute for Health and Welfare (THL), and the Ministry of Education and Culture (OKM).

One interviewee highlighted the idea of obtaining all information from a single source as a development initiative. This could be implemented through centralized dashboards or reporting tools that consolidate key HR data onto one platform according to user needs. This approach enhances the accessibility and usability of information without requiring all data to be physically located in one system.

Visualization and analytics solutions

All eight interviewees mentioned that visualization and analytics solutions, such as Power BI and Tableau, are used in their organizations. According to the interviewees, these tools are the most widely used within the organization and are also utilized by supervisors. Interviewees reported that the organization's analytics and visualization tools lack predictive HR analytics capabilities. Instead, these tools focus solely on analyzing historical and current data. Manual tracking, for instance using Excel or the traditional pen-and-paper method, was mentioned by three interviewees. Manual tracking is still in use for certain tasks, such as forecasting personnel needs and maintaining vacancy registers. Results of the use of different data tools are presented in Figure 18 as a horizontal bar chart. The chart immediately provides a visual understanding of how much more common the use of visualization and analytics tools is compared to manual tracking.

One interviewee emphasized that visualization and analytics tools offer numerous possibilities for power users who have a thorough understanding of the source systems. In contrast, supervisors and management often have insufficient knowledge of the data produced by these systems. Two interviewees stated that many individuals in leadership positions do not use these tools, suggesting that their use has not yet become an established part of the organization's routine practices.

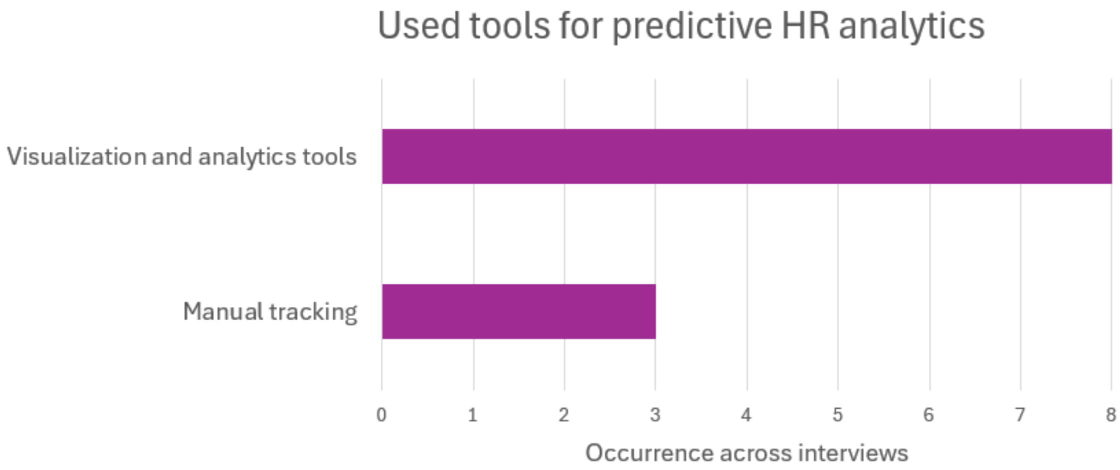

FIGURE 18. Used tools for predictive HR analytics (n=8).

One interviewee pointed out that Power BI views are often initially created to meet specific needs, but over time, these views may no longer align with users' current requirements for knowledge. This can lead to users perceiving the views as unhelpful, which in turn reduces the tool's adoption and usage rate.

One interviewee mentioned that an AI-generated explanation and quick analysis have been added to Power BI reports. Users have been instructed that the explanation and analysis are created by AI and should be approached critically. This helps users interpret the view and the conclusions drawn from it.

Visualizations play a critical role in facilitating comparisons and improving understanding. One interviewee highlighted the importance of seeing how the data has changed in percentage terms when comparing different periods, such as how situation has evolved compared to the same time last year. The use of percentages makes data comparison and understanding more intuitive and clearer. Another interviewee noted that data becomes easier to compare when users can view selected years side by side as trend lines, rather than sequentially. Viewing years sequentially makes visual comparisons more challenging. To enhance clarity, it is recommended to present trend lines for different years in distinct colors, avoiding confusion caused by using identical colors for both. Predictive analytics is often presented graphically, and this approach ensures that forecasts and comparisons are visually clear and easy to understand.

One interviewee emphasized that data should be examined as comprehensively as possible across different levels of the organizational structure. The interviewee highlighted the value of visualizing changes in percentage terms, particularly for comparing different periods, such as year-over-year results. Presenting data as percentages enhances clarity and makes comparisons more intuitive and easier to interpret. One interviewee pointed out turnover as an example: since turnover is examined from the perspective of both internal and external turnover, as well as entry and exit turnover, the data should also be viewable with various filters, such as excluding temporary workers.

One interviewee highlighted different forecasting methods used in predicting HR metrics. For instance, an analytical forecast, which is particularly helpful for trend analysis, is based on the rate of change. In this method, it is assumed that the change will occur at a similar rate as in the previous year or another reference period. Another forecasting model mentioned by the interviewee was the rolling forecast, where the model is continuously updated with data from, for example, the previous 12 months. This approach enables up-to-date and dynamic forecasting. The third forecasting model was based on the actual results of the previous year, predicting that, for instance, the start of the year will follow the same pattern as the start of the previous year, and similarly, the end of the year will mirror the end of the previous year. This model is particularly suitable for situations where seasonal variations are expected to recur. The interviewee also mentioned formula-based forecasts, which rely on predefined formulas that can combine elements such as growth rates, seasonal variations, or moving averages to generate predictions.

One interviewee pointed out that, in an ideal scenario, users could define various scenarios using different forecasting models, allowing the perspective to shift accordingly. This would enable users to freely explore various variables, such as payroll categories, additional and overtime work, shift allowances, the number of temporary employees and substitutes, paid work contributions, sick leaves, employee turnover, and vacation data.

Seasonal variations often affect the number of temporary employees and substitutes, as well as additional and overtime work and shift allowances. When forecasting shift allowances, it is essential to account for the fact that these allowances are paid retroactively. For example, January payments may still include shift allowances from December.

4.5 “*Basic trust is quite strong*” - Employee attitudes toward the use of their data

According to the interviews, there was significant variation in personnel awareness of how their data is used in analytics even within the same wellbeing services county. This may be due to insufficient communication, varying information sharing, or an organizational culture where transparency is not equally implemented. This situation highlights the need to improve communication and increase personnel’s understanding of the use of analytics.

Five interviewees stated that personnel are aware of how their data is used. Two interviewees did not comment on the question, as this issue has not been explored within the organization. One interviewee stated that the organization's personnel are unlikely to be aware of how their data is used. No detailed investigation or research has been conducted within the interviewees' organizations regarding how employees perceive the use of their data in analytics. The interviewees' perceptions of employee awareness regarding the use of their data are presented in Figure 19.

The interviewees who assessed that personnel are aware of how their data is used stated that the personnel generally have a neutral attitude toward the use of their data. This was considered to result from employees' trust that authorized individuals handle data properly and in compliance with regulations, and that unauthorized individuals do not have access to personal data.

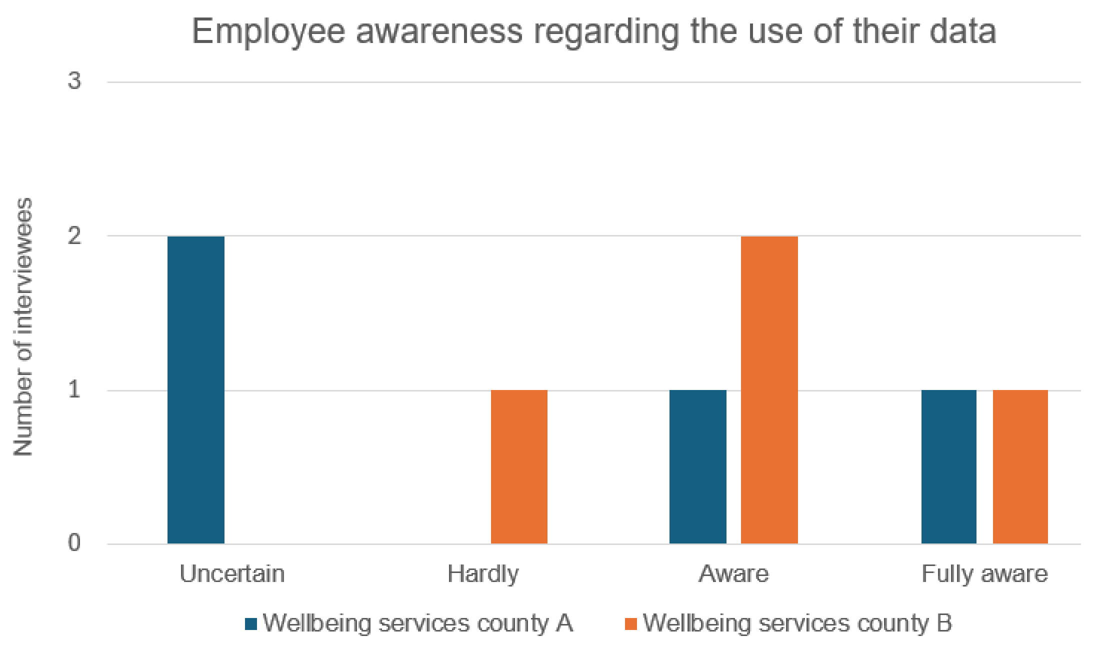

FIGURE 19. Employee awareness regarding the use of their data (n=8).

The interviewees who assessed that personnel are aware of how their data is used stated that the personnel generally have a neutral attitude toward the use of their data. This was considered to result from employees' trust that authorized individuals handle data properly and in compliance with regulations, and that unauthorized individuals do not have access to personal data.

As an example, Helsingin Sanomat reported that the unauthorized access of employee data at Hus in December 2024, which involved the personal information of hundreds of individuals, could significantly undermine employee trust in the proper and legitimate handling of their data. The incident may raise concerns about insufficient oversight and the potential misuse of personal information without justifiable reasons. The organization must protect personal data appropriately and ensure a secure environment where only authorized individuals have access to this information. (Helsingin Sanomat 4.12.2024.)

From the perspective of workforce scheduling, employees are involved in the planning process, and schedules may even be created collaboratively. In this case, employees are well aware that their data is being used in HR analytics. One interviewee also pointed out that, in most cases, personnel do not have access to HR analytics tools, which may influence the situation. If personnel had access to these tools, they might also be more interested in understanding the purposes for which their data is being used.

The interviewees who stated that personnel are well aware of how their data is used emphasized the importance of internal communication and the significance of transparency. According to them, it is crucial to inform the individuals involved about which data is being used in analytics.

Privacy considerations in HR reporting and analytics are especially critical when reports include information about individual employees or teams. One interviewee emphasized that it is essential to define an appropriate reporting format in collaboration with internal stakeholders, such as management, to ensure the report meets the organization's needs. Additionally, leveraging the expertise of the data protection team is crucial for designing safeguards that ensure personal data is handled by proper principles. It is important to ensure that the data of individual employees or teams cannot be recognized at a too detailed level. Ensuring data privacy requires implementing solutions that eliminate the possibility of isolating personal information from the report.

The interviewees explained that the ethical use of data is ensured by defining, on a case-by-case basis, which information is visible to users in reporting. The interviews highlighted the importance of privacy protection and data anonymization, particularly in small groups and when dealing with sensitive information, such as sick leave data. For example, when the group being analyzed consists of no more than five individuals, the data cannot be viewed to maintain confidentiality. According to the interviewees, efforts to develop processes are carried out with data security as a priority.

4.6 "*One potential path*" - Identifying future skill needs and development areas of personnel

The interviews revealed that neither wellbeing services counties currently have a competence management system in production use, but both are launching related projects. Therefore, predictive HR analytics is not yet in use in identifying future skill needs, development areas, or employee performance and potential in either of the interviewees' organizations. A more thorough analysis of competence management would have been necessary in the interviews, as the interviewees’ knowledge of the topic was limited.

The interviewees considered competence management reporting and predicting to be significant, especially in the context of retirement, to ensure that the loss of competencies can be managed. Two interviewees thought that with regional analysis of competencies it is possible to determine whether competencies are evenly distributed across the wellbeing services county’s operational areas or concentrated in a specific region.

The customer needs concerning predictive competence management are presented in Figure 20, where their frequency in the interviews is illustrated using a word cloud. The frequency of the data source is reflected in the size of the words. The more mentionings a word has, the larger its font size.

FIGURE 20. Word cloud of customer needs in competence management.

The importance of competencies, qualifications, medication administration licenses, and the overall requirement for licenses was emphasized in the interviews. Medication administration licenses are a key part of healthcare professionals' competencies, and professional legislation regulates social and healthcare services, setting requirements for monitoring qualifications and training. One interviewee pointed out how the development of clients, patients, and citizens in certain areas significantly affects the overall picture of competencies and training. The rise in the elderly population or certain diagnoses from a public health perspective will require additional training and recruitment in the coming years. Another interviewee mentioned a personnel and training plan, which is used to assess future competence needs.

One interviewee stated that predictive HR analytics offers significant benefits for examining the availability of future workforce and improving employer branding. This enables the prediction of the number of job applicants and employee needs, which helps in preparing for future challenges. Additionally, analyzing people's movements can provide valuable insights for the efficient allocation of resources. One interviewee pointed out that it would be interesting to examine which factors influence how certain units attract a lot of interested applicants or which professional groups receive the most applications.

4.7 "*Reporting current data is challenging*" - Training planning and career development

The interviewees' opinions were divided regarding training planning and predicting. It seemed that if the trainings were entered into two systems within the well-being service county, the interviewees did not consider predictive HR analytics for training planning and career development to be relevant at the moment. If trainings are entered into two different systems, it creates problems with the availability of reliable data and increases the risk of incomplete reporting. Despite these challenges, one interviewee mentioned that internal discussions about future training needs are taking place within the organization. This indicates that, although predictive HR analytics is not currently considered relevant, the topic elicits differing views and discussions within the organization. An interviewee from another of the organizations also referred to a similar situation, mentioning that training data gets distorted between systems while other interviewees from the same organization did not mention this kind of situation. This may reflect variations in the interviewees' roles and responsibilities, readiness for change, organizational priorities, and differing perceptions of the potential of predictive HR analytics.

Redundant and overlapping entries also pose challenges on a broader scale, as a report by the Ministry of Social Affairs and Health indicated that physicians, nurses, and social workers spend up to half of their working hours on documenting patient and client information, with approximately one-third of this documentation being redundant. The amount of documentation has increased in recent years, placing a significant burden on these professional groups. According to the report, documentation could be streamlined by developing national documentation guidelines, utilizing dictation solutions, and clarifying the division of labor. AI is seen as a promising solution, with related experiments and funding already underway. The next step is to identify concrete measures to enhance the efficiency of documentation. (Ministry of Social Affairs and Health 4.12.2024.)

One interviewee felt that in a tightening economic climate, it is increasingly important to analyze an organization’s service needs accurately to allocate training resources effectively. Organizations must identify skill gaps and set training objectives to address these deficiencies.

Interviewees thought that training provides employees with significant career and development opportunities, influenced by organizational changes, societal needs, and available resources. For instance, apprenticeship training can offer clear career pathways, encouraging employees to deepen their expertise by pursuing further studies in their field.

One interviewee noted that employees within an organization already possess a considerable number of skills and qualifications, which are further developed through work experience. However, continuous and systematic training is essential for strengthening the organization's skills base, and this approach is often perceived as meaningful from the employees' perspective.

Anticipating training needs and forecasting training volumes were seen as valuable for predicting turnover and addressing regional requirements. One interviewee pointed out that if an employee wishes to transition to a different specialization or role, the organization can facilitate this through additional training. Transparent communication within the organization enhances its appeal as an employer and strengthens employee commitment and motivation.

4.8 *"It is a bit in its infancy"* - Employee engagement and turnover

The utilization of predictive HR analytics in employee turnover and engagement varied among the interviewed organizations: in one wellbeing service county, predictive analytics was not yet in use, whereas in another wellbeing service county, internal development work on predicting turnover had been ongoing.

A word cloud presented in Figure 21 has been created from the interview responses concerning development suggestions for predicting turnover in HR analytics. The frequency of topics is reflected in the size of the words. The more mentioningss a word has, the larger its font size.

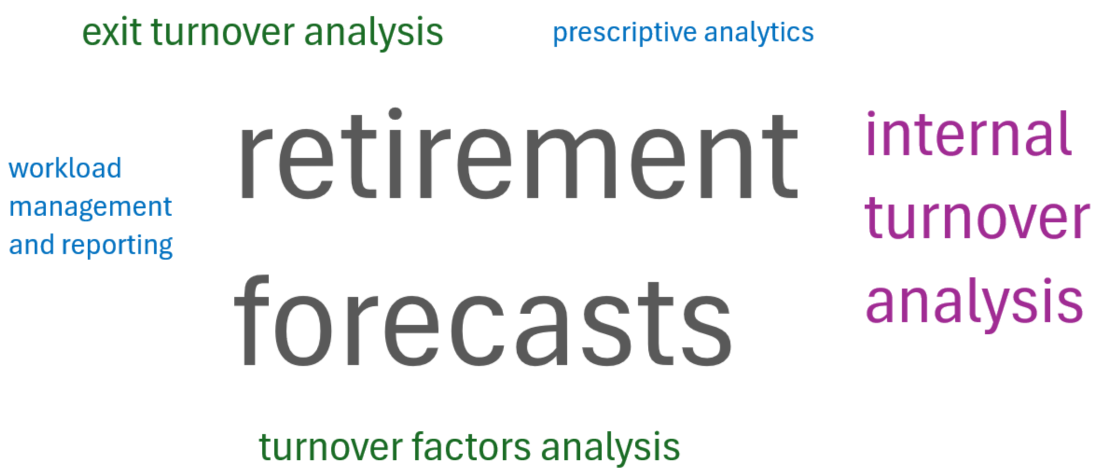

FIGURE 21. Word cloud of development suggestions for predicting turnover in HR analytics.

Six interviewees assessed that retirement forecasts help examine where in the organization and how many employees will reach retirement age, the magnitude of retirement waves in different areas, and which professional groups will be affected. Retirement forecasts facilitate preparation for these situations. For example, recruitment efforts can be directed at units facing personnel shortages. Forecasting based on retirement data allows for predicting the number of retirements in various professional groups, ensuring that training and skills development are targeted at the right individuals and groups where expertise will be most needed. In the long run, retirement forecasts should be combined with how work is evolving. This way, it is possible to assess whether the same number of representatives from the professional group is needed as before, and which skills will be emphasized. Strong evidence is needed to understand what kind of expertise will be needed in the future.

By using the QWL measurement utilized by another of the wellbeing service counties, it is possible to identify risks related to turnover. The interviewees from this organization emphasized the significance of this tool in their operations. If commitment and turnover go hand in hand, the organization can then identify negative changes in the work atmosphere and take corrective actions to improve the situation. According to the interviewees, deeper insights from retirement forecasts and turnover analyses can be obtained with more complex analytics when combined with the quality of work life indicators, employee absenteeism rates, or disability risks. Particularly, disability pensions constitute a significant financial burden, as their costs include not only pension expenses but also indirect costs such as recruitment and training expenses, and productivity losses.

In other wellbeing services county where there is no QWL measurement or any other similar tools in use, one interviewee mentioned that the organization collects data on turnover, its causes, and factors related to employee well-being, such as job commitment and job satisfaction. Entry and exit turnover are examined through Power BI reports but the reports do not include any predictive analytics.

Examining factors influencing turnover is important because it helps organizations identify factors and prevent issues that may increase turnover. This examination reduces recruitment and onboarding costs, and prevents productivity declines. Additionally, it improves job satisfaction by better understanding employees' needs and expectations. Ensuring the continuity of skills is essential for smooth operations, especially in critical roles. Managing turnover also supports the organization's competitiveness, as committed employees drive innovation and customer satisfaction.

Two interviewees highlighted the necessity of examining and predicting internal turnover. Efforts are being made to improve internal mobility, making it easier for employees to move within the organization. This would benefit the entire organization by enabling skilled employees to transition between various interesting positions. The possibility of internal mobility enhances attractiveness and reduces turnover.

Exit turnover can also be a strategic indicator in the organization. Based on the difference between the actual and target values, considerations are made on how to improve the organization's image, what kind of exit surveys are conducted, and the reasons for employee departures.

One interviewee also highlighted that it is important for the organization to consider corrective actions based on predictive analyses of sick leaves and turnover. In this case, prescriptive analytics algorithms and machine learning models could provide recommendations on what actions should be taken. For example, if predictive analytics indicates a high risk of illness in a particular unit, prescriptive analytics could suggest concrete measures such as improving working conditions or increasing wellness programs.

4.9 *“Monitoring and forecasting sick leaves is necessary”* - Employee well-being

According to five interviewees, examining the risks associated with sick leave is crucial to understanding the trends in absences. Analyzing the data across different organizational levels is important for gaining deeper insights into the situation. Analyzing absences helps to understand whether the cause is, for instance, seasonal influenza or other factors, such as workplace conditions or stress. Examining absences across different occupational groups may reveal whether certain groups experience more absences than others, potentially indicating specific workplace conditions or risks.

Comparing current sick leave data with corresponding periods from previous years helps identify whether absenteeism rates are exceptionally high or low. Regarding predicting sick leaves, one interviewee mentioned a trend indicator that would help monitor if the number of sick leaves in a unit or at the organizational level starts to increase, or if a cumulative review shows that the number of sick leaves is rising compared to the previous year.

Long-term absences impact both employee job satisfaction and turnover rates. One interviewee highlighted a turnover forecasting service provided by Keva, which also allows for examining the number of employees on partial or full disability pensions, aiding in the analysis of the situation. Another interviewee thought that long-term absences may lead to expertise narrowing, as temporary workers or substitutes do not possess the same level of competence as the absent permanent employees. Additionally, aspects related to customer relations, such as familiarity with the customer or their comprehensive assessment, may weaken. There is a risk of compromised expertise when skilled key employees are absent, especially if further changes occur. In such cases, the responsibilities shift to other permanent employees, impacting the entire work community.

The situations of individuals with partial work ability require increasingly more attention. One interviewee noted that there is a growing number of younger employees who are no longer able to perform their work. It is crucial to support the well-being of employees with partial work ability and to find tasks that suit them. A general concern one interviewee pointed out was that absenteeism, especially for mental health reasons, has increased across various parts of the organization, and this trend is linked to a reduction in performance and workability. A current trend highlighted in public discussions is that mental health issues are a significant cause of absenteeism. According to Yle, long-term absences from work due to mental health reasons cost Finland at least one billion euros annually, equivalent to the absence of approximately 26,000 full-time employees for an entire year. Supporting mental health and work capacity would be significant not only for individuals but also for employers and society. (Yle 28.8.2024.)

Using the QWL measurement utilized by another of the wellbeing service counties, it is possible to identify risks related to sick leave, burnout, and disability. The interviewees from this organization emphasized the significance of this tool in their operations. The results guide the organization’s actions, indicating what measures can be taken to reduce the identified risks.

In forecasting, it is beneficial to focus on situations that require intervention and to assess whether the collaboration processes with occupational health services are functioning properly. It is also important to explore the root causes of the increasing number of absences and why the number of absences might rise. Simultaneously, it is essential to review factors in daily operations, such as potential management issues, and identify signs that might indicate such situations developing.

One interviewee highlighted the importance of leadership and the support provided for managers. The presence and support are key factors in maintaining employees' well-being and workability. Managers should be easily accessible and actively involved in employees' daily work. Regular discussions with employees help managers to stay informed about their situation and any potential challenges.

4.10 *"The right personnel at the right time in the right workplaces"* - Work shift planning and personnel needs

Currently, neither of the wellbeing services counties applies predictive analytics in work shift planning or anticipating personnel needs. Not all interviewees were involved in work shift planning or forecasting personnel requirements, which was reflected in the interviews: the topic was either discussed superficially (two interviewees) or omitted altogether (three interviewees). Three interviewees had experience with this area.

The wellbeing services counties operate across extensive areas geographically, allowing for the reallocation of resources both between units and across municipalities. According to the interviewees forecasting personnel needs facilitate identification and mitigation of risks. However, not all risks can be foreseen; one interviewee pointed out as an example that redundancy negotiations in a neighboring wellbeing services county can increase the number of applications for open positions in a neighboring wellbeing services county.

In the work shift planning systems, data is typically reviewed in 3- or 6-week cycles. The interviewees thought that there is a need in organizations for longer-term planning. One of the interviewed wellbeing services counties has used a manually filled Excel document for forecasting personnel needs over a longer horizon. The aim is not to rely on past data but to plan human resources, for example, six months in advance. The document is updated in real-time, to identify resource shortages and surpluses. This approach aids in allocating resources to units that require labor and facilitates the planning of absences such as vacations, allowing for better consideration of approval processes for certain tasks. Real-time monitoring of units is also made easier, although this requires a commitment to real-time data entry. According to the interviewees automating personnel needs forecasting is crucial due to the manual nature of the current process.

One interviewee highlighted that more efficient utilization of personnel resources requires identifying units with surplus labor and reallocating it to units with shortages. Additionally, forecasting personnel needs, such as estimating the number of substitutes needed for the next summer, relies on analyzing seasonal variations and changes in the operating environment. These operational models can enhance operational efficiency, achieve cost savings, and balance the workload of personnel, thereby also promoting employee satisfaction.

In the units where expertise is evenly distributed among employees, organizing substitutions becomes smoother, as skilled workers are allocated evenly across shifts. This reduces the need for external substitutes and simplifies the management of substitutions. In a balanced model, shifts are not composed solely of experienced personnel or only new employees; instead, skill levels are distributed evenly across different shifts.

One interviewee mentioned that in optimizing activity-based work shift planning, defining operational needs in a way that a computer can process them has been found challenging but necessary. Automated systems improve the accuracy and consistency of these definitions because they are based on strict rules that cannot be deviated from. This differs significantly from traditional, manually made solutions, where the margin of error is greater and resource use can be more flexible, such as using minimal resources or partially qualified personnel. However, automation requires more proactive and precise management of skills, which may require changes to previous practices.

Admitting resource deficiencies, especially those related to skills, can be challenging for units and supervisors. These issues are easier to overlook when they remain at the discussion level and do not require documentation. However, automated systems make these deficiencies visible and harder to dispute, which can change attitudes toward resource management. Collaborative work shift planning can reveal weak control mechanisms and unclear rules, which may provoke resistance. Changes, such as increasing the formality of operations and tightening rules, can be challenging as they alter established practices.

Predictive models of HR analytics could be used more extensively in the future to anticipate personnel needs, and this should also consider the assessment and forecasting of service needs, as one interviewee pointed out. This would require data from sources other than HR, as examining the development of service needs requires consideration of morbidity, population age structure, care days, procedure days, and reception days. Once the direction of service demand and the areas of focus are clear, personnel planning and forecasting become easier. This way, it will be known how many employees are needed for each service and what kind of competency profiles the organization should direct to each area.

According to the interviewees in forecasting work shift planning, it is important to consider the need for skilled personnel and their availability, as well as examine the gap between them. By identifying resource shortages in advance, it is possible to invest in employee onboarding and continuous learning. Additionally, internal skill development and career path planning are crucial, allowing the organization's personnel to assist units facing a shortage of skilled workers.

As one interviewee mentioned, monitoring and forecasting annual working hours through a cumulative review of the past and current year is important from the perspective of an individual's work contribution and personnel budgeting. This allows the observation of the components and processes that construct an individual's annual working hours. Forecasting the future is crucial to determine whether an individual's annual working hours or the personnel budget will be exceeded before the year ends. This enables corrective actions to be taken, and the report also serves as a useful tool in development discussions and monitoring an individual's occupational well-being.

One interviewee highlighted that more efficient utilization of personnel resources requires identifying units with surplus labor and reallocating it to units with shortages. This is based on analytics which uses historical or real-time data to detect imbalances in resource allocation. Forecasting personnel needs, such as estimating the number of substitutes needed for the next summer, relies on analyzing seasonal variations and changes in the operating environment. Predictive analytics is used in this context, enabling the assessment of future needs and preparation through recruitment, training, or work shift planning. These operational models can enhance operational efficiency, achieve cost savings, and balance the workload of personnel, thereby also promoting employee satisfaction.

4.11 *"A friend, not an enemy"* - Utilization of AI

Interviews revealed that AI in predictive HR analytics is still a relatively new topic within the wellbeing services counties, and its development opportunities may not yet be fully recognized. The utilization of AI in both wellbeing services counties is still in its early stages. Both organizations have initiated measures to integrate AI into their operations, but the process is still in its initial phase.

Interviewees perceived AI as a significant tool, particularly in supporting managerial work, even though its full utility may still be somewhat unpredictable. One interviewee mentioned that there has been discussion of utilizing AI in predictive HR analytics at the beginning of the operations, but over time, discussions about the use of AI have faded. One interviewee emphasized the importance of genuine, user-centered use cases. AI is expected to offer substantial benefits and support, but its role is difficult to define in advance. While AI is not intended to replace human work, its role as an aid in decision-making and management is seen as a positive development. Therefore, AI is not meant to perform tasks autonomously but to support and enhance existing processes, requiring human oversight.

The attitude towards AI was positive among all eight interviewees, and it was seen as providing crucial assistance in performing work tasks. AI was considered as a support that enables employees to focus on core tasks that align with their expertise and skills, while freeing up time from routine background tasks. The partnership brought by AI was also emphasized in how it can free up time from routine tasks that significantly consume employees' time – even half a day or more per week. In the future, AI is expected to handle these tasks more quickly and automatically, allowing employees to focus on areas of work that are more aligned with their expertise and interests. This change not only enhances efficiency but also brings significantly more rewarding experiences, as work focuses more on tasks that motivate and provide personal satisfaction.

One interviewee pointed out how AI can handle more data than a human, and the data processing is faster than a human. AI can do better than humans at analyzing trends and outliers and making comparisons. This improves the quality of decision-making and makes time use more efficient.

One interviewee suggested that AI could assist in certain tasks with higher skill requirements, such as manual tasks related to salary increases and local bargaining reserves, which typically fall under the responsibility of the organization's HR manager or negotiation manager.

4.12 Development suggestions for predictive HR analytics

In this chapter, the most significant and the most voted development suggestions in the interviews are presented in Table 2. The most noted development suggestions are the ones that were mentioned by three or more of the interviewees. All development suggestions are presented in Appendix 4.

Compiling the development suggestions into a separate subchapter from the previous chapter improves the clarity and consistency of this thesis. Summarizing the development suggestions in a separate subsection promotes a structured layout of the report and enhances its overall readability. The suggestions presented in a separate summary chapter allow for their comprehensive review, making it easier for the reader to grasp the identified development areas without needing to search through different parts of the report. Additionally, organizing and comparing the suggestions in their chapter supports their prioritization and clarifies their significance. The subsection also enables smooth references to earlier chapters, allowing the reader to easily return to details if needed.

TABLE 2. The most significant and voted customer needs

Development suggestion	Interviews	Theme	Subchapter
Retirement forecasts	6	Employee engagement and turnover	4.2.8
Automated, smooth, and seamless system integrations	5	Challenges in implementation or use	4.2.3
The risks associated with sick leave	5	Employee well-being	4.2.9
The data provides a range of options and the widest possible range of information	4	Utilization and expected benefits	4.2.2
Versatile indicators and metrics	4	Utilization and expected benefits	4.2.2
An user-friendly and intuitive interface	4	Challenges in implementation or use	4.2.3
Transitioning from manual tools and practices to electronic solutions	4	Data sources and tools	4.2.4
Entering training data only once into the source system	4	Training planning and career development	4.2.7
Deeper insights from retirement forecasts and turnover analyses with quality of work life indicators, employee absenteeism rates, or disability risks	4	Employee engagement and turnover	4.2.8
Calculation methods for metrics and key performance indicators need to be aligned across source systems and reporting tools	3	Challenges in implementation or use	4.2.3
Visualization and analytics solutions need to include more predictive analytics	3	Data sources and tools	4.2.4
Automating personnel forecasting	3	Work shift planning and personnel needs	4.2.10

5 DISCUSSION

Based on the interviews, it appears that the primary focus of HR analytics in the interviewed wellbeing services counties currently lies in descriptive analytics where information is examined through past or present data and events. Predictive HR analytics is not yet widely implemented in these wellbeing services counties and it was seen in its infancy. As noted in the international studies within the theoretical framework, the use of predictive HR analytics varies between the private and public sectors, with the usage being particularly lower in the public sector.

The interviewees regarded predictive HR analytics as a vital component of the organization's operations and management, with a constant demand for its insights into finance, resource management, and decision-making benefits. In the face of economic challenges, the importance of predictive analytics has significantly increased, offering valuable guidance and support for strategic action planning.

Many of the challenges mentioned in the theoretical framework were also highlighted by the interviewees. Specifically, the fragmentation of data, user-friendliness and intuitiveness of applications, and data inaccuracy cause significant challenges that impact data reliability, timeliness, and quality. The wellbeing service counties have only had a short operational period so far. As they continue to operate, the availability of long-term data will improve forecasting possibilities, data comparability, and decision-making.

Both interviewed organizations had visualization and analytics solutions like Power BI and Tableau in use, but these tools do not yet have predictive HR analytics features available. The other from the two organizations uses the QWL tool for forecasting and risk management, while the other organization primarily performs predictive analytics manually using Excel.

The interviewees' opinions were divided regarding the present state of utilization of predictive analytics, personnel awareness of how their data is used in analytics, and training planning and predicting, even within the same wellbeing service county. The differing opinions could be explained by the differences in job descriptions, insufficient communication, varying information sharing, an unevenly transparent organizational culture, readiness for change, organizational priorities, and differing perceptions of the potential of predictive HR analytics.

The interviews revealed that neither of the wellbeing service counties currently have a competence management system in production use. Therefore, before identifying future skill needs, development areas, or employee performance and potential can be implemented, it is necessary to ensure the smooth implementation of descriptive analytics and implement it systematically in these organizations.

The most significant and voted customer needs are a cross-section of almost all the themes of the thesis. System integration, problems with intuitive interfaces, and inconsistent calculation methods were perceived as challenges in the use and implementation of predictive HR analytics. Manual tools should be replaced with electronic ones. Additionally, these electronic tools should incorporate more predictive analytics alongside descriptive analytics. Retirement forecasts with deeper insights and turnover analysis are important for employee engagement and turnover. The risks concerning sick leaves help in proactive measures for employee well-being. Training data needs to be entered into only one system, which affects predictive analytics in training planning and career development. Users expect the data to provide a diverse range of information that can be viewed from different perspectives and with various metrics. In work shift planning and forecasting personnel needs, automation and predictive analytics should be prioritized over manual work.

There have been no studies on predictive HR analytics in wellbeing services counties, so this research is pioneering and fills a gap in the existing research field. The lack of prior research emphasizes the importance and originality of this research, paving the way for further exploration and development of this subject.

As a suggestion for further research, mapping the customer needs of multiple, if not all, wellbeing service counties would allow for results to be examined on a broader scale. From a future research perspective, it could be beneficial to focus on a specific area, enabling a more in-depth analysis of the topic while also facilitating the recruitment of interview participants. For example, a more thorough and deeper analysis of prediction needs concerning competence management, training planning and career development, and work shift planning and personnel needs would have been necessary for the interviews, as the interviewees' knowledge of the topic was limited. One potential further research topic could also be to study employee awareness of how their data is used in analytics since there was a variation of the opinions even within the same wellbeing services county and no similar research has been conducted yet.

The ethical perspective of predictive HR analytics is addressed as a separate entity in this study, as the confidentiality and secure storage of employees' personal data is crucial nowadays, and the implementation of data protection is also guided and monitored from a legislative perspective. Internally applied frameworks serve as guidelines and are an important part of transparent communication. From a data protection perspective, the actions of an individual employee have an extremely significant impact and responsibility. Internal reflection within the organization, along with necessary experts, is important to ensure that data protection is considered from as versatile perspectives as possible and that the implementation meets the organization's needs.

During this research process, my learning has progressed in waves rather than steadily, with continuous phases of ups and downs. At the beginning of the research process, I encountered some challenges with research permits, as the preparation and processing of the permits took more time than expected. This affected the scheduling of interviews and also impacted the overall timeline of the research process. I utilized the time spent on processing permits to strengthen the theoretical section, allowing me to gain more comprehensive and up-to-date research information on various applications and studies of predictive HR analytics. Life, like research permit processes, is full of surprises, and this process has increased my resilience and my approach to changing situations. The use of research methods, critical thinking, and tolerance of uncertainties have deepened through this research. Diamonds are formed under pressure, which applies also very well to this research process.

The use of predictive HR analytics requires continuous development of both technology and organizational practices. Improving system functionality, data quality, and collaboration are key to overcoming challenges and leveraging the potential of analytics.

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APPENDICES

Appendix 1. Thematic interview framework in Finnish

Appendix 2. Thematic interview framework in English

Appendix 3. Translations of direct quotations

Appendix 4. Development suggestions based on the interviews

Appendix 1. Thematic interview framework in Finnish

1. Ennakoivan analytiikan rooli ja merkitys HR-strategiassa

- Ennakoivan HR-analytiikan merkitys
- Ennakoivan HR-analytiikan käyttö
- Hyödyt, joita odotetaan saavutettavan ennakoivan HR-analytiikan avulla
- Haasteet käyttöönotossa ja käytössä

2. Tietolähteet, työkalut ja datan hallinta

- Tietolähteet (esim. henkilöstödata, suorituskykymittarit, rekrytointidata)
- Ohjelmistot ja työkalut
- Työntekijöiden suhtautuminen tietojensa käyttöön

3. Taitojen ja osaamisen ennustaminen

- Henkilöstön tulevien osaamistarpeiden ja kehitysalueiden tunnistaminen
- Koulutusten suunnittelu ja urakehitys

4. Työntekijöiden sitoutumisen, työhyvinvoinnin ja suorituskyvyn ennustaminen

- Työntekijöiden sitoutuminen ja vaihtuvuus
- Työhyvinvointi
- Työntekijöiden suorituskyky ja potentiaali
- Työvuorosuunnittelu
- Henkilöstötarve

5. Tulevaisuuden näkymät

- Kehitys ja tarpeet tulevaisuudessa
- Uudet mahdollisuudet ja trendit
- Tekoälyn hyödyntäminen

Appendix 2. Thematic interview framework in English

1. The role and significance of predictive HR analytics

- The significance of predictive HR analytics
- Utilization of predictive HR analytics
- Expected benefits of predictive HR analytics
- Challenges in implementation or use

2. Data sources, tools, and data management

- Data sources
- Software and tools
- Employee attitudes toward the use of their data

3. Predicting skills and competencies

- Identifying future skill needs and development areas of personnel
- Training planning and career development

4. Predicting employee engagement, well-being, and performance

- Employee engagement and turnover
- Employee well-being
- Employee performance and potential
- Work shift planning
- Personnel needs

5. Future expectations and prospects

- Development and future needs
- New opportunities and trends
- Utilization of AI

Appendix 3. Translations of direct quotations

Chapter	Direct quotation in English	Direct quotation in Finnish
4.2.1	Looking ahead with every-day risk management	*“Tulevan suunnittelua ja arjen riskienhallintaa”*
4.2.2	Window to the future	*”Näkymä tulevaisuuteen”*
4.2.3	Sometimes we have had to learn these things the hard way	*”Välillä ollaan menty -- kanta-pään kauttakin näissä asi-oissa”*
4.2.4	Numerous systems on use	*”Käytössä olevia järjestelmiä on paljon”*
4.2.5	Basic trust is quite strong	*“Perusluottamus on aika vahva”*
4.2.6	One potential path	*”Yksi -- mahdollinen kehitys-suunta”*
4.2.7	Reporting current data is challenging	*“Nykyhetken datan raportointi on haasteellista.”*
4.2.8	It is a bit in its infancy	*”Se on vähän lapsenken-gissä.”*
4.2.9	Monitoring and forecasting sick leaves is necessary	*“Sairauspoissaolojen seu-ranta ja ennakointi on tar-peen”*
4.2.10	The right personnel at the right time in the right work-places	*”Oikeanlaista henkilöstöä oi-kea-aikaisesti oikeissa työpai-koissa”*
4.2.11	“A friend, not an enemy”	*“Ystävä eikä vihollinen”*

All translations are done by the thesis author.

Appendix 4. Development proposals of the interviews.

Development suggestion	Interviews	Theme	Subchapter
Retirement forecasts	6	Employee engagement and turnover	4.2.8
Automated, smooth, and seamless system integrations	5	Challenges in implementation or use	4.2.3
The risks associated with sick leave	5	Employee well-being	4.2.9
The data provides a range of options and the widest possible range of information	4	Utilization and expected benefits	4.2.2
Versatile indicators and metrics	4	Utilization and expected benefits	4.2.2
An user-friendly and intuitive interface	4	Challenges in implementation or use	4.2.3
Transitioning from manual tools and practices to electronic solutions	4	Data sources and tools	4.2.4
Entering training data only once into the source system	4	Training planning and career development	4.2.7
Deeper insights from retirement forecasts and turnover analyses with quality of work life indicators, employee absenteeism rates, or disability risks	4	Employee engagement and turnover	4.2.8
Calculation methods for metrics and key performance indicators need to be aligned across source systems and reporting tools	3	Challenges in implementation or use	4.2.3
Visualization and analytics solutions need to include more predictive analytics	3	Data sources and tools	4.2.4
Automating personnel forecasting	3	Work shift planning and personnel needs	4.2.10

Thresholds or alerts in the tools	2	Utilization and expected benefits	4.2.2
Costs of employees' unused annual holiday	2	Utilization and expected benefits	4.2.2
Flexible and adaptable product configurations	2	Challenges in implementation or use	4.2.3
Strong and close collaboration with system providers and other wellbeing service counties	2	Challenges in implementation or use	4.2.3
A regional analysis of competencies	2	Identifying future skill needs and development areas of personnel	4.2.6
Anticipating training needs and forecasting training volumes	2	Training planning and career development	4.2.7
Factors influencing turnover	2	Employee engagement and turnover	4.2.8
Examining and predicting internal turnover	2	Employee engagement and turnover	4.2.8
Examining and predicting exit turnover	2	Employee engagement and turnover	4.2.8
Examining and predicting personnel budgeting	2	Utilization and expected benefits	4.2.2
Long-term predictions for addressing financial challenges, or looking at retirements, or job profiles	1	The meaning and significance	4.2.1
The focus on proactive planning and risk management	1	Utilization and expected benefits	4.2.2
Effective integration of HR data with financial figures, performance metrics, and changes in the operating environment	1	Utilization and expected benefits	4.2.2

The availability of long-term data	1	Utilization and expected benefits	4.2.2
Ready-made solutions for all needs	1	Challenges in implementation or use	4.2.3
User management solutions for parallel employment relationships	1	Challenges in implementation or use	4.2.3
Centralized dashboards or reporting tools	1	Challenges in implementation or use	4.2.3
Use of mood indicators	1	Data sources and tools	4.2.4
Include various comparison options in the tool	1	Data sources and tools	4.2.4
Users can define various scenarios using different forecasting models	1	Data sources and tools	4.2.4
A prediction of the number of job applicants and employee needs	1	Identifying future skill needs and development areas of personnel	4.2.6
Identify skill gaps and set training objectives from a service needs point of view	1	Training planning and career development	4.2.7
Analyze factors affecting unit attractiveness and application trends by professional group	1	Identifying future skill needs and development areas of personnel	4.2.6
Prescriptive analytics	1	Employee engagement and turnover	4.2.8
Comparing current sick leave data with corresponding periods	1	Employee well-being	4.2.9
Examination of long-term absences	1	Employee well-being	4.2.9
Root causes of the increasing number of absences	1	Employee well-being	4.2.9
Strengthen leadership support	1	Employee well-being	4.2.9

Improve and support change management	1	Work shift planning and personnel needs	4.2.10
More extensive use of predictive models	1	Work shift planning and personnel needs	4.2.10
Examination of skilled personnel and their availability	1	Work shift planning and personnel needs	4.2.10
Monitoring and forecasting annual working hours	1	Work shift planning and personnel needs	4.2.10
Assist in tasks with higher skill requirements, such as the labor-intensive manual tasks related to salary increases and local bargaining reserves	1	Utilization of AI	4.2.11