Empowering Career Crafting in the Future of Work with Data-driven Tools

by

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Abstract

The rapid advancement of technology, particularly in the realm of A.I., is causing significant shifts in work dynamics and career paths. Automation driven by A.I. is reshaping tasks and job requirements, pressuring workers to constantly upskill to remain relevant in a rapidly changing professional landscape. Predictions suggest a need for around 12 million occupational transitions in the U.S. by 2030. Low-skill workers face the greatest challenges in reskilling, while the evolving skill landscape lacks clear guidance for workers. Organizations must prioritize helping employees adapt to technological progress to ensure retention and productivity. To address these issues, it's essential to develop tools that empower the workforce to identify skill gaps and navigate career changes. This dissertation delves into the transformative effects of technology on work and careers, exploring the interplay between A.I. advancements, changing career trajectories, and the need for effective tools to support workers. The work reviews the impact of technology on labor, examines evolving career concepts, introduces the philosophy of Value-Sensitive Design (VSD) for creating decision-making tools, and presents prototypes aimed at assisting individuals in making informed career choices, ultimately contributing valuable insights to the evolving world of work.

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Chapter 1

Introduction

Leaps in technological progress [6] are transforming work, employment, and career trajectories. New advances in A.I. are automating various tasks and reducing the longevity of skills in the workforce. Consequently, today's workers face the pressure to upskill and adapt their career paths at unprecedented speeds in the expanding professional possibility space. Indeed, it is projected that 12 million occupational transitions may need to take place by 2030 in the U.S. alone [5]. Furthermore, lower-skill workers bear the brunt of the reskilling challenge [**?**], and neither academics nor policymakers fully understand the quickly evolving skill landscape to offer sound guidance for workers to invest in the right set of skills to remain relevant [8]. For companies, helping their workforces keep up with technological progress is quickly becoming imperative for employee retention and their bottom lines. As a result, it is crucial to develop insights and tools that will empower the future workforce to recognize skill gaps and smoothly transition between different occupations to build a better future of work.

Understanding previous waves of technological change and their impact on labor can provide valuable insights into how emerging technologies will shape the work of tomorrow. Today, we know that advances in robotics, ICTs, traditional A.I., and generative A.I. enhance worker productivity [10] and enable innovation, albeit through different mechanisms. Traditional and generative A.I. can automate tasks and, potentially, entire occupations. It has been estimated that in the U.S., this automation potential ranges between 9-47% of jobs [7, 3]. The effects of such an extensive threat of job loss are partly offset by the surge in AI-related job vacancies, especially in large cities, highlighting that the challenges and benefits of A.I. vary significantly between and within countries and across industries and skill groups. For instance, the effects of traditional A.I. on the labor market are disproportionately shouldered by low-to med-skill workers [9], but generative A.I. is expected to affect white-collar work.

Changes in tasks, productivity, wages, and employability are an active field of study for labor economists, yet less is known about how technology shapes career journeys [1]. Career scholars have recognized a shift from linear, more hierarchical career trajectories to more flexible, dynamic, self-driven, boundaryless careers [4]. Characteristic of boundaryless careers is the increase of cross-firm, cross-occupational movements. Thus, a recent survey of the highest trending topics in career research cited career decision-making as the second most trending topic [1]. As a response to the increased demand in career crafting, several AI-driven systems have been to either match job-seekers to employers [2], provide automated career counseling [11], and, more recently, match seekers' C.V.s to possible online job descriptions using Large Language Models [12].

An expanding professional possibility space, too vast and costly to explore unguided, paired with the increasing speed at which workers are expected to reskill, demands the development of tools to help workers navigate their careers. However, I contend that many of the tools developed so far suffer from the following limitations: 1) a technology-first approach that often poses solutions that are at odds with the realities and challenges that their users face, 2) the recommendations or matching process is often opaque leading to a reduced understanding about what makes their experience and skills a good match for the suggested position or employer, 3) most of the systems leverage data about the workers and the jobs but don't include social information and 4) most systems prioritize delivering the best recommendations over affording their users with the ability to autonomously explore. Additionally, the models developed with the tools in mind also provide data-driven insights into career transition dynamics and wages that can inform organizations and policy.

This dissertation advances a framework for thinking about career journeys by synthesizing different bodies of literature about the future of work and identifying the opportunities and challenges they pose for workers and their careers. More specifically, this dissertation sets out to 1) Develop a comprehensive view that examines the transformations occurring in the world of work. This view encompasses the influence of technological advancement and the interplay of external factors and gains insight into its effects on individual workers' career paths; 2) Attain a more profound understanding, grounded in data, regarding the evolution of careers within the context of the contemporary work landscape; 3) Develop data-driven models that power tools to support workers in transitioning within their careers, and 4) prototyping two instances of such the tools.

The first part of this thesis introduces the problem of crafting careers in the age of AI. The second chapter in this work describes the state of the art about the impact of recent technological advances from robotics and ICTs to generative A.I. in the world of work through the synthesis of previously separate bodies of literature. The thirs chapter discusses how the concept of careers has changed and its relationship with skills and provides empirical evidence of its evolution. The fourth chapter summarizes the philosphy behind Value-Sensitive Design (VSD) and how it will guide the design process in creating the decision-making tools to help workers navigate the new AI-driven labor markets. It also describes the values the prototypes seek to embody. Finally, this thesis presents two decision making-tool prototypes to help different workforce members make decisions about their professional trajectories. The first case study outlines the lessons learned from previously published work and presents a tool to help migrants and refugees decide their labor market destinations'. The second case study shows explorative work on U.S. workers' strategies to advance their careers. I finish with concluding thoughts from the work in the thesis.

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Chapter 2

Minds, (Labor) Markets and Machines: The unfolding Future of Work

The impact of technological change in the world of work is multifaceted, encompassing both positive and negative effects on the nature of work, organizations, and local or national labor markets. Moreover, due to their specific affordances, different technologies influence labor markets and the economy in diverse, even contrasting ways. Thus, understanding how AI will shape the future of work requires a more detailed examination of previous waves of technological progress and AI's specific characteristics to envisage its effects more accurately.

In this chapter, I set out to synthesize the literature on AI's impact on the labor market from economics and computational social science, along with the research on the gig economy and human-machine collaboration. Despite the valuable contributions made in these areas, they have largely remained separate, and my goal is to bring them together to create a cohesive and comprehensive perspective on AI's role in shaping the world of work.

This chapter is dedicated to the synthesis of the literature focusing on the two most recent waves of technological change: the introduction of robotics and Information and Communication Technologies (ICTs) and the AI revolution. Of particular significance to this thesis is the influence of AI on the labor market. Hence, I distinguish between the effects of traditional AI and generative AI on both the labor market and the future workforce. 2-1 summarizes the main points in this chapter and organizes the subsections along a timeline (x-axis) and the level of aggregation on which technological innovations have had an impact (y-axis).

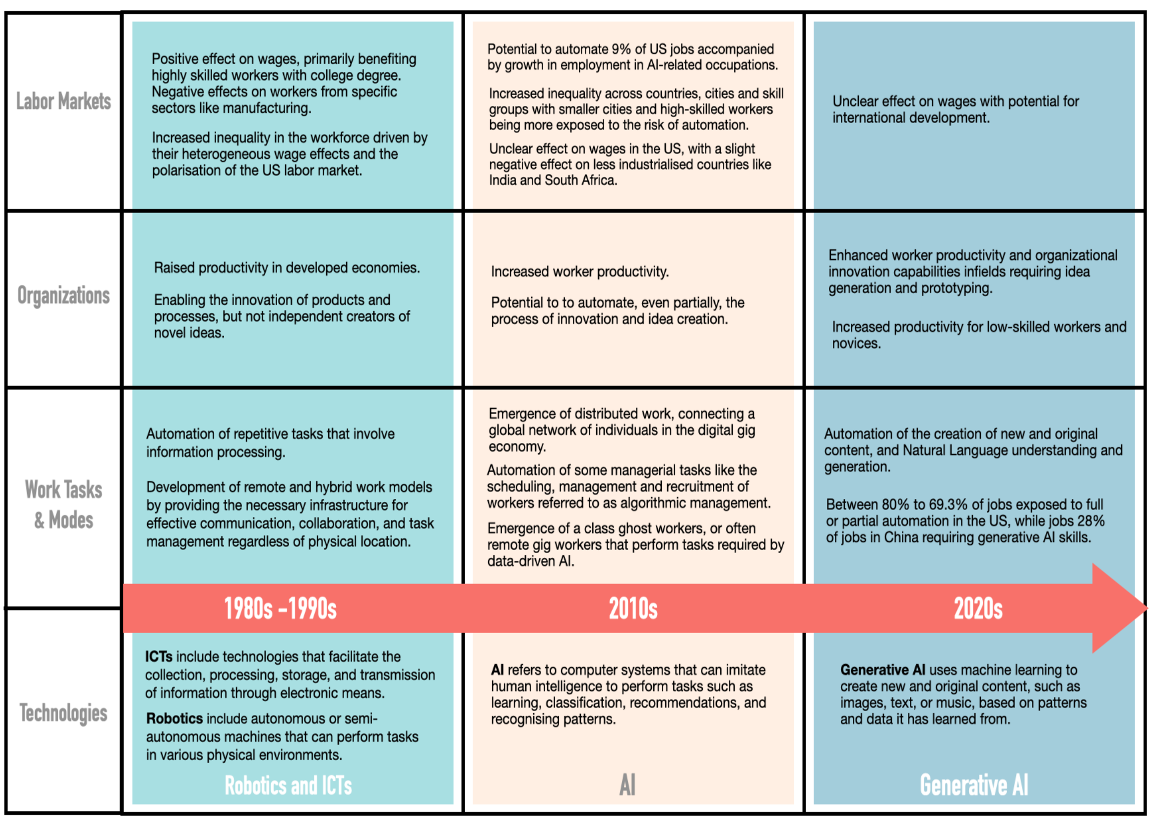

Figure 2-1: This figure summarizes the changes in the labor market brought about by different technologies across the different levels of aggregation from work tasks to broader labor market effects.

2.1 Robots and ICTs

2.1.1 The Nature of Work: Tasks, Work Modalities

ICTs and robotics have substantially transformed the work landscape by automating repetitive tasks that involve information processing or carry inherent risks [47]. This shift has had the most profound effect on middle-skill jobs, including tasks like clerical duties, data entry, and routine administrative work. As a consequence of this automation trend, blue-collar workers have experienced decreased opportunities to enter the lower levels of white-collar employment. Instead, they have often been compelled to transition into service-oriented roles, such as food service, cleaning, security, transportation, maintenance, and lower-paying care positions [8]. At the macro level, this phenomenon is referred to as the polarization of the US labor market [9].

ICTs have also played a pivotal role in fostering remote and hybrid work models [56] by providing the necessary tools and infrastructure for effective communication, collaboration, and task management regardless of physical location. ICTs such as high-speed internet, video conferencing software, project management platforms, and cloud-based tools enable seamless remote communication, file sharing, and real-time collaboration, allowing individuals and teams to work together from different locations. Such diversification in the availability of work models has positive and negative effects on labor markets. For instance, remote and hybrid work can increase worker productivity by reducing commute times and allowing for more flexible schedules. These work modes can also lead to cost savings for employers and employees, as they may not need to maintain as much office space and equipment, and workers can perform their duties further from expensive urban centers. For companies, these types of work modes increase their access to a larger talent pool, as they are now unrestricted by geography. On the other hand, recent insights suggest that similar numbers of employees prefer remote and onsite work, causing misalignments between firm and employee expectations[62].

2.1.2 Organizational Processes: Worker Productivity and Innovation

Firm data that ICT investment tends to produce positive effects on external users both within and across sectors [16]. In general, it has been observed that ICTs raise productivity in developed economies [34]. Similarly, robotics have contributed to a 0.36% increase in annual labor productivity growth and have raised total factor productivity [42]. In terms of innovation, ICTs are facilitators or enablers, not autonomous creators, of product, process and organizational innovation [16]

2.1.3 Labor Markets: Employment, Wages, and Inequality

Similar to previous waves of technological change, dating back to 19th Century England and the Luddite movement, the widespread adoption of ICTs and robots sparked concerns about job displacement. Critics argue that such displacement could harm workers and the overall economy, leading to increased unemployment [36]. However, labor economists generally agree that mass unemployment due to ICTs will unlikely become a significant issue in the next few decades [6, 11].

Furthermore, compelling evidence suggests that ICTs positively impact wages, primarily benefiting highly skilled workers with college degrees [7]. However, their effect on mid-skill and lower-skill workers is not as straightforward. A recent survey [45] indicates that most studies report positive wage and employment effects for high-skilled workers and adverse effects for mid-skill workers. As for low-skilled workers, the survey reveals mixed results, with nearly an equal number of studies reporting both positive and adverse effects for this skill group. Focusing on particular industries or economic sectors helps clarify the effects of ICTs and robotics on low-skilled worker wages. Several studies suggest that advances in software and robotics were associated with lower wages and opportunities in the US manufacturing sector [37, 4, 15]. A similar, albeit smaller effect was also reported for mid-skill workers in the manufacturing sector in Europe [24]. Meanwhile leading to improved employment stability, higher wage growth, and increased earnings for workers in service providers [42].

Unfortunately, ICTs and advances in robotics have also increased inequality in the workforce [14], driven by their heterogeneous wage effects and access to different modes of work for individuals in different skill groups. First, the polarization of the US labor market due, in part to the automation of mid-skill occupations, has eroded formerly robust urban wage premium paid to non-college workers and their up-skilling opportunities for better wages [8]. Additionally, remote or hybrid work is only available for some workers because specific duties cannot be performed remotely[53], and other workers may be unable to afford or access the technology needed to work from home. This difference in access to different work modalities exacerbates inequalities between communities, neighborhoods, and cities, especially during pandemic times[46], just like digital inequalities have been shown to affect the prospects of offline work[50].

To summarize, adopting robotics and ICTs in the labor market has brought both challenges and benefits. While concerns persist about job displacement and potential inequality, evidence supports the positive effects on wages and employment, which seem greater than the adverse effects. These technologies have the potential to drive economic growth and create new job opportunities, but policymakers must be mindful of the differential impacts across various skill groups to ensure a more equitable and inclusive future workforce.

2.2 Traditional AI

AI's impact in the world of work arises from well-known changes from technological progress, such as the creation, transformation, and obsolescence of certain occupations, and shifts in worker productivity, wages, and the nature of work activities. However, AI has also introduced unprecedented changes at remarkable speed, chipping away at several foundational notions of work and organizations. This has led many to question whether AI is a fundamentally new concern different from past technological advances. According to Brynolfson and McAffe [18], the answer might be yes. If so, what makes AI's impact on the labor market different from previous technological changes?

The remainder of this chapter explains how AI is shaping the world of work in more traditional ways akin to the impacts described for ICTs and robotics and answers this question by describing the novel changes brought about by AI for each of the aggregation levels considered in this chapter.

The Nature of Work: Task independence, human-machine collaboration and reliance on data

AI exhibits distinct characteristics compared to previous waves of general-purpose technologies, such as internal combustion engines or electricity [20, 21]. For instance, unlike previous technologies that were explicitly programmed to perform specific tasks, AI systems can learn and adapt from data, improving their performance over time without constant human intervention. AI also can continually improve their performance through iterations, making them more flexible and adaptable to fast paced environments. These, along with other AI-specific features, bring about novel changes in how work is performed and what are the main inputs in the production process. These novel changes can be grouped into three distinct categories:

- The emergence of the gig economy and ghost work and algorithmic management.
- Large-scale collaborations between humans and machines.
- Greater dependence on data as a critical production factor.

The gig economy, ghost work, and algorithmic management.

The cultural idea of work has evolved alongside the tools available to the times. In the pre-industrial era, work was linked to craftsmanship - artisans specialized in different trades would make a product from start to finish. After the industrial revolution, factories helped break the product-making process into parts making jobs more associated with groups of tasks instead of a finished product[60]. This idea of jobs as 'bundles of tasks' persists today among labor economists[12].

With the advent of AI and platform technology, some tasks can now be performed independently of occupations. Thus, they can be completed by individuals or teams outside the confines of traditional employment [43]. The unraveling of these occupation bundles has paved the way for decentralized and distributed work, connecting a global network of individuals with newfound flexibility. The consequences of such unraveling are two-fold: First, a hidden workforce that powers artificial intelligence has emerged. Unfortunately, due to their recent development, the workers that make up this important engine in the digital economy do not have the same benefits or protection as workers in traditional labor markets, creating another kind of inequality in the global labor force [43].

Secondly, the concept of jobs is once again undergoing a transformation, breaking down traditional agreements between employers and employees and enabling tasks to be accomplished independently. Perhaps one of the most significant departures of AI from previous general purpose technologies in the workplace is the potential for AI to schedule and assign tasks, and manage and recruit human workers. This practice, commonly denoted as Algorithmic management [52, 55], not only automates several tasks previously performed by human workers, they also significantly shape power dynamics at work and increase the opacity in several organizational processes [49].

Human-Machine Collaboration.

While previous waves of automation made workers more efficient, AI increased the need for human-machine collaboration at work to exploit the skill complementarity of human and artificial workers. AI excels at processing vast amounts of data, pattern recognition, and automating repetitive tasks. On the other hand, humans possess creativity, emotional intelligence, critical thinking, and adaptability. Combining the strengths of both AI and human abilities creates a powerful synergy that allows for more comprehensive and efficient problem-solving. Hence, recent research has classified the ways in which human-teams can incorporate AI as a team member [28].

While AI can assist with data-driven decision-making, many complex decisions require human judgment, empathy, and ethical considerations. Human workers can leverage AI insights to make better-informed choices and navigate ambiguous situations effectively.

Finally, AI is increasingly being used to augment human capabilities not just replace them. By automating mundane tasks, AI frees up human workers to focus on more value-added activities, fostering higher productivity and creativity.

Reliance on data as a production factor

Several authors argue that data has become a new form of capital, with AI playing a crucial role in this shift [58]. Viewed through the lens of data as raw material and the product of digital labor, datafication emerges as a political, economic regime driven by the logic of perpetual data capital accumulation and circulation. AI's automation heavily relies on vast amounts of data, a critical aspect not as significant in previous technological advances that relied more on pre-programmed rules and routines. Additionally, AI-driven technologies can use diverse data sources, such as images, videos, audio, and text, which were not easily utilized as inputs with earlier technologies. This has fundamentally transformed how data is utilized and highlights its growing importance in shaping the modern economy.

This focus on data and datafication does not replace financialization but adds new sources of value and accumulation tools. Instead of competing, Wall Street and Silicon Valley are converging around data capital as the next frontier for accumulation and circulation [59]. Additionally, studies link workers' skills in the processing of big data with up to a 3% increase in firm productivity [61].

This heavy use of data raises concerns about the control and misuse of information from individuals due to data externalities - either revealing data about others or decreasing the value of others' data[2].

2.2.1 Organizational Processes: Worker Productivity, Job-redesign, and automation of Innovation

According to Acemoglu [2] AI could be used for increasing worker productivity and expanding the set of tasks in which humans have a comparative advantage, rather than focusing mainly on automation. If it is used in this way, it may counterbalance some of the adverse effects of industrialization on labor and may generate more positive welfare effects and beneficial distributional consequences.

For companies, the shift toward skill-based work presents an opportunity to re-imagine non-automatable tasks and create innovative new jobs. Some argue that the focus should be on job redesign and business process re-engineering, as investing in the reshaping of work can yield substantial value for firms [20].

According to [26], AI has the potential to automate, even partially, the process of innovation and idea creation. The automation of learning enables the generation of new ideas and insights through automated processes, given the availability of necessary data input. Deep learning, in particular, presents an alternative paradigm where complex multi-causal phenomena can be predicted using a "black box" approach, which abstracts away from underlying causes but provides a singular prediction index for sharp insights. However, this approach comes with a potential cost - by de-emphasizing the understanding of causal mechanisms and abstract relationships, it may overlook the importance of human judgment in achieving significant advancements in science, which often rely on leveraging a deeper understanding.

2.2.2 Labor Markets: Employment, Wages, and Inequality

Some argue that AI may generate less economic growth than previous waves of automation [41]. Nevertheless, the AI-driven disruption in the global economy and the labor market is undeniable. According to a report by McKinsey [22], artificial intelligence has the potential to contribute approximately 13 trillion dollars to global economic activity by 2030.

While prevailing academic research suggests that technological advances in the 19th and 20th Centuries did not result in net job losses [11], various risk assessments [40] paint a concerning picture, indicating that up to 47% of total US employment is at high risk of automation by AI. Recent studies [6], however, take into account task heterogeneity across occupations and find a much lower automation risk of approximately 9% of US jobs. Additionally, almost all jobs in the US economy have at least one task susceptible to automation through machine learning [19, 20].

On the other hand, there is a surge in AI-related job vacancies, accompanied by changes in the skill requirements of remaining job postings. There is also evidence of reduced hiring in non-AI positions for firms engaged in AI activities. As a result, whether this trend leads to net job losses depends on the relative magnitudes of job creation and job destruction effects [4, 44].

It is crucial to recognize that the impact of AI-driven job loss and creation is not uniform and varies significantly between and within countries. For example, according to [6], only 6% of jobs in South Korea face a risk of automation, whereas in Austria, this number rises to 12%. Even within countries, studies indicate that smaller cities are more susceptible to automation due to the types of occupations prevailing in their labor markets [39]. Furthermore, within cities, AI will affect different groups of workers with varying skill levels, particularly impacting high-skilled labor, which is different from the patterns seen in previous technological advancements [65]. Empirical evidence from the UK further supports these findings, as it suggests that working in research and development intensive firms benefits lower-skilled workers more than higher-skilled workers compared to other types of firms [5].

The impact of AI on US wages remains a topic of debate. It can be harmful if machines only substitute human labor, but positive if machines instead complement human workers and increase overall productivity [54]. Some experts suggest that AI might lead to a relative wage decline for low to mid-skilled workers [51] but increase wages for high-skilled workers, especially those with skills that complement AI [29]. This observation is consistent with the job polarization phenomenon found by Acemoglu and Autor [3] and Autor and Salomons [10], translating job polarization into wage polarization. On the other hand, empirical studies have shown small wage increases overall [35]. Notably, the service sector is reaping the rewards of increasing wage raises, with this upward trend showing growth over time [37].

In other countries, like India, AI has had an adverse effect on wages, leading to reduced wages for all job vacancies except for the lowest-paying roles [1]. Similarly, in South Africa, studies have found a similar trend, with AI showing a significant negative relationship with average wages but a positive association with gross domestic product per capita (GDPC) [41].

Technological change has a heterogeneous impact on the labor market, and AI is no exception. While AI has been found to reduce wage inequality between workers in the 90th and 10th percentile of the wage distribution, it leaves the top 1% untouched [65]. Furthermore, it has been suggested that workers face unequal re-skilling pressures, with some authors arguing that this time, it is higher-skilled workers who carry the largest burden of re-skilling due to rapidly changing work tasks [30]. However, a recent study revealed that [63]. That same study found that larger labor markets buffer from skill obsolescence more than smaller ones, providing workers in bigger metropolitan areas an advantage over those in small cities. More traditional forms of labor inequality, like the gender wage gap, also seem unaffected by advances in AI. This lack of progress may be attributed to gender-based occupational segregation and an ongoing imbalance in the distribution of care work between men and women. Authors from a recent study argue that technological advances alone are insufficient to close the gender wage gap. Instead, additional policies and interventions, such as increasing women's access to education and leadership roles, are needed to achieve gender equality in the workplace [27].

2.3 Generative AI

The emergence of generative AI has sparked a revolutionary shift in the labor market, presenting unique opportunities and challenges that differ from those brought about by traditional AI technologies. Conventional AI primarily focuses on data analysis and decision-making, but generative AI has the ability to create new and original content, such as images, videos, text, and even human-like conversations. Such capabilities endow AI with the potential to disrupt numerous industries and occupations with low automation potentials due to their reliance on what was thought to be uniquely human skills.

Among the many examples of generative AI, one of the most popular is OpenAI's ChatGPT. ChatGPT is an instance of a larger family of models called Large Language Models (LLMs) that can engage in natural language conversations, produce human-like text, and provide information on a wide range of topics.

2.3.1 The Nature of Work: Augmented Creativity, and Natural Language Automation

Generative AI's potential for automation rests on its ability to understand natural language, which is required for many work activities. According to a report by McKinsey, the work functions most susceptible to change or augmentation by generative AI in the next decade are Creativity, Natural-language understanding, Natural-language generation, Output articulation and presentation, Generating novel patterns and categories, and Sensory perception [25]. These tasks could fall under a 'general skills' category described by [48]. However, the authors note that even high-skilled occupations require a combination of specialized and significant command of such skills, making the ramifications far-reaching for low, med, and high-skilled workers.

So far, numerous studies have attempted to forecast the impact of generative AI on labor markets globally. In the US, risk assessments vary widely, with some suggesting that up to 80% of jobs could be affected [32]. Others estimate that 32.8% of occupations may face a full impact, 36.5% may experience partial automation, and 30.7% may remain unaffected [67]. Similarly, Mickinsey [31], estimated that including generative AI in the calculations for automation will increase the amount of work saved in the US labor market from 21.5% of the hours worked to 29.5% percent by 2030. In China, researchers project that 28% of current jobs rely on LLMs, but this figure is expected to grow, with 45% of jobs requiring skills related to LLMs in the near future [23].

The occupations projected to be most affected by Generative AI are office support, customer service, food service, workers in STEM and legal fields, educators, and artists. Sectors like creative arts, content creation, and design, which rely heavily on human creativity, might already witness significant impacts [33]. For instance, work-for-hire occupations traditionally used conventional tools, such as illustration or stock photography, might experience some displacement. On the other hand, by lowering barriers to entry and increasing the efficiency of creative tasks, generative AI could significantly change who works as an artist, potentially resulting in increased employment, even if average wages decrease. Recent research [38] highlights the need to quantify the specific activities of various artistic workers before comparing them to the actual capabilities of technology to assess the effects of AI on automation accurately. Journalism, copywriting, and customer service may also see substantial transformations as generative AI systems become increasingly proficient at generating written content and interacting with customers.

2.3.2 Organizational Processes: Worker Productivity and Augmentation of Innovation

LLMs are also shown to enhance worker productivity [57]. Findings suggest that ChatGPT significantly improves average productivity in writing tasks and reduces inequality among workers by benefiting those with lower abilities, compressing the productivity distribution. Further, ChatGPT exposure increased job satisfaction and self-efficacy, signaling that some workers might also psychologically benefit from its use. In line with these results, a recent study found that generative AI increased worker productivity, especially for novices and low-skilled workers, and improved employee retention [17]. In aggregate, McKinsey reports that Generative AI could enable labor productivity growth f 0.1% to 0.6% percent annually through 2040 [31].

Generative AI transforms innovation work by accelerating idea generation, automating routine tasks, and enhancing the overall efficiency of the innovation process. It empowers workers to focus on higher-level strategic thinking, refining ideas, and maximizing the impact of their innovative endeavors. So far, it is being used to aid workers in the design of pharmaceuticals, chips, and chemical compounds [66].

2.3.3 Labor Market, Wages, Inequality and Economic Development

The recency of generative AI makes it difficult to measure medium and long term impacts on the labor market in terms of wages and inequality. However, some international agencies believe in its potential to help with international economic development, especially for particular cases like disaster relief [66].

2.4 Other Forces Shaping the World of Work

Climate Change

Federal investment to address climate and infrastructure, as well as structural shifts, will also alter labor demand. The net-zero transition will shift employment away from oil, gas, and automotive manufacturing and into green industries for a modest net gain in employment. Infrastructure projects will increase demand in construction, which is already short almost 400,000 workers today. We also see increased demand for healthcare workers as the population ages, plus gains in transportation services due to e-commerce.(McKinsey report)

Climate change is poised to exert significant influence on the labor market in the near future. The rise in environmentally conscious practices is likely to drive job opportunities in sectors such as renewable energy, sustainable agriculture, and environmental conservation. Conversely, industries heavily reliant on fossil fuels might face workforce challenges as they transition towards more eco-friendly practices. Additionally, the need for climate adaptation and disaster response is expected to lead to a rise in roles related to disaster recovery, resilience planning, and climate-related risk assessment.

Aging Populations

As the aging population grows, older workers are likely to experience longer careers and reduced chances of early retirement. This trend emphasizes the importance of strategic career planning to ensure financial security during extended work years. To navigate this landscape, individuals will need to consider not only the need to sustain longer careers but also the feasibility of transitioning into occupations that align with their evolving skills and capabilities later in life. Additionally, the expanding aging population will contribute to the growth of care-taking and healthcare-related occupations, further shaping the dynamics of the labor market.[31]

Mass Migrations and Displaced Workers

Mass migrations are anticipated to exert a substantial impact on the labor market in the near future. As populations move due to factors such as climate change, political instability, or economic disparities, host countries will experience an influx of diverse skills, cultures, and talents. This influx could contribute to a more dynamic and multicultural workforce, fostering innovation and creativity. However, managing the integration of migrants into the labor market will be essential to ensure fair treatment, prevent exploitation, and maximize the potential benefits of their skills. Furthermore, host countries may witness shifts in labor demand, requiring flexibility in workforce planning to accommodate the changing demographics and skill sets brought by these migrations. Many people are exploring the ways in which the gig economy can help migrant attain jobs, the problem is that the gig economy is till very unregulated and could lead to a further increase in inequality. [64].

2.4.1 Other factors shaping labor markets today

Some authors argue that in spite of what techno-positive researchers argue, the changes in employment and job quality observed in today's labor market are not due to technology-driven automation. For example, in his book titled 'Automation and the Future of Work', [13] Benanav argues against solely blaming automation for poor job quality and stagnant wages. He points out that the pace of labor-saving technological change hasn't significantly accelerated, and industrial efficiency has been growing slowly for decades. One of the main culprits, in his view, is secular stagnation. This phenomenon, characterized by low investment rates, slow growth, and limited job creation, is caused not by technical progress but by the extant economic policies. He also suggests that blaming robots or certain groups for social issues in sluggish economies might divert attention from addressing the root causes of these challenges, emphasizing the need to find solutions for sharing the remaining work and preventing societal fractures.

2.5 Final Thoughts

In sum, in this dynamic landscape, the nature of work is evolving again, opening doors to exciting possibilities and ushering in a future where the boundaries of traditional employment are pushed beyond imagination. Adaptability and innovation become the currency of success for individuals navigating their careers and companies seeking to thrive in the ever-changing world of work. However, to reap the benefits of AI, we must avoid its pitfalls by rethinking the way AI is being designed and implemented in labor markets [2].

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Chapter 3

Professional Pathways: Careers in the Age of AI

In the preceding chapter, I synthesized the intricate repercussions of technological transformations on work tasks, organizational processes, and broader labor market dynamics like employment . Now, my focus turns to a pivotal element within the work landscape: the workforce itself. Here, I delve into the effects of technological shifts and market forces, on career trajectories, transitions, and the evolving skill profiles of workers as they navigate today's labor landscape. This comprehensive exploration lays the foundation for the subsequent chapters, where I construct a series of models designed to provide workers with valuable insights for making informed decisions about their career transitions.

In the initial section of this chapter, I will provide an overview of the evolving shifts within the concept of a career and elucidate the emerging career paradigms documented in career and vocational literature. Subsequently, I will present empirical evidence that either corroborates or challenges these theoretical frameworks. Lastly, I will delve into the skill-based model that has gained widespread acceptance among contemporary labor economists. This model will form the foundation for the data-driven analysis detailed in the subsequent chapter.

3.1 A short primer on career theory

The term "career" encapsulates the intricate patterns and sequences of occupations and positions that individuals engage with throughout their professional lives [15]. This encompasses the evolution of roles, achievements, and positions that a person undertakes, reflecting the gradual accumulation of knowledge and skills both within and across various industries.

Traditionally, careers were often perceived as linear trajectories that evolved within stable environments, frequently confined to just one or two firms. Consequently, the language employed to depict careers mirrored these conceptions, typically employing terms that denoted hierarchical advancements such as "career ladders" or "career progression" [12]. However, in recent times, there has been a linguistic shift towards less rigid terminology, giving rise to expressions like "career path," "career trajectory," or "work portfolio" [12]. Indeed, a phrase that has gained traction within the career and adult development literature to describe these novel careers is the 'Boundaryless career' [4]. These boundaryless careers are characterized by traits like flexibility, adaptability, and the absence of predetermined career routes or organizational frameworks. Instead, they involve navigating a sequence of job opportunities that extend beyond the confines of a single firm or occupational domain. These careers demand individuals to proactively seek fresh learning and growth prospects while embracing ambiguity and change [10]. The authors in [10] additionally note that from a societal perspective, boundaryless careers might contribute to heightened economic dynamism and innovation. However, they also acknowledge that these careers could intensify inequality and insecurity for those lacking the necessary resources or skills to navigate this evolving landscape. This assertion further underscores the need for tools like the ones I propose in this thesis.

The modern concept of career is rooted in Human Capital theory [13], which regards individuals as rational actors who invest in their education to maximize their future returns. This theory suggests that investing in education and training can enhance a person's human capital, leading to increased job opportunities, higher wages, and economic growth on a broader scale. The theory underlines the importance of education and skill development as critical factors in driving individual and societal success in a knowledge-based economy. However, this theory shares some of the limitations of classical economics, such as assuming perfect rationality [3], and has also been criticized for disregarding market imperfections and dysfunctions, as well as cultural and individual differences such as race, gender, and ethnicity [12].

3.1.1 Empirical Data and the Boundaryless Career

Several studies and technical reports underscore the applicability of the boundaryless career concept in describing contemporary career trajectories. A notable example is a report conducted by McKinsey [5], which projected the need for an additional 12 million occupational transitions by the year 2030. As individuals transition from contracting industries, the economy could experience a shift towards higher-wage job sectors. The data reveals a crucial dynamic: workers in lower-wage positions face a significantly greater likelihood—up to 14 times—of needing to switch occupations compared to their counterparts in higher-wage roles. Moreover, for many of these transitions to be successful, additional skill development will be necessary. It's noteworthy that women are poised to encounter occupational changes 1.5 times more often than men in this evolving landscape [5].

Reinforcing these trends, a significant surge in occupational shifts occurred between 2019 and 2022—significantly higher, by 50 percent, compared to the preceding three-year period [5]. These findings collectively underline the transformative nature of today's career landscape, highlighting the imperative for workers to adapt, upskill, and transition to new roles, with particular attention to those in lower-wage positions and underrepresented groups like women.

Other studies present empirical evidence that doesn't to support the flexibility touted by the theory of boundaryless career. For instance, in a recent study [9] the authors found that the entry point to the labor market has become more restrictive in determining one's career trajectory than in earlier decades. This suggests that career paths might have become more rigid than the theory suggests. The authors also found that occupational mobility is increasingly likely to occur within a more limited range of occupations because the overall network of occupations has become less interconnected [9]. Different research proposed a network-based approach to comprehending the occupational structure within the United States [14], and found a notable shift in the U.S. labor market consistent with the previous study. These authors found that the U.S. labor structure has become more segmented, and is now characterized by an increased prevalence of exchange within specific sets of occupations. The reason this is an important change, is not just that there is less cross-occupational mobility as predicted by boundaryless career scholars, but this fragmentation has been shown to reduce wage contagion and increased the inequality in occupational wages [8].

3.1.2 The Skill-based model

Modern labor economists frequently adopt a skill-based framework to analyze the impact of automation on job dynamics and to understand wage disparities among workers possessing different levels of expertise. In this context, a skill describes a worker's capacity to perform diverse tasks effectively. Therefore, to effectively fulfill the demands of a particular occupation, a worker must acquire a specific skill set. Notably, as highlighted by [1], the distinction between skills and tasks gains prominence when workers of a specific skill level exhibit the ability to engage in a range of tasks. These workers can adapt their skill portfolios in response to shifts in labor market conditions and technological advancements.

This skill-based framework allows economists to discern the intricate relationship between skill acquisition, task allocation, and the broader economic landscape. By understanding how skills enable workers to navigate various tasks and adjust their task profiles over time, economists gain insights into the mechanisms that shape occupational dynamics in an ever-changing job market. This approach not only aids in comprehending the effects of automation but also sheds light on the nuanced forces driving wage differentials and workforce adaptations across different skill levels.For example, skills have been used to measure the connectivity od labor markers, which is shown to increase their resilience in the face of external shocks [11].

Workers do not accumulate skills at random. Instead, skill acquisition is often regarded as a cumulative, directional, and path-dependent process shaped by prior knowledge [6, 2]. Similarly, skills are not distributed uniformly within the complex landscape of human capital. Certain skills are closely connected, while others are so distinct that they are only linked to a few other skills. This heterogeneity in skill connectivity forms hierarchical, nested structure [7]. This implies that some skills have prerequisites and can only be attained once previous skills have been acquired. For example, individuals first need to learn algebra and geometry before tackling more abstract math. As workers grow in their careers, they journey down these nested paths, acquiring more specialized skills. according to [7], more specialized skills helps workers reap higher wage premiums. Yet, specialization, without deepening of general skills, does not guarantee higher wages.

A deeper grasp of the underlying skill structure can help draw pathways to more sophisticated or specialized skills, facilitating the access to skills that might otherwise be perceived as unattainable by some workers. Knowledge of such structure can also help draw more direct career paths workers, and highlight the skills needed for successful career transitions. Finally, understanding the networked structure of skills can help researchers understand that skills are not independent of each other - changing one skill alone is unlikely to result in a successful occupational shift. Instead, to offer more effective recommendations, researchers will need to provide workers with groups of two, three, or four closely interconnected skills that need to be acquired for a career change. Nonetheless, our present understanding of the skill landscape remains inadequate in guiding workers to strategically invest in skills to enhance their market value [7].

In conclusion, acknowledging the interwoven nature of skills within a nested structure reveals the complexities of skill acquisition and its effects on workers' career trajectories. This understanding underscores the importance of tailored skill development strategies and informed decision-making in navigating the evolving world of work. As technology and industries evolve, strategic skill adaptation becomes essential for seizing new opportunities and achieving sustained career success.

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Chapter 4

Value Sensitive Design: Designing tools for Workers and their Careers

4.0.1 AI-career advising tools

Value Sensitive Design (VSD) is a comprehensive design philosophy and approach that addresses the complex interplay between technology and human values. It recognizes that technology is deeply embedded in our lives and can have profound societal impacts. Instead of treating ethics and values as secondary considerations, VSD integrates them from the outset of the design process, ensuring that technological solutions are not only functional but also align with human well-being and societal norms.

At the heart of VSD is the meticulous investigation of stakeholders and their associated values. This involves engaging a wide array of individuals and communities who may be affected by the technology, including end-users, experts, and marginalized groups. By fostering an inclusive dialogue, designers can gain insights into the diverse perspectives, needs, and concerns of these stakeholders. These insights then inform the design process, enabling the creation of technology that is more attuned to the nuanced and multifaceted values of the various stakeholders.

One of the distinctive aspects of VSD is the concept of value articulation. This step involves translating the abstract notion of "values" into concrete and actionable requirements for the technology. It requires identifying the ethical, cultural, environmental, and societal values that are relevant to a particular context. These articulated value requirements become the guiding principles for the design, ensuring that the technology reflects the desired moral and social attributes.

Throughout the design and development phases, constant evaluation is integral to VSD. Technology features, user interactions, and system behaviors are scrutinized against the established value requirements. This iterative process allows for refining and aligning the technology to ensure that it positively contributes to society. By embracing the VSD framework, designers can navigate the intricate landscape of ethical considerations, anticipate potential ethical challenges, and create technology that harmonizes with human values and the broader societal fabric.

4.1 Values

Transparency

Transparency is paramount in the design of technological tools for career crafting as it empowers workers with clear insights into the tool's functionalities, data usage, and decision-making processes. By fostering transparency, workers can make informed choices, trust the tool's recommendations, and actively engage in shaping their career trajectories with a comprehensive understanding of the tool's impact.

Equality

Equality assumes a critical role in the design of technological tools for career development as it ensures that access, benefits, and opportunities are equitably distributed among all users, regardless of their background or circumstances. Designing with equality in mind helps counteract biases and systemic barriers that could otherwise perpetuate existing inequalities. By prioritizing equal access to information, resources, and opportunities, these tools have the potential to contribute to a more inclusive and diverse workforce, fostering fair and just career advancement for everyone. This value is especially important when using data to provide recommendations, as some individuals who might belong to minority groups that are often underrepresented in data.

Self-determination

Refugee relocation algorithms became popular during the Syrian refugee crisis in 2015. However, these algorithms have been criticized for further eroding the migrants' agency and perpetuating technology-first, black-box approaches to social challenges. Due to the lack of transparency in many machine learning techniques, it is unclear in these types of AI-based decision tools could, even by accident, embed undesirable biases against some segments of the population. Additionally, like my research about returnees and migrants showed, while some individuals might be very similar the choices they make for themselves might be starkly different. Thus, agency and self-determination is a priority for the tool I propose in this chapter

Privacy

Privacy is important for everyone, but it's especially crucial for underrepresented minorities like migrants and refugees. This is because data collected from these groups can be sensitive and if not properly protected, it can lead to harmful consequences such as discrimination of individuals who are already in extreme or vulnerable circumstances.

Chapter 5

21st Century tools for Navigating the Future of Work

This chapter delves into two data-driven tool prototypes crafted to assist workers in navigating their careers amid the evolving work landscape. The first prototype, Voyage Viewer, is tailored for migrant workers, analyzing similar individuals' destinations to aid location-based decisions. The second tool, Career Compass, extends its support to all U.S. workers, local or international. The models behind the second prototype draw on the skill based framework described in the previous chapter to make recommendations about potential occupational shifts.

Following the Value Sensitive Design structure, each prototype includes sections dedicated to stakeholders, empirical background, and technical investigations. These tools stand as innovative solutions, helping workers make informed career choices amidst the complexities of the modern job market. By incorporating stakeholder insights, empirical research, and technical explorations, these prototypes aim to present alternatives to tech-first solutions by offering human-centric, data-driven alternatives that seek to minimize harm.

5.1 Voyage Viewer

5.1.1 Theoretical Framework: Stakeholders

Direct and indirect stakeholders

To narrow down the initial exploration into the design of decision-making support tools for navigating new working environments, I chose to develop a tool specifically aimed at aiding migrant and refugee relocation. As a result, the primary users of Voyage Viewer are migrants and returnees who utilize the dashboard for making informed decisions. Additionally, there are indirect stakeholders in the form of members within the destination communities where migrants choose to establish themselves, and policy makers who might use the insights to design policies aimed at helping workers integrate into their local labor markets.

5.1.2 Empirical Framework: Migrants' Spatial and Economic Patterns

The Voyage Viewer prototype will seek to address the Venezuelan migration crisis across South America, which particularly affects neighboring countries like Colombia. In a published paper [3], I investigate the spatial and economic integration patterns for migrants and returnees in Colombia between 2016 and 2019. To do so, I used data collected by the Colombian statistical bureau, DANE, through their monthly household survey called Gran Encuesta Integrada de Hogares (GEIH). GEIH involves around 19,000 randomly selected households monthly, addressing various subjects across nearly 24 modules. The data for thus research came from the modules related to the workforce, demographics, and migration. While data from this survey is available since 2006, a change in the module's survey questions in 2016, only allows data to be comparable between January 2016 to December 2019. This period involves 867,889 distinct households and 2,878,194 anonymous individuals, all residing in Colombia.

The data used in this study is not without limitations. First, it is important to note that this survey is meant to be statistically representative of the local Colombian population, hence, it is likely to under sample Venezuelan migrants. Nonetheless, I expect that the patterns I uncover might be made stronger if the survey were to correctly sample incoming Venezuelan migrants. The second concern is related to the data's spatial resolution. Location is provided at the department level rather than the more detailed city level. This discrepancy hampers the direct translation of insights from regional centers to city-specific contexts. Additionally, data collection covers only 24 out of the 33 administrative divisions in Colombia, omitting regions like Amazonas, Arauca, Casanare, and others. While these excluded areas only make up 3% of Colombia's total population, they are not accounted for in the analysis. Furthermore, the data likely does not include migrants without permanent housing or those living in shelters. While this might not greatly affect estimates for the local population, it could substantially underestimate the number of migrants and returnees who are in these living conditions.

To analyze the data, I advanced migration and mobility studies by developing an asymmetrical gravity model suitable for other recent mass displacements like the Syrian and Ukrainian refugee crises. I also computed propensity scores to match migrant, returnee and local workers to minimize the effect of unobserved variables in my estimation of the economic and spatial differences across the three groups. In this study, the data revealed that despite similarities in culture, language, history, and time of migration, migrant and returnee populations have startlingly different temporal, spatial, and economic integration patterns. Indicating that even slight differences might lead different populations to make varying decisions, and thus underscoring the need for more personalized recommendations.

Spatial Patterns

Migrants and returnees have different mobility patterns, suggesting that different mechanisms drive their spatial trajectories and spatial behaviors. For example, migrants are more present in inner Colombian regions than returnees which remain clustered near the Venezuelan border in the north, and about as spatially constrained as in 2016. We quantify changes of the spatial distribution of individuals by measuring the weighted average of the distance of migrants and returnees to Caracas, Venezuela every year. Over time, the average distance to Caracas increases for migrants, while remains bounded for returnees. This happens as migrants head towards the inner-most parts of Colombia where big cities such as Bogotá, Medellín or Cali are located.

Economic Patterns

I used unemployment rates and differences in monthly average and median income to inquire about migrant and returnee economic integration in Colombia. Unemployment rate is calculated for each type of migrant as the relative number of unemployed individuals relative to the total economically active population in each cohort. In 2016 both migrants and returnees showed similar unemployment rates around 17%. Since then a change of regime happened. Returnees decreased their unemployment rates at a faster pace than migrants (slopes of -1.04% vs -0.4% monthly unemployment decrease respectively). As a result, the gap between returnees and locals unemployment rates is drastically reduced in a period of four years, while the gap between migrants and locals remained significantly higher. A potential explanation for this trend includes the rapid growth of the migrant population after 2016. However, in the SI we show that the ratio between employed migrants and the active migrant population is consistently lower than the ratio between employed returnees and the active returnee population across the whole observation period.

I also measured differences in median monthly income among the three populations across the whole observation period using propensity score matching. This method aims at approximating a randomized experiment using observational data. It divides the population into treatment and control groups, while controlling for possible confounding variables such as demographics. Thus, here it helps reducing estimation biases of the average effect of being a migrant. We define migrants and returnees as the treatment group and locals as the control group. I matched pairs of individuals from both groups based on age, gender, year of appearance in the data, department, and level of education. To check the quality of the matches, we used computed a chi-squared test of independence for these variables before and after matching and confirmed that all variables are balanced after matching. Then, we

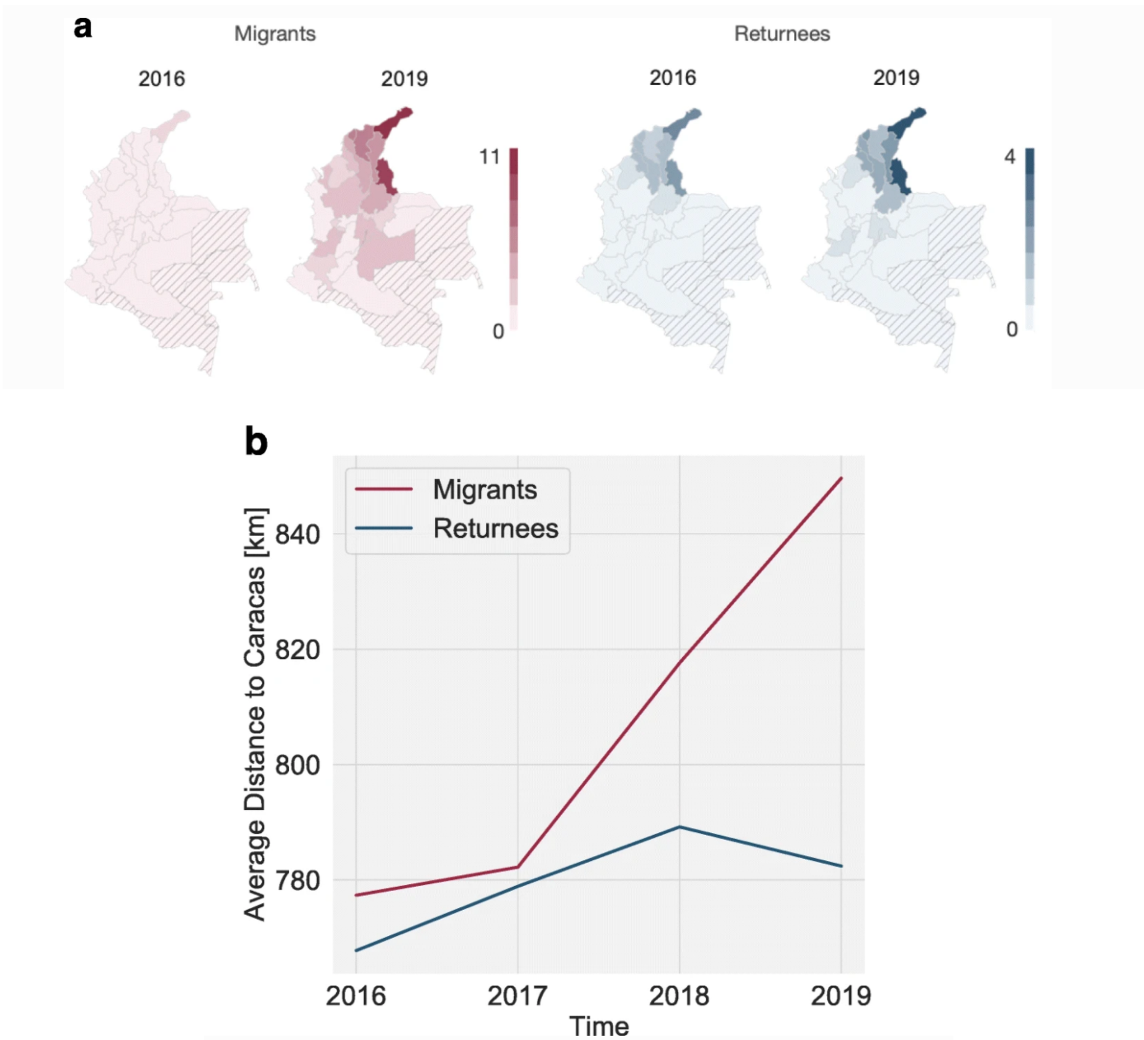

Figure 5-1: Inset A shows the temporal Evolution of Migrant Stock Distribution between 2016 and 2019. The maps display the distribution for two distinct populations—Venezuelan migrants (in red) and Colombian returnees (in blue). The figure includes corresponding scales where darker signals a higher number of migrants or refugees. The maps show that both populations have different spatial patterns. Inset B shows that both populations vary significantly in terms of their distance to the Venezuelan border, with returnees maintaining a shorter distance than Venezuelan migrants.

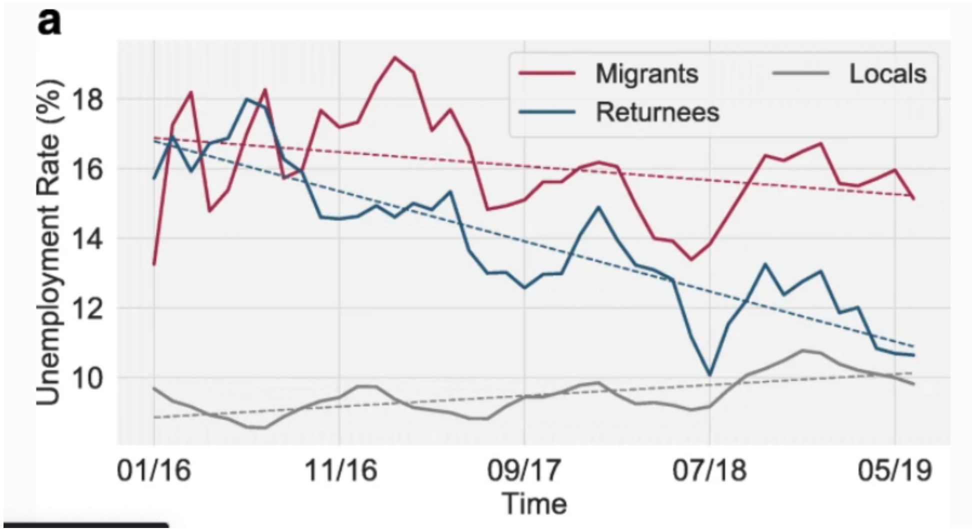

Figure 5-2: This figure shows the unemployment rates for migrants and refugees in Colombia between the years of 2016 and 2019

bootstrapped 100 samples made up of 60% of the data and applied a two-sided t-test. I found that migrants and returnees show significantly lower median monthly incomes than their local counterparts. Moreover, the gap between returnees and locals is smaller than the gap between migrants and locals. This shows that returnees consistently show economic advantages over migrants and should be considered as a different type of population in terms of migration and integration policies.

My analysis about migrants' mobility patterns between Colombia and Venezuela revealed that despite similarities in culture and language, migrant and returnee populations have startlingly different spatial and economic integration patterns. Lessons from this work emphasize that even minor differences between two populations can lead to drastically different decisions and outcomes. Thus, access to personalized information is vital when faced with critical decisions about relocation.

Technical Framework

Inspired by the results from the first study, I started to probe into the development of systems that leverage big data, and social learning to provide personalized information

Figure 5-3: This figure shows the first iteration of the Voyage Viewer platform. It shows snippets of the 'people like me' page.

and visual analytics to help individuals make relocation and migration decisions. Hence, I implemented a public data dashboard called Voyage Viewer. Voyage Viewer embraces a decentralized, grassroots approach where power and decision-making are in the hands of many instead of a selected few, creating self-governed communities that can learn and are empowered to make informed decisions. This decentralized paradigm makes the resulting communities more resilient and reduces unintended consequences. These technical investigations were published in the proceedings iof the Eurographics Association [2].

For the evaluation of the VA design, I conducted a usability evaluation and a third-party accessibility evaluation. The usability evaluation included a total of ten participants, who were all located in Colombia, and a mix of genders. I found that the ability to filter, select and get more information upon hovering over plots supported participants' insights. On

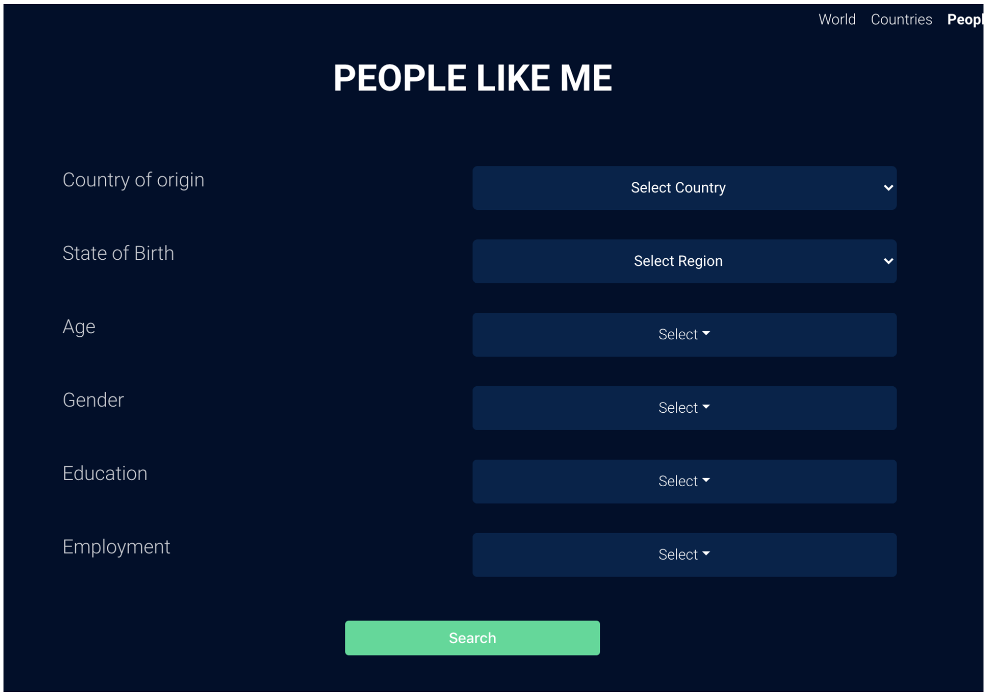

Figure 5-4: This figure shows the inclusion of a form to access the 'people like me' page after the second iteration of Voyage Viewer.

average, this feature was rated 8.5 out of 10. Moreover, one user pointed out that they would like more fine-grained filters to obtain more detailed information like differentiating people like you by type of job or distinguishing those with Masters from PhDs instead of aggregating them in one category. The app's usability was rated 8.88, and the performance was rated at 10 out of 10. During the unstructured feedback conversations, 75% of participants explicitly said they considered the app to be useful, and one remarked on the pleasant aesthetics of the plots. No comments about the data quality, usability or app performance came up during the unstructured feedback conversations.

Most users agreed on the need to provide more indicators about the different jobs taken by migrants at their destinations, crime rates, weather and cost of living in destination communities. One participant commented on the need to include testimonies to contextualize the lived experience of migrants. As a result of the user feedback, visualizations showing the cost of living per destination and the tone of news about migrants were included on Voyage Viewer. Feedback from the accessibility experts led to changes in font styles and sizes, a

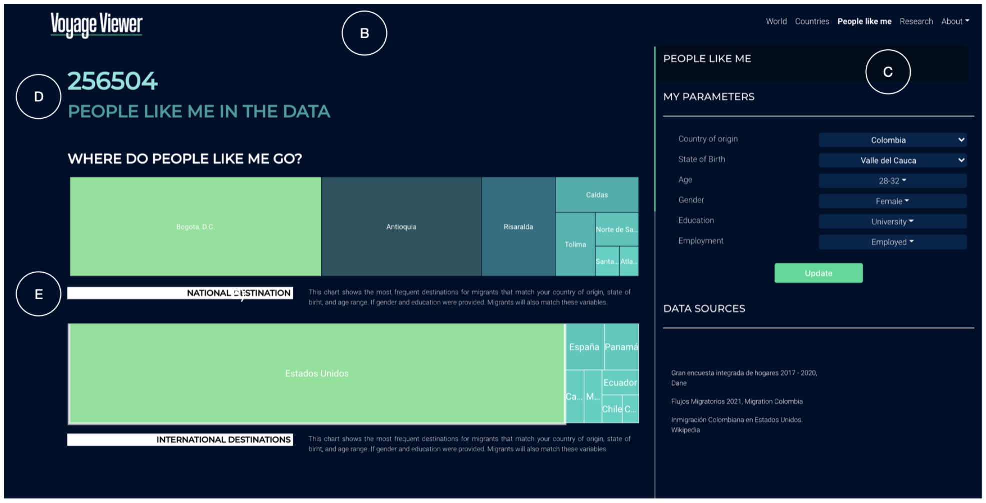

Figure 5-5: This figure shows the second iteration of the Voyage Viewer platform. It shows snippets of the 'people like me' page.

revised color palette and appropriate use of CSS labels to make the dashboard usable with text-to-speech tools.

In addition to qualitatively evaluating the use of the tool with a focus group, a small pilot survey was performed on the online participant recruitment service Prolific. The standard sample included n=200 US participants. Participants were shown information about hypothetical cities names in the same format as the Voyage Viewer platform (income distribution, where people typically migrate too, etc.). Hypothetical city names were used to avoid pre-existing biases towards real life cities. Control participants were told the visualizations represented general trends for the US population, while the treatment group were told the information visualized was about people like them, determined by previous demographics at the start of the survey. At the small scale of the study, no significant differences were found between the control and treatment groups with respect to subjective evaluation metrics like confidence in the choices made. The treatment group had a better performance in information recall, when asked about income data at the end of the study. This effect was not significant given the small sample size. This pilot study highlights the challenge in quantitatively assessing the effect of data on migration decisions. This area is ripe for future work to understand how best to measure the effects that complex personalized data has on decision making.

5.2 Career Compass

5.2.1 Theoretical Framework: Stakeholders

Direct and indirect stakeholders

To expand the reach and influence of the prototypes, Career Compass addresses a broader audience, encompassing all US workers seeking job changes, relocations, or entry into the labor force. This includes both local individuals and international participants.

5.2.2 Empirical and Technical Framework: Occupational transition strategies

Three strategies to increase your wage: Change your occupation, your city or both

To build the models that power career compass, I studied how three different groups of strategies affected worker wages. The first group of strategies is related to changing occupations only without changing the labor market conditions in which that occupation is held. The second group is related to changing the local labor market while keeping the occupation constant. The final group encompasses strategies that might lead worker to change both their occupation as well as the labor market in which they work. Finding the effects of each of these strategy groups on worker wages is an important endeavor to inform career transitions.

To study the effect of each of these strategies on wages, I used two large-scale resume datasets from two different companies - Burning Glass and FutureFitAI. Together, these datasets compile information from personal resumes for over 5 million unique workers across the U.S. for over the last three decades. In these data, we can observe workers' detailed occupations (as defined by the Bureau of Labor Statistics' SOC Code Classification), the places where the occupations were held, the dates for each occupation, and workers' educational backgrounds. Coupled with U.S. census data, I was able to infer individual wages based on occupation, location, year, and workers' experience (years since entering the labor market). To account for cost of living, which varies greatly between large and small cities, I computed disposable incomes by subtracting city-level living costs from individual annual wages. Since the grunt of the re-skilling challenge falls on low-skill workers, I decided to only take observations belonging to workers who were located on the bottom 25th percentile of the wage distribution based on the disposable income of their first occupation.

To disentangle the effect of each of the three strategies, I devised an experimental setup with three different treatment conditions and a baseline. The three treatment conditions were then compared against a control group. The treatment conditions and the baseline are as follows:

- Treatment 1: Effect of changing occupations but not cities.
- Treatment 2: Effect of changing cities but not occupations.
- Treatment 3: Compound effect of changing occupations and cities in the same move.
- Control: Worker who did not change cities or occupations.

To approximate such experimental setup and minimize bias from unobserved variables, I computed propensity scores using logistic regression with variables about workers' origin city, origin occupation, educational quality, and year starting in the labor market. Educational quality was approximated by using the Carnegie Index, which places all higher education institutions in the US into different tiers based on criteria like research output, teaching, and type of programs offered. Using the propensity scores, I perform one-to-one matching capping the distance between propensity scores to keep only close matches in our dataset. To check the quality of the matching procedure, we check for differences in the propensity score distributions between treatment and control groups using a KS test. After I found no statistical difference between the propensity scores distributions between treatment and control groups I concluded that the matching was successful at produced had produced balanced groups. Once the treatment and control groups have been matched, I measure the Average Treatment Effect on the Treated (ATE) by computing the average

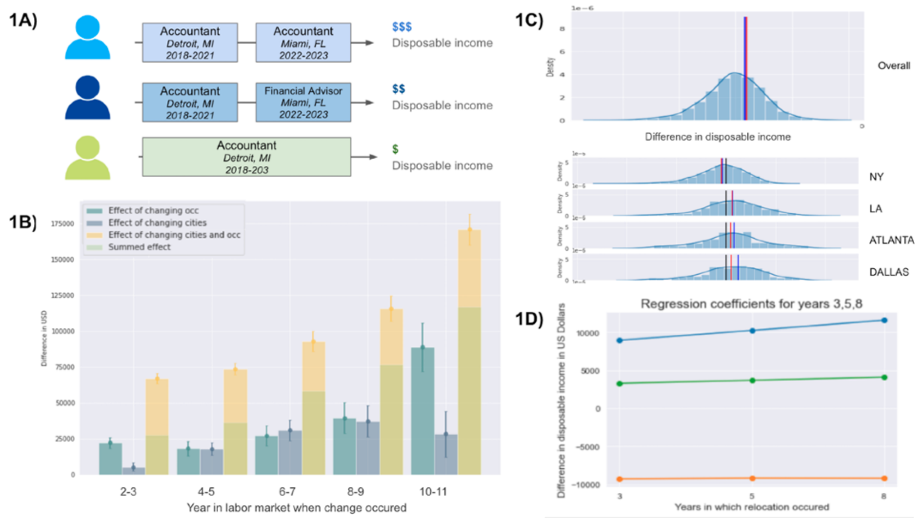

Figure 5-6: This figure shows typical career trajectories for workers in our data. 1B) Shows average treatment effect for Treatment 1, 2, and 3 in different years for the careers of workers in our sample. The green bar shows the effect for an occupation change, the blue car shows the effect of city change, and the yellow bar shows the effect of occupation and city change. The yellow bar shows an effect that is larger than the sum of the previous two bars. 1C) Shows the difference between the disposable income gained by movers coming from the top ten MSAs versus movers from non-top ten MSAs overall and for specific cities. 1D) Shows the most important coefficients from our model that explain the increment in disposable income.

disposable income for the treatment and control groups.

The results suggest that while changing occupations and cities separately positively affects disposable income on average, changing both cities and occupations has a larger effect on disposable income. This effect is larger than the sum of previous effects and increases with work experience, as shown in Figure 5B. We observe the same effect across both datasets. We split our dataset based on workers' origins and destinations to ensure that the effects we observe are not solely due to rural-to-urban migrations. The first group exclusively contained workers whose origin and destination cities were among the top ten most populous Metropolitan Statistical Areas in the U.S., shown in blue in Figure 5C. The second group contained workers whose origin cities were outside the top ten most populous areas in the US, shown in red in Figure 1C. When we compared the difference in disposable income for our groups, we saw that both have a positive difference, with the first group having a smaller, yet still positive, difference on average. When looking at particular cities, we see that while both groups get an average in LA, Boston, Atlanta, and Dallas, both groups see a positive increase in their disposable incomes after the move. In contrast, both groups perceive a negative effect on their disposable income when moving to New York City.

To explain the positive difference in disposable income after changing cities and occupations, we develop a linear model to understand which occupation and urban variables are associated with a higher increase in disposable income. We find that occupational variables are more important, followed by urban variables, and career stage variables are least important. In particular, we find that moving to more cognitive occupations, with a lower probability of automation, has the largest impact on disposable income. How unique a worker's occupation is in the local labor market is slightly more important than the diversity of the market, but they both contribute to an increase in disposable income. Finally, this work suggests there is path dependency in traditional careers because uncommon job transitions in early career years have a low economic cost, but common transitions are highly rewarded in mid or late career. The results for this regression can be found in table XXX.

How to change your occupation

Now that I have shown that each of these three strategies are effective for increasing a worker's disposable income, I will dive deeper into how workers should change their occupation in order to increase their returns. To do this, I use data from ONET, a comprehensive and widely used database and system developed by the United States Department of Labor. It serves as a valuable resource for gathering and organizing information about various occupations and the skills, knowledge, tasks, and responsibilities associated with them. ONET offers a detailed and standardized framework to describe and analyze the characteristics of different jobs in the workforce. It includes a vast collection of occupation-specific data, such as job descriptions, required skills, educational requirements, work environment details, and potential career paths.

Using the data from ONET, I create skill vectors that represent each occupations by mapping individual occupations to their respective sets of basic and cross-functional skills and abilities. This mapping produces 756 vectors with 86 dimensions, where each dimension is a skill or ability. Initially, the vectors are weighted by the importance score of each skill, provided by ONET. However, since there are several skills that are very common, in order to distill the skills that are truly characteristic of each occupation, I compute the Revealed Competitive Advantage (RCA) for each skill in each occupation as it has been done in the literature [1]. If the RCA for a skill in an occupation is equal to or greater than 1, it is considered to be essential to that occupation. Using these vectors as input, I am able to compute the similarity between occupations by applying cosine similarity. The product of this operation yields a matrix of similarity between occupations. Since occupations are very similar to themselves, I remove the 1's from the matrix diagonal.

To visualize this network of occupational similarity, I only use edges that have weights greater than 0.8, meaning that I use a very stringent threshold. Once I produce a sparser network, I use an agglomerative clustering algorithm to cluster the network. The results of the clustering are quite clean, showing three distinct clusters that correlate to what can be thought of as low-skill, med-skill and high-skill occupations. The clusters can be observed in the following image.

I use the network, without the thresholding used for visualization purposes, as the groundwork for a simple occupation recommender system. I begin by recommending the next-step transitions by choosing the top 5 closest occupations in the network to the ego, or the occupation that is being queried. Just using this naive approach does not provide good results, because occupations located in low-skill neighborhoods will produce recommendations that are located in the same neighborhood. Thus, changes within the same neighborhood for low and med-skill occupations are likely to result only in small or non-important wage gains. To improve upon this naive recommender, I followed the skills-based model previously discussed and regressed wage changes across occupations on the changes in skills. This simple model assumes skills are independent from each other, which they are not, but it is a step forward in the right direction. This model yields a good result by explaining almost 60% of the variance in wage changes with an R-squared of 0.599. According to this model, only 16 out of the 86 skills have statistically significant coefficients with p-values smaller than 0.05

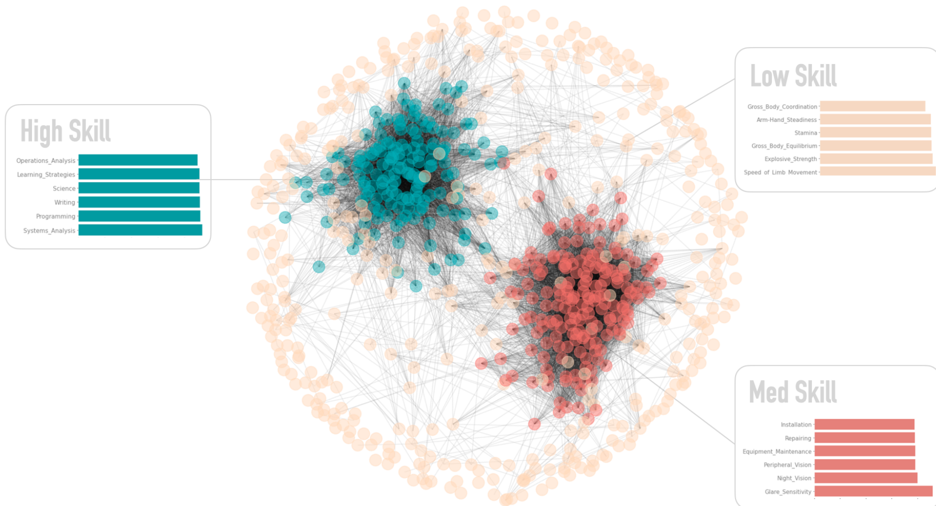

Figure 5-7: This figure shows the three clusters in the occupational similarity network after a force layout has been used to position the nodes. The blue cluster corresponds to high-skill occupations, the orange cluster to med-skill occupations, and the yellow cluster corresponds to low-skill occupations.

contributing to the changes in wages. These skills and their corresponding coefficients are:

Variable	Coefficient
Science	0.306295
Glare Sensitivity	0.265935
Mathematical Reasoning	0.214968
Manual Dexterity	0.208824
Social Perceptiveness	0.162003
Judgment and Decision Making	0.153375
Troubleshooting	0.146921
Operations Analysis	0.125907
Management of Personnel Resources	0.121673
Speed of Closure	0.112187
Monitoring	0.083781
Perceptual Speed	0.068753
Far Vision	-0.086453
Selective Attention	-0.120947
Finger Dexterity	-0.128488
Trunk Strength	-0.153723
Repairing	-0.227025
Mathematics	-0.254630

I incorporate only the skills with positive coefficients because I want the recommender to move towards highly paying skills and not necessarily away from low-paying ones. Workers don't necessarily have to forget low-paying skills but should incorporate high paying skills to increase their wage. Additionally, only adding the skills with positive coefficients might provide enough information without increasing the probability of overfitting. The simple recommender that uses both neighboring occupations as well as occupations with more higher paying skills provides recommendations with larger wage increases than the previous version. However, these recommendations lack some coherency and might not fit what are considered more natural or normal transitions. In other words, this recommender increases the wages but might not necessarily suggest occupations that might fit into more traditional notions of careers. Thus, to improve on this I incorporate data from observed career transitions. This inclusion increses the career coherence suggestions. I hope to use these model as part of a broader family of models to power an open-source tool to help workers make better career decisions.

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Chapter 6

Conclusions

The unique characteristics of AI set it apart from previous waves of technological progress, introducing profound shifts in how work is conducted and production processes are structured. Such changes have led to the rise of the gig economy and algorithmic management, the need for human-machine collaboration, and the elevated significance of data as a production factor.

The emergence of generative AI marks a significant turning point in the labor market, introducing a range of distinctive opportunities and challenges that set it apart from traditional AI technologies. Generative AI's capacity to create original content across various mediums, including natural language, opens new avenues for automation in areas traditionally reliant on uniquely human skills.

The changes brought about by AI have increased the professional possibility space making it harder for workers to navigate due to the diversity in occupations and work modes. Thus, workers will increasingly need to rely on data-driven tools like recommender systems to make better career choices. To increase their effectiveness, these tools need to go beyond showing optimal next-step moves and allow the creation of paths, highlight the gap in skills, and show alternative roots to arrive to a desired occupation.