STAY OK

RETHINKING WELLBEING AT WORKPLACES IN THE EUROPEAN SMES

ARTIFICIAL INTELLIGENCE FOR WORKER MANAGEMENT

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Introduction

Objectives:

- Understanding the context of the labor market: Explore the structure, supply-demand dynamics and factors influencing the labor market such as skills, qualifications and economic cycles;
- Understanding the underlying technology of artificial intelligence: Learn the basics of AI technology, including how it operates, key models like neural networks and its application in various sectors.

1.Context of the module

The focus of Module 3 is on increasing performance and efficiency of corporate workforces, particularly using artificial intelligence. The ability to optimize employee performance and operational efficiency is important in a world which competes on high efficiency and low prices. This module highlights various strategies, tools, and future trends that can help organizations achieve these goals.

We are using the term "worker management" to describe the overarching theme but what does it mean?

Worker management does not refer to enterprises which are owned and managed by the workers (e.g., Atkinson, 1973; Sauser, 2009), but rather to an approach of overseeing and guiding employees to ensure that they perform effectively and efficiently.

It includes activities such as recruitment, performance evaluation, training, and development, as well as the implementation of technologies to enhance productivity. This bundle of approaches has several benefits such as employee goals which align organizational objectives or a productive and engaged workforce. They also lead to improved performance, higher employee satisfaction, and better retention rates. However, we will also look at some of the dark sides such as the lack of privacy or an illusion of accuracy which is widespread.

You will gain a comprehensive understanding of the intersection between artificial intelligence (AI) and worker management. It will focus on job matching, recruitment, and employee performance evaluation.

This module will conclude with a discussion of the ethical implications of using AI in worker management, discussing issues such as biases, privacy concerns, and the transparency of AI outputs.

1.1 The labor market

Just consider how much time the usual individual spends working. It ranges from 32 expected years in Romania to more than 45 years in Iceland. Across the European Union, the Netherlands, Sweden, Denmark and Estonia had the longest expected duration of working life in 2023, each with more than 40 years. (Eurostat, 2024). That is a significant part of our lives. Nobody would dispute the importance of work for our lives.

Gini has formulated it in an article on " Work, Identity and Self: How We Are Formed by the Work We Do" in 1998 in the following way:

> *No one is neutral about the topic of work. Everyone has an opinion. The reason is simple. Work, food and sex are the most commonly shared behavioral traits of adult life. While the latter two are subject to aesthetic taste and availability, and, therefore constitute a discretionary choice, work, for 95% of us, is an entirely non-discretionary matter. Most of us must work.*

It is thus in our interest to improve the way how work is managed in every conceivable way. It is also worth mentioning that organizations such as 80,000 Hours are trying to help employees to make the 80,000 hours people are working as societally impactful as possible.

Let us start by looking at the labor market. Basically, it functions as a gigantic sorting machine. It matches individuals with companies. Individuals need to find a job and companies need to find employees willing and able to take on these jobs.

The underlying criteria are skills, qualifications, personal traits, and experiences which need to be matched with millions of job opportunities. The labor market is thus matching demand and supply.

Just take a moment to consider this statement for our own experiences. How does it work in your environment?

In addition, public institutions have an interest in a functioning labor market and invest large amounts of capital in the development of skills through education and training.

The institutions which make up the labor market are shown in the illustration below.
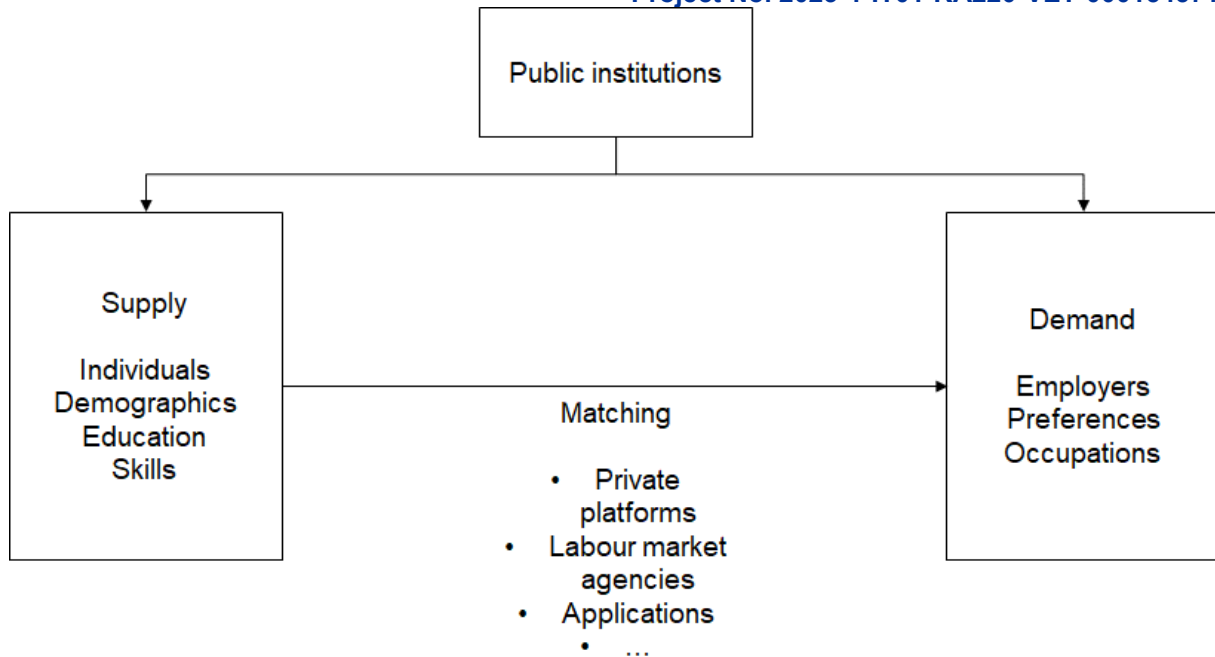
Figure 1: Labor market
Source: Spiess-Knafl & Olowode (2024)

Given the central position of the labor market, it is still surprising that we do not know more about the underlying mechanism. For example, we do not really know which skills are relevant for which jobs and which skills lead to future success.

There are regular discussions about the skills which are necessary in the 21st century.

A recent World Bank blog post made the observation that modern skills might be important but foundation skills tend to be more important:

> *These skills included computing, foreign languages, creativity, critical thinking, and various soft skills. Although these skills are undoubtedly important, focusing on them took attention away from the less exciting challenge of ensuring that all students achieve a basic proficiency level of literacy and numeracy.*

Another author has written in The Atlantic that the most important job skill in the 21st century is the ability to talk to an AI system.

We cannot be sure if this will indeed be the case. However, we are not running short of all kinds of recommendations and speculations.

Similarly, there are regular recommendations on how to change the national education systems to copy the latest winner or front-runners in the PISA contest. In his bestseller

"Hidden Potential" Grant (2023) discusses what can be learnt from the Finnish education system.

In general, the labor market is a perfect environment for big data analytics and artificial intelligence where models analyze occupations and skills and map them to each other. In one instance, Brown and Souto-Otero (2020) analyze 21 million job adverts to understand employers' job requirements. Such large datasets are rarely available outside in other areas.

1.2 Supply and demand in the labor market

The demand in the labor market is driven by the needs of companies and is usually described in terms of occupations or job descriptions. Several key factors influence this demand.

The most relevant factor are the economic cycles which consist of growth and recessions periods. During economic booms, businesses expand, leading to an increased need for employees across various sectors. Conversely, during recessions, companies may downsize which leads to reduced hiring (e.g., Bachmann, 2005). Recessions have all kind of knock-on effects as well (Huckfeldt, 2022). We have all seen these effects during the recent pandemic which led to large knock-on effects across all sectors of the economy.

On the other side, technological advancements lead to the emergence of new industries and new job opportunities. For example, the rise of the tech industry has led to a high demand for software developers, data scientists, and cybersecurity experts. Similarly, the green energy sector is driving demand for jobs in renewable energy and sustainability-related areas. You can also think of all ESG data providers and those who help to comply with EU sustainability requirement such as CRSD, CSDDD or SFDR.

Government policies and public incentives can stimulate labor market demand. Tax incentives, grants, and subsidies for certain industries can encourage companies to hire more employees. For instance, government initiatives to promote infrastructure development can lead to increased demand for construction workers, engineers, and project managers. Again, during the recent Corona pandemic we have seen large government subsidies to keep the workforce of large and small companies intact.

We also need to consider employee turnover, whether through retirement, resignation, or other reasons. Employee turnover creates vacancies that need to be filled. High turnover rates in certain industries such as accounting or consulting can lead to a continuous demand for new hires. Companies must attract and retain talent to maintain their operations, often leading to ongoing recruitment efforts.

These are all factors driving the demand in the labor market. We also need to look at the supply side of the labor market. It is primarily driven by individuals and is typically described in terms of the skills they possess. Various factors influence the supply of labor, including demographics, education, and personal circumstances.

The supply of young individuals entering the labor market is a significant contributor to overall labor supply. This group includes recent graduates from high schools, colleges, and vocational programs. Obviously, they lack extensive work experience.

Another part of labor supply consists of experienced individuals seeking new job opportunities. This group includes those who are unemployed, underemployed, or employed but looking to change jobs for better opportunities, higher wages, or more suitable working conditions. Factors driving job search activities include economic necessity, career advancement, job dissatisfaction, and geographic relocation.

Longer educational pathways have a substantial impact on labor supply. As individuals spend more time in education, they delay their entry into the labor market. While this results in a temporarily reduced supply of labor, it typically enhances the quality of labor by producing more highly skilled and educated workers. Advanced degrees and specialized training programs equip individuals with the expertise required for complex and high-demand occupations. This is not likely to change in the foreseeable future.

Demographic changes, such as aging populations and migration patterns, also affect labor supply. As the population ages, a larger proportion of the workforce may retire, reducing the available labor supply. Conversely, migration can either increase or decrease labor supply, depending on whether more individuals are entering or leaving the workforce in a particular region.

The overall participation rate of different demographic groups, including women, minorities, and older workers, influences labor supply. Policies and cultural shifts that encourage higher workforce participation among these groups can expand the labor pool. For example, increased access to childcare and family-friendly workplace policies can enable more women to join and remain in the workforce (e.g., for a discussion of the Italian context de Philippis, 2017).

A better understanding is relevant on different levels. On a personal level, individuals need to decide how to allocate their learning budget and time. Individuals need to understand which skills are necessary for which jobs. There are already platforms where individuals can identify in-demand skills and tailor their learning paths accordingly.

On a public institutional level, it is necessary to adapt educational curricula and trainings for the population (unemployed as well as employed persons) as long-run economic growth is shown to be driven by educational efforts (Hanushek, 2016). There is also a rich literature showing that education increases individual productivity (Woessmann, 2016). In addition, labor market agencies need to decide which trainings and courses they should offer to unemployed persons and match skills with occupations in their work with clients.

On a corporate level, it is necessary to decide which skills will be relevant for their future needs. They might also need to predict which individual each representing a different cluster of skills will be best suited for different positions.

The labor market can thus be described as a relatively unstructured environment with an abundance of data. This makes it a natural environment for big data and machine learning approaches. Skills and occupations should be a natural playing ground for artificial intelligence. The data is abundant and relatively unstructured. There are many positive aspects but a growing body of evidence shows how the algorithms made wrong decisions (e.g., Birhane, Prabhu, and Kahembwe 2021; Zou and Schiebinger 2018; Bender et al. 2021)

1.3 History of the labor market

Historically, careers were linear, characterized by long-term employment, predictable career patterns and job security. Today's job market demands flexibility, adaptability, and lifelong learning (for an overview see McNulty, 1966, or Williamson, 1995).

Since the 1990s, we are witnessing the widespread introduction of computers which led to the automation of repetitive tasks. This era saw the decline of certain professions and the rise of new ones in IT and data processing, setting the stage for the Information Age.

As a side note, it is interesting to note jobs never really disappear but take different forms. For example, the lift boy in hotels was responsible for operating the elevator but also served as a customer relationship manager. Keep this aspect in mind when we discuss potential job displacement driven by artificial intelligence.

At the same time, globalization has transformed the workplace through international cooperation and trade. Companies leveraged global resources, leading to the sustained growth of multinational corporations and the relocation of jobs to lower-cost countries. This shift required workers and employers to adapt to a connected global economy. This will also the time when expats were in high demand.

Obviously, we have seen multinationals before the 1990s but the collapse of the Soviet Union as well as the opening of the Chinese market led to a change in the economic opportunities.

In addition, demographic shifts have diversified the workforce, with increased female employment and broader inclusion of various demographic groups. This diversity enriches teams, fosters creativity, and enhances problem-solving capabilities, challenging organizations to create inclusive work cultures to fully leverage this potential (e.g., Campbell & Mínguez-Vera, 2008; Erhardt et al., 2003; Lorenzo & Reeves, 2018).

The transition from an industrial-based economy to one focused on services and knowledge has transformed the job landscape. Traditional manufacturing jobs have declined, making way for service and knowledge work. This change requires continuous education and adaptation to new job profiles, with companies developing innovative work models.

Rising educational levels and access to diverse educational pathways have also changed the labor market. Higher and specialized qualifications are now prerequisites in many industries, enhancing job opportunities and increasing competition. This trend underscores the

importance of continuous learning and adaptation in a rapidly changing economic environment.

From 1990 onwards, digitization fundamentally transformed work through the advent of the internet and new digital technologies. These changes enabled unprecedented connectivity, remote work, and virtual teams. While digitization increased productivity, it also demanded continuous education in digital skills to keep pace with technological advancements. The impact of artificial intelligence will be covered in more detail in the coming chapters.

The rise of the gig economy and freelancing, fueled by internet flexibility, has led to a preference for short-term contracts and project-based work over traditional employment. While this offers flexibility and work-life balance, it also introduces challenges like uncertain income and lack of social security, highlighting the need for new employment models. If you are interested in the economic theory of the firm, take a look at the work of (Coase, 1937)

The growth of remote work, driven by advances in communication technology, offers flexibility and access to global talent. While it increases productivity and satisfaction for some, it also poses challenges in team cohesion, communication, and work-life separation, necessitating new strategies for effective remote work management.

This is the background for the discussion of this module.

1.4 Lifecycle of a worker in a company

In general, there are various stages of the employee lifecycle.

Gladka et al. (2022) have analyzed the various stages which have been used to analyze the lifecycle of employees and most follow similar structures shown in the table below.

Titles of the ELC stages	Characteristic of the ELC stages from the perspective of the	
	employee	employer
Attraction		
Search and Discover	Labor market analysis and development of expectations towards potential employers	Labor market analysis and development of requirements towards candidates
Consider and Apply	Job postings analysis and response to the selected ones	Search and attraction of candidates
Assess	Participation in evaluations and/or interviews; evaluation of job offer	Pre-screening and selection through evaluations and interviews; making the final decision
Accept	Acceptance of the job offer; contract signing	Pre-hiring checks; contract preparation
Retention		
Explore	On-boarding	Organization of the employee on-boarding
Build-up	Acquiring necessary knowledge; performing core duties	Ensuring the core and necessary training; employee assessment
Maturity	Achieving performance maturity	Monitoring of employee's satisfaction and performance
Repeat or decline and leave	Expansion of professional horizons; horizontal / vertical move or leave	Providing with additional professional opportunities, employment termination

Figure 2: Stages of the Lifecycle from the perspective of employees and employers
Source: Gladka et al. (2022)

The recruitment and hiring process begins with identifying the need for a new hire and crafting a detailed job description. Companies then utilize various channels to advertise the open position, including job boards, social media platforms, company websites, and recruitment agencies. The search for candidates may also extend to active headhunting, employee referrals, and participation in job fairs, allowing companies to tap into diverse talent pools.

There is relatively little need for artificial intelligence at this stage. AI-based tools may help to write the job descriptions but there are limited other options.

Once applications start coming in, the screening process begins. Recruiters and hiring managers review resumes and cover letters to shortlist candidates who align with the job's requirements. Obviously, there is a lot of potential for AI to review often hundreds of applications and check them with the requirements. It is also helpful to have a standardized approach to limit potential biases in the review phase.

Initial interviews, often conducted over the phone or through video calls, help further narrow down the pool of applicants. In some cases, candidates are also asked to complete assessment tests or assignments that are relevant to the job they are applying for, adding another layer of evaluation. There are already AI-based tools to contribute to this area and which will be introduced in more detail later.

Following multiple rounds of interviews and assessments, the best candidate is selected. This decision is based on various factors, such as their skills, experience, cultural fit within the company, and potential for growth.

Once a suitable candidate is identified, the company extends a job offer, which outlines the salary, benefits, job title, and other employment terms. At this stage, there may be some negotiation before the candidate formally accepts the offer.

In preparation for the new hire's arrival, the company ensures that everything is ready for their onboarding. This involves setting up their workspace, arranging the necessary equipment, and completing all required administrative paperwork. Additionally, an onboarding schedule is typically developed to guide the new hire through their first few days or weeks, covering training and orientation activities designed to help them integrate smoothly into the company.

The onboarding and integration process begins with orientation sessions designed to familiarize new employees with the company's culture, values, policies, and procedures. These sessions help newcomers understand the organization's mission and how their specific roles contribute to the overall goals of the company.

<u>Culture Amp</u> has shown this chart showing the difference active onboarding can have. It definitely makes sense to familiarize new employees with the colleagues and culture.

Engagement by Tenure Month
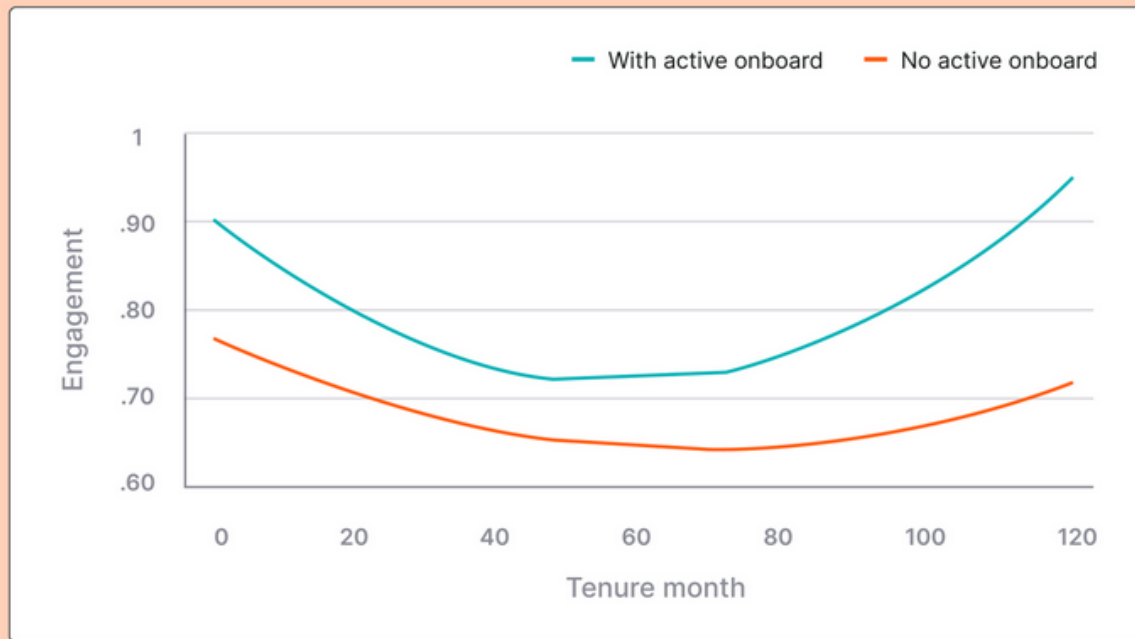
Following orientation, initial training programs are offered to ensure that new hires are equipped with the skills and knowledge they need to perform their jobs effectively. These training sessions may cover technical aspects of the job, compliance requirements, and specific role-related instructions. To foster continuous learning, companies also introduce ongoing development opportunities, allowing employees to expand their skill sets over time.

To further support a smooth transition, many companies assign mentors or buddies to new hires. These mentors serve as guides, providing answers to questions, offering advice, and helping the newcomers navigate both their roles and the broader organizational environment.

To ensure that new hires are adapting well and meeting the company's expectations, performance monitoring is often initiated early on. There are AI-based tools which are used to support the performance monitoring and management of employees. Regular feedback sessions and performance reviews allow for any potential issues to be identified and addressed promptly, ensuring that the new employees receive the necessary support to succeed in their roles.

Career development and progression are essential aspects of an employee's journey within a company, beginning with performance management. Regular performance reviews are a

fundamental part of this process, where employees and managers work together to set clear goals, provide constructive feedback, and evaluate performance metrics.

To further support career progression, companies design structured career paths that guide employees through various stages of growth and advancement. In investment banking, graduates start as analysts and are promoted to associates after three years of work and to vice presidents after six years if they receive positive reviews.

By establishing clear criteria for promotions, companies enable employees to work towards specific milestones and competencies that are required for higher-level roles, making the path to advancement more transparent and achievable.

Continuous learning is another key component of career development. Companies often offer a range of learning opportunities, such as workshops, courses, certifications, and the attendance of conferences. These initiatives help employees enhance their skills and stay current with industry trends, ultimately contributing to both their personal development and the company's success. This might increase the value of the employee for other companies, but in the long run it pays off to have a well-qualified workforce.

Succession planning is also important for organizational sustainability. This is not only important for C-level jobs but across the complete organization. By identifying and developing high-potential employees, companies can build a strong talent pipeline for leadership roles. Through targeted development programs, these future leaders are supported to ensure they are well-prepared to step into key positions when the time comes.

According to data from the OECD published in 2024, the typical tenure at a company are on average around 10 years. That might change in the future and reach US levels which are below that number. That indicates that there is a need to have a good offboarding and alumni management.

The offboarding and alumni management process begins with exit interviews when an employee decides to leave the company. These interviews are conducted to gather valuable feedback on the employee's experience, providing insights that can help the company improve employee satisfaction and retention strategies.

A critical part of offboarding is the transfer of knowledge. Ensuring that the departing employee's knowledge and responsibilities are passed on to the remaining staff is essential for a smooth transition. This process often includes detailed documentation and training sessions that help retain continuity and minimize disruptions in workflows.

Employees do not often have a strong incentive to document their work. That is especially true for software engineers as it makes them less replaceable. However, there are also AI-based tools which help to document existing workflows.

The formal exit process involves managing all administrative tasks related to the end of employment. This includes settling final pay, retrieving company property, and deactivating the departing employee's access to company systems. Clear communication throughout ensures that all necessary steps are completed efficiently and without confusion.

Even after employees leave, maintaining positive relationships can benefit the company. Alumni networks and engagement initiatives keep ex-employees connected to the organization, which can lead to future collaborations, rehires, or referrals. These networks also enhance the company's reputation and strengthen its employer brand, creating a lasting positive impact.

1.5 How to think about artificial intelligence

Let us now move to artificial intelligence. It is a new exciting area which will be around for the next decades.

In traditional programming, a program uses explicitly defined rules to process input data and generate output data. This approach is stable and deterministic, ensuring predictable outcomes. For example, converting temperature from Fahrenheit to Celsius involves a straightforward calculation with predefined steps.

Artificial intelligence takes a different route. It uses input data and corresponding output data to learn and generate the rules. This method is particularly useful in situations where writing explicit rules is complex or impractical. For instance, distinguishing between images of cows and horses would require an exhaustive list of rules in traditional programming. Instead, AI systems can be trained with numerous examples of both animals, enabling the system to learn the distinguishing features and classify new images correctly. The machine is thus learning.
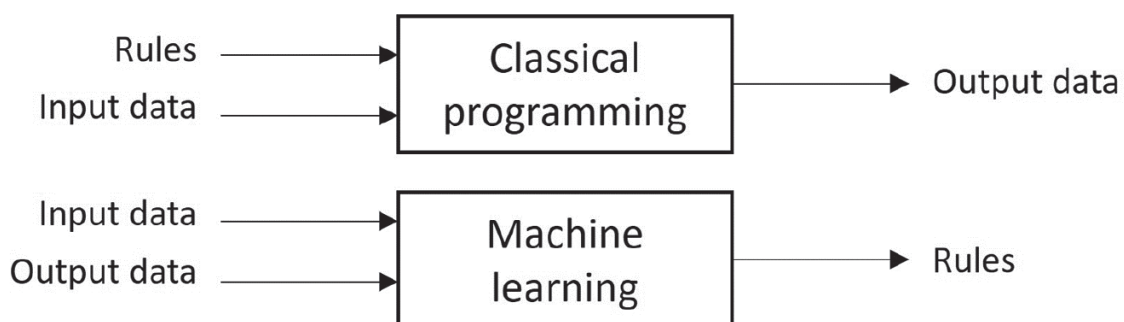

Figure 3: Classical programming compared to machine learning
Source: Spiess-Knafl (2022)

Neural networks, a subset of AI, exemplify this approach. They approximate the relationship between input and output data through extensive training. By adjusting internal parameters

during the training process, neural networks minimize the error between predicted and actual outcomes, thus learning the underlying rules.

A practical illustration of this is the image search feature on smartphones. When you search for a term like "zebra," the algorithm identifies and returns relevant images. This capability is surprising given the complexity involved in distinguishing a zebra from other animals. A traditional algorithm would struggle with this task, but an AI-based approach efficiently handles it by learning from vast datasets of labeled images.

Exercise

Think about the following two questions:

- How would you write the rules to differentiate a cow from a zebra? How many rules would you need, and you how would you write them?
- What are the rules to identify dogs as dogs and cats as cats?

For us, it is straightforward and intuitive, but nobody has ever achieved to write a complete set of rules to separate images. That is also the reason why the rules-based algorithms of the 1970s were not successful in the end.

Below are examples from a smartphone picture app. It shows the animals but also a zebra crossing which is an amazing result. This is surprising when you think about it. How could you write a program which identifies zebras, horses or women. You know the differences but you would need a few thousand lines of codes to separate cows from horses. In the case of the zebras, you would show the system 10,000 images of zebras and 10,000 images of horses and the system would learn to separate the images of zebras and horses.

You can also test it on your smartphone. Note the zebra stripes on the right-side image.

In practice, the strength of artificial intelligence lies in handling vast amounts of data to identify patterns and make predictions. Platforms like Netflix and Spotify use AI to recommend

content by analyzing user preferences and behavior, a task that would be nearly impossible with manual classification.

The ability of artificial intelligence to generate rules from data has profound implications across multiple fields. In healthcare, AI-based systems assist in diagnosing diseases by learning from medical images and patient records. In finance, AI algorithms detect fraudulent transactions by identifying patterns that signify unusual activity.

The evolution of AI represents a significant shift from rule-based systems to data-driven learning. This paradigm enables more flexible, adaptive, and accurate solutions, paving the way for innovations that were previously unimaginable.

Much of our world is already a black box and it will get more "black-boxy" over time as a significant part of all tasks will be completed by neural networks in the near future. It is driven by the nature of the neural networks outlined above.

The maps of population density show impressively the difference between different datasets. One dataset is provided by Eurostat.

It includes the following variables and is based on the 2021 Census:

- Sex (male and female)
- age (under 15 years, 15-64, 65 years and over)
- current activity status (number of employed persons), voluntary bases
- country / place of birth (place of birth in reporting country, place of birth in other EU country, place of birth elsewhere)
- place of usual residence (total population)
- place of usual residence one year prior to the census (usual residence unchanged, move within the reporting country, move from outside the reporting country)

It is thus an exact measure of the European population based on census data.
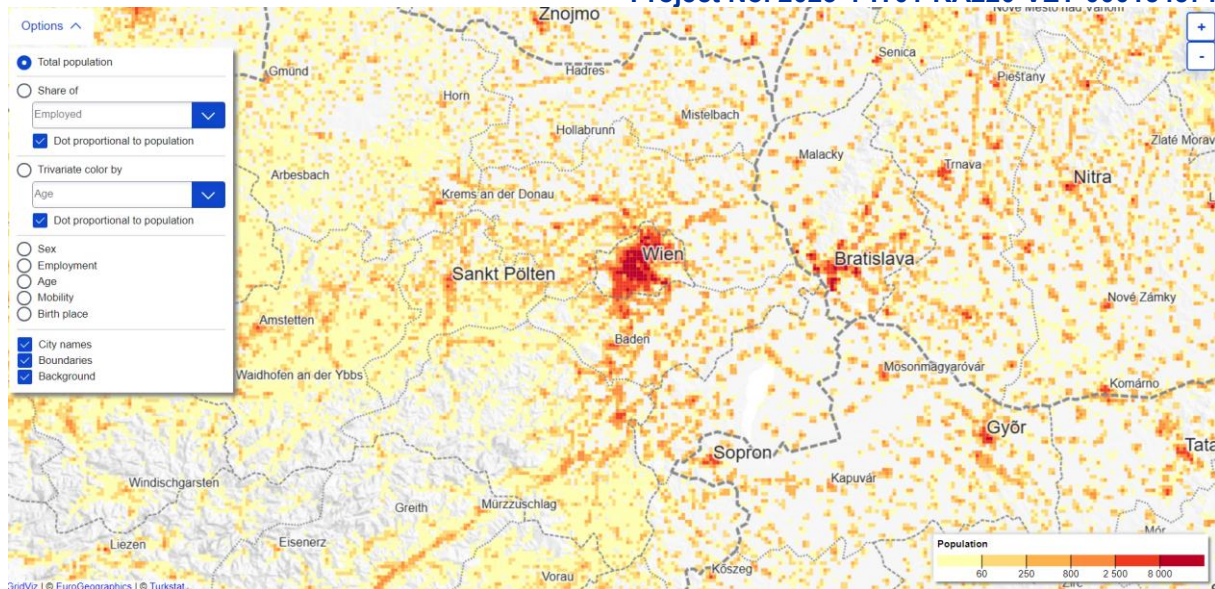
Compare this data to a dataset based on machine learning. Data for Good at Meta has used machine learning to estimate population density in grids of 30 x 30 meters (if you are interested in the methodology). The differences between the census data and the AI-based data shows the potential for machine learning across all domains.
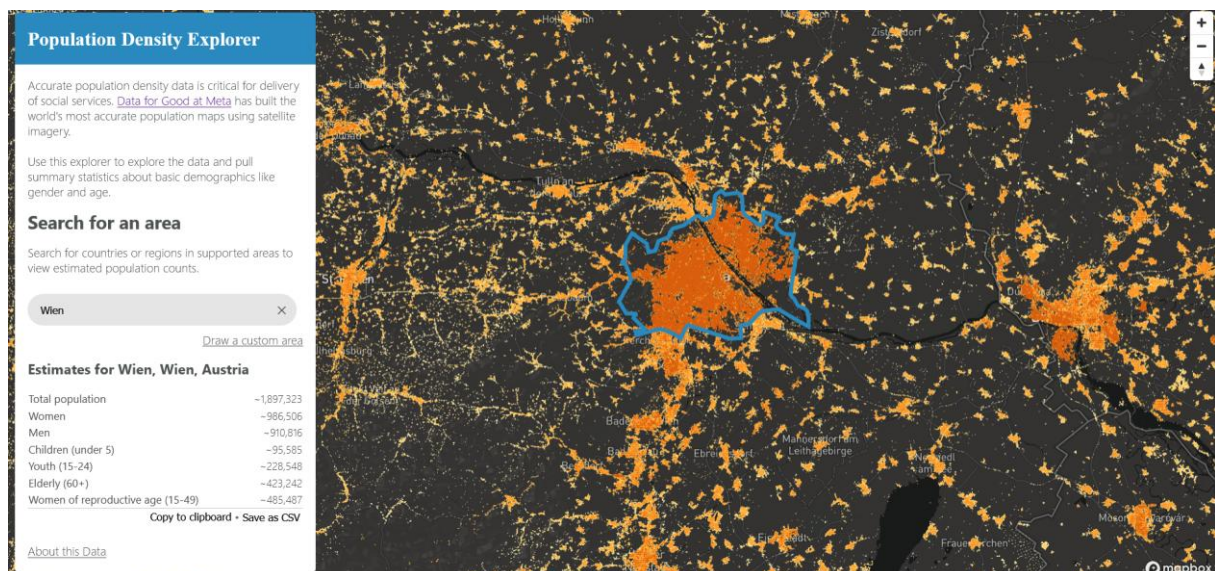
1.6 Different AI-based models

Artificial Intelligence (AI) encompasses a variety of models, each with unique approaches and applications. A good overview was written by Domingos in his book on "The Master Algorithm"

published in 2017. The models we discuss in this chapter include neural networks, symbolic AI and evolutionary algorithms.

Neural networks are a foundational model in AI which receives the most funding. It is loosely inspired by the human brain's structure and function. They consist of interconnected nodes, or neurons, that process data through layers shown in the image below.

These networks learn by adjusting the weights of connections based on the data they process. This training process, often involving backpropagation, minimizes the difference between predicted and actual outcomes.

They are widely used in image and speech recognition, natural language processing, and predictive analytics. Below is an image of a very simple neural network which shows the weights and biases. The largest models use more complicated structures and have billions of these parameters.
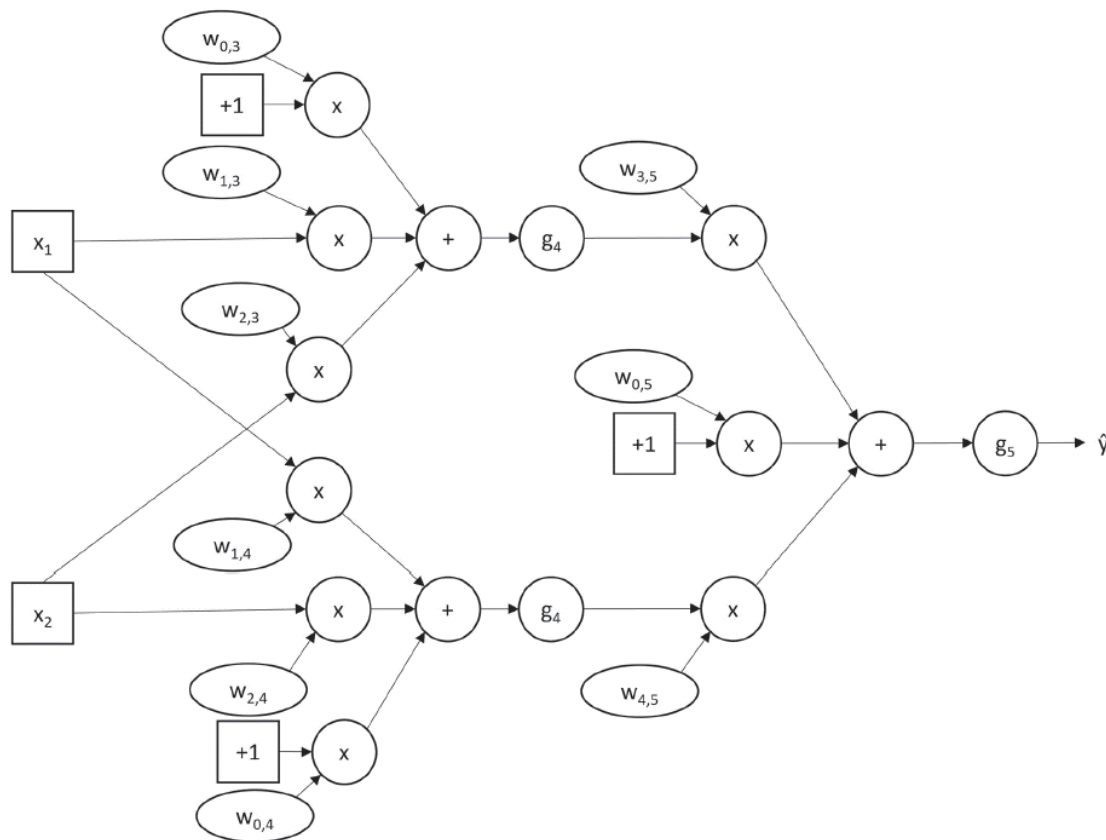
Figure 4: Structure of a Neural Network
Source: Russell & Norvig (2020)

Symbolic AI or rule-based AI relies on predefined rules and logic to process information and make decisions. Unlike neural networks, which learn from data, symbolic AI operates on explicit representations of knowledge.

Symbolic AI systems use symbols to represent objects, actions, and relationships. They manipulate these symbols according to logical rules to derive conclusions or perform tasks. These systems require human experts to define the rules and knowledge base. The process involves encoding domain knowledge into a format the AI can process.

Symbolic AI is effective in areas requiring clear, logical reasoning and decision-making, such as expert systems, automated theorem proving, and game playing. They are also relevant when it comes to knowledge programs. Some are referring to it as Retrieval-augmented generation (RAG).

Below is one example for a knowledge graph which can also be expanded across other domains. The advantage of these knowledge graphs is that they do not hallucinate and their answers are factual.
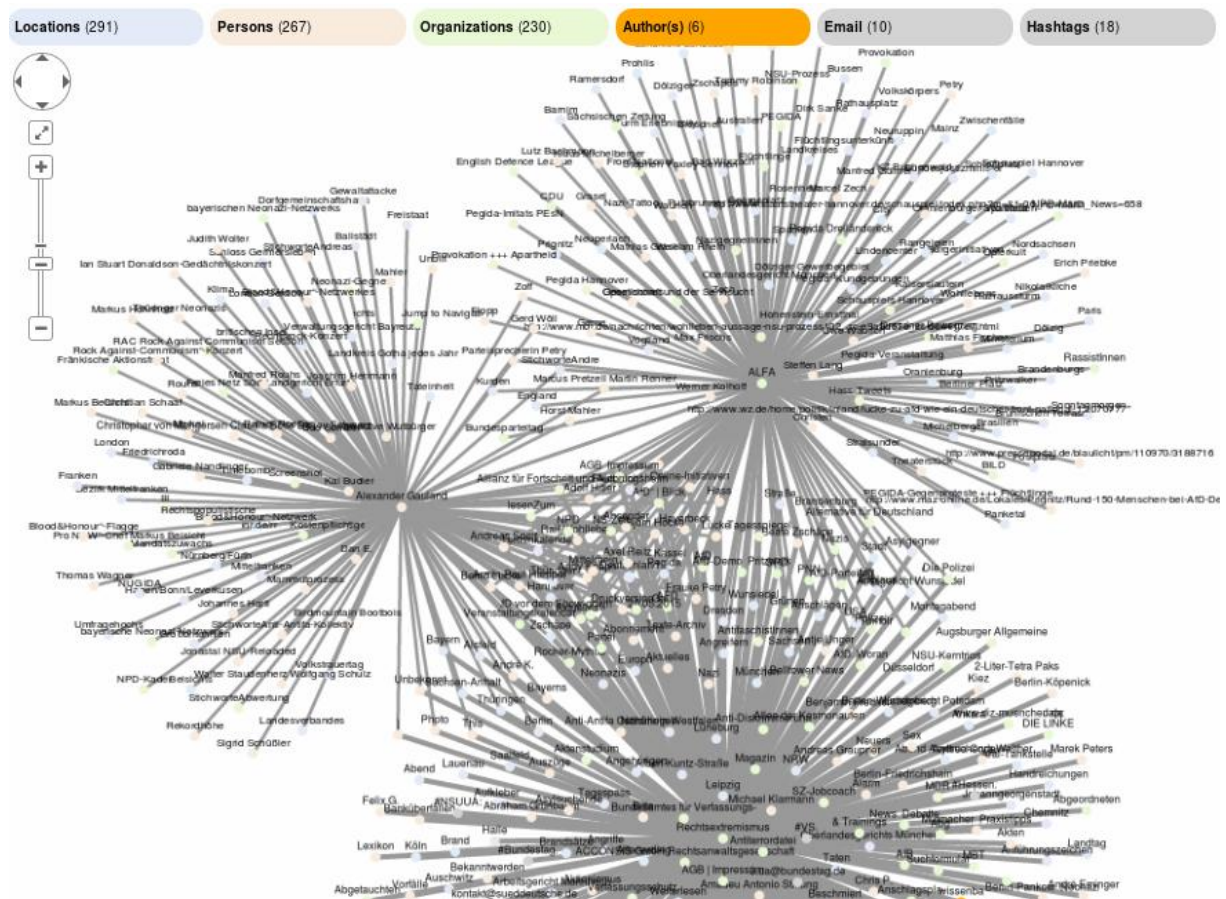
Evolutionary algorithms are inspired by the process of natural selection. They use mechanisms such as mutation, crossover, and selection to evolve solutions to problems over successive generations.

These algorithms start with a population of potential solutions, which evolve over time based on their fitness scores. The fittest solutions are selected to produce offspring for the next generation. These algorithms are particularly useful for optimization problems, where they can explore a vast search space and converge on optimal or near-optimal solutions.

Definition

Artificial intelligence (AI) encompasses systems and machines designed to mimic human intelligence to perform tasks. These systems continuously improve their performance based on the data they gather and process. AI systems can learn from experience, adjust to new inputs, and perform human-like tasks such as visual perception, speech recognition, decision-making, and language translation. At the moment, large language models and image recognition are the best-known tools.

A typical definition proposed by a working group organized by the (European Commission, 2018c) defines AI as follows:

> *"Artificial intelligence (AI) refers to systems that display intelligent behavior by analyzing their environment and taking actions – with some degree of autonomy – to achieve specific goals.*
>
> *AI-based systems can be purely software-based, acting in the virtual world (e.g. voice assistants, image analysis software, search engines, speech and face recognition systems) or AI can be embedded in hardware devices (e.g. advanced robots, autonomous cars, drones or Internet of Things applications)."*

This definition emphasizes several important aspects of AI.

First, AI systems exhibit intelligent behavior, as they can analyze their environment and make decisions based on that analysis, mimicking behaviors that would be deemed intelligent in humans. Additionally, these systems possess a level of autonomy, enabling them to operate independently and carry out tasks without continuous human oversight.

AI is also inherently goal-oriented, designed to achieve specific objectives, whether set by humans or determined through the system's own analysis. As a final point, artificial intelligence can be integrated into both software applications and physical devices, expanding its scope and applicability across various fields.

1.7 Current developments and outlook

At present and for the foreseeable future, billions of Euros are being invested in the development and advancement of artificial intelligence models. These investments span various levels, including foundational model development, implementation, and deployment across numerous industries. The rapid pace of AI development is changing businesses, driving innovation, and reshaping the future of work and society.

The interesting part is that many models are being provided on an open-source basis and can be used by anyone for any purposes.

Significant financial resources are being allocated to the creation and refinement of foundational AI models. These models, which include deep learning networks, reinforcement learning algorithms, and natural language processing (NLP) systems, serve as the building blocks for more specialized applications.

Examples of notable foundational models as of summer 2024 include:

- GPT-4o by OpenAI: This state-of-the-art language model has demonstrated remarkable capabilities in generating human-like text, answering questions, and performing a variety of language-based tasks. It also helped to popularize the concept in the wider public.
- AlphaFold by DeepMind: This model has made significant strides in predicting protein folding, a complex biological problem, with implications for drug discovery and medical research.
- DALL-E by OpenAI: An AI model that generates images from textual descriptions, showcasing the potential of AI in creative fields. You might have also used MidJourney or other models.

The implementation of AI is becoming increasingly prevalent across various sectors and will continue to do so for the foreseeable future. Companies are integrating AI into their operations to gain a competitive edge and improve customer experiences.

AI is used in healthcare for diagnostic tools or personalized medicine. They are useful to analyze medical images, predict patient outcomes, and assist in early disease detection.

In finance & banking, artificial intelligence is used for fraud detection, algorithmic trading, credit scoring, and customer service automation.

The adoption of AI in businesses is not limited to corporations (Spiess-Knafl, 2022). AI-based models are used to monitor environmental changes or optimize energy usage. There are also AI-driven personalized learning platforms which show educational content based on to individual needs, thereby improving learning outcomes.

Attention-Check Question

Which of the following best describes the difference between traditional programming and artificial intelligence?

A. Traditional programming uses data to learn and create rules, while AI systems apply predefined rules to generate output.

B. Traditional programming relies on explicitly defined rules to process data and generate predictable outcomes, while AI learns patterns from data to create rules and make predictions.

C. Traditional programming is more effective in identifying patterns in large datasets, while AI is limited to simple tasks.

D. Traditional programming mimics human intelligence, while AI cannot make decisions independently.

Which stage in the employee lifecycle involves ensuring that departing employees' knowledge and responsibilities are transferred to remaining staff, and why is this process important?

A. Recruitment
B. Onboarding
C. Career Development
D. Offboarding

Please select the correct answer and briefly explain the significance of this stage for organizational continuity.

2.Skills-based hiring and well-being

Objectives:

- Understanding the skills-based hiring process by learning how digital transformation is changing recruitment practices in companies;
- Exploring the role of well-being in the workplace by examining how companies use AI and other tools to enhance workplace well-being.

2.1 Hiring process

What does it mean to hire employees? Hamilton and Davison (2018) provide a delineation of this conventional recruitment process in their paper "The search for skills: Knowledge stars and innovation in the hiring process", detailing the steps involved in attracting and securing the right candidates for the job.

The traditional recruitment process unfolds in six steps: It begins with workforce analysis to identify staffing needs, followed by recruitment efforts to attract candidates. Candidates are then screened to filter the applicant pool, after which the most fitting individuals are selected. These candidates are hired and officially brought into the organization, where they embark on development programs to enhance their skills and integrate into their new roles.

Traditional Process:

Workforce Analysis → Recruit → Screen → Select → Hire → Develop
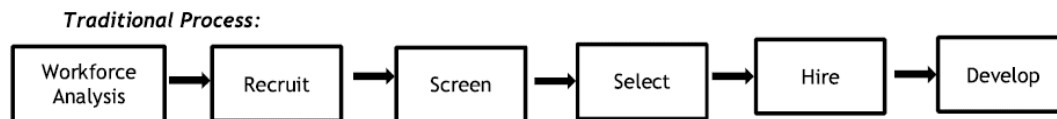
Figure 5: Traditional recruitment process
Source: Hamilton and Davison (2018)

Companies need to have a good understanding of the skills they are looking for. There might also be the need for foresight and prediction of future needs.

Exercise:

Take your company and think about the skills you might need in 2030 and in 2040. What kind of services will be offered, and which skills are necessary to deliver these services.

Employer might want to know which persons to hire and how the future performance can be predicted (Tambe et al., 2019). This is itself biased as performance is an imperfect score and depends on historical data which is often incomplete and distorted. In addition, employers might be hesitant or even legally prohibited to use social media data.

2.2 Digital Transformation in Recruitment

The digital transformation in recruitment has changed the way companies attract, evaluate, and hire talent. In general, the recruitment process has become more efficient, data-driven, and candidate-friendly. Until quite recently, companies had to process hundreds of paper-based applications sent to apply for specific jobs.

Take a company such as PwC. Alone in Germany, they have 14,000 employees with a constant fluctuation of staff as many see it as a good entry-level position and often leave after a few years. That means that they need to attract and process thousands of applications every year.

Two key components of this transformation are Applicant Tracking Systems (ATS) and the use of social media and professional networks.

Applicant Tracking Systems have significantly streamlined the recruitment process by automating several time-consuming tasks. These systems are designed to handle large volumes of applications efficiently, ensuring that the recruitment process is both faster and more effective.

ATS platforms also allow recruiters to post job openings across multiple job boards and social media platforms simultaneously. This automation saves time and ensures a wider reach, increasing the pool of potential candidates.

One of the most labor-intensive parts of recruitment is screening resumes. These platforms can automatically filter resumes based on predefined criteria such as keywords, skills, and qualifications. This helps in quickly identifying the most suitable candidates, reducing the time-to-hire and improving the quality of hires. We will come back to these screening tools later in the module. However, we can already say that there might be some ethical problems in using standardized tools.

These systems also streamline the interview scheduling process. By integrating with calendar systems, ATS can automatically propose interview times based on the availability of both candidates and interviewers. This reduces the back-and-forth communication typically involved in scheduling interviews and enhances the candidate experience.

Social media and professional networks have become integral to modern recruitment strategies. Platforms like LinkedIn, Twitter, and Facebook are not only used for sourcing candidates but also for building a strong employer brand.

Networks such as LinkedIn provide a vast database of potential candidates. Recruiters can use advanced search features to find candidates with specific skills and experiences. LinkedIn also offers tools for recruiters to reach out directly to passive candidates who may not be actively looking for a job but are open to new opportunities.

Social media platforms play a crucial role in shaping and promoting an employer's brand. Companies can showcase their culture, values, and work environment through regular posts, employee testimonials, and behind-the-scenes content. A strong employer brand attracts top talent by creating a positive perception of the company as a desirable place to work.

Social media enables recruiters to engage with potential candidates by participating in relevant discussions, joining professional groups, and sharing industry insights. This engagement helps build relationships with potential candidates and keeps the company on their radar for future opportunities.

It is important to maintain a positive candidate experience throughout the hiring process. That is similar to what software designers call the "User Experience". It can help to enhance the company's reputation but also increases the likelihood of candidates accepting job offers and referring others to the organization. To achieve this, companies must focus on maintaining clear communication, providing timely feedback, and ensuring a smooth onboarding process.

The figure below shows the logic adapted from the lending business. You want that the applicants accept your job offer and you only reject those applications which you do not deem good enough.
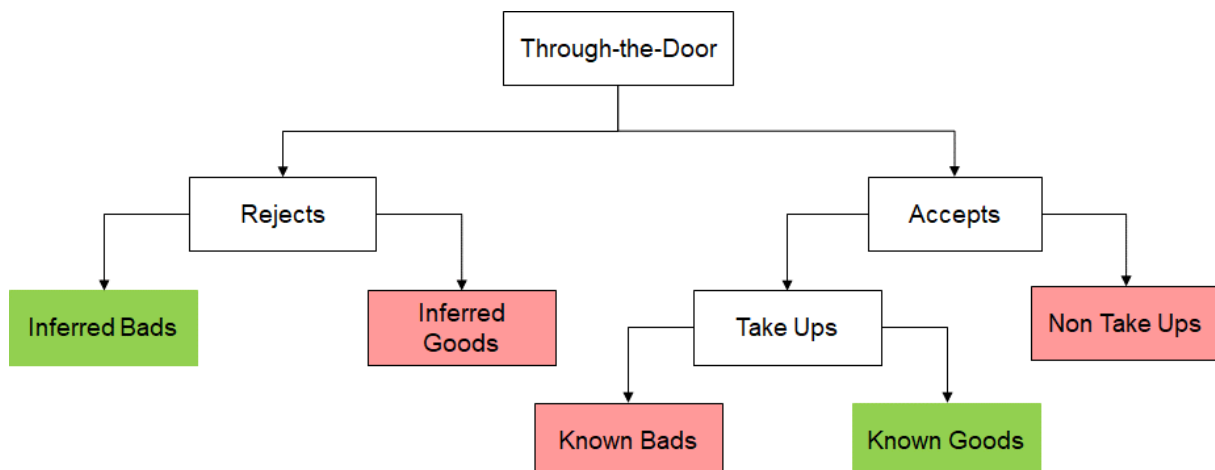
Let us stay for a moment at this user experience.

Clear and consistent communication is important for a positive candidate experience. Everyone appreciates being kept informed about their application status and the next steps in the hiring process. This includes acknowledgement of the receipt of applications, regular updates on the status of the application process and timelines.

Once an employee signs the employment contract, onboarding is the next step. Onboarding is a critical phase that can set the tone for an employee's experience with the company. A smooth onboarding process helps new hires feel welcome, prepared, and integrated into the organization.

There should be processes which include setting up the workspace, arranging equipment, and preparing any required documentation. Larger companies can create an orientation program that introduces new hires to the company's culture, values, and key team members. A tour of the office and introductions to colleagues can help new employees feel more comfortable.

A structured training plan that covers essential job functions, company policies, and any necessary tools or systems. Ensure new hires have access to resources and support to help them get up to speed quickly.

Some companies also use mentor or buddy systems to help new employees navigate their new roles and the organizational environment.

2.3 Compliance and Legal Considerations

The compliance with legal and regulatory standards is also a part of worker management. Companies must ensure fair treatment of candidates, protect their rights, and maintain the integrity of the organization. These considerations encompass labor laws, equal opportunity regulations, and data privacy requirements.

Let us go through the individual steps.

Labor laws protect workers' rights and promote fair employment practices. During recruitment, companies must ensure compliance with these laws to avoid legal consequences and foster fairness. The labor laws include minimum wage regulations or other industry-wide agreements, ensuring job postings and offers meet statutory wage and working hour requirements, and paying appropriate overtime where applicable. Employment contracts must be clear and legally compliant, detailing job duties, salary, benefits, working hours, and termination conditions. Additionally, companies must follow non-discrimination laws by ensuring job advertisements and hiring decisions are free from bias based on race, gender, age, disability, religion, or other protected characteristics.

It is also in the interest of the employer to have good contracts as conflicts around the labor contracts are quite common and can cost significant amounts of money.

Equal opportunity policies aim to promote diversity and inclusion in the workplace. Employers must ensure that all individuals have fair access to job opportunities. This involves enforcing diversity and inclusion policies, such as setting diversity targets, providing bias training for recruiters, and fostering a supportive environment for all employees. Recruitment practices must also be accessible to everyone, including candidates with disabilities. Additionally, equal pay laws must be upheld, requiring equal compensation for work of equal value regardless of gender or other protected characteristics, with regular reviews of pay practices to ensure compliance.

For example, at PwC in the United States the DEI strategy is built around an equity of experience. DEI stands for diversity, equity and inclusion.

Our people's success is contingent on equity of experience

Data privacy laws protect candidates' personal information throughout the recruitment process. Companies must handle candidate data responsibly, collecting only necessary information and securely storing it with robust cybersecurity measures. Candidates must give informed consent before their data is collected, processed, or shared, and they should be informed of how their data will be used and protected. You might often notice all the little boxes you need to click in the recruiting process.

Companies must also respect candidates' rights to access and delete their personal data, providing clear procedures for exercising these rights. Compliance with data protection regulations like the GDPR in the European Union is important, as these laws impose strict data handling requirements and significant penalties for non-compliance.

2.4 Occupations, skills and qualifications

Let us now move to the issue of occupations, skills and qualifications. It is not always entirely clear how to differentiate between education, knowledge, skills and occupations. The following illustration shows the links and relationships between occupations, skills and qualifications with skills in the middle.

It shows that occupations require a set of skills. At the same time, skills are acquired through qualifications.
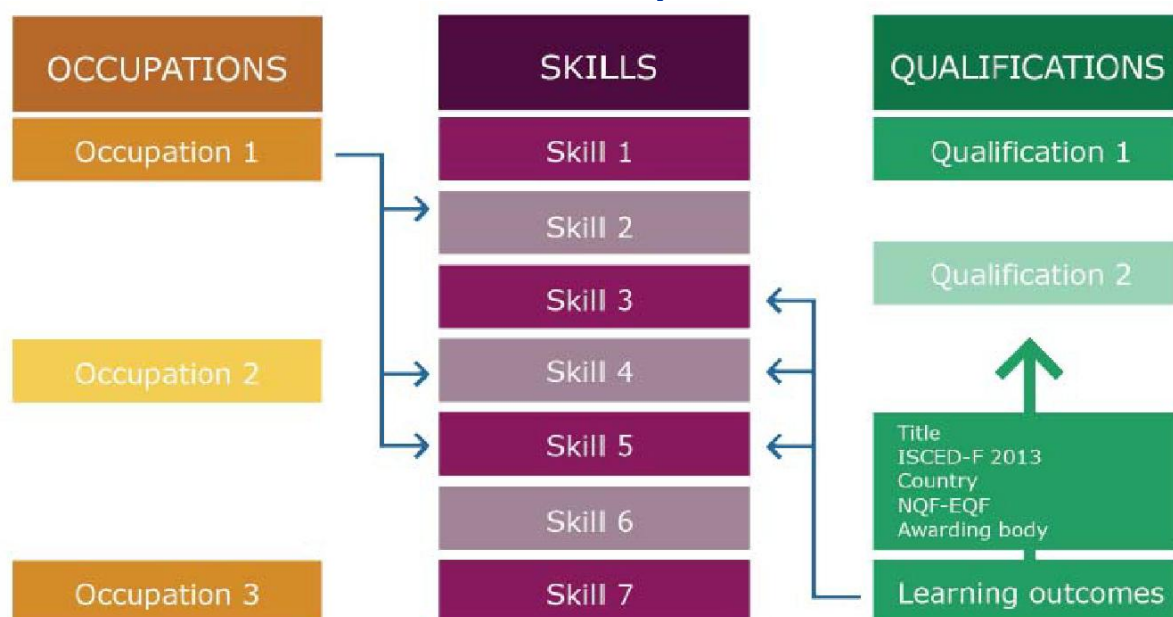
Figure 6: The link between Skills, Occupations and Qualifications
Source: European Commission (2018)

The classification developed by the European Commission lists 2.942 occupations and 13,485 skills and competences.

For example, the ESCO classification has the following skills in the category information skills / documenting and recording information:

- conserve new media
- create semantic trees
- document seismic research
- document prior learning assessments
- ensure proper document management
- handle paperwork related to warehouse stock
- handle shipment paperwork
- log emergency call information electronically
- manage documentation of prior learning assessments
- operate mailing information systems
- record archaeological finds
- record lessons learnt from your sessions
- register information on arrivals and departures
- register visitors

In total, there are 13,485 skills comparable to this list.

The occupations are listed in the following categories:

0 - Armed forces occupations

1 - Managers

2 - Professionals

3 - Technicians and associate professionals

4 - Clerical support workers

5 - Service and sales workers

6 - Skilled agricultural, forestry and fishery workers

7 - Craft and related trades workers

8 - Plant and machine operators and assemblers

9 - Elementary occupations

For example, the list of assemblers has the following sub-categories shown below:

82 - Assemblers

821 - Assemblers

8211 - Mechanical machinery assemblers

8212 - Electrical and electronic equipment assemblers

8219 - Assemblers not elsewhere classified

2.5 Skills

Recent discussions have increasingly focused on the evolving nature of job skills in the face of technological advancements. Over the last years we have seen different streams of discussions.

Deming (2017) has shown how social skills are increasingly important as jobs requiring high levels of social interactions have become more important. In the study he found that a winning combination are math as well as social skills. Heckman and Kautz (2012) summarized personality traits, goals, motivations, and preferences as soft skills.

Digital skills are another category often discussed. Van Laar et al. (2017) see information digital skills, communication digital skills, collaboration digital skills, critical-thinking digital skills, creative digital skills and problem-solving digital skills.

In general, skills are not clearly defined. For example, ESCO defines a "skills and competences" pillars which includes knowledge, skills and competences. Some examples are listed in the table below.

The complication is that skills can be defined in a number of ways such as in the examples below. Take the example of "operating wrecking balls below. There are various ways to label such skills.

Reuse Level	Preferred Label	Alternative Labels	Description
Sector-Specific	operate wrecking ball	- demolish structure with wrecking ball - operating wrecking ball - wrecking ball control - wrecking ball operation - operation of wrecking ball - control wrecking ball - demolition with wrecking ball	Use a wrecking ball to demolish a structure or parts of it. Hoist the wrecking ball into the air with a crane. Drop the ball or swing it in a controlled manner to hit the structure. Prevent misses as the weight and momentum of the ball may destabilize the crane.
transversal	write Hungarian	- writing Hungarian - correspond in written Hungarian - show competency in written Hungarian	Compose written texts in Hungarian.
Occupation-specific	clean beer pipes	- ensure beer pipes are washed clean - clean pipes of beer - wash beer tubes	Disinfect beer pipes on regular basis according to guidelines to ensure the beer is tasty and hygienic.
Cross-sector	interpret religious texts	- explain religious texts - explain religious teachings - clarify religious teachings - clarify religious texts - decipher religious teachings - translate religious texts - translate religious teachings - decipher religious texts	Interpret the contents and messages of religious texts in order to develop spiritually and help others in their spiritual development, to apply the appropriate passages and messages during services and ceremonies, or for theological learning.

Table 1: Examples of different skills

Source: ESCO

There are various options how artificial intelligence can be used to process the data. One way is using natural language processing tools.

One such tool is the Universal Sentence Encoder which can be used to analyze the semantic similarity between different skills (Spiess-Knafl, 2022).

This method visually represents semantic similarities through color-coded clusters, facilitating the clear identification of skills among applicants. These results can be used to accurately classify related occupations, such as different types of technicians.
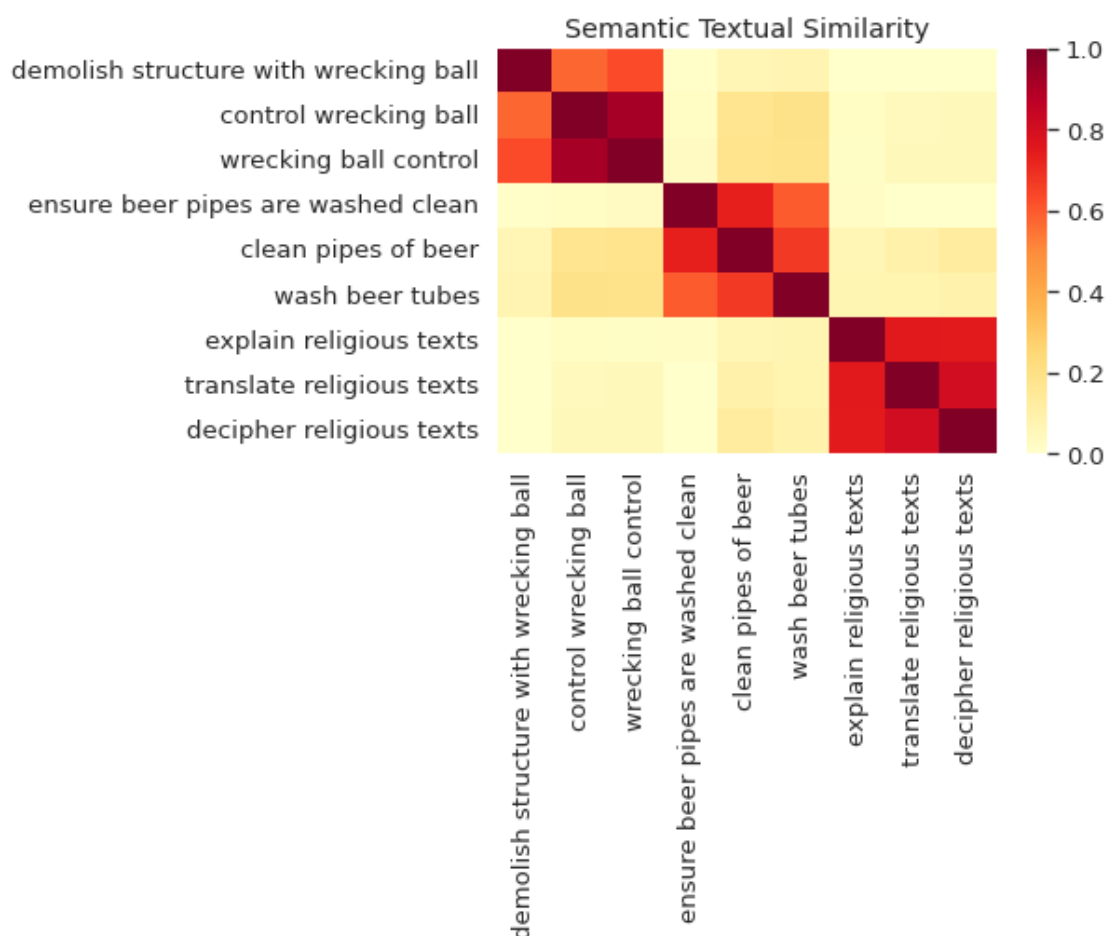
Figure 7: Semantic Similarity of different descriptions
Source: Spiess-Knafl (2022)

You can also try it out by using this link: https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/hub/tutorials/semantic_similarity_with_tf_hub_universal_encoder.ipynb

Another option is to identify an occupation which fits with the personal skill set. Companies which offer matching services use mostly natural language processing. SkillLab is a company which helps individuals to map their work experience into a set of clearly identified skills. Once the model has identified a few dozen skills it can start suggesting occupations which require these skills.
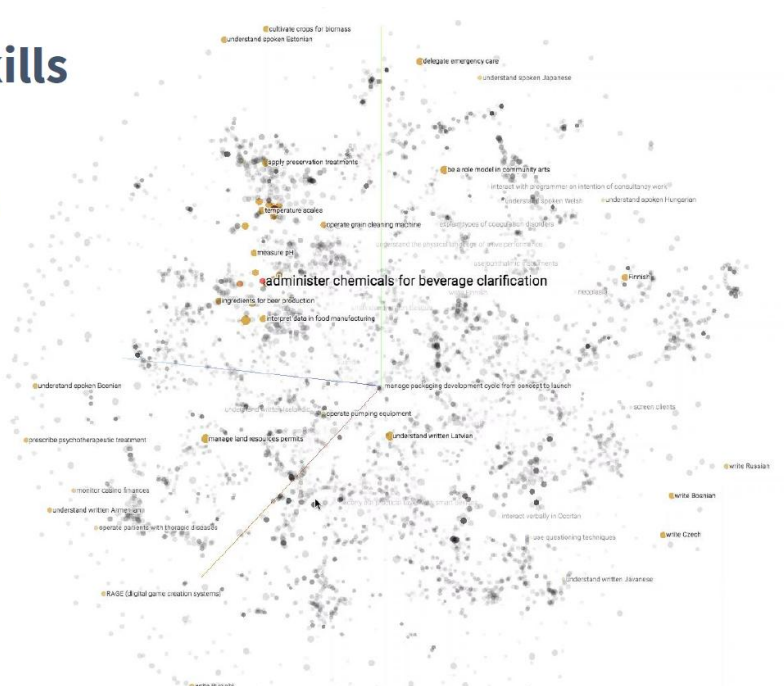
Figure 8: Skills map
Source: SkillLab

Several other companies use AI to analyze and structure skills.

LinkedIn uses AI to analyze job postings and member profiles to identify in-demand skills and recommend relevant job opportunities. The platform leverages machine learning models and natural language processing to match skills with job requirements.

The Burning Glass Institute uses AI to analyze labor market data, providing insights into skill demands and job market trends. The models process large datasets of job postings to identify emerging skills and occupations.

In a recent report, they have looked at the share of job postings that have at least one data science skill. This is a US statistic but the average of 22% might also be similar in the European Union.

FIGURE 2 – Share of job postings listing at least one data science skill as a share of all job ads in the state, 2023
Source: Burning Glass institute analysis of Lightcast posting data

State	Share		State	Share
Distr. of Columbia	30.0%		Michigan	20.9%
Iowa	25.4%		Wyoming	20.9%
Virginia	25.2%		Minnesota	20.8%
California	25.2%		West Virginia	20.6%
Arkansas	24.5%		Tennessee	20.6%
Maryland	23.9%		Ohio	20.4%
South Dakota	23.9%		Kansas	20.1%
Utah	23.7%		Alabama	20.0%
Illinois	23.5%		Oregon	20.0%
Washington	23.4%		Wisconsin	19.7%
Delaware	23.3%		New Mexico	19.6%
Colorado	23.3%		South Carolina	19.5%
Massachusetts	23.0%		Hawaii	19.4%
North Carolina	22.9%		Nevada	19.4%
Texas	22.9%		Mississippi	19.2%
New York	22.7%		Indiana	19.1%
Georgia	22.6%		Kentucky	18.8%
Nebraska	22.4%		Alaska	18.7%
Oklahoma	22.0%		Louisiana	18.7%
New Jersey	21.9%		Florida	18.1%
Rhode Island	21.7%		Maine	18.0%
Connecticut	21.6%		New Hampshire	17.5%
Missouri	21.6%		Montana	17.4%
Arizona	21.3%		North Dakota	17.0%
Pennsylvania	21.2%		Vermont	15.6%
Idaho	20.9%		National average	22.0%

Pymetrics uses neuroscience-based assessments and AI to match job seekers with suitable roles based on their inherent skills and attributes. The platform employs machine learning algorithms to analyze assessment data and predict job fit. We will come back to this approach later in the module.

Faethm uses AI to forecast the impact of technology on jobs and identify the skills needed for the future workforce. The platform integrates machine learning and predictive analytics to model job transformations and skill requirements.

There is little information on the website, and it is not clear if they can really deliver on their promises. For example, on the website, they show the following illustration for" workforce segments are at risk of being stranded by AI". It seems to be a stretch to make reasonable assumptions about which part of the population will lose their jobs.
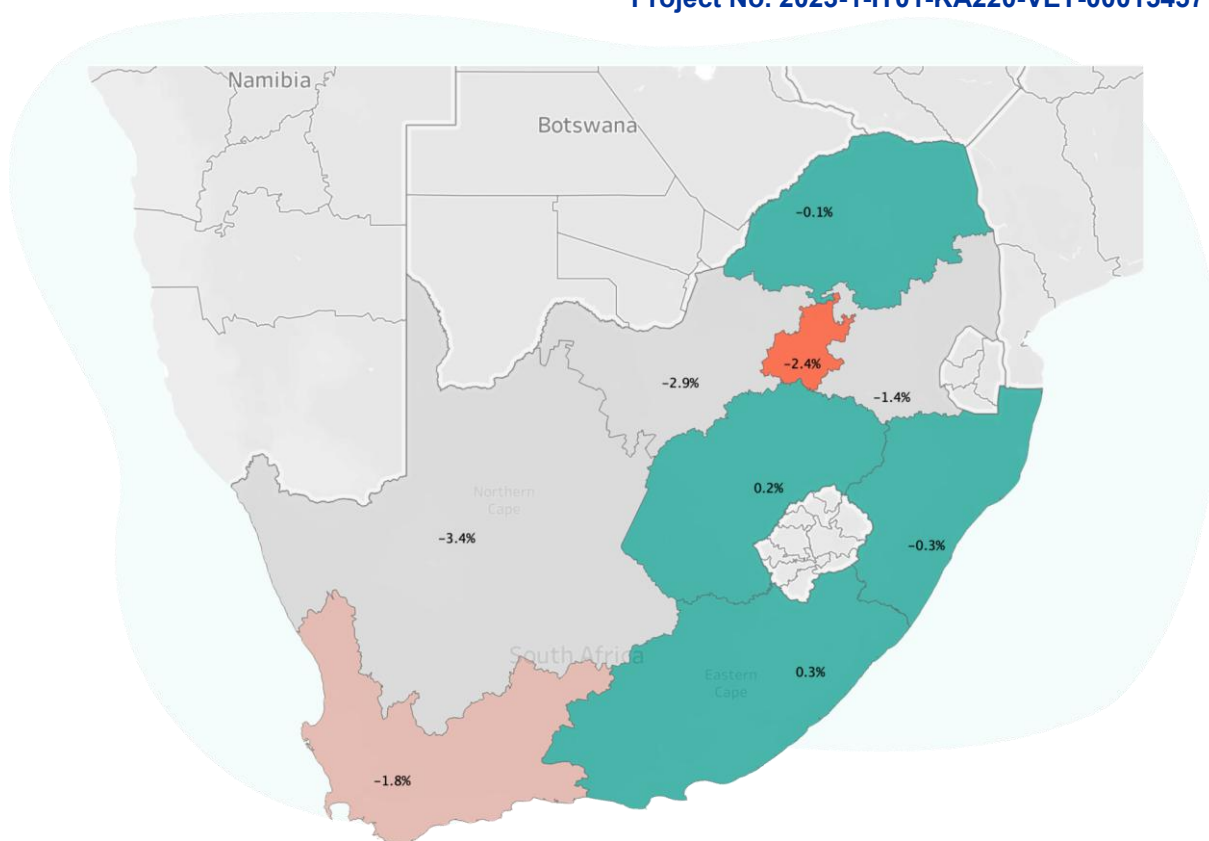
That is one of the aspects to always remain skeptical of impressive claims. It is thus necessary to check the assumptions and consider if the results are consistent with your own assumptions. If you are interested in this area you might like the book and newsletter on AI Snake Oil.

2.6 The other side: Occupations

Occupations refer to the various activities where individuals spend most of their professional careers. They encompass the roles and responsibilities associated with different jobs and are essential in understanding the labor market's dynamics. Defining occupations accurately is crucial for job matching, career development, and workforce planning. Below are examples of different occupations, highlighting their varied nature and the importance of precise definitions.

Occupations are those activities where people spend most of their time pursuing a professional career. There are different approaches to defining occupations. The following table shows some examples of different occupations together with alternative labels and longer descriptions.

Preferred Label	Alternative Labels		Description
Fuel station manager	• supermarket filling station manager • gas station manager • fuel site manager • retail fuel forecourt manager	• retail fuel manager • petrol site manager • fuel retail manager • retail forecourt manager • filling station manager • petrol station manager	Fuel station managers assume responsibility for activities and staff in a fuel station.
Relocation officer	• relocation consultant • relocation commissioner • relocation services officer • relocation specialist	• relocation director • relocation and department officer • relocation manager	Relocation officers help businesses and organisations with the move of employees. They plan the whole move. Relocation officers advise on real estate. They plan moving services and look after the general well-being of the employees and their family.
Cashier	• supermarket cashier • check out operator • shop cashier • toll booth attendant • checkout operator • department store cashier • hypermarket cashier	• checkout assistant • filling station cashier • check out assistant • checkout operative • outlet centre cashier • check out operative	Cashiers operate the cash register, receive payments from customers, issue receipts and return change due.
Bicycle mechanic	• scooter technician • bicycle fixer • bike repairer • bicycle repairer • bicycle shop attendant	• bike technician • cycle repairer • bicycle maintenance technician • bike shop worker • scooter mechanic	A bicycle mechanic maintains and repairs varieties of bicycle models and parts. They may customize alterations according to the specifications of their clients.

	● bike shop assistant ● cycle technician ● bicycle technician ● bike mechanic ● cycle mechanic	● bicycle shop assistant ● scooter repairer ● bicycle repairman ● bicycle shop worker ● bike shop attendant	
Meter reader	● gas meter reader ● metering data reader ● electricity meter reader ● water meter reader ● smart meter reader	● metering data analyst ● billing information analyst ● utility meter reader ● billing information reader ● smart meter data reader	Meter readers visit residential and business or industrial buildings and facilities in order to note down the readings of the meters which measure gas, water, electricity and other utility uses. They forward the results to the client and to the supplier.

Table 2: Examples of different occupations
Source: ESCO

The following figure shows how semantic similarity tools classify similar occupations. The tool classified "scooter technician", "bicycle fixer" and "bike repairer" correctly. However, for "supermarket cashier", "toll booth attendant" and "checkout operative" it gave lower similarity scores.
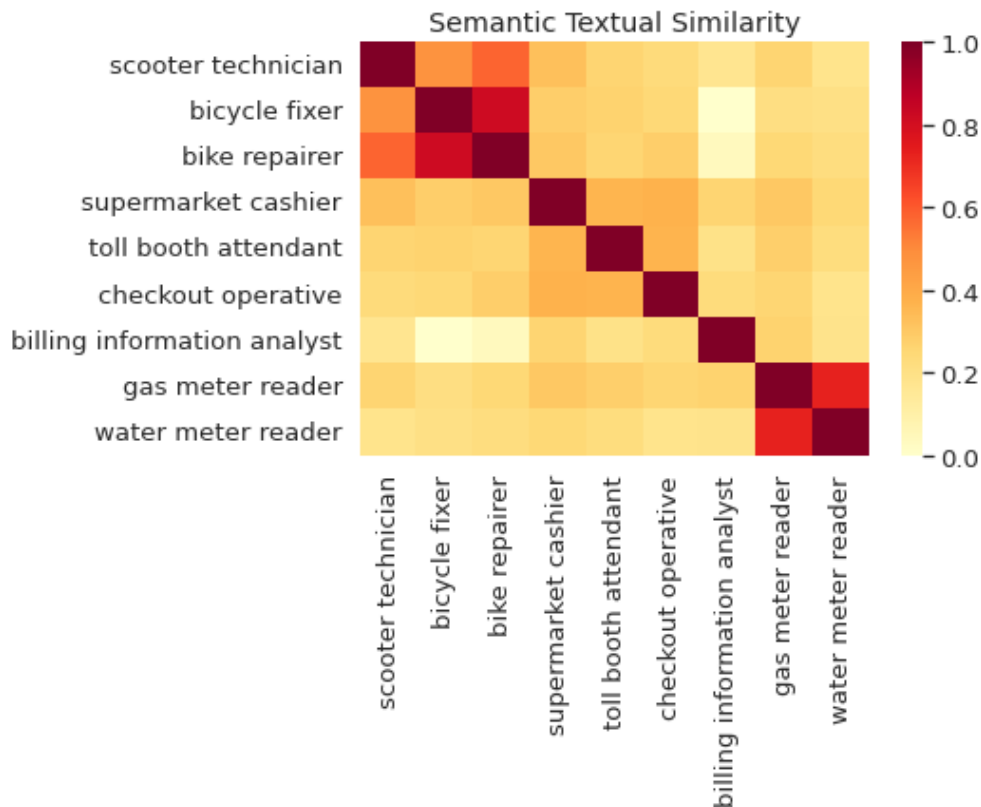
Figure 9: Semantic Similarity of different descriptions
Source: Own illustration based on Tensorflow Universal Sentence Encoder

However, you can see how you can use these tools to map occupations which are described differently.

2.7 Education and qualification

The impact of education extends beyond academic achievement, influencing various socio-economic outcomes including poverty (Raffo et al., 2009), health (Ross & Wu, 1995), crime (Lochner, 2011) or even happiness (Oreopoulos & Salvanes, 2011) among others. Education thus impacts almost all other aspects of our daily lives.

Beyond these societal impacts, education plays a pivotal role in enhancing individual economic prospects, as evidenced by its strong correlation with earnings. Hanushek et al. (2015) find that a one-standard-deviation increase in numeracy skills increases earnings by 18 percent. Montenegro and Patrinos (2013) show that this positive correlation between education and earnings is not isolated to a single economy but is a consistent trend across 131 economies, underscoring the universal value of education. The cross-economy average is 10 percent per year of schooling.

The impact of education is also shown in the research mapping the different Sustainable Development Goals (SGDs) such as in the image below. Education usually plays a central role as better education leads to better health, higher incomes and better lives for the next generation.
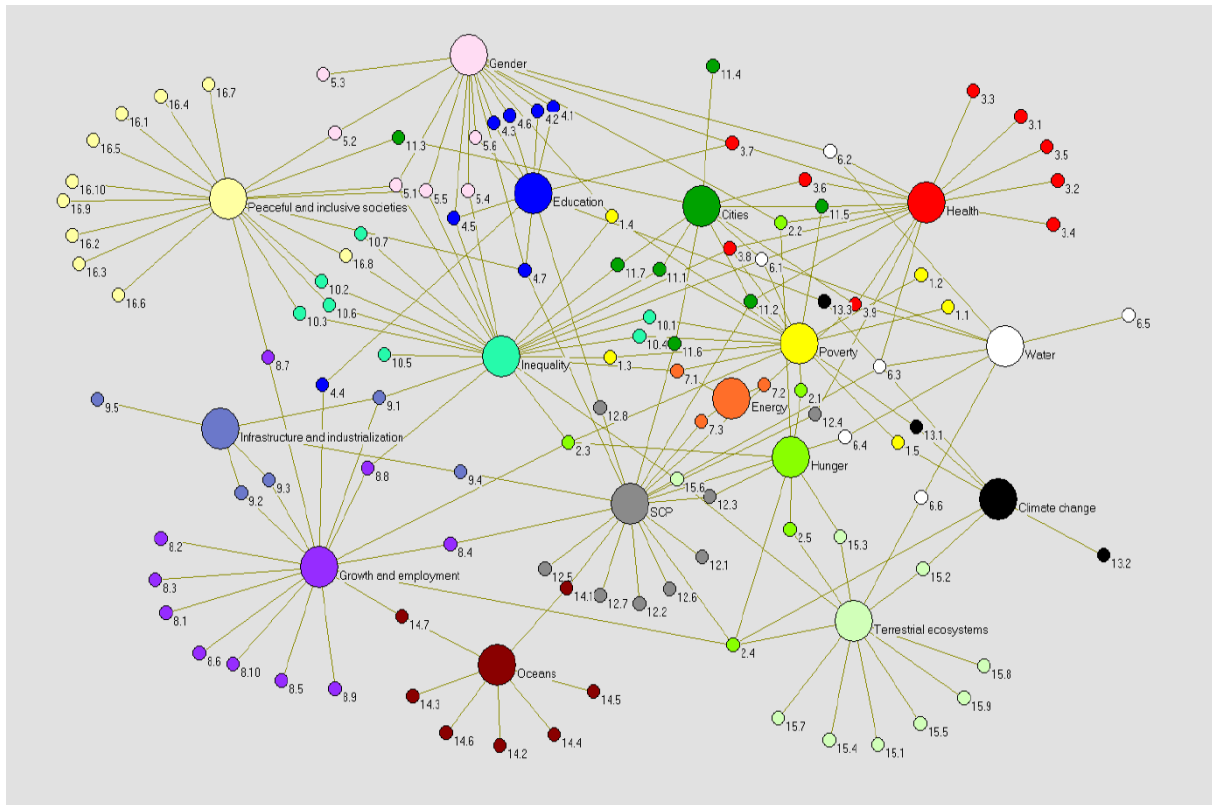
Figure 10: The SDGs as a network of targets
Source: Blanc (2015)

Education tied to a certain occupation is referred to as vocational education whereas general education is not related to any specific occupation. While vocational education is helpful for the transition into the labor market, there is also a risk for unemployment later in the career (Woessmann, 2016). Annabi (2017) discusses the productivity gains because of investments in education.

There is a strand of research discussing the role of credentials and qualifications for the labor market. A consensus is that credentials help to signal productivity and potential to employers. Brown and Souto-Otero (2020) analyze 21 million job advertisements and find that there is a greater emphasis on job readiness. Surprisingly, only one in five advertisements has listed minimum educational requirements.

2.8 Mismatch

There is also a mismatch between supply and demand in the labor market (Spiess-Knafl, 2018). The first number to look at is the number of job vacancies.

Across the European Union, there are 2.2% job vacancies with some variation between countries. While vacancies are higher in Germany (2.9%), the Czech Republic (4.8%) and Austria (2.8%) they are lower in Greece (0.7%), Spain (0.9%) and Poland (1.2%) as of the first quarter of 2018 (Eurostat 2018).

Although there is a lot of talk about the loss of jobs, the evidence is pointing to the contrary. Job churn is at a record low even for the United States (R. Atkinson & Wu, 2017). Job churn is defined as the sum of the absolute values of jobs added in growing occupations and jobs lost in declining occupations. This leads many to argue that policy makers should be worried about productivity growth that is too slow.

Data from the European Commission (2018) illustrated in the Beveridge curve show that there is labor (i.e., skills) shortage but simultaneously low unemployment. That might lead to the conclusion that skills need to be more efficiently allocated among European companies. Moreover, skills need to be developed in life-long learning programs.
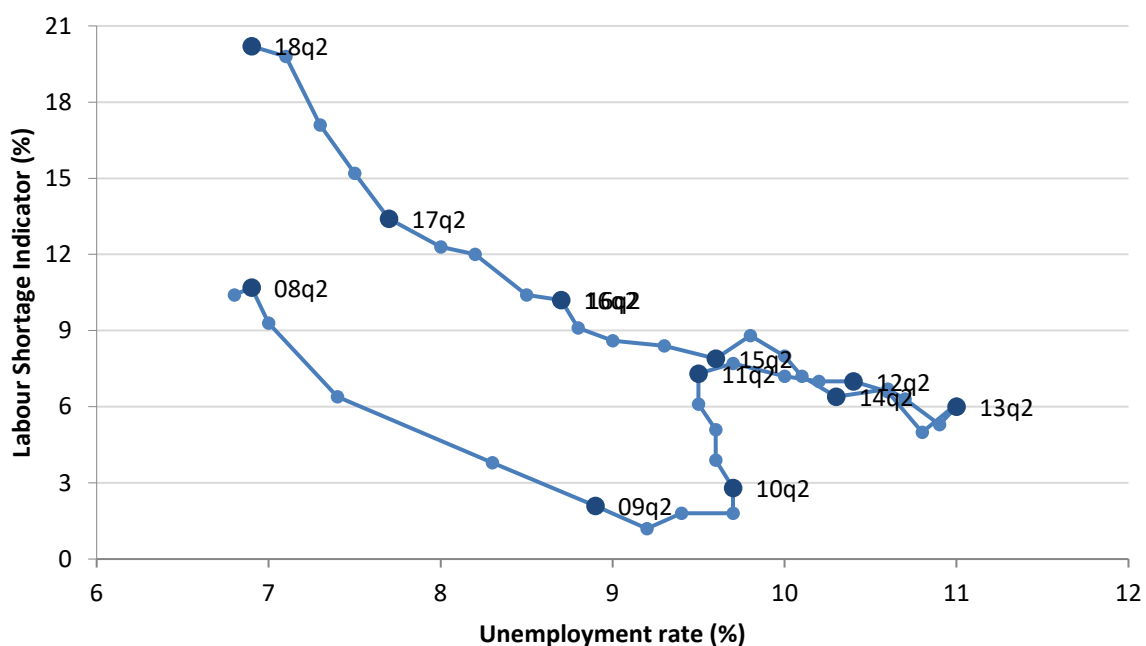

Figure 2: Beveridge curve 2008-2018 – European Union
Source: European Commission (2018)

The low rate of job losses might be explained by the dynamics of the economy and the development of job portfolios. As already outlined above, each job consists of a number of

tasks and skills and a good example might be the lift boy you have encountered in the introduction. This specific job might have disappeared but has reemerged in another form. His duties included customer relationship management, security and concierge services among other things that can be now found in other roles. Each job requires thus a number of skills (language skills, technical skills, personal skills, methodological skills, IT-skills, project management skills, etc.) and is a bundle of different skills.

Skills remain an important driver of wages. There are two ways to estimate wages, and both are related to skills. Thousands of studies are based on Mincer (1974) which links wages to years of schooling and experience. A recent study by Montenegro and Patrinos (2014) found that the cross-economy average rate of return is around 10% per year of schooling. Those studies are based on easily accessible and observable schooling data. Hanushek et al. (2015) use data from the PIAAC (Programme for the International Assessment of Adult Competencies) and show that a one-standard-deviation increase in numeracy skills (based on a normalized data set) is associated with an 18% wage increase among workers.

The development of skills remains an issue as shown by the lifetime employment of persons educated in different systems. A vocational system might bring benefits earlier in the career but results in higher unemployment later in life as shown in the following figure.
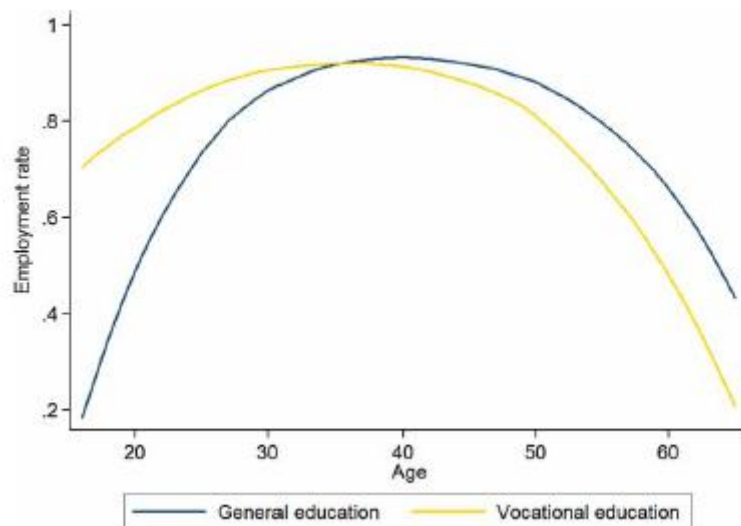

Figure 3: Education Type and Life-Cycle Employment in Denmark, Germany and Switzerland
Source: Hanushek et al. (2017)

The higher unemployment for persons educated in the vocational systems underlines the need for life-long learning.

2.9 Workplace Well-Being

Let us now move to workplace well-being.

A good place to start is to look at existing literature reviews. Aryanti et al. (2020) analyze 75 academic journals and identify the following dimensions which are important for workplace well-being:

- The best use of time: This aspect is defined as the feelings of employees in knowing their work time is important because it forms the balance of employees in dividing work time and personal life (work-life balance).
- Working Conditions: This aspect is defined as employee satisfaction with the work environment such as working spaces and organizational culture.
- Supervision: This aspect is defined as the employee's superior treatment, such as good treatment, providing support and assistance when needed, appropriate feedback, and appreciation from superiors. Several studies have found that employees who have a good relationship with supervisors tend to have high welfare and low stress.
- Promotional opportunities: This aspect is defined as the condition of the work environment that allows employees to develop professionally.
- Recognition of good performance: This aspect is defined as employees' feelings that in their work environment, employees who produce a good performance, and they get equal treatment.
- Appreciation as an individual at work: This aspect has a definition as the employee's feeling that they are valued and accepted as individuals both by their colleagues and superiors.
- Wages: This aspect is defined as employee satisfaction with wages, benefits, and rewards in the form of money earned and the work environment.
- Job security: This aspect is defined as satisfaction with security in their work position.

We all have a good intuitive understanding of what workplace well-being means but let us take a look at the some of the instruments which are used to measure workplace well-being. Measuring employee well-being can be accomplished through various methods, including self-report surveys, biometric data, and observational assessments.

Commonly used instruments include the Gallup National Health and Well-Being Index for the United States and the WHO-5 Well-Being Index, which evaluate multiple dimensions such as purpose, social engagement, financial security, community belonging, and physical health.

In general, well-being is considered on a more general level. For example, the WHO has published a paper in 2023 on "Harnessing the benefits of well-being policies and investments for health" and has used planetary well-being, human well-being, economic well-being and social well-being as main criteria.
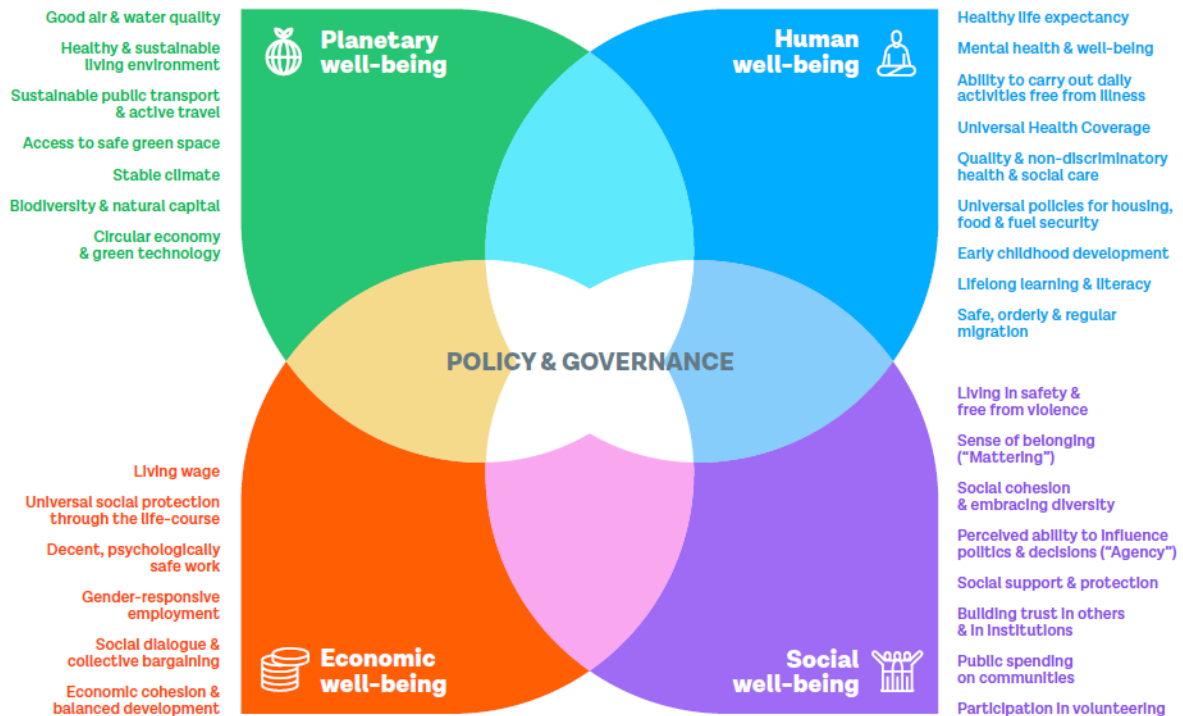
Figure 11: Dimensions of well-being
Source: WHO (2023)

Differences in well-being can arise across various dimensions, such as gender, age, and job role, necessitating tailored approaches to assessment and intervention.

There is a good argument that a healthy workplace leads to various benefits as shown in the PATH model by Grawitch et al. (2006).
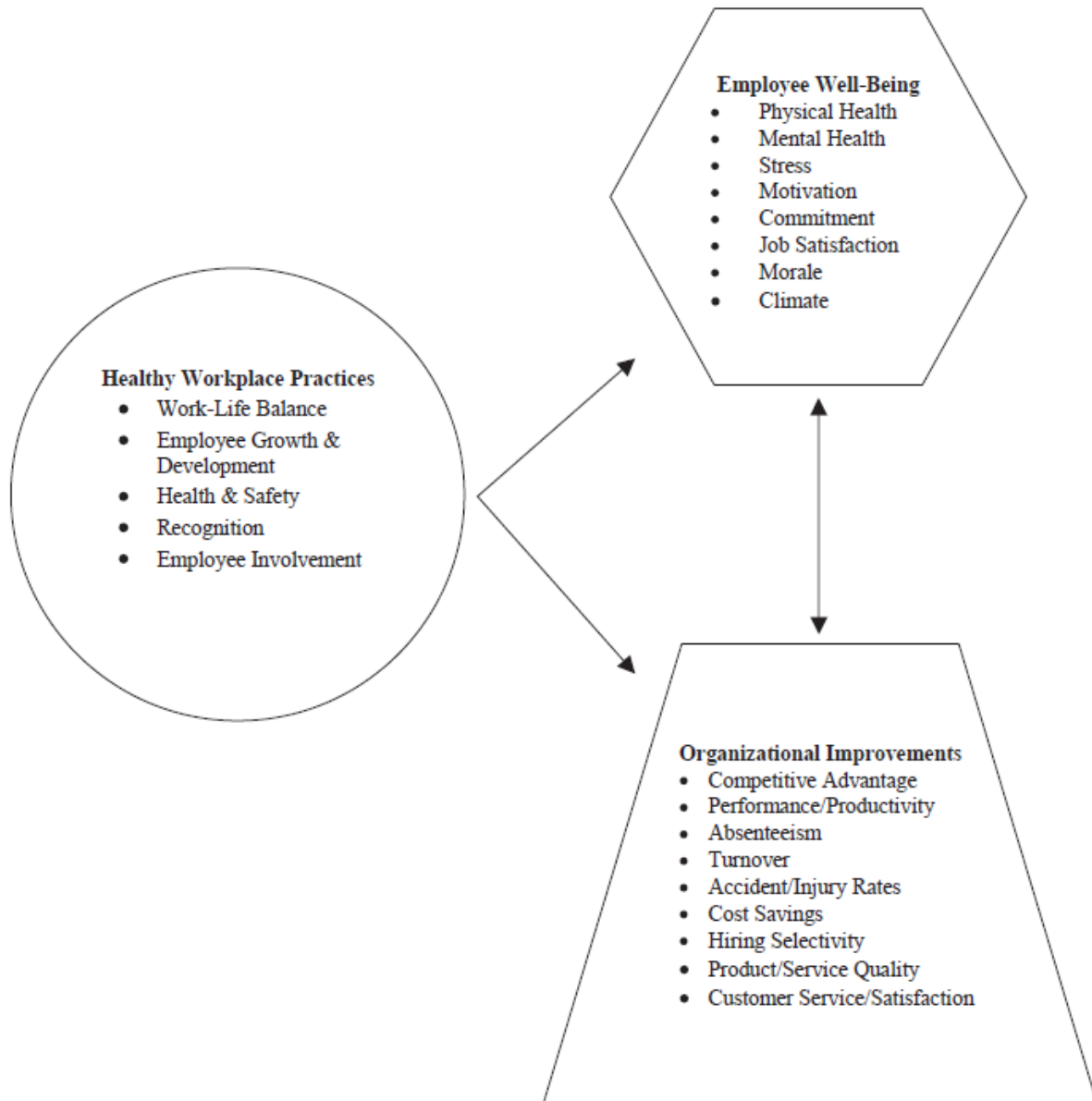
Figure 12: Path model
Source: Grawitch et al. (2006)

The interesting aspect is the relationship between the different dimensions as shown in the illustration below. There is a good argument that employees which like to go to work will have lower levels of sick leave, lower turnover rates or show a higher satisfaction with their job.

Healthy Workplace Practice	Employee Well-being Outcome	Organizational Improvement Outcome
Work-life balance	Organizational commitment (+) Job satisfaction (+) Employee morale (+)	Productivity (+) Absenteeism (−) Turnover (−)
Employee growth & development	Job satisfaction (+) Job stress (−) Motivation (+)	Organizational effectiveness (+) Competitive advantage (+) Quality (+)
Health & safety	Job stress (−) Physical health risks (−) Organizational commitment (+)	Health care costs (−) Absenteeism (−) Accident/Injury rates (−)
Recognition	Job satisfaction (+) Motivation (+) Job stress (−)	Hiring selectivity (+) Productivity (+) Turnover (−)
Employee involvement	Job satisfaction (+) Organizational commitment (+) Employee morale (+)	Productivity (+) Turnover (−) Absenteeism (−)
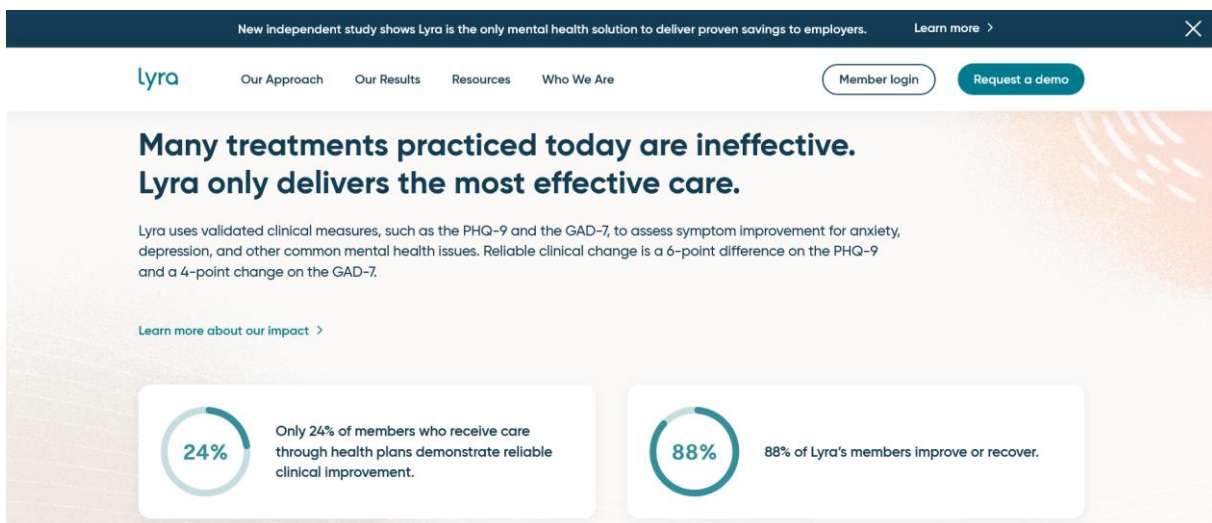
Table 3: Examples of the Relationship Between Healthy Workplace Practices, Employee Well-Being, and Organizational Improvements
Source: Grawitch et al. (2006)

Beyond that, there are also cynical approaches which consider a large share of our existing jobs as "bullshit jobs". This was a popular argument outlined by the late David Graeber (2019).

To improve employee well-being, several companies are utilizing artificial intelligence (AI).

The first example we are discussing in this module is Lyra Health. It uses artificial intelligence to provide personalized mental health care solutions to employees. Their platform connects users with therapists and coaches tailored to their specific needs.

They do not offer a lot of details but on their website, they offer a description:

Lyra takes the guesswork out of finding the right provider. When members begin their search, our artificial intelligence (AI) matching technology immediately matches them with providers who specialize in their clinical needs.

In addition, members can add preferences about their provider's

- Identity (gender, race/ethnicity, LGBTQIA)
- Languages spok en
- Experience working with veterans
- Experience working with faith-based background
- Availability to meet virtually or in person

Our AI matching technology also considers each provider's past success in helping members with similar needs and will only recommend top providers who have delivered care in the most timely, cost-effective way. And our advanced provider preferences help members find high-quality, proven providers with the same identity, if desired, to help members improve faster. Therefore, more members are healthy and organizations spend less money.

However, you can see that they are using artificial intelligence to match clients with providers in a wide sense. It is not entirely clear why a normal database with some feedback mechanisms would not be sufficient.

Virgin Pulse uses AI to promote holistic employee well-being through personalized wellness programs, including physical activity tracking, nutrition advice, and mental health resources. Their AI platform analyzes user data to create customized wellness plans that align with individual health goals and preferences.

They are following different steps. In a first step, they need to access corporate data.

Step 1

Harmonix® enhances your data

First, we combine your data with ours to give you a better and more predictive view than on your own. With Virgin Pulse, you have access to the most expansive and accurate consumer and provider databases in the industry. We have proprietary data on over 275 million people across thousands of variables to help you understand your population and market landscape in a whole new way all powered by our proprietary platform Harmonix®. The Harmonix platform collects, cleanses, and analyzes data to create a single, secure data record for every member.

Risk Breakdown by Employee
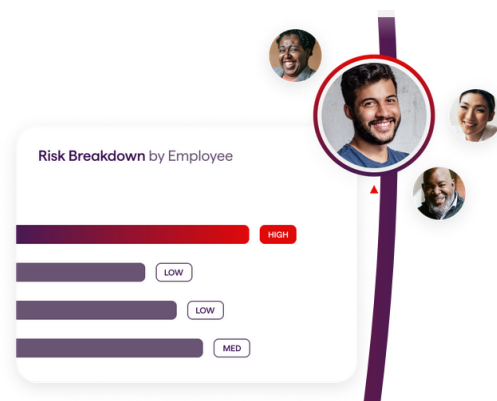
In a second step, they use artificial intelligence to predict individual needs.

Step 2

AI predicts individual needs

Our data analytics capability enables uber-personalization. We do not rely on simple persona-based messaging, but we have the ability to target communications, recommendations and resources to the person with the greatest need and greatest receptivity to the actions we are asking the person to take.

We can predict with up to 90% accuracy individuals' needs, risks and receptivity using genetic algorithms and machine learning. We help demystify big data with predictive models based on billions of touchpoints and millions of completed actions. This moves you from a reactive to predictive stance – a critical strategic advantage when it comes to activating people in their health and wellbeing.
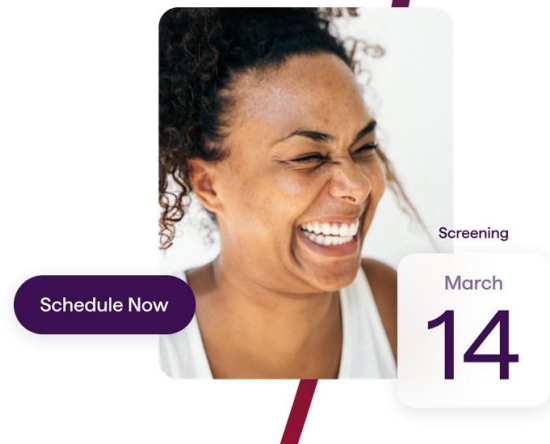
In a third step, they use artificial intelligence to drive engagement. Each client will have different preferences regarding options

Step 3

Insights drive engagement

Our patented machine learning, genetic algorithms and advanced analytics have been recognized by the Validation Institute to reveal quality insights about individual health status, impactability and receptivity of health programs. Powered by data, our methodologies have been instrumental in achieving true personalization.

We provide unique insights about your population that you've never had before – like how receptive they are to interventions, which communications channels they prefer and what digital health resources they need. By leveraging the ideal combination of machine learning and behavior change expertise, we can provide your people with the right resources at exactly the right time.
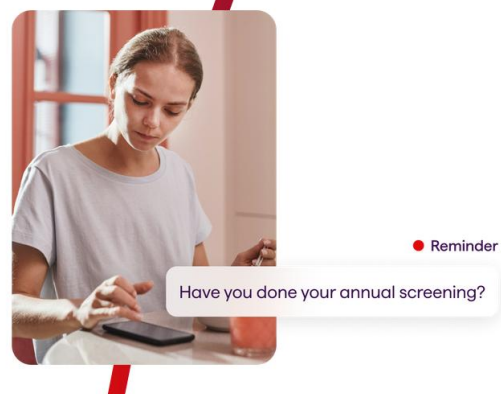
They also offer a platform where employees can access the services.

Step 4

Homebase for Health brings it all together

Homebase for Health® leverages the extensive data foundation and predictive insights to create personalized experiences that drive repeatable engagement. Innovative health plans, employers and health systems worldwide rely on the SaaS platform to improve outcomes, reduce costs and deepen relationships with their populations. Wherever a person may be in their health and wellbeing journey, Virgin Pulse is their Homebase for Health.
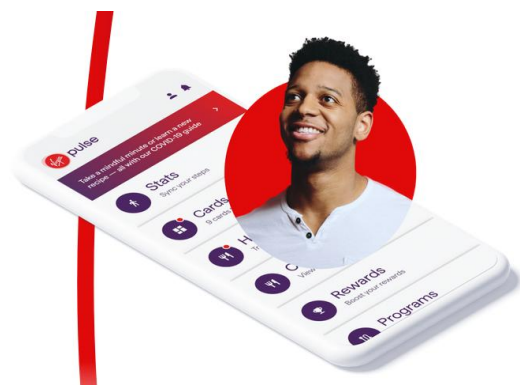
Attention-Check Question

Which of the following best describes the impact of digital transformation on recruitment?

A)   Recruitment   has   become   slower   but   more   personalized.
B)   Recruitment   has   remained   unchanged   by   digital   tools.
C) Recruitment has become more efficient, data-driven, and candidate-friendly.
D) Recruitment now relies entirely on social media platforms.

According to the chapter, which of the following is true about skills in the context of recruitment and occupations?

A)   Skills   are   universally   defined   and   easy   to   classify.
B) Skills can be defined in various ways and may require natural language processing to classify.
C) Skills are solely tied to education and cannot be acquired through work experience.
D) Skills do not play a significant role in job matching or career development.

3. Predicting performance and workforce management

Objectives:

- Learning how AI is used in performance prediction by understanding how AI tools are used to forecast employee performance and workforce needs;
- Exploring AI's role in workforce management by discovering how AI optimizes scheduling, monitoring and engagement to improve workforce efficiency.

3.1 Introduction

One of the key issues is to synchronize the needs of the economy and the skills of the younger generation. The focus of this discussion is how artificial intelligence tools may help in the selection of applicants.

That has become a lot easier with the emergence of new digital tools. These tools have expanded the relationship between information reach and information richness as illustrated in the figure below.

We have thus much richer data than we have been used to.
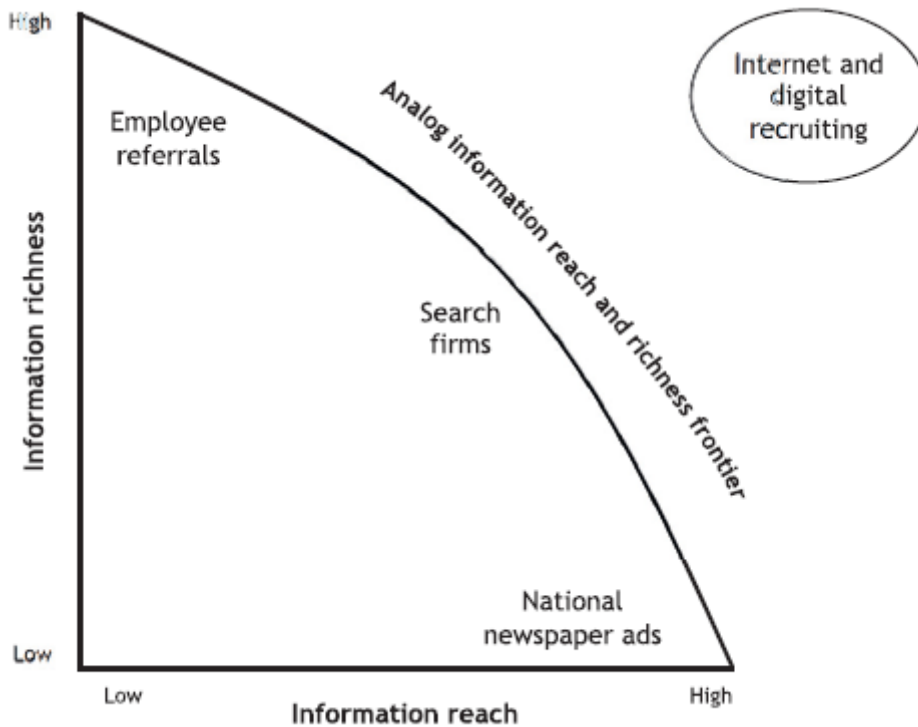
Figure 13: Analog information reach and richness frontier
Source: Black and van Esch (2020)

At the other side, individuals want to understand which skills are relevant for their future work biography. There is a large body of literature which covers the career-making decisions of individuals. Recent years have seen dynamic changes driven by technological change (Autor et al., 2003). In an interesting research paper, Borbély-Pecze (2020) has analyzed the changing relationship between individuals and their job in the case of Hungary.

There are many companies offering psychological surveys and trying to match psychological profiles with potential jobs. Journeys is another concept which illustrates career paths to students and maps it for them.[1]

3.2 Perspective of Employers

Employers are tasked with assembling and sustaining a workforce that is both skilled and efficient, a responsibility that encompasses both hiring new talent and overseeing existing employees, commonly referred to as talent acquisition and talent management.

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[1] https://journeysmap.com/

The core of this process involves pinpointing the specific skills and roles that are currently lacking within the organization, which then informs the creation and dissemination of job advertisements.

There are many applications which evaluate the performance of employees. Brown, Burke, and Sauciuc (2021) discuss the benefits of integrating artificial intelligence in performance evaluation systems. The main argument to implement these tools is that the idea that AI reduces the level of bias in these evaluations. Altemeyer (2019) discusses business cases where machine learning tools were used to select the best employees in the past and automatically identify similar applicants.

HireVue is one such example. It has already delivered 22 million job interviews where applicants can submit videos which are then analyzed automatically.
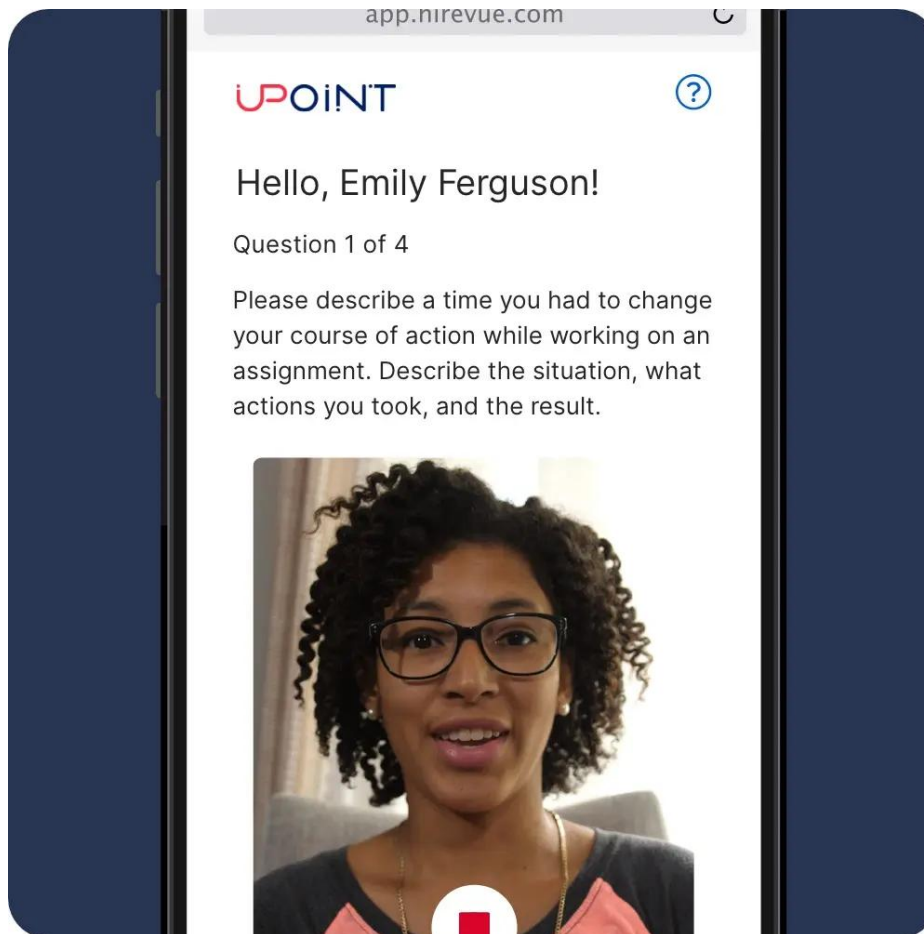
They <u>explain</u> their use of AI in the following way:

> *At HireVue, we use static algorithms because that is the best way to provide fair and similar treatment for all candidates. We believe that algorithms should be highly controlled and tested by experts (Occupational Psychologists and Data Scientists)*

throughout the entire lifecycle of the model. As such, they can then help to reduce hiring bias and make the process fairer. We deploy AI that is both static and deterministic, meaning algorithms are not being re-trained or "learning" on the fly and they provide a repeatable output each time they are used; this should be the standard in hiring. With our AI systems, the algorithm is trained and tested in the "lab" and then locked before deployment. The system can only "learn" new things if someone chooses to update it.

Despite the company's emphasis on diversity, there is a concern that such algorithms may inadvertently disadvantage unemployed individuals or those whose first language differs from that of the hiring company, potentially resulting in less favorable outcomes for these candidates. The inexplicability of artificial intelligence does not help to mitigate these concerns.

HiredScore is another example. It stresses diversity and inclusion and promises to increase both. It is a concept for companies with many applications (more than 500,000 per year) which need to be treated consistently and somewhat automatized.

HiredScore uses advanced AI-based algorithms to screen, rank, and match candidates to open positions based on their qualifications, experience, and fit for the company. This reduces the manual data handling involved in the hiring process. Their algorithms can also help in identifying talent within internal databases, existing employees, or those in talent pipelines.

They claim that they are doing "Automated bias AI testing which demonstrates unbiased AI for every client's program automatically". This is something which has not been achieved.

The company is claiming that that their system is designed to reduce unconscious bias in hiring decisions by focusing on skills and qualifications rather than demographic data. In practice, they ignore factors that could introduce bias (e.g., gender, ethnicity) and instead focus on relevant qualifications and job criteria. However, as we will discuss in more detail in the last chapter, there are many other aspects which point towards gender and ethnicity. It is relatively easy to identify the gender or ethnicity using the address, mandatory service in the military, sports activities or foreign languages.

Take the example of someone who is living in a district with a large Turkish-born population, has listed Turkish as a language and is playing soccer. All these data points can be found on a CV and are indicators for gender and ethnicity. Obviously, there is a high probability that this person has a Turkish ethnicity and is male.

3.3 Other institutions

There are many intermediaries which are in the field such as job platforms or labor market agencies, whose primary function is to align skills with job opportunities. These entities are repositories of vast data, which they leverage to discern skills for recommending apt job

opportunities to job seekers, while employers invest in these insights to find eligible candidates.

Roca (2019) introduced a model that uses the extensive skill dataset on LinkedIn, demonstrating the essential role of big data in navigating the complexity and diversity of skills. However, the challenge of ensuring data quality and relevance persists even on major platforms. Notably, current platforms are yet to offer substantial options tailored to the needs of NEETs, indicating a gap in service that is crucial to address.

Public sector and labor market agencies play a critical role in fostering a functional labor market, striving to facilitate employment and enhance skill development among the working population. Authorities are keen on comprehending the skill landscape through extensive surveys to inform their strategies and resource allocation.

Labor market agencies need to allocate resources to train unemployed persons and find positions for them. The Austrian labor market agency implemented an algorithm which was basically classifying job seekers in three categories depending on the probabilities of finding a job within a certain period of time (Allhutter et al., 2020). The model had four types of job seekers:

- Job seekers with a complete historical employment record of 4 years prior to model generation
- Job seekers with an incomplete or "fragmented" employment history
- Job seekers with a "migration background"
- Young adults.

Despite its potential, especially in identifying and assisting vulnerable groups like NEETs and marginalized individuals, such a system faced limitations due to concerns around privacy and legitimacy, leading to its short-lived operation.

Parallel initiatives, such as the Jamaican Youth through Empowerment & Training (JET) program, demonstrate the utility of AI in pinpointing marketable skills, thereby enabling targeted training for youths. This analysis enabled the program to tailor training programs in digital, entrepreneurial, and soft skills to meet the specific needs of 1000 youths aged between 17 and 34 (Trust, 2022). The initiative gather data from open-source platforms such as social media platforms, websites, and job portals to analyze in real time and identify the needed skills in the Jamaican labor market.

The AI4Belgium strategy by the Belgian government is another example of such initiatives as it is leveraging AI for effective labor market demands. With a goal to maximize the opportunities of AI, the Belgian government invested in various AI-driven programs and initiatives, such as promotion AI education, training, and research programs, as well as attracting and retaining AI experts and professionals (Government of Belgium, 2019). As part of the investment, the collaboration between the government employment agency and FARI (AI for the common good), an institute in Brussels led to the incorporation of AI in the job-

matching process to provide employment solutions to both job seekers and employers. The initiative adopted a free form text matching principle which allows jobseekers to find potential jobs which are ideally not possible when a traditional recruiter method is used (FARI, 2022).

3.4 What is performance?

There is no commonly accepted single definition for employee performance. In general, employee performance refers to the effectiveness with which job responsibilities are carried out and goals are achieved. It encompasses a range of behaviors and outcomes that contribute to organizational success.

Key components of employee performance include task performance, which involves the execution of job-specific duties, and contextual performance. Additionally, it might include adaptive performance, which is the ability to respond to change, and proactive performance, which involves anticipating and acting on future needs.

A good place to start is a systematic literature review which was carried out by Atatsi et al., (2019). They show how the different aspects are related to each other. Unsurprisingly, there are many aspects which are relevant shown below.

It also makes sense. Young graduates might be more motivated and willing to work longer hours. Job autonomy will also contribute positively to employee performance. The list can go on and on.
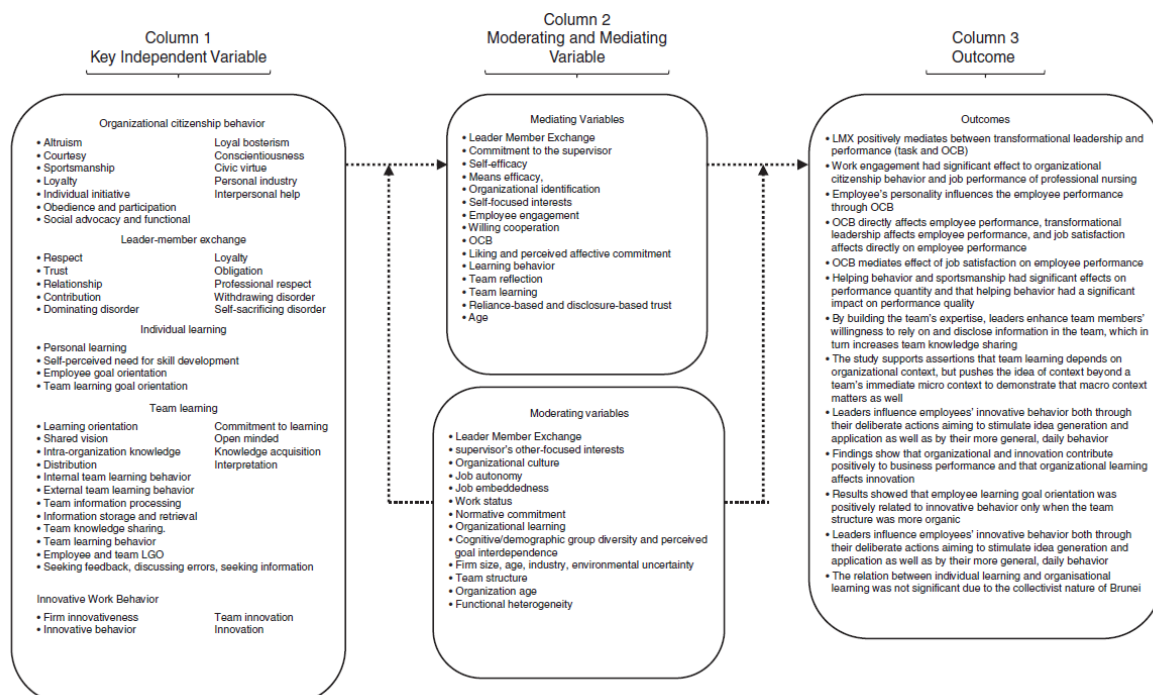
Figure 14: Relationship
Source: Atatsi et al. (2019)

The abbreviations stand for organizational citizenship behavior (OCB), leader–member exchange (LMX), learning, innovative work behavior (IWB)

Typical Key Performance Indicators (KPIs) are essential for measuring employee performance and vary depending on the role and organizational goals. Common KPIs include:

1. **Productivity**: Measures the output of an employee relative to input, such as hours worked or resources used.

2. **Quality of Work**: Assesses the accuracy, thoroughness, and effectiveness of the work performed.

3. **Efficiency**: Evaluates the ability to maximize output with minimal waste of time and resources.

4. **Customer Satisfaction**: Gauges the level of satisfaction customers have with an employee's service or product.

5. **Attendance and Punctuality**: Tracks the consistency and reliability of an employee's presence at work.

6. **Goal Achievement**: Measures the extent to which an employee meets or exceeds predefined goals and targets.

Each KPI provides insights into different aspects of performance, enabling a comprehensive evaluation that supports targeted improvement efforts.

Several internal and external factors influence employee performance.

Internal factors play a crucial role in determining employee performance within an organization. One of the most significant factors is the skills and competencies that an employee brings to their role. These encompass the knowledge, skills, and abilities essential for executing job responsibilities effectively. An employee with the right competencies is more likely to perform tasks efficiently and contribute positively to organizational goals.

Motivation is another vital internal factor. The level of engagement and drive an employee has towards achieving their goals directly impacts their productivity and the quality of their work. Highly motivated employees are typically more proactive, diligent, and committed to their tasks, leading to better performance outcomes.

Health and well-being, both physical and mental, also profoundly influence an employee's ability to perform effectively. Good health enables employees to maintain high energy levels and focus, while mental well-being helps them manage stress and maintain a positive attitude.

Conversely, poor health can lead to absenteeism, decreased productivity, and higher error rates.

Finally, the work environment significantly affects performance. Supportive and resource-rich environments provide employees with the tools, support, and conditions they need to thrive. This includes access to necessary resources, constructive feedback, and a culture that promotes collaboration and respect. On the other hand, stressful or resource-poor environments can hinder performance by causing burnout, reducing morale, and limiting access to essential tools and support.

Several external factors significantly influence employee performance within an organization. One of the most impactful is organizational culture. A culture that fosters collaboration, innovation, and recognition can greatly enhance performance by creating an environment where employees feel valued and motivated. When employees are encouraged to work together, think creatively, and are recognized for their achievements, they are more likely to perform at their best and contribute to the organization's success.

Leadership is another critical external factor. Effective leadership provides clear direction, support, and feedback, which are essential for high performance. Leaders who communicate expectations clearly, offer the necessary resources and guidance, and provide constructive feedback can inspire and empower their teams to achieve their goals and excel in their roles.

Economic conditions also play a significant role in employee performance. Economic stability or instability can affect job security, the availability of resources for training, and overall employee morale. In stable economic conditions, employees are more likely to feel secure in their jobs and have access to the resources they need to develop their skills and improve their performance. Conversely, economic instability can lead to uncertainty, reduced resources, and lower morale, all of which can negatively impact performance.

Technological advancements are another crucial factor affecting performance. Access to modern tools and technologies can significantly improve efficiency and output by enabling employees to perform their tasks more effectively and with greater ease. On the other hand, outdated systems can impede performance by causing delays, increasing the likelihood of errors, and making it more difficult for employees to complete their work efficiently.

3.5 AI-Based Performance Evaluation

Artificial Intelligence (AI) is revolutionizing performance evaluation by offering advanced tools and techniques that enhance traditional methods. Traditional performance evaluation methods often rely on periodic reviews and subjective assessments, which can be time-consuming and prone to biases. In contrast, AI-based approaches leverage data-driven insights and continuous monitoring to provide more accurate, objective, and timely evaluations. This section explores the differences between traditional and AI-based

performance evaluation methods, the role of performance management systems, the use of predictive analytics, and future trends in performance evaluation.

There are different fields of research which have been tackling employee performance management. Claus & Briscoe (2009) have analyzed performance management systems across borders which was mostly centered around expatriates. Researchers in psychology departments have analyzed how individuals react to incentives (e.g., Ariely et al., 2009; Bareket-Bojmel et al., 2017). Accounting researchers have found that there is an optimal interval for reporting employee performance (Hecht et al., 2020).

Modern performance management systems integrate AI to streamline and enhance the evaluation process. These systems often include features such as continuous feedback mechanisms, goal tracking, and real-time performance analytics. AI-powered tools can analyze vast amounts of data from various sources, such as emails, project management software, and customer feedback, to provide comprehensive performance insights.

Predicting employee performance using AI systems presents several challenges and limitations that organizations must navigate to ensure effective implementation. One of the primary challenges is data quality and availability. AI systems rely on high-quality, comprehensive data to generate accurate predictions. If the data is incomplete or biased, it can lead to erroneous conclusions, undermining the reliability of the AI's assessments. Therefore, ensuring the integrity and completeness of the data is critical for the success of AI-based performance prediction systems.

Privacy concerns also pose a significant challenge. The collection and analysis of detailed performance data raise important privacy issues. Organizations must implement transparent policies and robust data protection measures to safeguard employee information. Without these protections, employees may feel their privacy is being violated, leading to a lack of trust in the system.

Another limitation is the resistance to change that can arise among employees and managers. The introduction of AI-based systems can be perceived as intrusive, with fears of surveillance and potential job displacement. This resistance can hinder the adoption and effectiveness of the technology. To overcome this, organizations need to communicate the benefits clearly and involve stakeholders in the implementation process to build trust and acceptance.

Interpretability of AI models is another critical concern. All AI models based on neural networks and particularly those that are complex, can be impossible to interpret. This lack of transparency can make it challenging to understand the rationale behind specific evaluations and predictions. Without clear explanations, it becomes hard for managers and employees to trust and act on the AI's insights. Developing AI systems that offer greater interpretability and clarity is essential to addressing this challenge.

Predictive analytics leverages AI and machine learning algorithms to forecast employee performance and potential. These tools analyze historical data and identify patterns that can

predict future outcomes. For example, predictive analytics can identify high-potential employees, anticipate performance dips, and suggest targeted interventions to address specific issues.

Utilizing predictive analytics in the realm of employee performance offers numerous advantages that can significantly enhance organizational effectiveness. One of the primary benefits is talent identification. Predictive models can analyze various data points to identify employees with high potential for leadership roles or specialized tasks. This capability allows organizations to recognize and nurture talent, ensuring that high-potential individuals are given the opportunities to grow and contribute meaningfully to the company.

Performance improvement is another application of predictive analytics. By forecasting potential performance issues before they become problematic, managers can take proactive measures to address these challenges. This might include targeted training sessions, additional support, or other interventions designed to bolster employee performance and prevent issues from impacting overall productivity.

Succession planning is also greatly enhanced by predictive analytics. Organizations can use these tools to identify and develop talent pipelines, ensuring they are prepared for future leadership needs. This strategic approach to succession planning helps maintain continuity and stability within the company by ensuring that future leaders are well-prepared and equipped to step into their roles when needed.

Lastly, predictive analytics enables personalized development plans for employees. By leveraging AI to analyze individual strengths and areas for improvement, organizations can create tailored development plans that are more effective and engaging. This personalized approach not only enhances employee growth but also boosts job satisfaction and retention by demonstrating a commitment to each employee's professional development.

3.6 Workforce Management

Workforce management (WFM) is a set of processes used by an organization to optimize the productivity of its employees. This involves forecasting labor requirements, creating and managing staff schedules, tracking attendance, and ensuring compliance with regulations.

Workforce management involves a wide range of key components that are essential for aligning an organization's human resources with its broader objectives.

Strategic Workforce Planning ensures that the workforce is aligned with organizational goals, helping to maintain the right number of employees with the necessary skills. This is closely followed by Talent Acquisition and Development, which focuses on recruiting, hiring, and training employees to meet both present and future workforce needs.

Another element is Performance Management, which involves monitoring and evaluating employee performance to promote continuous improvement and support the achievement

of organizational targets. Employee Scheduling is also important for manufacturing or service provision companies, as it ensures that work schedules are optimized to make the most of available labor resources while also accommodating employee preferences and availability.

Compliance Management is essential to ensure that the organization adheres to labor laws and internal policies, reducing the risk of legal complications and fostering a culture of fairness. Lastly, Employee Engagement plays a key role in maintaining a motivated, satisfied, and committed workforce through the implementation of strategies that foster a positive work environment.

These components collectively form the foundation of effective workforce management, contributing to an organization's overall success.

Effective workforce planning and forecasting employ a variety of techniques to accurately predict future workforce needs and ensure that qualified personnel are available when required.

AI is playing an increasingly pivotal role in workforce management by automating various processes and delivering valuable data-driven insights.

One of the most powerful applications of AI is in Predictive Analytics, where AI algorithms forecast labor demand and highlight potential skill gaps, allowing organizations to plan their workforce needs proactively. Additionally, Automated Scheduling uses AI-powered tools to generate optimal work schedules that not only maximize productivity but also respect employee preferences and adhere to legal requirements.

In terms of Employee Monitoring, AI systems can track performance metrics in real time, offering managers actionable insights that can be used to boost productivity. Talent Acquisition also benefits from AI, as it can streamline the recruitment process by efficiently screening resumes, assessing candidates, and predicting their job fit.

3.7 Companies using AI to manage the workforce

A typical company such as UKG offers many different solutions.

SOLUTIONS BY NEED

- AI in HR
- Human Resources
- Compliance
- Talent Management
- HR Service Delivery
- Reporting and Analytics

- Payroll
- Employee Experience
- Time & Attendance
- Absence Management
- Scheduling

The company employs AI to optimize workforce management solutions, including timekeeping, scheduling, and employee engagement. It uses AI to analyze historical labor data, predict staffing needs, and create optimized schedules that align with business demand. Their AI tools also help in monitoring employee attendance and productivity, providing insights to improve workforce efficiency.

Several companies are leveraging artificial intelligence (AI) to revolutionize the way employee performance is evaluated. These companies use advanced AI tools and techniques to provide more accurate, objective, and timely performance assessments. Here are five notable examples:

Workday is another company that is active in this space. It incorporates AI and machine learning into its human capital management (HCM) suite to improve performance management and employee development. Its algorithms evaluate performance data continuously, providing real-time feedback and recommendations. The platform also uses predictive analytics to forecast employee performance and identify potential leaders.

For managers, they offer dashboard such as the ones below.

Manager Dashboard

Supervisory Organization Global Support Center   Include Subordinate Organizations   Yes

Average Compensation by Country / Tenure

Team Talent Summary

Employee Name	Retention	Is High Potential	Rating - Current	Critical Job
Bettina Strauss	●		★★★★	
Elsa Ramos Vasquez	◆	✓	★★★★	
Katarina Lindgren	▲	✓	★★★★	
Manny Soto	●		★★★☆	
Maria Venter	▲		★★★★	
Nikhil Rao	▲	✓	★★★☆	
Scott Wilkinson	◆		★★★★	

View More ...

My Team's Learning Transcript

35
Count

Canada   France   Germany   Japan
Korea, Republic of   Sweden   United Kingdom
United States of America   Australia   Mexico
Other

Classroom   Web-based   Document-based
On the job

View More ...

Average Base Pay (USD) $51,076
Average Tenure 10
Count 113

Review Ratings Summary

2 - Needs Improvement

3 - Meets Expectations

Performance by Potential/Agility

≡ MENU

Manager Insights Hub ⊢

🔲 **Team Overview**

🔲 **Direct Reports** ⌃
  Cynthia Cook
  Jessica Rogers
  Matthew Paulson [C]
  Monica Bautista
  Ross Smith
  Sam Choi
  View All Direct Reports

🔗 **Suggested Links** ⌃
  Assess My Team's Potential
  Manage Succession Plan
  Compare Team
  My Team's Performance Revi...

Profile Lennon Wheeler

Prepare for Performance Reviews

It's time to check in! Now through the end of August, we're encouraging each people leader to have Career Performance Reviews with each of their team members. Thes...

Read More

Team Career Highlights

Cynthia Cook
1 Highlight

◎ Has overdue goals

Open Page

Monica Bautista
2 Highlights

☆ Received Feedback over 90 days ago

💡 Last updated development items over 90 days ago

Open Page

Ross Smith
4 Highlights

◎ Has overdue goals

☆ Received Feedback over 90 days ago

💡 Last updated development items over 90 days ago

◎ Last updated goals over 90 days ago

Open Page

Completed in the Past 3 Months

Goals   Gigs   Mentorships

Humu is a company that employs AI to drive behavioral change and improve employee performance through personalized "nudges" based on performance data. They analyze performance data and uses behavioral science to send personalized nudges that encourage positive actions and habits. These nudges are tailored to individual needs and organizational goals, enhancing overall performance.

Below is one such example.

Nudge your entire workforce to improve

Everyone—from ICs to senior leaders—receives short, science-backed recommendations called nudges in the flow of work at the exact moment when it's easiest to take action. Admins have dashboards that give them real-time visibility into progress within each team and allow them to influence nudges as priorities shift.
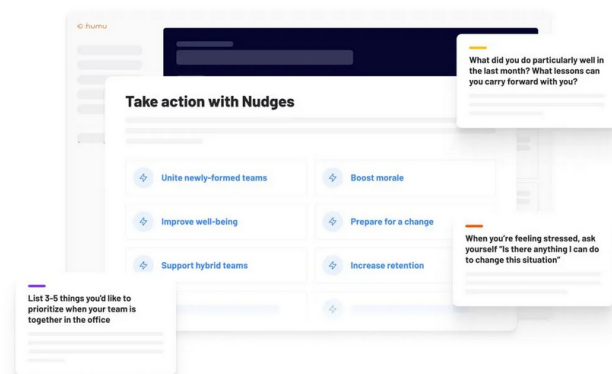
Attention-Check Question

In what way does predictive analytics enhance workforce management?

A) It replaces the need for human managers.

B) It forecasts labor demand and highlights potential skill gaps to help organizations proactively manage their workforce.

C) It automates employee promotion decisions without human input.

D) It provides instant feedback on employee morale.

4. Increasing performance and efficiency

Objectives:

- Understanding techniques for measuring performance by learning about various methods such as Key Performance Indicators (KPIs) and AI-based tools used to assess both individual and team performance.
- Exploring how AI can help to improve efficiency by discovering how AI-driven solutions enhance workplace efficiency through automation, real-time analytics, and optimized resource management.

4.1 Introduction

In this rather short chapter, we will cover performance and efficiency. Let us start with performance.

Performance within an organization refers to the execution of job duties and responsibilities, as well as the achievement of organizational goals and objectives. It encompasses a wide range of behaviors, activities, and outcomes that contribute to the effectiveness and success of the organization.

Key Performance Indicators (KPIs) are critical metrics used to measure performance across various departments. These indicators differ depending on the department and its specific objectives. Some indicators include:

- **Sales**: Sales revenue, conversion rates, customer acquisition cost.

- **Marketing**: Brand awareness, lead generation, return on marketing investment.

- **Human Resources**: Employee turnover rate, time to fill positions, employee satisfaction.

- **Operations**: Efficiency, quality control, on-time delivery rate.

- **Finance**: Profit margins, return on investment, budget variance.

It shows that performance is different across different domains and functions within a company. Each unit should thus identify and track the KPIs most relevant to its strategic goals to ensure that performance is measured accurately and improvements can be made where necessary.

Performance can be evaluated at both the individual and team levels.

- **Individual Performance**: This involves assessing an employee's specific contributions to their job role. Factors such as productivity, quality of work, and adherence to deadlines are commonly evaluated. Performance reviews, self-assessments, and peer reviews are typical tools used for individual performance evaluation.

- **Team Performance**: This focuses on how well a group of employees works together to achieve common goals. Key metrics for team performance include team productivity, collaboration, innovation, and collective problem-solving abilities. Successful teams often exhibit strong communication, mutual support, and synergy.

There are many examples where you want to ensure high team performance. Think of all the flight crews, surgeons in the hospitals or sports teams. It is also easier to measure team performance as you know the final results.

It is not always easy to assess individual performance. How do you assess the performance of a salesperson responsible for selling medical equipment in Rouen or in the region around Lisbon? There are many factors at play that might impact the individual performance of a salesperson.

Evaluating both individual and team performance helps organizations to identify high-performing employees and teams, provide targeted feedback, and foster a culture of continuous improvement. Effective leadership plays a pivotal role in aligning individual and team performance with organizational objectives, thereby enhancing overall performance.

4.2 Techniques for Measuring Performance

To accurately assess performance, a variety of methodologies and tools are employed.

One commonly used method is the performance appraisal, where managers regularly evaluate an employee's performance based on predefined criteria. This helps identify strengths and areas for improvement.

Another effective approach is the 360-degree feedback system, which gathers comprehensive feedback from multiple sources, including an employee's peers, subordinates, supervisors, and the employee themselves through self-assessment. This holistic approach provides a more complete picture of performance.

In addition to qualitative evaluations, quantitative methods such as Key Performance Indicators (KPIs) are essential. These metrics allow organizations to measure how effectively an individual, team, or the company as a whole is achieving critical business objectives

Another strategic tool is the balanced scorecard, which offers a broader perspective by evaluating performance across multiple dimensions, such as financial results, customer satisfaction, internal processes, and growth and learning opportunities.

Benchmarking is another valuable technique, enabling organizations to compare their performance against industry standards or best practices. This comparison helps pinpoint areas where the organization can improve, driving continuous growth and development.

4.3 Companies using AI to increase performance

Artificial Intelligence (AI) is impacting how organizations measure and predict employee performance, providing advanced tools and techniques for more accurate, objective, and real-time evaluations.

15Five is a typical example how artificial intelligence can be used to improve operational performance. They are helping to write reviews or prepare 1:1 conversations with team members.
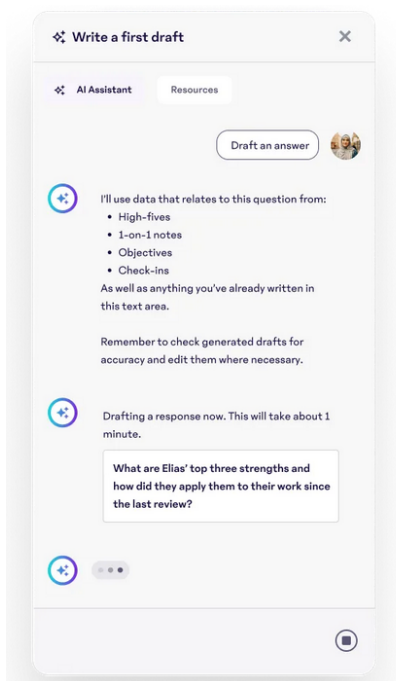
AI Assisted Reviews

Write better and less biased performance reviews - faster - with the assistance of AI.

Learn More about AI Assisted Reviews >

AI Manager Copilot

Real-time, AI-powered assistant to help managers be more effective by recommending actions and guiding with best practices.

Explore Manager Copilot >
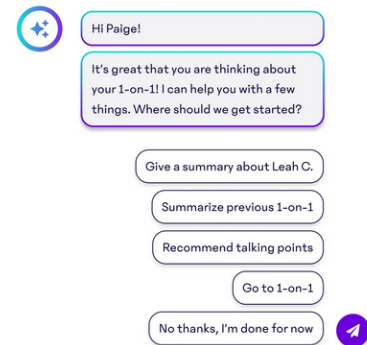
This approach is quite similar to Reflektive (https://www.reflektive.com/) which also uses continuous performance management and real-time feedback. Similarly, they offer support for 1:1s. It's not entirely clear which managers need questions for interactions but it is surely helpful to have some back-up questions.

Encourage meaningful dialogue with Conversation Starters.

Encourage more dynamic and purposeful 1:1s with Conversation Starters designed to help managers engage employees in meaningful ways, while driving consistency.

"The Reflektive program was a transformational change for all of us in terms of the effort that was being put in, as well as the enormous time savings and value we were getting out of it."

SmartPak
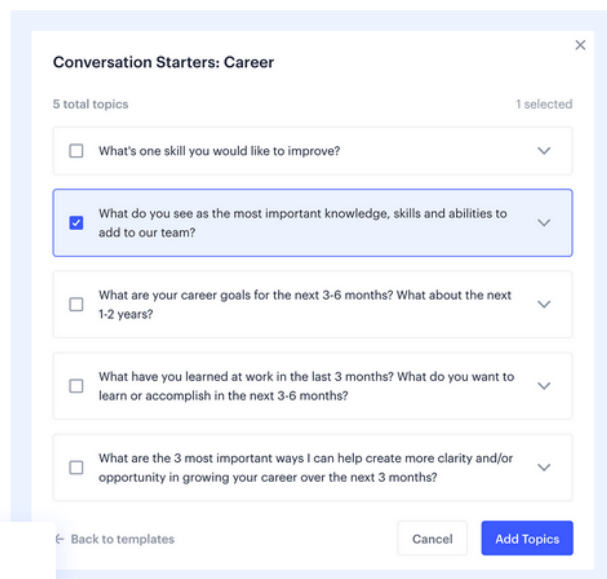
Betterworks uses AI to help organizations across various dimensions. For example, they provide assistance in writing goals or improve performance reviews.

Goal Assist

Write quality goals

Employees can effortlessly compose precise and measurable goals that align with team and company objectives. They're able to craft well-constructed goals in a fraction of the time using Goal Assist. This feature draws on an employee's performance data—such as previous goals and developmental conversations—from various Betterworks modules. Better goals lead to greater clarity, enhanced focus, and improved achievements—all contributing to better business outcomes.

4.4 What is Efficiency?

Efficiency and effectiveness are related but distinct concepts in organizational performance.

Efficiency means "Doing things right". It focuses on the process and measures how well resources are used to achieve outputs. An efficient process minimizes waste and maximizes resource utilization.

Effectiveness means "Doing the right things". It focuses on the outcome and measures the extent to which objectives are achieved. An effective process delivers the desired results, regardless of the resources used.

Both efficiency and effectiveness are important elements for organizational success. While efficiency ensures resources are not wasted, effectiveness ensures that the goals and objectives are met. Balancing both is key to optimal performance.

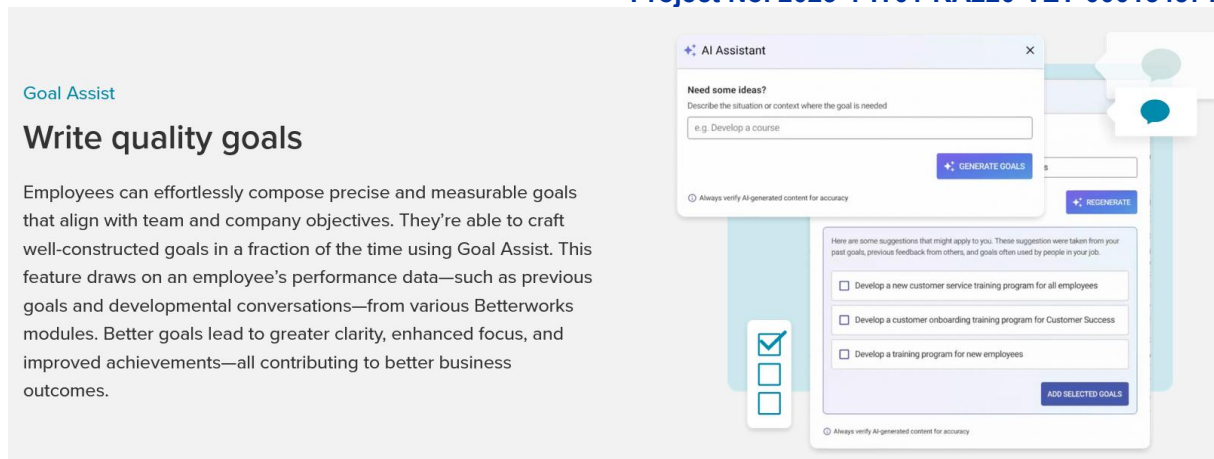Efficiency in the workplace refers to the ability to accomplish a task or achieve a goal with the least amount of resources, time, and effort. It is a measure of how well resources are used to achieve desired outcomes with minimal waste. Understanding efficiency is key for organizational success as it directly impacts productivity, cost-effectiveness, and competitiveness. Efficient organizations can produce higher outputs with fewer inputs, leading to better profitability and sustainability.

Technological advancements play a significant role in enhancing workplace efficiency by automating tasks, streamlining processes, and improving resource allocation. Automation reduces manual labor and errors by using software and robotics to perform repetitive tasks. Workflow management systems further optimize business processes, leading to better

coordination and increased efficiency. Data analytics helps identify inefficiencies and allows for more informed decision-making, resulting in better operations overall.

In terms of resource allocation, resource management software ensures that resources are effectively assigned based on availability and project needs. Capacity planning ensures that resources are available and used efficiently to meet future demands, helping organizations remain responsive to changing conditions.

Effective time management also contributes to increased efficiency. Prioritization ensures focus on high-impact tasks that align with organizational goals, while time-blocking allows for dedicated periods of focus on different activities, enhancing productivity. Additionally, automating routine tasks frees up time for more strategic efforts, reducing distractions and allowing employees to focus on more critical work.

Attention-Check Question

What is an example of organizational effectiveness?

A) A company reducing waste in its manufacturing process.
B) A company successfully meeting its strategic goals and customer needs.
C) A company minimizing employee turnover to reduce hiring costs.
D) A company increasing productivity through automation.

5. Decision-making support

Objectives:

- Understanding the structure of scripts and workflow in companies by learning how scripts are designed and implemented to automate tasks and streamline workflows within organizational structures;
- Exploring the development of AI agents in workflow management by discovering how AI agents optimize workflows by monitoring real-time data, predicting potential bottlenecks and enabling efficient task routing.

5.1 Introduction

This chapter covers the decision-making support for employees.

The complexity of tasks and how they are managed has evolved significantly over the past decades, largely due to advancements in technology and changes in business practices.

Comparison of Task Complexity:

- **1950s**: Tasks were predominantly manual, and paper based. Processes were linear, and information flow was slow due to physical document handling and limited communication tools. Decision-making was often centralized, and the scope for automation was minimal. This was a time when something like centralized planning was considered by at least some to be a feasible option.

- **1990s**: The advent of personal computers and early software applications started to automate some tasks. Email became a primary communication tool, speeding up information exchange. However, many processes were still relatively isolated, with limited integration between different systems.

- **2000s – 2010s**: The rise of the internet and enterprise software like ERP (Enterprise resource planning) systems led to greater integration and automation of business processes. Cloud computing started to gain traction, providing more flexible and scalable solutions. Workflow management systems became more sophisticated, incorporating basic automation and monitoring capabilities.

- **Today**: Modern workflow management systems are highly integrated, leveraging cloud computing, and increasingly artificial intelligence to automate complex processes. Real-time data analytics and IoT devices provide continuous insights and optimization opportunities. Decision-making is becoming more decentralized and we will start to see AI agents which will be assisting in real-time, data-driven decisions.

Let us take a step back and think about the structure of our world. The digitalization started some 50 or 60 years ago and there is a reason it won't finish any time soon: Collectively, we run trillions of scripts every day. A script is a sequence of steps to execute a certain task or operation:

- Delivering newspaper to apartment number 47.
- Organizing transplant organs.
- Ordering a new logo from a designer based in Vietnam.
- Writing the shareholder agreement for a new company.
- Paying for the bread in the bakery.
- Invoicing a client for the services delivered in the last month.
- Sending a damage report to the insurance company.
- Preparing an ESG report for an investment company.

Many of the scripts are crystal clear and we can create complete contracts. That is the crypto world where "code is the new law" (Pistor, 2019). A typical case would be a loan secured by a crypto collateral which will be liquidated in case of a defined default case. That can all be done in a fully pre-determined fashion.

The other extreme is best captured by Helmut Qualtinger describing his native Austria:

> *Austria is a labyrinth where everyone knows their way around.*

There will also be a need for humans to navigate these labyrinths which exist everywhere.

For example, there are limits for online dispute resolution mechanisms. Ast & Deffains (2021) have outlined the history of the online dispute resolutions industry and find the first examples in the 1990s with iCourthouse. eBay tried a crowd-based model to resolve user disputes in the 2000s. Obviously, one of the key challenges is that rulings were hard to enforce in private settings as only public courts can use the police to enforces rules.

Let us assume that there are really trillions of scripts which are executed every day. A script typically starts with a push or pull request ("a trigger"): "Do task A" or "Send me information B". The individual then needs to extract data from somewhere to perform the specific task and load it in some form of database, which can also be his or her memory.

For example, if you order at your local pizzeria, you read the menu, memorize the drink and the pizza until the waiter takes your order. If you want to take a vacation, you will start researching potential destinations and start putting them together in a document.

Using computer science terminology, it might look like the illustration below. I am not saying that it makes perfect sense to use ELT (Extract, Load, Transform) to describe the structure of scripts, but it is a nice approximation.

Project No. 2023-1-IT01-KA220-VET-000154571

| Input from sources	Extract information	Load data	Transformation	Ouput
Each script starts with some form of push or pull request	Data is extracted to perform the specific task	Data is organized in some form (database, memory, ledger, paper notes)	Processing of data	Output of the task
Desire to take a vacation	Research destinations	Save all information	Create an itineray	Completed travel plan
Need to learn a new skill	Gather materials	Organize a study schedule	Process the data in the textbooks	Mastering of new skills
Competitive analysis	Collect data on competitors	Store data in trend collection	Analyze data	Recommend steps
Meal order	Check the menu	Remember drinks and foods	Place the order	Meal ordered
Project update report	Collect updates from colleagues	Compile updates into a report format	Distribute to stakeholders	Stakeholders informed
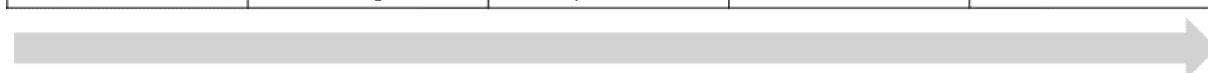
The tasks described above are also much stronger linked than before. Scripts often need to pull data from other sources to complete their tasks.
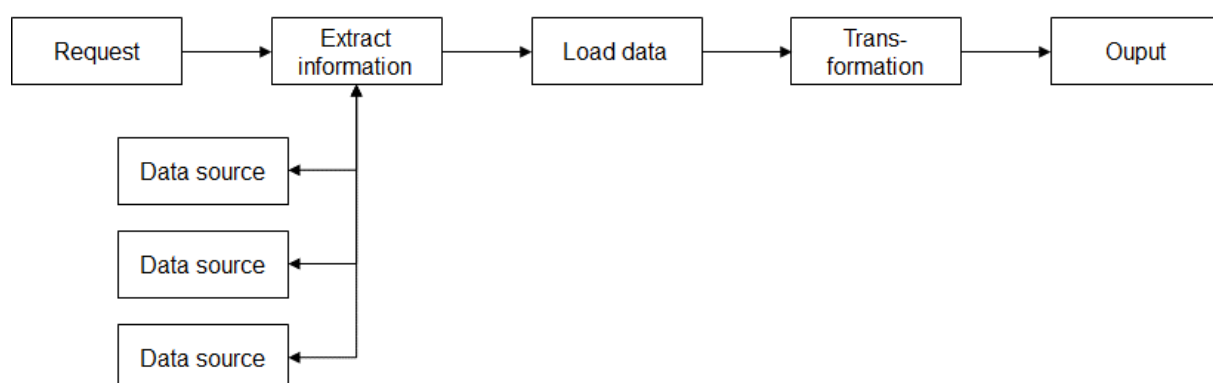
This might be relatively straightforward for many topics, but it becomes incredibly complex for other areas.

Let us now apply the general idea of computational complexity to the random list of tasks from above. All except the newspaper delivery are much less time-consuming than 10, 20 or 50 years. Some would not even have been possible:

- Delivering newspaper to apartment number 47 (it has not changed much in the last decades)
- Organizing transplant organs (using market exchanges as outlined by Alvin Roth)
- Ordering a new logo from a designer based in Vietnam (using online platforms)
- Writing the shareholder agreement for a new company (using generative AI)
- Paying for the bread in the bakery (use digital payments)

STAY OK logo top-left; Co-funded by the European Union flag top-right

- Invoicing a client for the services delivered in the last month (using e-mails and digital signatures)
- Sending a damage report to the insurance company (using apps and e-mails)
- Preparing an ESG report for an investment company (using tools based on symbolic AI)

5.2 Decision-making support and the development AI agents

Modern workflow management systems are designed to execute and automate scripts efficiently, ensuring that business processes are carried out smoothly and with minimal human intervention. Scripts in this context refer to predefined sequences of operations or tasks that are triggered by specific events or conditions. These systems automate repetitive tasks, manage approvals, and route tasks to the appropriate personnel or departments.

Scripts are initiated by specific triggers such as the completion of a previous task, the arrival of a certain time or date, or the input of specific data. For example, in a procurement process, the receipt of a purchase order might trigger a script that initiates the approval workflow.

Once triggered, the workflow system assigns tasks to the appropriate individuals or teams based on predefined rules and roles. This ensures that tasks are directed to the right people without manual intervention.

Workflow systems automate various steps in the process. For instance, they can automatically send emails, update databases, generate reports, or move files between systems. Automation reduces the need for manual input, minimizing errors and speeding up processes.

Workflow management systems continuously monitor the progress of scripts. They provide real-time updates and status reports, allowing managers to track the execution of tasks and identify any bottlenecks or delays.

Every step of the script execution is logged for compliance and auditing purposes. This ensures that all actions are recorded, and any deviations from the standard process can be investigated.

Artificial intelligence (AI) and machine learning are significantly enhancing the functionality and efficiency of scripts in workflow management systems. AI-driven tools can optimize workflows by learning from past data and making intelligent decisions.

There are various options how artificial intelligence can improve workflow.

AI-based algorithms analyze historical data to predict future outcomes. For example, predictive analytics can forecast potential delays in a project and adjust timelines and resources accordingly to mitigate risks (e.g., Hamdan et al., 2024). Technically, there are thousands of different patterns which are difficult to handle manually but can be efficiently monitored with AI.

There is also an element called "efficient routing" as AI can determine the most efficient path for task completion by analyzing factors such as current workloads, employee expertise, and historical performance. This ensures tasks are assigned to the most suitable personnel.

Natural Language Processing (NLP) tools which are commonly known as ChatGPT or Claude enables workflow systems to understand and process human language. This can be used for automating customer service interactions, processing emails, and interpreting unstructured data.

AI-based tools can automate complex decision-making processes by evaluating multiple criteria and selecting the best course of action. For example, in financial services, AI can automatically approve or reject loan applications based on predefined risk parameters.

This leads to the development AI agents.

An agent refers to something that takes certain action. A very simple <u>agent</u> would be the heating system in your house. Whenever the temperature is below a certain temperature, it would start heating the house.
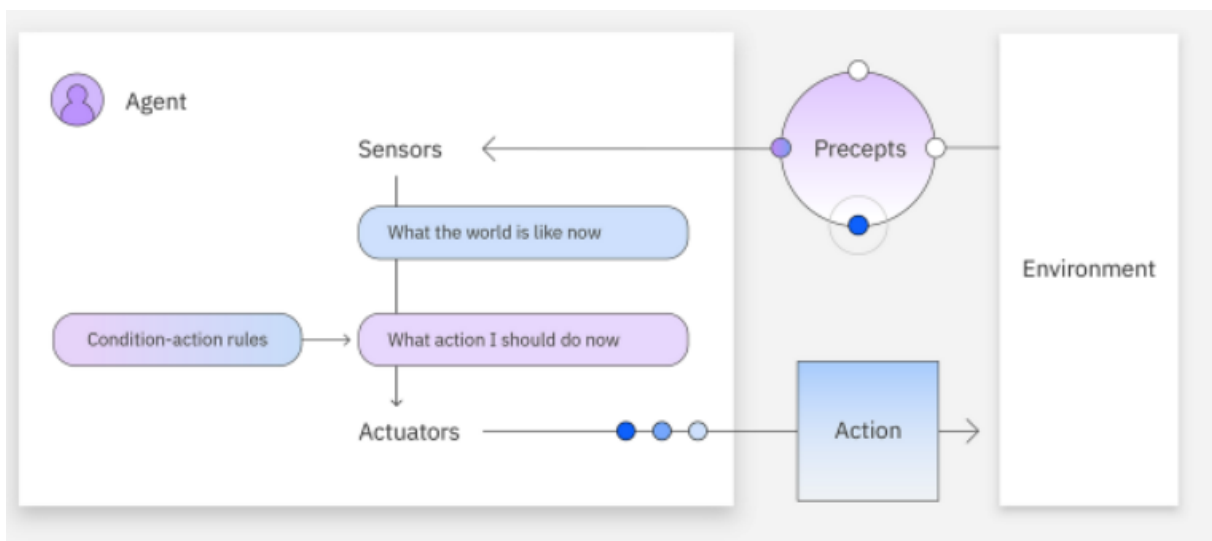
AI agents are software programs designed to perform tasks autonomously by mimicking human decision-making processes. These agents rely on machine learning algorithms, natural language processing, and other AI technologies to analyze data, learn from it, and act on it. In the context of decision-making support, AI agents can assist employees by automating repetitive tasks, suggesting data-driven decisions, and providing real-time insights, thereby enhancing productivity and accuracy. For example, AI agents are increasingly used in customer service, handling inquiries and providing solutions without human intervention.

AI agents are not just static tools; they can adapt and improve over time. They use machine learning to analyze past decisions, learn patterns, and refine their actions to better align with organizational goals.

The deployment of AI agents in workflow management systems can help to streamline processes and reduce human errors. These agents monitor workflows, predict bottlenecks, and adjust resource allocation to ensure tasks are completed efficiently. For example, in a supply chain, AI agents can predict potential delays and reroute shipments to minimize disruption. Their ability to manage and optimize workflows in real-time allows organizations to operate more efficiently and respond faster to changing conditions, ultimately improving overall performance.

A more complicated AI agent could have the <u>structure</u> as shown below. This AI agent would even have the ability to learn and it called a learning agent. It consists of four elements as described by <u>IBM</u>:

- **Learning:** This improves the agent's knowledge by learning from the environment through its precepts and sensors.

- **Critic:** This provides feedback to the agent on whether the quality of its responses meets the performance standard.

- **Performance:** This element is responsible for selecting actions upon learning.

- **Problem generator:** This creates various proposals for actions to be taken.

This type of learning agent can be used for recommendation engines but also all other kind of repetitive work we have outlined above.
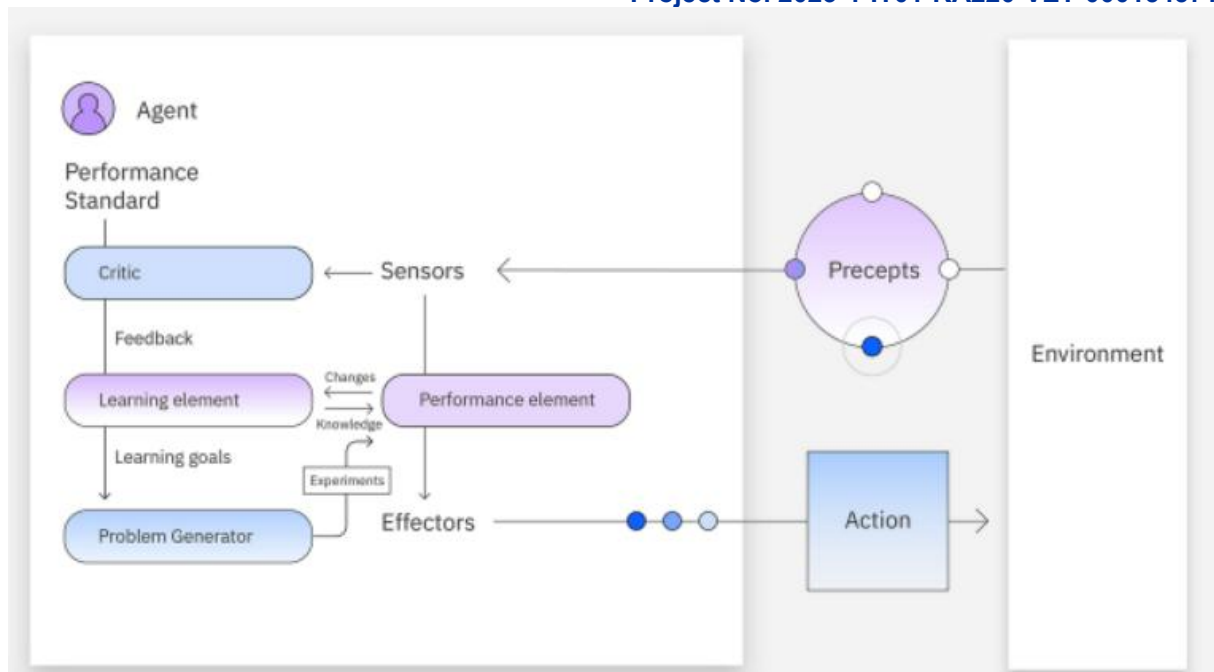
Exercise: Think of a use case in a company which you know well. What kind of work can be taken over by such learning agents?

5.3 Industry cadence

It is a bit of a side note, but it is also important to keep in mind how fast an industry operates. Byrne Hobart described the following observation:

> It's popular to say that every company is becoming a tech company, and to some extent that's true. But companies need to be judicious about evolving towards sectors of the economy that operate on a faster cadence than they're used to.

Some industries are operating on a very slow schedule. A typical fashion retailer needs to order stock for the fall season probably 6-8 months earlier. This makes sense: Textiles need to be ordered, factories scheduled and shipping container booked.

Think of the airline industry or space agencies which need decades to develop new airplanes or rockets.

Some fashion companies are now producing on much shorter schedules. Zara has cut the production time to 2-3 weeks, while the total production time from concept to final product is 2-3 weeks for Shein. Some software companies are able to change their codebase in a matter of hours and quickly ship it to their customers.

There are many areas where the instantaneous availability of data has led to a sharp reduction in the time to complete a cycle (however it is defined). However, it is not clear that an increase in the cadence of an industry increases the complexity (especially when tasks are becoming more digital at the same time).

5.4 Examples for software solutions

The German company SAP is one of the leading enterprise resource planning (ERP) systems globally, used by more than 425,000 companies across various industries. SAP provides comprehensive solutions for mapping, managing, and optimizing business processes. The company offers modules for finance, human resources, supply chain and sales among others.

Why is it needed? Take a look at the following business process map which is fairly typical for processes in companies.
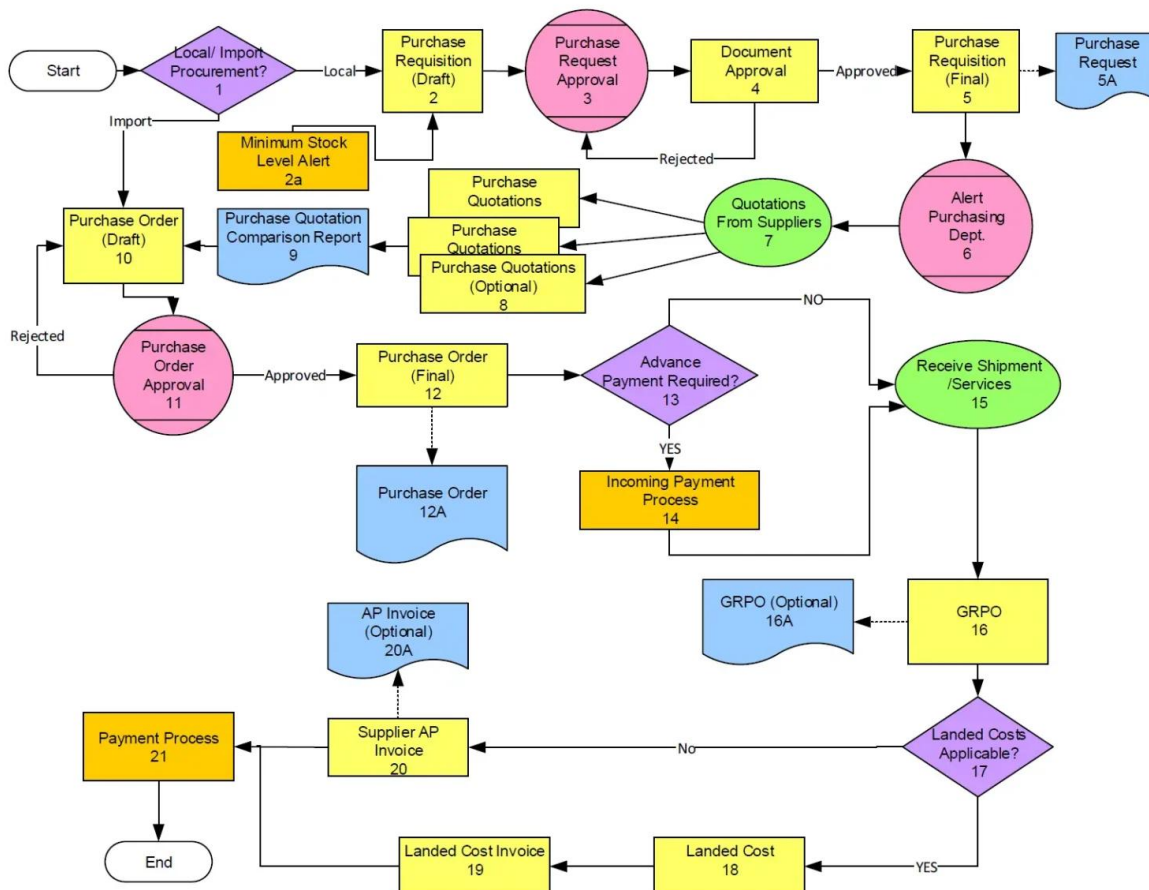
The flowchart illustrates the typical purchase process, beginning with the identification of a need that triggers either a local or import procurement.

For local procurement, when the required good is available locally, the process starts with drafting a purchase requisition, which is then submitted for approval. Upon approval, a purchase order is issued to the supplier, initiating the procurement.

If the good needs to be imported, the process becomes more complex. It involves requesting quotations from multiple suppliers, comparing these quotations, and, in some cases, obtaining additional approvals before proceeding.

Once the purchase order is finalized, the supplier ships the goods and sends the corresponding invoice. Upon receiving the shipment, the buyer verifies it against the purchase order to ensure accuracy before making the payment. In some cases, the process may include further steps, such as advance payments, receiving reports, or managing landed costs, which are the additional expenses incurred during the importation process.

In general, SAP structures organizational workflows by integrating different business functions into a unified system. It does this by creating a network of interrelated processes and tasks, enabling seamless coordination across departments. These tools allow companies to define specific tasks, assign roles, and establish approval chains. Workflows can be mapped in a step-by-step process, specifying triggers (such as a purchase order being received) and the subsequent actions that need to occur (like sending the order to the finance department for approval).

The system breaks down business processes into individual components, creating a visual flow that tracks every step from start to finish. Each step is assigned to the appropriate department or individual, ensuring that tasks are completed efficiently and according to predefined business rules. This level of granularity enables businesses to streamline operations, reduce redundancies, and ensure that workflows follow established protocols without manual intervention.

SAP automates many routine tasks within these workflows, minimizing human error and speeding up the execution of processes. For example, in a manufacturing workflow, once a production order is triggered, SAP can automatically initiate procurement for materials, schedule production slots, and generate the necessary documentation without requiring human input. This automation not only enhances efficiency but also ensures that processes adhere to organizational rules and regulatory requirements.

The features explain the success of the companies in this ERP and workflow management space. The other companies are Oracle, Microsoft or IBM.

Attention-Check Question

Which of the following is an example of how AI agents are used to improve workflow management systems?

A) AI agents eliminate all manual tasks by making independent decisions.

B) AI agents automate repetitive tasks, monitor workflows, and suggest improvements to optimize processes.

C) AI agents increase the number of manual approvals required for routine tasks.

D) AI agents are only capable of responding to customer service inquiries.

6. Ethics

Objectives:

- Understanding the ethical challenges of AI in worker management by exploring key ethical issues such as bias, privacy, and transparency in AI systems;
- Learning about methods to address and mitigate these concerns.

6.1 Introduction and the question of data

We have heard a lot about the potential applications.

Companies developing machine learning do not spend a large amount time to consider the ramifications and implications of their actions. Given that the companies expect large profits and face significant competition, it is also understandable that some

There are many ethical concerns which should be addressed in this area (Mittelstadt et al., 2016). Algorithms have been found to be problematic in a range of industries such as bank loans, court judgements, predictive policing or the evaluation of teacher performances (O'Neil 2016). There was also widespread resistance against the use of algorithms in labor market agencies.

One of the key ethical concerns is focused on the unfiltered and problematic datasets. Birhane, Prabhu, and Kahembwe (2021) analyze one of the largest datasets for AI purposes which is a run by a California-based non-profit organizations. It contains 400 million samples of image-text-pairs such as "blue cats". [2]

After searching through the dataset, they find that it only

> "*risked amplifying hyper-sexualized and misogynist representation of women, but also presented results that were reminiscent of Anglo-centric, Euro-centric, and potentially, White-supremacist ideologies*".

Even when datasets are retracted, they remain widely available as they have already been used to train models. Data is sold, merged and used in derivative forms. The users have no control over how the data is being used.

Zou and Schiebinger (2018) point out that a major issue is the construction of the data sets on which the systems are trained. The images are often from US-centric databases which tend to underrepresent darker-skinned persons.

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[2] For more information: https://laion.ai/laion-400-open-dataset/.

ImageNet is a major database for the training of AI systems (Russakovsky et al., 2015). Having common datasets save a lot of efforts for the researchers but they can also lead to biases if there are biases in the data. For ImageNet, Shankar et al. (2017) find that almost half of the images are coming from three countries which are the United States (32%), Great Britain (13%) and France (4%). Although these countries only account for a fraction of the global population, they contribute half of all images.

Exercise

Consider the implications how datasets are distributed: Take a database which contains only a set of high-performing employees. What is the likelihood that it will mainly consist of white men with an academic degree from a few well-known institutions?

Another ethical concern is the lack of algorithmic accountability which means that AI systems are almost always a black box for the general public. The general public does not have access to the training data and also to the neural network itself.

There is an understandable resistance to provide access to these systems which are often at the core the company's operations. The problem of a black box is also that the old saying "Garbage in, garbage out" applies as well. In addition, these models are not interpretable for humans. This might change in the future, but it seems to be long shot comparable to understanding the functioning of the human brain.

Although, deep learning models or neural networks might perform better, some analysts prefer regression models as the most relevant features can be easily identified. There is thus a trade-off between an understanding of the data and the performance of the system.

To build fair and unbiased AI systems, it is essential to ensure diversity and inclusion during data collection and annotation.

6.2 Reproduction of biases

AI system also reproduce biases and structural disadvantages for certain groups. In a famous study, Buolamwini and Gebru (2018) evaluate commercial AI-gender classification systems. A first problem is that the training data contains on average around 80% of lighter-skinned persons. They also find that these commercial gender classification systems have error rates of up to 34.7% for darker-skinned women, while the error rate for light-skinned men is 0.8%.

Bender et al. (2021) show that large language models are not necessarily diverse in its results. It has to do with the persons contributing to content on the internet as one factor. Translation using AI system is reflecting inequalities and biases in society.

The table below shows the limits and gender biases in automatic translation. There is a tendency to identify better paying jobs with males and caring professions with females. The

sentences below are Hungarian and Malay. Although, there is no indication of gender in the sentences below, the automatic translation identifies men with managers and intelligences and women with caring professions and beauty. It is easy to understand the reasoning of the AI system but it is also obvious that these translations help to preserve stereotypes.

Original gender-neutral sentence	Translated sentences
ő vigyáz a gyerekekre.	she takes care of the kids.
ő egy menedzser.	he is a manager.
ő szép.	she is beautiful.
ő okos.	he is clever.
ő takarítja a házat.	she cleans the house.
ő egy mérnök.	he is an engineer.
dia menjaga anak-anak.	she takes care of the children.
dia seorang pengurus.	he is a manager.
dia cantik.	she's beautiful.
dia pandai.	She is smart.
dia mengemas rumah.	she's tidying up the house.
dia seorang jurutera.	he is an engineer.

Table 7: Translation of gender-neutral sentences
Source: Spiess-Knafl (2022)

Researchers have tested the translations in 12 gender-neutral languages and have found that the translations do not reproduce the real-world distribution. In reality, the female representation in certain occupation is much higher than in the translated sentences (Prates et al., 2020).

Misclassifications and errors can also often be found. In 2015, a Black software designer tweeted that Google's image recognition software was misclassifying him and a black female friend as gorillas. Understandably, the tweet caused a PR disaster for Google and the company blocked image searchers for gorillas, monkeys, chimps and chimpanzees since then. The same error happened at Facebook in 2021. Users who were watching a video featuring Black men were asked if they wanted to watch more "videos about primates" (Jones 2021).
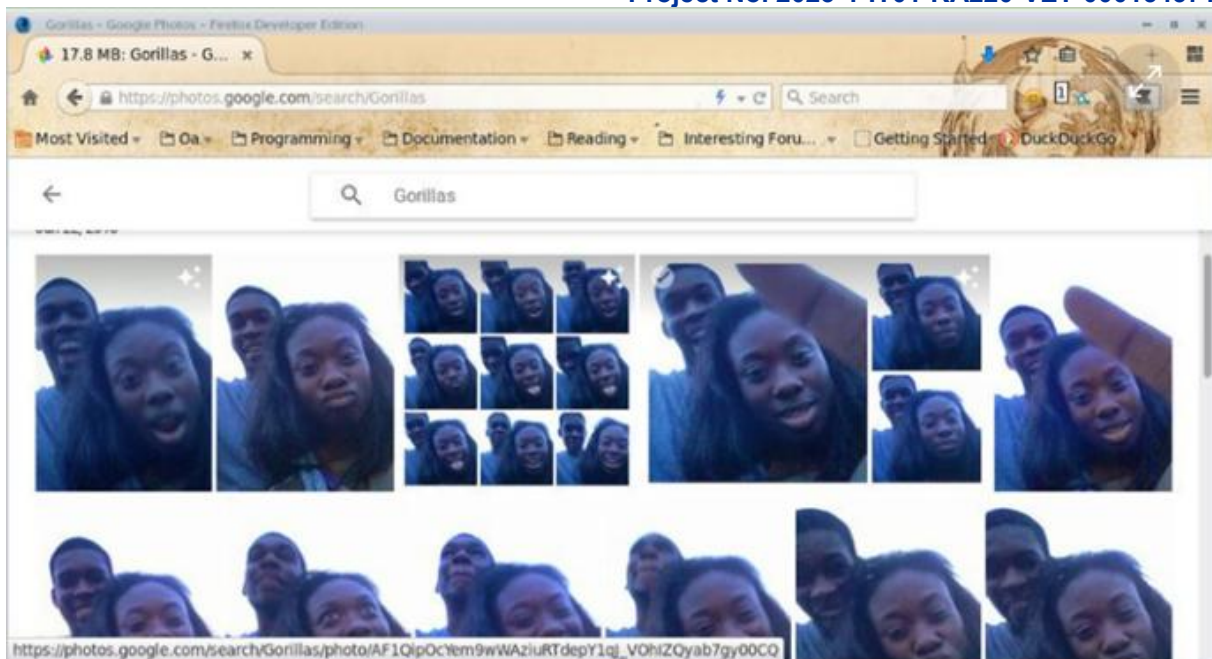
This points towards the implications of errors but also the difficulties of the technology.

The introduction above has shown how important training data is for the development of the AI systems. However, for users it is usually impossible to keep track of their own data and reclaim them later.

Users have many devices which are actively collecting data and intruding into their privacy. Véliz (2020) is illustrating the typical daily routine which involves web searches, Alexas, loyalty programs, house control, car management systems and so on. All of these devices are potentially problematic and have been found to violate the privacy of its users.

6.3 Bias Against Minorities

Bias in AI systems can lead to discriminatory outcomes that disproportionately affect minority groups. This bias can manifest in various ways, including unequal access to services, biased hiring practices, and unfair treatment by automated systems. For example, facial recognition technologies have been found to be less accurate in identifying individuals with darker skin tones, leading to higher rates of false positives and false negatives for these groups. Similarly, AI-driven hiring platforms may inadvertently favor candidates from majority groups due to biased training data, perpetuating existing inequalities.

Bias in AI systems can arise from several factors, leading to significant ethical and social implications. AI systems learn from historical data, and if this data reflects existing biases, the AI can perpetuate or even amplify these biases. For instance, if an AI system is trained on historical hiring data where certain demographics were underrepresented, it may learn to favor similar candidates, thus reinforcing systemic discrimination. The implications of bias in

AI systems are far-reaching, affecting fairness, equity, and trust in AI technologies. Unchecked bias can lead to loss of opportunities, unfair treatment, and harm to marginalized communities, undermining the potential benefits of AI.

Bias in AI systems can stem from various sources throughout the AI development lifecycle. We have already covered the data collection phase but there are other areas as well.

The choice of algorithms and how they are configured can introduce bias. For example, certain algorithms may inherently favor majority groups if not properly balanced.

A bias can also be introduced during the implementation phase, where the deployment context may inadvertently favor certain groups over others. For example, language models deployed in specific regions may not account for local dialects or minority languages.

Once deployed, AI systems may reinforce their own biases through feedback loops, where biased outcomes lead to further biased data, perpetuating a cycle of discrimination.

6.4 Privacy

Even anonymous data can often be linked to certain persons. A famous example is the de-anonymization of the Netflix Prize dataset. Netflix has shared the anonymous movie rating of 500,000 individuals. Narayanan and Shmatikov (2008) have used the Internet Movie Database to successfully de-anonymize users from the dataset. Their results are impressive as "8 movie ratings (of which 2 may be completely wrong) and dates that may have a 14-day error, 99% of records can be uniquely identified in the dataset. For 68%, two ratings and dates (with a 3-day error) are sufficient". This has important implications as the de-anonymization might reveal political or sexual preferences.

Other issues include data glitches. For example, autonomous weapon systems operate on data that are often faulty. Disinformation is another concern (Buchanan et al., 2021) or the energy needs of language models (Bender et al. 2021). At least, the energy needs are more efficient than the operation of some cryptocurrency networks.

The use of AI technologies raises significant privacy concerns, particularly related to the collection, storage, and use of personal data.

Collecting vast amounts of data for AI training often involves capturing sensitive information about individuals. The ethics of data collection hinge on obtaining informed consent and ensuring that individuals are aware of how their data will be used.

AI technologies, such as facial recognition and predictive analytics, enable extensive surveillance capabilities. While these technologies can enhance security, they also pose risks to individual privacy and can lead to unwarranted surveillance and profiling.

Examples of AI systems that have raised privacy concerns include social media platforms that track user behavior to deliver targeted advertising and smart devices that continuously monitor user activities. These systems often collect more data than necessary, raising questions about data minimization and user consent.

Striking a balance between technological innovation and privacy protection requires careful consideration. Strategies for protecting privacy while leveraging AI capabilities include:

- Implementing transparent data practices and holding organizations accountable for data misuse can help build trust and ensure ethical AI deployment.
- Providing users with control over their data, including options to opt-out or limit data sharing, can enhance privacy protections.
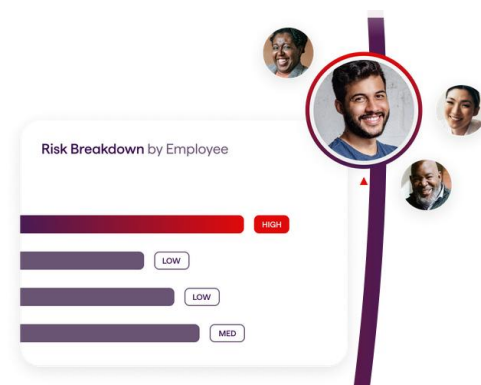
6.5 Intellectual property

You might remember the example of Virgin Pulse. They have collected data on 275 million people which they use to offer services. Nobody has really given his explicit permission that his or her data is used for these purposes. See screenshot below.

There are many instances where public data is being transferred to private companies. In this context, the data sharing agreement between the Royal Free Hospital and a Google's AI subsidiary, DeepMind, is often discussed. DeepMind received access to five years of patient data to predict acute kidney injuries. The results would then inform the development of a app to provide information about a patient situation. The data sharing agreement raised concerns as patients might not be willing to share sensitive health data with a Google subsidiary (Hawkes, 2016). It was later found that the data was shared on an inappropriate basis although the effectiveness of the app was confirmed (Iacobucci, 2017).

This illustrates the tensions between the need to have good data to develop useful products but also the trust which is needed in this area. Later, when Deep Mind' health team joined Google Health, researchers pointed that there is a need to address the deficit of trust to unlock the opportunities of the technology (Morley et al., 2019).

There are also other instances. For example, web crawlers collect information from the internet to use it for all kind of different purposes. Nobody asks the creators and writers if they do consent in having their work used for whatever purpose.

6.6 Methods for Detecting and Mitigating Bias and Auditability

Several tools assist in this effort, such as IBM's AI Fairness 360, which checks for bias and provides mitigation algorithms, and Google's What-If Tool, integrated with TensorFlow to analyze feature impact on predictions. Microsoft's Fairlearn offers fairness metrics and tools to address bias.

Let us take a look at what they are doing.

Bias often originates during data collection and preparation. Mitigating this involves sourcing diverse data to represent all demographic groups and using data augmentation methods like oversampling and synthetic data generation. Preprocessing techniques such as reweighting samples, anonymizing data, and handling missing data fairly also reduce biases before model training begins.

Algorithmic solutions are vital for addressing bias during model training. Fairness-aware algorithms embed fairness constraints within learning processes to balance accuracy and equity. Adversarial debiasing trains models alongside adversarial networks to detect and minimize bias. Post-processing techniques, like adjusting thresholds and re-ranking outputs, ensure fairness after training.

Reducing bias requires a commitment to best practices and ethics. Inclusive design involves engaging diverse stakeholders to reflect varied perspectives. Transparency and accountability are critical, with clear documentation and explanations of model decisions. Continuous monitoring and feedback loops allow for ongoing bias detection, and ethical frameworks guide the development of AI systems that prioritize fairness, accountability, and transparency.

Let us start with an audit pymetrics has commissioned. It is interesting as it outlines the aspects which are in the scope and outside of the scope of the audit by Wilson et al. (2021)

During the audit we focused on the following specific questions:

(1) Correctness. pymetrics' documentation describes their process for performing adverse impact testing on trained models before they are deployed. Does the model training source code

correctly implement adverse impact testing as the four-fifths rule using the minimum bias ratio (a.k.a. impact ratio) metric as described in the documentation? Is fairness

assessed for the seven demographic categories defined by the EEOC (five racial and ethnic, two gender)?

(2) Direct Discrimination. Using demographic data as training features for models can be construed as a form of direct discrimination. This motivates us to ask do trained models use demographic data directly as input, or is demographic data only used for post-training adverse impact testing?

(3) De-biasing Circumvention. There are numerous examples of deployed ML-based systems that had their safety systems subverted by clever and malicious users . These experiences motivate us to ask is there any way for training data that is erroneously corrupted or intentionally biased to somehow avoid the adverse impact tests, thus resulting in an unfair model being released?

(4) Sociotechnical Safeguards. pymetrics' process for producing models involves human intervention, which raises the issue that human errors may subvert fairness guarantees. Does pymetrics have checks in place to ensure that human errors (either benign or malicious) do not result in an unfair model being released?

(5) Sound Assumptions. Using ML is never as simple as loading data and inputting it into a training algorithm. Data must be preprocessed and transformed to prepare it for analysis. This process concretizes assumptions about the data that may influence the adverse impact assessment. Are there assumptions about data and data preprocessing baked into pymetrics' model training process that could cause the adverse impact assessment to fail or mislead?

This is all interesting but also take a look at everything which was outside of the scope of the audit (Wilson et al., 2021):

Just as important as defining what we were auditing is understanding what we were not auditing. This point is critical for properly contextualizing any audit, so as to focus on specific criteria for success or failure. In particular, our audit did not cover the following aspects of pymetrics' products and business.

- *Prior to conducting the audit, we agreed with pymetrics that we would not question their choice of fairness objective (the UGESP four-fifths rule) or fairness metric (minimum bias ratio). Although there are many other potential fairness objectives and metrics, including others designed to prevent disparate impact [38, 42, 63], pymetrics chose their existing objective and metric based on what they felt was most appropriate in the context of their business, i.e., candidate screening. This objective and metric were proposed by the relevant U.S. regulators themselves.*
- *Similarly, we agreed not to question pymetrics' choice of race, ethnicity, and gender categories that they evaluate for fairness since these categories are delineated as protected by the EEOC. Further, we agreed to not evaluate fairness for intersectional*

groups (i.e., combinations of demographic categories like Black males or Asian females) since they are not considered protected by the EEOC.

- *We only audited pymetrics' game-based candidate screening product. We did not audit other products and services.*
- *We did not investigate the ability of pymetrics' games to measure human capabilities, whether those capabilities map to job performance, or whether other assessment methods would be superior in some respect (e.g., fairness or accuracy). As computer scientists, evaluating these aspects of the pymetrics system were beyond our capabilities. Additionally, we do not comment on the rationality and ethics of using these measures to evaluate a candidate's suitability for employment.*
- *pymetrics recently started offering an additional suite of numerical and logical reasoning games. We did not have access to datasets that included data from these games, so we cannot comment on their impact to fairness. That said, the control flow in the pymetrics source code ensures that all models eventually must pass fairness checks, regardless of whether the model includes or does not include data from these additional games.*
- *pymetrics performs post-training adverse impact testing on models using a held-out set of data. Prior to conducting the audit, we agreed with pymetrics that we would not question their choice to use post-training testing. While pre-training and during-training model de-biasing methods exist, they require that training data include complete demographic information, which is not always available in employment contexts.*
- *During our audit, we did not focus on evaluating or maximizing the predictive performance of pymetrics' models—fairness was our main concern. That said, during our testing, we did obey the minimum baseline predictive performance requirements that pymetrics demands of all their models.*
- *We did not audit pymetrics' process for performing annual adverse impact back-testing on deployed models.*
- *We did not examine pymetrics' cybersecurity posture, e.g., we did not perform penetration tests. We did not attempt to become a pymetrics client, play their games while posing as an employer or a job seeker, have any contact with pymetrics employees outside the narrow confines of this audit, or attempt to conduct insider attacks given our privileged access to pymetrics systems, data, and employees.*
- *We did not examine pymetrics' posture with respect to data privacy or compliance with laws like Europe's General Data Protection Regulation, the California Consumer Privacy Act, the U.S. Children's Online Privacy Protection Act, etc. However, pymetrics has developed an information security program compliant with the internationally recognized ISO/IEC 27001 information security standard and undergoes semiannual security audits by an internationally accredited certification body.*

6.7 Legal and Ethical Frameworks

The landscape of laws and ethical guidelines addressing bias in AI is evolving rapidly, reflecting the increasing awareness and importance of ethical AI development.

At the international level, regulations such as the General Data Protection Regulation (GDPR) in the European Union have significant implications for AI. The GDPR mandates transparency in automated decision-making processes and grants individuals the right to explanation, ensuring that AI systems do not operate as black boxes. Furthermore, the GDPR enforces strict data protection standards, aiming to prevent discriminatory practices in data processing.

Various countries and US states have introduced or are discussing laws specifically targeting AI and algorithmic fairness. For example, the Algorithmic Accountability Act proposed in the United States requires companies to conduct impact assessments of automated decision systems to identify and mitigate biases. Other nations, such as Canada and Singapore, are also developing frameworks to regulate AI ethics and fairness.

Organizations like the Institute of Electrical and Electronics Engineers (IEEE) and the International Organization for Standardization (ISO) have proposed standards to promote fairness in AI. The IEEE's Global Initiative on Ethics of Autonomous and Intelligent Systems and ISO's standards on AI aim to provide guidelines for ethical AI design and deployment, focusing on transparency, accountability, and inclusivity.

Various coalitions and non-profits, such as the Partnership on AI and the AI Ethics Guidelines by the European Commission's High-Level Expert Group on AI, advocate for ethical AI practices. These guidelines emphasize principles like fairness, accountability, transparency, and human-centric AI, aiming to ensure that AI technologies benefit all parts of society equally.

6.8 Ethical Responsibilities of Employers

Employers have significant ethical responsibilities to ensure that AI systems used within their organizations are fair and supportive of all employees.

Employers should be transparent about how AI is used in their organizations. Clear communication about the purpose, functioning, and impact of AI systems helps build trust and understanding among employees.

It can be considered to provide training on recognizing and mitigating bias in AI is essential for both employees and managers. This training should cover the ethical implications of AI, the sources of bias, and strategies for reducing bias in AI applications. Only a few companies are considering this to be important.

AI-driven decisions can sometimes negatively impact employees. Employers should develop support systems to assist those adversely affected. This includes providing opportunities for retraining and upskilling to help employees adapt to changes brought by AI technologies.

The use of AI in human resources, including hiring, performance evaluations, and promotions, should be governed by ethical guidelines. These guidelines should ensure that AI systems are fair, transparent, and free from discrimination.

Protecting employee data should be protected when using and training AI systems. Employers must ensure that data collection and processing comply with privacy laws and regulations, and that employees' privacy rights are respected.

6.9 Job Losses and social security

AI-powered automation is reshaping industries by driving efficiency, productivity, and accuracy. However, this progress often comes with the unintended consequence of job displacement. As AI and automation increasingly handle routine, repetitive, and even complex tasks, certain jobs are rendered obsolete, causing significant workforce reductions. Research suggests a large share of global jobs could be automated. This shift impacts sectors differently, with manufacturing, retail, and administrative roles facing the highest risk of automation. However, reconsider the example of the liftboy at the beginning.

The economic impact of AI-driven job displacement is profound. While automation boosts productivity and economic growth, it can also exacerbate income inequality and trigger socio-economic instability if displaced workers aren't provided with adequate support and opportunities for reskilling. A reduction in jobs within certain industries can drive up unemployment rates, curb consumer spending, and heighten reliance on social services. Additionally, regions heavily dependent on automation-vulnerable industries may experience deeper economic disruption, intensifying regional disparities.

To alleviate the negative effects of AI-induced job displacement, it is important to implement effective workforce transition strategies focused on reskilling workers to meet the demands of the evolving job market. Promoting continuous education and skill development is essential for helping workers adjust to new job requirements.

Governments and employers should collaborate to create training programs that equip workers with skills suited for the AI-driven economy. Expanding access to vocational and apprenticeship programs will facilitate career transitions, with these initiatives aligning with current industry demands and focusing on equipping workers with in-demand skills.

Partnerships between industries and training institutions can help identify critical skill gaps and develop targeted reskilling programs, while employers can further support these efforts by providing on-the-job training and internship opportunities. Utilizing online education platforms can make training more accessible to a broader audience by offering flexible,

affordable, and personalized learning options tailored to diverse learner needs. Offering career guidance and support services can help displaced workers navigate their transition, providing assistance with career planning, job search strategies, and emotional support.

Government policies also play a crucial role in addressing job displacement due to AI. Investment in education, particularly in STEM (Science, Technology, Engineering, and Mathematics) fields and digital literacy, should be prioritized, alongside funding reskilling and upskilling initiatives to prepare the workforce for future employment opportunities.

Offering incentives to businesses that invest in workforce training and development can encourage employers to actively participate in reskilling efforts through tax credits, grants, and subsidies.

Social safety nets and support systems are also important for supporting displaced workers and ensuring a smooth transition to new employment.

Social security systems are meant to protect individuals from risks. The following elements are usually covered by social security systems (Forde et al., 2017):

- Healthcare (costs)
- Sickness (benefits paid during sick leave)
- Maternity (costs and benefits)
- Disability (benefits)
- Old age (pension benefits)
- Survivors (benefits)
- Employment injuries/accidents at work and occupational diseases (costs)
- Family (benefits)
- Unemployment (benefits)
- Guaranteed minimum resources (benefits)
- Long-term care (costs)

It is interesting to note that the systems are managed quite differently across Europe. While some are tax-financed, others are contribution-based.

Social security rights are often tied to the employment status but there are exceptions. For example, in Germany homeworkers and artists enjoy social security protection disconnected from their employment status (Chesalina, 2018).

Attention-Check Question

Which of the following best illustrates an ethical concern associated with AI in the workplace?

A) AI systems always operate without bias and require no ethical oversight.

B) The use of AI in the workplace raises concerns about bias in decision-making, privacy violations, and lack of transparency in AI outputs.

C) AI-driven tools only enhance fairness and objectivity, eliminating the need for ethical considerations.

D) There are no ethical challenges in deploying AI for worker management.

7.Quiz

What is a critical challenge of AI-driven recruitment processes?
A) AI eliminates bias in hiring completely
B) AI recruitment tools provide perfectly fair outcomes for all candidates
C) AI may unintentionally replicate biases present in historical data
(Correct Answer: C)

Which of the following AI-driven practices can improve workplace well-being?
A) AI always increases workplace productivity without any impact on well-being
B) AI replaces the need for human resources entirely
C) AI systems can predict employee burnout and suggest timely interventions
(Correct Answer: C)

Which sector is most vulnerable to AI-driven automation?
A) Healthcare
B) Manufacturing
C) Education
(Correct Answer: B)

Which of the following accurately describes the relationship between automation and job displacement?
A) Automation primarily replaces low-skilled jobs with minimal impact on other sectors
B) Automation can displace both low-skilled and complex jobs across various industries
C) Automation has no significant effect on complex jobs, only affecting routine tasks
(Correct Answer: B)

What is a key benefit of using AI in recruitment?
A) AI handles all interviews for hiring managers
B) AI automatically crafts highly creative job descriptions
C) AI automates the screening of resumes and filtering applicants based on set criteria
(Correct Answer: C)

Which of the following techniques is commonly used to measure employee performance?
A) Relying on subjective opinions from peers
B) Using random evaluations once a year
C) Utilizing Key Performance Indicators (KPIs) to track productivity, quality, and goal achievement
(Correct Answer: C)

Which of the following factors contributes to the effectiveness of AI in improving workplace well-being?

A) AI systems can predict employee burnout and suggest interventions

B) AI systems replace all human roles in HR management

C) AI reduces the need for employee well-being initiatives

(Correct Answer: A)

Why is reskilling considered essential in an AI-driven economy?

A) Reskilling helps workers transition into completely new industries unrelated to their previous roles

B) Reskilling enables workers to adapt to the evolving demands of the job market and secure future employment

C) Reskilling is only necessary for low-skilled workers affected by automation

(Correct Answer: B)

How does AI enhance decision-making support in organizations?

A) By replacing all human decisions

B) By automating low-level tasks and providing insights

C) By eliminating the need for human oversight

(Correct Answer: B)

What is a key concern related to intellectual property in AI-driven systems?

A) AI automatically respects all intellectual property rights

B) AI can create unique works that may pose challenges in determining ownership and rights

C) AI eliminates the need for intellectual property laws altogether

(Correct Answer: B)

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