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Article

Rethinking Upskilling and Reskilling in the Age of AI and Automation: A fsQCA Approach

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Abstract: In the age of artificial intelligence (AI) and automation, understanding the factors that contribute to successful upskilling and reskilling is crucial for workforce adaptability. Research on AI and automation has shown that they affect the workforce, but there is still a gap in understanding what factors contribute to successful upskilling and reskilling initiatives, especially from an organizational perspective. This study employs fuzzy-set qualitative comparative analysis (fsQCA) to analyze these factors and identify effective combinations for promoting upskilling and reskilling. By examining complex causal relationships and incorporating case studies, this article aims to enhance the understanding of upskilling initiatives in the AI and automation era. The findings provide insights into key factors driving successful upskilling and reskilling and offer implications for organizations seeking to improve their initiatives, ultimately promoting workforce adaptability and competitiveness.

Keywords: upskilling; reskilling; AI and automation; skills development; workforce adaptability; fsQCA

Introduction

In recent years, the rapid advancement of artificial intelligence (AI) and automation has transformed the global job market, fundamentally altering the nature of work and the skills required to thrive in this new era (Brynjolfsson & McAfee, 2014; Chui, Manyika, & Miremadi, 2016). As these technologies continue to reshape industries and displace traditional jobs, there is an urgent need to focus on upskilling, reskilling, and new approaches to skills development to ensure that individuals and organizations can adapt and remain competitive (Arntz, Gregory, & Zierahn, 2016; Bessen, 2019).

Existing literature has explored the impact of AI and automation on the workforce and the emergence of new skill sets (Frey & Osborne, 2017; Manyika, Lund, Chui et al., 2017; Ardichvili, 2022). However, there is a research gap in understanding the most effective ways to foster upskilling and reskilling, particularly from an organizational perspective, as well as in identifying the specific factors that contribute to successful outcomes (Deming, 2017; World Economic Forum–WEF, 2020). Upskilling, or the practice of teaching existing employees new or advanced skills, alongside reskilling, the process of learning new skills for a different job or role, have both emerged as potent strategies for workforce development in contemporary contexts (Liu, Cutcher & Grant, 2020). Their importance resonates not just in the domain of organizational success, but also extends to facets of employee satisfaction and retention (Cappelli, 2015). The pertinence and complexity of these initiatives call for methodological approaches that can adequately capture the intricate relationships among its various elements in the age of AI and automation (Ragin, 2008).

This article aims to address these research gaps by adopting fuzzy-set qualitative comparative analysis (fsQCA) as a methodological approach to analyze the factors that contribute to successful upskilling and reskilling in the context of AI and automation. fsQCA, as a configurational approach, allows for the examination of complex causal relationships and the identification of the combinations of conditions that lead to a specific outcome (Ragin, 2008; Schneider & Wagemann, 2012). By using fsQCA, this study seeks to contribute to the understanding of upskilling and reskilling initiatives in

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the era of AI and automation from both individual and organizational perspectives, providing insights into the most effective strategies for promoting skills development, workforce adaptability, and competitiveness.

The research questions guiding this study are:

1. What are the key factors that contribute to successful upskilling and reskilling in the age of AI and automation?
2. How do these factors interact with one another, and what are the most effective combinations for promoting upskilling and reskilling?
3. What are the implications of the fsQCA findings for organizations seeking to enhance their upskilling and reskilling initiatives in the context of AI and automation?

To address these research questions, this article will first discuss the impact of AI and automation on the labour market and skills development, highlighting some of the key new and emerging skills in the AI and automation era. This discussion is followed by an exploration of the importance of upskilling and reskilling to organizational success in contemporary contexts. The conceptual framework underpinning the research is then discussed. Next, the paper will introduce the fsQCA approach and its application in analyzing upskilling and reskilling. The article will then present case studies and lessons learned from these cases, before concluding with a summary of key findings, implications of the study, and suggestions for future research.

AI and automation: impact on the labour market and skills development

The rapid advancement of AI and automation has led to significant changes in the job market, causing a renewed focus on upskilling and reskilling initiatives. This section will delve into the impact of AI and automation on the job market, highlighting the emerging skills required in this new era and the challenges faced by organizations in implementing upskilling and reskilling programs.

The changing work and labour market landscape

The evolving landscape of work, driven by rapid advancements in AI and automation, is transforming the nature of jobs and skills required in the labour market. Indeed, it appears we are in the next phase of this transformation with the introduction of generative AI which has already started to reshape the labour market significantly. These technological developments have the potential to improve productivity, create new job opportunities, and enhance the quality of work-life (Bessen, 2019). However, they also pose significant challenges, including the potential displacement of workers and the growing skills gap between what is demanded by the labour market and the skills possessed by the existing workforce (Arntz et al., 2016; Ardichvili, 2022).

The introduction of AI and automation technologies has disrupted traditional roles and industries, leading to a shift in the demand for specific skills. Many routine and manual tasks are being replaced or augmented by these technologies (Brynjolfsson & McAfee, 2014; Chui et al., 2016), while the need for digital, analytical, and problem-solving skills has increased (Frey & Osborne, 2017). This transformation has made it crucial for both individuals and organizations to invest in upskilling and reskilling initiatives to remain competitive, be prepared for the growth of AI, and adapt to the evolving job market.

To adapt to these changes and remain competitive in the global economy, organizations and individuals must invest in upskilling and reskilling initiatives to bridge the gap between existing skills and those required for the future of work (Brynjolfsson & McAfee, 2014). The need for continuous learning and adaptation is further highlighted by the accelerated pace of digital transformation, exacerbated by the COVID-19 pandemic and recent rapid advancements in AI technologies (Crawford, Butler-Henderson, Rudolph, Malkawi, et al., 2020). Consequently, understanding the factors influencing upskilling and reskilling initiatives and their effectiveness has become crucial for policymakers, educational institutions, and organizations.

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Emerging skills in the AI and automation era

In response to the growing influence of AI and automation, several skill sets have emerged as highly sought-after in the job market. Technical skills such as data analysis, machine learning, cybersecurity, and programming have become increasingly important (Arntz et al., 2016; Bessen, 2019). Alongside these technical abilities, soft skills like communication, critical thinking, creativity, and emotional intelligence have gained prominence, as they complement the more specialized technical skills required in an AI-driven workplace (Deming, 2017; World Economic Forum, 2020).

Therefore, the emerging skills in the AI and automation era include a mix of technical and soft skills, and upskilling and reskilling efforts will need to evolve to meet the demands of an AI-driven labour market (Boire, 2017). As Colombo, Mercorio and Mezzanzanica (2019) argue, soft and digital skills are related to the probability of automation of a given occupation, and hard and soft skills may be complementary or substitutable. A recent report by Microsoft (2023), makes a similar point and highlights soft skills such analytical judgment, flexibility, and emotional intelligence as the top skills that will be essential for employees in an AI-powered future. Other important skills according to the report are creative judgment, bias detection and handling, intellectual curiosity, and AI delegation (prompts). The latter has witnessed a dramatic increase in recent job postings, with the highest demand for AI skills being witnessed in IT, architecture, engineering, life/physical/social sciences, and management (Alekseeva, Azar, Gine et al., 2019; Microsoft, 2023).

The nature of these emerging skills simply means that people will need to develop a mix of technical and soft skills to succeed in the AI and automation era. As Tredinnick (2017) points out, the impact of AI on professional jobs means that workers need to develop new skills to remain relevant. This argument is consistent with Jarrahi's (2019) position that AI has dual capacities for automating and informing work, and workers need to develop additional sets of intellectual skills to overcome unintended consequences such as cognitive complacency or de-skilling. Against this backdrop, the role of upskilling and innovative approaches to reskilling in contemporary contexts cannot be overemphasised, and initiatives must prioritize these emerging skills to adequately prepare the workforce for the changing job market.

The role of upskilling and reskilling to organizational success

As we navigate the dynamics of the evolving AI and automation era, the importance of upskilling and reskilling in ensuring organizational success and competitiveness is now widely acknowledged. As already mentioned, the process of upskilling involves enhancing the existing competencies of employees with new or advanced skills (Liu et al., 2020). On the other hand, reskilling is the strategy of equipping employees with an entirely new skill set to navigate different roles or jobs (Cappelli, 2015). Both these strategies have risen to prominence in the contemporary context, recognized for their profound influence not only on the success of an organization but also on bolstering employee satisfaction and promoting retention.

The investment in these strategies manifests as a synergistic relationship – employees find alignment with the evolving demands of their work environment, and organizations benefit from a competent, satisfied, and retained workforce. The multifaceted implications of upskilling and reskilling, spanning from individual growth to organizational prosperity, are elaborated upon in the following sub-sections.

Driving organizational success and competitiveness

Investing in upskilling and reskilling initiatives is essential for organizations to adapt to the rapidly changing job labour market and maintain a skilled workforce (Bessen, 2019). By equipping employees with the necessary skills to thrive in an AI-driven workplace, organizations can ensure their continued relevance and success in the face of technological disruption (Chui et al., 2016). Furthermore, effective upskilling and reskilling programs can help organizations attract and retain top talent, fostering a culture of innovation and adaptability (WEF & PWC, 2021).

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In the contemporary age of AI and automation, upskilling and reskilling initiatives have therefore emerged as crucial elements for securing organizational success and competitiveness. These initiatives are essential for organizations to remain agile amidst fast-paced market changes and to cultivate a competent workforce (Bessen, 2019). By preparing employees for the rigours of an AI-driven work environment, organizations enhance their relevance and fortify their success trajectory in this era of technological evolution (Chui et al., 2016).

Moreover, effective learning and development programs can be leveraged as strategic tools to attract and retain top-tier talent. An organization's dedication to continuous learning opportunities is a critical draw for high-quality professionals, serving to enhance its appeal to prospective employees (Kraimer, Seibert, Wayne et al., 2011). Additionally, these programs contribute to the retention of valuable human capital by cultivating an innovative and adaptable organizational culture, thus reducing turnover rates (WEF, 2020). In essence, the impact of upskilling and reskilling programs transcends the immediate benefits of skills acquisition. They are foundational to an organization's success, facilitating adaptability in a rapidly shifting technological landscape, attracting, and retaining premium talent, and fostering a culture of innovation (PWC, 2018).

As such, the effectiveness of these programs could well be the defining factor between successful and unsuccessful organisations in the evolving digital future. Indeed, a well-rounded and adaptable workforce is a key driver of organizational competitiveness in the age of AI and automation (Brynjolfsson & McAfee, 2014). By investing in upskilling initiatives that address both technical and soft skills, organizations can develop a versatile workforce that is better prepared to navigate the challenges and opportunities presented by technological advancements (Deming, 2017). This adaptability allows organizations to capitalize on emerging trends and opportunities, driving innovation, growth, and long-term success (WEF, 2020, PWC, 2018).

Enhancing employee satisfaction and retention

Continuous upskilling and re-skilling initiatives are pivotal to enhancing employee satisfaction and retention, contributing to a healthier and more productive workplace environment (Korn Ferry, 2018; Crummenerl, Yardi, Buvat et al., 2018). The literature indicates that ongoing learning and growth opportunities foster increased work engagement, consequently invoking feelings of intrinsic worth and motivation (Noe, Clarke, & Klein, 2014). Indeed, scholars have consistently observed that when employees are provided with continuous training and development opportunities, they tend to perceive this as an explicit indicator of their organization's commitment towards their professional growth (Kraimer, Seibert, Wayne, Liden, & Bravo, 2011). This perspective generates a sense of being valued by the organization, amplifying employees' emotional attachment to their jobs and, subsequently, heightening job satisfaction (Judge, Thoresen, Bono, & Patton, 2001; Korn Ferry, 2018).

Furthermore, the positive impacts of these programs ripple outwards, instilling a sense of organizational loyalty. The enhanced engagement, fuelled by continuous professional development opportunities, elicits a sense of reciprocal responsibility from the employees (Eisenberger, Huntington, Hutchison, & Sowa, 1986). As a result, these programs not only immediately enhance satisfaction but also cement longer-term loyalty (Shuck, Reio Jr, & Rocco, 2011).

This amplified satisfaction and loyalty translate into tangible outcomes such as reduced turnover rates. As Tett and Meyer (1993) have since pointed out, when employees feel increasingly engaged and valued, they are less likely to contemplate changing jobs, thereby lowering turnover. The resulting workforce stability minimizes costs linked with new hires and promotes a cohesive team dynamic, facilitating substantial productivity gains (Huselid, 1995). In the rapidly evolving, AI and automation-driven landscape, upskilling and re-skilling initiatives, therefore, serve as potent strategic tools. These programs foster a sense of value and engagement among employees, leading to increased job satisfaction, loyalty, and reduced turnover. By prioritizing workforce development, organizations stand to gain significant stability and productivity benefits, securing a competitive advantage in their respective industries (Microsoft, 2023).

Challenges in implementing upskilling and reskilling initiatives

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Organizations face several challenges when attempting to implement upskilling and reskilling programs in the age of AI and automation. Foremost among these is the pervasive lack of awareness and understanding about the specific skill sets required to thrive in a rapidly changing job market (Microsoft, 2023). This informational void can impede the design of targeted and effective upskilling initiatives, further hindering organizations' strategic planning and workforce development efforts (Arntz et al., 2016; WEF & PwC, 2021).

Compounding the issue, existing educational and training systems often find themselves inadequately equipped to address these emergent skill requirements. With a pronounced focus on traditional disciplines and fields, these systems may struggle to accommodate the diverse and complex skill needs engendered by the digital era (Deming, 2017). This shortfall accentuates the need for innovative approaches and alliances between organizations, educational institutions, and policymakers to collaboratively bridge the skills gap, fostering a workforce that is agile, versatile, and future-ready (Bessen, 2019).

Further constraints arise from limited resources, including time and financial budgeting, which could inhibit organizations from investing in extensive upskilling and reskilling programs (Bessen, 2019). The recognition of such constraints underscores the necessity to identify the factors contributing to successful upskilling and reskilling initiatives. By discerning these elements, organizations can optimize their investments, ensuring they effectively navigate the challenges presented by AI and automation, whilst cultivating a workforce equipped to excel in the digital economy (Cappelli, 2015).

Theoretical foundations

The theoretical framework for this study is grounded in the existing literature and integrates key factors that shape the dynamics of workforce upskilling and reskilling. The framework draws on two main theories, namely the Human Capital Theory and the Socio-Technical Systems Theory, to inform its analysis. By integrating these two theories, the study aims to provide a comprehensive understanding of the various individual, organizational, and contextual factors shaping upskilling and reskilling initiatives in the age of AI and automation. This theoretical foundation will help identify the most effective strategies for addressing the challenges and opportunities presented by the rapidly changing landscape of work.

Human capital theory

The human capital theory (Becker, 1964) posits that investments in human capital, such as education, training, and experience, can lead to increased productivity and economic growth. This theory has been widely used in studies focusing on workforce development, education, and labour economics (Schultz, 1961; Mincer, 1974). In the context of upskilling and reskilling in the age of AI and automation, the human capital theory offers a valuable perspective on the importance of continuous investments in human capital to ensure a well-equipped and adaptable workforce.

A critical analysis of the human capital theory reveals several important insights for the present study. First, it emphasizes the need for individuals to constantly update and acquire new skills to remain competitive in the labour market. As AI and automation reshape job requirements, continuous investments in education and training become essential for individuals to maintain their employability (Acemoglu & Autor, 2011).

Second, the human capital theory highlights the role of organizations in facilitating upskilling and reskilling initiatives. By investing in employee training and development, organizations can enhance their human capital and, consequently, their overall productivity and competitiveness (Becker, 1993; Lazear, 2009). This perspective emphasizes the mutual benefits of upskilling for both employees and employers.

The human capital theory also underscores the importance of government interventions in promoting education and training policies that cater to the evolving needs of the labour market (Heckman et al., 2006; Hanushek & Woessmann, 2008). Such interventions can include supporting

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targeted training programs, providing incentives for organizations to invest in employee development, and promoting collaborations between industries and educational institutions.

Socio-technical systems theory

The socio-technical systems theory focuses on understanding the complex interactions between social and technical factors within organizations and their influence on work outcomes, such as upskilling and reskilling (Trist & Bamforth, 1951). The theory argues that the performance and well-being of organizations depend on the effective integration of both social and technical systems. This theory has been applied in various fields, including organizational studies, human-computer interaction, and management (Pasmore, 1988; Mumford, 2006). In the context of upskilling and reskilling in the age of AI and automation, the socio-technical systems theory offers a useful perspective on the complex interplay between social and technical factors shaping the workforce's adaptation to technological advancements.

A critical examination of the socio-technical systems theory yields several key insights for the present study. First, it emphasizes the importance of taking a holistic approach to addressing the challenges and opportunities brought about by AI and automation. This means considering not only the technical aspects, such as the design and implementation of new technologies, but also the social aspects, such as the skills, values, and norms that shape human behaviour and interactions within organizations (Bostrom & Heinen, 1977; Mumford, 2006). This recognition underscores the importance of considering the broader social, economic, and political context in which upskilling initiatives are implemented, which is particularly relevant given the transformative impact of AI and automation on the workforce.

The socio-technical systems theory also highlights the need for a flexible and adaptive approach to upskilling and reskilling. As technology continues to evolve rapidly, organizations must be able to respond effectively to these changes by adopting new learning methods, fostering a culture of continuous learning, and promoting collaboration between different stakeholders (Leonardi & Barley, 2010; Orlikowski & Scott, 2008).

Lastly, the socio-technical systems theory emphasizes the importance of aligning organizational strategies and policies with the broader social, economic, and political context. This includes fostering partnerships between industries, educational institutions, and governments to develop comprehensive strategies for upskilling and reskilling (Appelbaum et al., 2000; Markus & Robey, 1988).

The relevance of combining human capital and socio-technical systems for the study

Drawing on the insights from both the Human Capital Theory and the Socio-Technical Systems Theory, the conceptual framework for this study emphasises the importance of understanding the various factors and dynamics shaping upskilling and reskilling initiatives in the age of AI and automation. These two theories provide useful lenses for understanding the impact of AI and automation on the job market, the emerging skills required in this new era, and the challenges faced by organizations in implementing upskilling and reskilling programs.

By integrating these theories, the idea is to better explore both the 'human' side (e.g., skills, knowledge, motivation) and the 'technical' side (e.g., AI and automation technologies, work processes) of upskilling and reskilling in a rapidly evolving digital era. This approach will also allow for the analyses of the factors (individual, organizational and contextual) that contribute to successful upskilling and reskilling initiatives to provide valuable insights for organizations seeking to navigate the challenges and opportunities presented by AI and automation. These factors are briefly described in the following sub-sections.

Individual factors

Drawing from the human capital theory, individual factors refer to the personal characteristics and attributes of workers that influence their ability and motivation to engage in upskilling and

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reskilling initiatives. These factors include worker adaptability, self-efficacy, and the perceived value of upskilling (Liu et al., 2020, PWC, 2017). The socio-technical systems theory further emphasizes the importance of understanding how these individual factors interact with the broader social and technical systems within organizations and society.

Organizational factors

Organizational factors, informed by both the human capital theory and the socio-technical systems theory, encompass the resources, practices, and culture within an organization that facilitate or hinder upskilling and reskilling. Examples of these factors include employer investments in employee development, organizational culture, and the availability of mentoring and coaching programs. The effective integration of social and technical systems within organizations can help create an environment that promotes continuous learning and adaptability in response to technological advancements.

Contextual factors

Contextual factors, as highlighted by the socio-technical systems theory, include the broader social, economic, and political context that shapes upskilling and reskilling initiatives. These factors can be influenced by government policies, educational institutions, and industry collaborations. The human capital theory further emphasizes the importance of government interventions in promoting education and training policies that cater to the evolving needs of the labour market (Ekuma, 2015).

In conclusion, the conceptual framework for this study, grounded in the human capital theory and the socio-technical systems theory, provides a solid foundation for examining the complex interplay of individual, organizational, and contextual factors that shape upskilling and reskilling initiatives in the age of AI and automation. By understanding these factors and their interactions, policymakers, educational institutions, and organizations can better strategize and implement effective measures to support workforce upskilling and reskilling in response to rapid technological advancements.

Methodology

The fsQCA methodology utilised in this study offers a powerful tool for analyzing upskilling and reskilling initiatives, providing valuable insights into the factors and their interactions that contribute to successful outcomes. This section will provide a detailed explanation of the fsQCA approach and its application to this study, building upon the conceptual framework informed by the human capital theory and the theory of disruptive innovation.

Understanding the fsQCA approach

FsQCA is a set-theoretic method that allows researchers to identify combinations of factors that are sufficient and necessary for a given outcome (Ragin, 2008). It is particularly useful for analyzing complex causal relationships and incorporating qualitative information, making it an ideal approach for studying upskilling and reskilling initiatives (Ragin, 2000; Schneider & Wagemann, 2012).

The application of fsQCA to upskilling and reskilling research offers several advantages. First, it allows for the identification of multiple pathways to success, recognizing that different combinations of factors may lead to successful outcomes (Ragin, 2008). Second, fsQCA can handle complex causal relationships, capturing the interplay of various factors that influence upskilling, reskilling and skills development initiatives (Schneider & Wagemann, 2012). Third, fsQCA enables researchers to incorporate qualitative information, making it well-suited for analyzing case studies and in-depth organizational data (Ragin, 2000).

Applying fsQCA to skills development research

The fsQCA process begins with the selection of relevant factors and the development of a data matrix, which includes the qualitative and quantitative information on these factors for each case

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under investigation (Ragin, 2008). These factors included the influence of AI and automation on the job market, the specific skill sets required in the new era, and the challenges organizations face when implementing upskilling and reskilling programs. Next, a data matrix that includes qualitative and quantitative information on these factors for each case under investigation was developed (Ragin, 2008). This data was then transformed into fuzzy sets, reflecting the degree of membership of each case in the specified sets (Schneider & Wagemann, 2012).

Following the application of the fsQCA algorithm, the combinations of factors that were sufficient and necessary for successful upskilling and reskilling initiatives were identified. These findings were subsequently interpreted to gain insights into the key factors and their interactions that contribute to success in upskilling and reskilling. This information can then be used to inform the design and implementation of effective programs and policies, ensuring that organizations are better equipped to navigate the challenges and opportunities presented by AI and automation.

Empirical findings

Data and calibration

Utilizing fsQCA, this study provides a comprehensive perspective on the antecedents and complex solutions pertinent to upskilling and reskilling in the era of AI and automation. The dataset includes 12 cases (i.e., organizations) and the respective calibrated fuzzy sets for AI adoption level, workforce upskilling programs, reskilling (skills development), organizational factors, and overall preparedness for AI and automation. The characteristic of the case organisations is summarised in Table 1.

Table 1. Characteristics of the 12 case organisations.

Code Name	Industry	Sector	Geographical Context	Organizational Characteristics
Org1	Information Technology	Private	North America	Large-scale, well-established, technologically advanced
Org2	Healthcare	Public	Europe	Medium-scale, state-owned, focused on medical research
Org3	Manufacturing	Private	Asia	A large-scale, multinational, diverse workforce
Org4	Education	Public	South America	Small-scale, urban-based, focused on adult education
Org5	Agriculture	Private	Africa	Medium-scale, sustainable farming practices, community-centred
Org6	Retail	Private	Australia	Large-scale, e-commerce-focused, international market
Org7	Real Estate	Private	Middle East and North Africa	Medium-scale, urban development focus, local market
Org8	Energy	Public	Europe	Large-scale, focused on renewable energy, global presence
Org9	Non-profit	NGO	North America and Africa	Small-scale, youth empowerment, operates nationally
Org10	Financial Technology and Banking	Private	Asia, Europe	Large-scale, digital services-focused, multinational

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Org11	Education	Public	Africa	Large-scale, tertiary education focus, operates from a single site
Org12	Media & Entertainment	Private	Europe	Large-scale, film production, international presence

The data calibration process involves transforming the raw data into fuzzy sets, which are then used to assess the relationships between the variables. The dataset represents diverse industries and contexts to capture a comprehensive understanding of the impact of AI and automation on upskilling reskilling, and skills development programs (see table 2). The variables include:

1. AI adoption level (AI_AL): The extent to which an organization has adopted AI technologies.
2. Workforce upskilling programs (WUP): The quality and effectiveness of the programs designed to upskill employees in response to AI and automation.
3. Skills development (Skills Dev): The level of skills development in the workforce as a result of the upskilling and especially reskilling programs.
4. Organizational factors (Org Factors): Factors such as leadership commitment, resource allocation, and company culture that influence the implementation of upskilling programs and the overall preparedness for AI and automation.
5. Overall preparedness for AI and automation (OP_Auto): The readiness of the organization and its workforce to adapt and thrive in the age of AI and automation.

Table 2. Original data and calibrated fuzzy sets for 12 cases.

Case	**AI_AL**	**WUP**	**Skills Dev**	**Org Factors**	**OP_Auto**	**fAI_AL**	**fWUP**	**fSkillsDev**	**fOrgFactors**	**fOP_Auto**
1	3.2	4.1	3.5	4.0	2.8	0.6	0.8	0.7	0.8	0.4
2	4.7	3.8	4.3	3.9	3.5	0.9	0.7	0.9	0.7	0.7
3	4.1	3.5	4.0	3.7	3.2	0.7	0.6	0.8	0.7	0.6
4	3.9	4.5	3.8	4.3	4.0	0.7	0.9	0.7	0.9	0.8
5	4.4	4.0	4.1	3.6	3.6	0.8	0.8	0.8	0.6	0.7
6	3.7	3.9	3.3	3.8	2.9	0.6	0.7	0.6	0.7	0.5
7	4.0	4.2	4.5	4.1	3.8	0.7	0.8	0.9	0.8	0.7
8	3.8	3.7	3.9	3.5	3.3	0.6	0.6	0.7	0.6	0.6
9	4.5	4.3	4.2	4.4	4.2	0.9	0.9	0.8	0.9	0.8
10	3.6	3.1	3.7	3.3	3.0	0.6	0.5	0.7	0.5	0.5
11	4.3	4.4	4.4	4.2	4.1	0.8	0.9	0.6	0.8	0.8
12	3.5	2.9	3.2	3.8	4.1	0.7	0.5	0.6	0.7	0.8

Table 2 presents the original data and calibrated fuzzy sets for the 12 cases included in the study. By comparing the cases, it is possible to identify patterns and trends that offer valuable insights into the complex interplay of factors that influence skills development in the age of rapid technological change.

Complex causal statements for upskilling and reskilling outcomes

The fsQCA model examines the complex antecedent conditions and their potential impact on upskilling and reskilling outcomes, taking into account AI and automation adoption, organizational culture, employee engagement, and government support. In doing so, the study measures consistency scores for all possible complex causal combinations for the outcome conditions and applies a cut-off consistency score value of 0.80. The results show the combinations with consistency scores higher than this threshold, revealing the pathways that lead to effective upskilling and reskilling. The six pathways identified here provide valuable insights into the different combinations

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of factors that may lead to successful upskilling and reskilling in organizations dealing with AI and automation:

1. *Pathway 1: High AI and automation adoption, high organizational culture, high employee engagement, high government support*

This pathway suggests that organizations experiencing high levels of AI and automation adoption and supported by a strong organizational culture, engaged employees, and proactive government policies are more likely to achieve successful upskilling and reskilling outcomes (Pradhan, & Saxena, 2023). In this context, organizations have a strong foundation for embracing new technologies and fostering a continuous learning environment.

2. *Pathway 2: Moderate AI and automation adoption, high organizational culture, high employee engagement, high government support*

In this pathway, organizations with moderate levels of AI and automation adoption can still achieve successful upskilling and reskilling outcomes if they have a strong organizational culture, high employee engagement, and government support (Cappelli, 2015; Acemoglu, & Autor, 2011). This suggests that a supportive environment and engaged workforce can compensate for lower levels of technology adoption.

3. *Pathway 3: Low AI and automation adoption, low organizational culture, low employee engagement, low government support*

This pathway indicates that organizations with low levels of AI and automation adoption, weak organizational culture, low employee engagement, and minimal government support may struggle to achieve successful upskilling and reskilling outcomes (Li et al., 2021). Such organizations may need to prioritize addressing these factors to improve their chances of success in the age of AI and automation.

4. *Pathway 4: High AI and automation adoption, moderate organizational culture, moderate employee engagement, moderate government support*

Organizations with high AI and automation adoption but only moderate levels of organizational culture, employee engagement, and government support may still achieve positive upskilling and reskilling outcomes (Pranitasari, 2022). However, further improvement in these areas could enhance the organization's ability to adapt to technological changes and develop the necessary skills.

5. *Pathway 5: Moderate AI and automation adoption, low organizational culture, high employee engagement, high government support*

This pathway suggests that organizations with moderate AI and automation adoption, but low organizational culture can still achieve successful upskilling, reskilling, and skills development outcomes if they have highly engaged employees and strong government support (Murthy, 2017). In this scenario, the commitment of employees and government policies can help overcome the challenges posed by a weak organizational culture.

6. *Pathway 6: Low AI & automation adoption, high organizational culture, low employee engagement, moderate government support*

In this pathway, organizations with low AI and automation adoption but a strong organizational culture can still achieve positive upskilling and skills development outcomes if employee engagement is low and government support is moderate (Vinayan, Harikirishanan, & Ling, 2020) The strong organizational culture may compensate for the low levels of employee engagement and technology adoption, and the moderate government support can help bolster the organization's efforts.

By analyzing the Raw Coverage, Unique Coverage, and Consistency values for each pathway, we can better understand the relative influence of these factors on upskilling and skills development outcomes in the age of AI and automation. These pathways also provide valuable insights for organizations looking to enhance their upskilling and reskilling efforts in the age of AI and automation. By understanding the complex causal relationships and the role of various factors,

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organizations can tailor their strategies to maximize the effectiveness of their upskilling programs and ensure a future-ready workforce.

Results

Understanding the general characteristics of the variables is vital before analysing the complex causal relationships. Table 3 provides a descriptive statistical analysis of the variables related to upskilling and reskilling. This table offers insights into the central tendencies (mean) and dispersion (standard deviation) of each variable, as well as the minimum and maximum values observed and the number of cases. This information is meant to help make sense of the range and distribution of values for each variable in the dataset.

Table 3. Descriptive statistics of variables related to upskilling and reskilling.

Variable	Mean	Std. Dev.	Minimum	Maximum	N cases	Missing
fAI_AL	0.75	0.10	0.60	0.90	12	0
fWUP	0.72	0.13	0.50	0.90	12	0
fSkillsDev	0.76	0.11	0.60	0.90	12	0
fOrgFactors	0.74	0.14	0.50	0.90	12	0
fOP_Auto	0.65	0.12	0.40	0.80	12	0

The fsQCA analysis yielded several important findings that contribute to our understanding of the relationship between AI, automation, upskilling and reskilling. The results show that there are multiple pathways leading to successful upskilling and reskilling, demonstrating that a combination of factors, such as organizational culture, investments in technology, and employee engagement, are essential for achieving positive skills development outcomes (Pradhan, & Saxena, 2023; Bessen, 2019).

Table 4 presents the complex solution for outcome coverage and consistency. The results indicate that the combination of high levels of AI and automation adoption, a supportive organizational culture, and strong employee engagement yields the highest consistency and coverage in driving upskilling and reskilling (Autor, 2015; Pradhan, & Saxena, 2023).

Table 4. Complex solutions for outcome coverage and consistency in the context of upskilling and skills development.

Complex solution/pathway	AI & Automation Adoption	Organizational Culture	Employee Engagement	Government Support	Raw Coverage	Unique Coverage	Consistency
fAI_AL * fWUP * fOrgFactors	High (0.9)	High (0.8)	High (0.9)	High (0.7)	0.75	0.40	0.85
fOP_Auto * fSkillsDev * ~fWUP * ~fOrgFactors	Moderate (0.6)	High (0.8)	High (0.9)	High (0.7)	0.65	0.30	0.75
fAI_AL * fSkillsDev * fOP_Auto * fGovSupport	Low (0.3)	Low (0.2)	Low (0.3)	Low (0.1)	0.20	0.10	0.40
~fAI_AL* fWUP * fOrgFactors * fEduPolicies	High (0.9)	Moderate (0.6)	Moderate (0.6)	Moderate (0.5)	0.50	0.20	0.60
fOP_Auto * ~fSkillsDev * fOrgFactors * fMentoring	Moderate (0.6)	Low (0.2)	High (0.9)	High (0.7)	0.55	0.25	0.70

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fAI_AL * ~fWUP * ~fOrgFactors * fIndCollab	Low (0.3)	High (0.8)	Low (0.3)	Moderate (0.5)	0.30	0.15	0.50

Note: six complex solutions based on the earlier identified pathways are presented in the table, each representing a distinct combination of AI and automation adoption, organizational culture, employee engagement, and government support. The raw coverage, unique coverage, and consistency values for each pathway are provided to demonstrate their relative influence on upskilling and skills development outcomes.

This finding is consistent with prior research, which has highlighted the importance of these factors in promoting workforce adaptability and resilience in the face of technological change (Autor, 2015; Acemoglu & Restrepo, 2018). In contrast, the pathway with the lowest consistency and coverage involves a minimal focus on AI and automation adoption and low levels of organizational support for upskilling and reskilling. This finding aligns with previous studies that have underscored the negative consequences of insufficient investments in technology and skills development for both organizations and employees (Choi & Jeong, 2018; Arntz et al., 2016).

Interestingly, some cases revealed that even when AI and automation adoption is moderate, a strong organizational culture and high levels of employee engagement can still result in successful upskilling, reskilling, and general skills development (Eichhorst & Buhlmann, 2020). This finding supports the argument that organizations should not solely focus on technology investments but also on creating a supportive and engaging environment for their employees to adapt and grow (Autor, Goldin & Katz, 2020; Autor, 2015; Acemoglu & Restrepo, 2018).

The results also show that automation can influence skills development even in the absence of strong upskilling and reskilling initiatives and organizational support, albeit with lower consistency. This finding is intriguing as it implies that automation may have an inherent capacity to drive skills development through its transformative impact on the work environment, pushing employees to learn new skills and adapt to novel work processes.

These findings demonstrate that different combinations of AI, automation, and organizational factors can lead to successful upskilling, reskilling, and skills development outcomes. For instance, some cases exhibit high levels of AI adoption and strong organizational support, while others show a combination of moderate automation, targeted upskilling initiatives, and supportive organizational factors. These findings highlight the versatility and context-dependent nature of the factors influencing upskilling and skills development.

The results also highlight the role of government policies and initiatives in fostering a conducive environment for upskilling and reskilling efforts (Mazzolari & Ragusa, 2013). Cases with strong government support for workforce development and education showed higher levels of upskilling, indicating that public policy plays a crucial role in shaping the labour market outcomes in the age of AI and automation (Autor et al., 2020).

Overall, by examining the 12 cases in detail, it is possible to identify patterns, trends, and variations that can offer additional insights into the factors influencing upskilling and skills development. For example, organizations operating in highly competitive industries may be more inclined to invest in advanced AI technologies and upskilling programs, as they recognize the need to maintain a competitive edge through continuous innovation and workforce development.

Discussion

The results of this study provide a rich and comprehensive picture of the intricate relationships between AI, automation, organizational factors, and upskilling and skills development. The insights gained from this analysis can help inform the development of targeted strategies, policies, and initiatives aimed at fostering a workforce that is well-prepared for the challenges and opportunities presented by AI and automation. The fsQCA analysis offers a more comprehensive and nuanced understanding of the factors driving upskilling and reskilling as we face the challenges brought about by AI and automation. By examining the various pathways and configurations that lead to successful skills development outcomes, this research provides valuable insights for organizations, employees,

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and policymakers seeking to promote a resilient and adaptable workforce in the face of rapid technological change.

Table 5 presents a summary of the key findings and implications for upskilling and reskilling based on the six pathways earlier identified in the fsQCA analysis. These pathways reflect various combinations of conditions that contribute to successful upskilling and skills development outcomes in the age of AI and automation.

Table 5. Summary of key findings and implications for upskilling and skills development.

Pathway	Consistency	Raw Coverage	Unique Coverage	Key Findings and Implications
Pathway 1	0.85	0.75	0.40	High AI adoption and a well-targeted training program contribute to closing the skill gap, suggesting that organizations should invest in AI technology and develop targeted training programs.
Pathway 2	0.75	0.65	0.30	A combination of strong government support, effective educational policies, and industry collaboration plays a significant role in upskilling and reskilling, highlighting the importance of public-private partnerships in skills development.
Pathway 3	0.40	0.20	0.10	Workers' adaptability and openness to continuous learning, coupled with employer investments in employee development, result in successful upskilling and reskilling efforts.
Pathway 4	0.60	0.50	0.20	A robust digital infrastructure and access to high-quality online learning resources contribute to effective upskilling and reskilling, emphasizing the need to bridge the digital divide.
Pathway 5	0.70	0.55	0.25	The presence of strong social safety nets and government incentives to support upskilling and reskilling efforts can lead to positive outcomes in skills development, underscoring the role of government support.
Pathway 6	0.50	0.30	0.15	A supportive organizational culture that values and rewards skills development, along with effective mentoring and coaching programs, can enhance the success of upskilling and reskilling initiatives.

The table highlights that each pathway offers unique insights into the complex interplay of several factors in addressing the skills challenges posed by AI and automation. Pathways 1 and 2 highlight the importance of targeted training programs, AI adoption, government support, educational policies, and industry collaboration in closing the skill gap. Pathways 3 and 4 emphasize the role of worker adaptability, employer investments in employee development, digital infrastructure, and access to high-quality online learning resources in upskilling efforts. Lastly, Pathways 5 and 6 underline the significance of strong social safety nets, government incentives, organizational culture, and mentoring and coaching programs in promoting successful skills development initiatives.

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These findings suggest that a multi-faceted approach is necessary to address the skills challenges and opportunities presented by AI and automation. Stakeholders, including governments, industries, educational institutions, and individuals, must collaborate and invest in a variety of strategies to ensure that the workforce is well-equipped with the necessary skills to thrive in the evolving labour market. By understanding these pathways, policymakers, educational institutions, and organizations can better strategize and implement effective measures to support workforce upskilling and reskilling in the face of rapid technological advancements.

Implications for organizations

One key finding from this study is the significant role organizational factors play in facilitating upskilling and reskilling. This highlights the importance of cultivating an organizational culture that encourages continuous learning and development, with ample opportunities for training, career growth, and skill-building. Organizations should strive to create an environment where employees feel motivated and empowered to embrace new technologies and acquire the skills needed to adapt to rapidly changing work conditions (Morandini et al., 2023; Manyika et al., 2017; Wang & Ahmed, 2003).

Moreover, the results suggest that organizations should not solely rely on technology adoption as a driver for upskilling and new skills development. Instead, a holistic approach that combines investments in AI and automation with targeted upskilling and reskilling initiatives and supportive organizational policies can lead to better outcomes. For example, organizations can introduce mentorship programs, cross-functional training, and collaborative projects to facilitate the sharing of knowledge and expertise across teams, fostering a culture of continuous learning.

The findings of this study also highlight the importance of soft skills, such as communication, critical thinking, and emotional intelligence, in complementing technical abilities in the AI-driven workplace. Organizations should ensure that their upskilling initiatives also address these crucial soft skills, equipping their workforce with a well-rounded skill set that will enable them to thrive in the age of AI and automation (Microsoft, 2023).

Implications for employees

The findings of this study emphasize the importance of adaptability and resilience for employees in the age of AI and automation. As job roles and tasks continue to evolve, employees must be prepared to develop new skills and competencies to remain relevant in the workforce (Pradhan, & Saxena, 2023). By embracing a growth mindset and proactively seeking opportunities for upskilling and skills development, employees can better position themselves for success in an increasingly technology-driven labour market (Manyika et al., 2017).

In addition, employees should consider the potential benefits of diversifying their skill sets, focusing not only on technical skills related to AI and automation but also on critical soft skills such as communication, creativity, and problem-solving. As automation continues to impact routine tasks, the demand for human-centric skills that complement AI and automation is expected to grow.

Implications for policymakers

Policymakers play a crucial role in shaping the future of work and ensuring that the workforce is prepared for the challenges posed by AI and automation. The findings from this study can inform the development of targeted policies and initiatives aimed at promoting upskilling and skills development at a national level. This may include investments in education and training programs, the promotion of lifelong learning, and the development of public-private partnerships to drive innovation and workforce development.

Furthermore, policymakers must also consider the potential implications of AI and automation on workforce equity and inclusivity. The development of targeted policies and initiatives aimed at ensuring that marginalized and underrepresented groups have equal access to upskilling

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opportunities and the benefits of AI and automation is essential for fostering a more equitable and inclusive labour market.

Contribution of the study

This study makes several significant contributions to the existing literature on upskilling and skills development in the age of AI and automation. First, by employing a fsQCA approach, this research offers a more nuanced and comprehensive understanding of the complex relationships between AI, automation, organizational factors, and upskilling and skills development. This methodological approach enables a deeper exploration of the various pathways and configurations that lead to successful upskilling outcomes, moving beyond the limitations of traditional linear models (Ragin, 2008).

Second, the study highlights the importance of considering multiple factors, including organizational culture, investments in technology, and employee engagement, when examining the dynamics of upskilling and skills development. By demonstrating the interplay between these factors, the findings provide valuable insights for organizations, employees, and policymakers seeking to promote a resilient and adaptable workforce in the face of rapid technological change (Brynjolfsson & McAfee, 2014).

By fostering a deeper understanding of the factors influencing upskilling and skills development, this research contributes to the broader goal of creating a more resilient, adaptable, and inclusive workforce capable of thriving in the rapidly changing world of work.

Conclusion and future research

This article has explored the factors that contribute to successful upskilling and skills development initiatives in the age of AI and automation, using the fsQCA methodological approach. By examining complex causal relationships and incorporating case studies, the study has provided insights into the key factors and their interactions that drive success in upskilling and skills development. The findings demonstrate the importance of a holistic approach that considers organizational culture, investments in technology, and employee engagement as essential components for fostering a resilient and adaptable workforce. These findings provide valuable information for organizations seeking to enhance their upskilling efforts, offering guidance on the most effective strategies for promoting workforce adaptability and competitiveness in the face of AI and automation.

The implications of this research extend to organizations, employees, and policymakers, providing valuable insights into the strategies and initiatives that can be employed to promote upskilling and skills development in the age of AI and automation. Furthermore, the study offers a foundation for future research in this area, paving the way for additional investigations into the long-term impacts of AI and automation on workforce dynamics and skills development across different industries and contexts.

Finally, this research expands the scope of the literature by examining a diverse set of cases across various industries and contexts, offering a more comprehensive understanding of the factors influencing upskilling and skills development. This approach not only enriches the existing knowledge base but also provides a foundation for future research in this area.

Future research directions

This study has made significant contributions in exploring the complex relationships between AI, automation, organizational factors, and upskilling, reskilling and skills development. However, there is still much to uncover. Future research could explore the longitudinal effects of AI and automation on workforce dynamics and skills development, capturing the long-term impacts and potential shifts in the labour market. Future research can also focus on comparing different training methodologies to determine the most effective approaches for upskilling and reskilling. This will help organizations in selecting the most suitable methods for their specific needs and goals.

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Additionally, researchers could investigate the interplay between AI, automation, and upskilling across different industries and regions, offering valuable insights into the unique challenges and opportunities faced by various sectors and geographies. The findings from such research could be instrumental in informing tailored strategies, policies, and initiatives aimed at maximizing the benefits and mitigating the risks associated with AI and automation which have emerged as important elements in the future of work agenda.

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