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The productivity dilemma: Examining the truth behind automation's impact on employment, and the mediating role of augmentation.

Abstract

Purpose: This paper provides a comprehensive review of the literature examining the relationship between automation and employment, with a focus on understanding the debates of automation displacement and enablement, and the mediating role of employee augmentation in driving organisational productivity.

Design/Methodology/Approach: A semi-systematic literature review was conducted across the areas of automation, work-design, and employee skills over the past 3 years.

Findings: The academic literature was found to still be in its infancy, with empirical evidence in an organisational setting scarce. However, research suggests that automation does not cause job displacement or a negative impact on employment. In contrast, data suggests that automation leads to new job creation, task enlargement and skills enhancement. The findings suggest that organisations should employ augmentation alongside automation to drive productivity, in a way that promotes strong work-design, builds trust, and leverages human creativity. A further recommendation is made for organisations to focus on continuous upskilling to combat the shortening shelf-life of skills and adapt to the constant change brought around by advances in automation.

Originality/Value: Through a synthesis of diverse perspectives and academic evidence, this paper contributes to the nuanced understanding of the complexities surrounding automation and its impact on employment. This literature review underscores the need for organisational strategies that leverage augmentation to harness productivity savings, alongside a renewed focus on widespread employee skills enhancement. In addition to creating new recommendations for practitioners and organisational leaders, this paper also furthers the research agenda through a list of research gaps for scholarly attention.

Key Words: Automation, Augmentation, AI, RPA, Displacement, Work Design, Employment

1. Introduction

Organisations are operating in unprecedented conditions, caused by volatile economic environments and geopolitical instability (KPMG, 2022), amongst the lingering effects of the COVID19 pandemic (McKinsey and Company, 2023). Consequently, leaders are searching for new methods to boost their competitive advantage, with many declaring an all-out strategic focus towards workplace automation (Davenport and Mittal, 2023). In previous years, organisations pursued workplace automation as a successor to outsourcing, to reduce costs and increase accuracy of high-volume and low complexity tasks (Jesuthasan and Boudreau, 2017; Wright et al, 2022). However, as technological capabilities evolve, organisations now seek to deploy automation across every function to support with data-driven decision making, new product offerings, increase process efficiencies, and create new business models (Davenport and Mittal, 2023).

Wright et al. (2022) advise that by pursuing a systemic deployment, organisations aim to achieve a cost reduction of 31% via automation in the next three years. This corresponds with findings from recent consultancy surveys, whereby Deloitte have observed organisations progressing along their automation maturity curve (Wright et al., 2022), with KPMG declaring 67% of global leaders are expecting to engage in emerging technologies in the coming years (KPMG, 2022). Bankins et al. (2023) have referred to this evolution as the fourth industrial revolution, or the second machine age. By 2023, innovation had become the top corporate priority for 79% of companies, according to the Boston Consulting Group (2023). This shift has led the McKinsey and Company to forecast that automation will add between \$2.6 - \$4.4 trillion US dollars annually to the global economy (McKinsey Digital, 2023).

However, whilst widespread automation is the goal, a myriad of challenges prevents benefit realisation. In an earlier study, the CIPD (2018) noted that an increase in workplace automation had not yielded an increase in productivity in UK organisations. This trend remained consistent globally by 2023, with the Boston Consulting Group (2023) finding only 45% of organisations had translated automation investment into business impact. In their survey, the Boston Consulting Group found organisations were decreasing in their ability to implement automation, with only one in five organisations feeling ready. Practitioners suggested several factors are impeding organisations in these efforts.

1. There is a dystopian narrative in mainstream media surrounding large-scale job losses through automation which is growing more pronounced as technological capabilities evolve (Deloitte, 2023). This narrative fuels the fears of workers concerned by job security (Wright et al., 2022), ultimately forming change resistance and uncertainty (KPMG, 2023; McKendrick, 2023; Wright et al., 2022).
2. Secondly, organisations find themselves in the midst of a global talent crisis (KPMG, 2022) and are facing challenges in building new capabilities to meet technological change (McKinsey and Company, 2023; Wright et al., 2022). Davenport and Mittal (2023) found many organisations embark on automation pilots, but few subsequently migrate into production. Davenport and Mittal (2023) explain how deploying pilots to production for greater scale requires the mass upskilling of workers, which organisations are struggling with today.

Additionally, in this author's previous systematic literature review in this journal (Murphy, 2024), a research gap was identified in our understanding of how organisations should design work in a way that supports employee augmentation alongside automation, to reap productivity benefits.

This paper addresses these gaps by conducting a follow-up semi-systematic review on automation's impact on the workforce and exploring the current status of augmentation and upskilling.

1.1 Theoretical Framework

Based on the aforementioned gaps, this literature review builds its searches from three research terms:

1. **Automation** is the process by which technology increases labour productivity, by performing some or all of the tasks previously reserved for humans (Filippi et al., 2023; Furendal and Jebrai, 2023), often enabling work to be performed faster and more efficiently (Sobzcak, 2021). The field of automation emerged in the 1950s (Garibray et al., 2023) initially focusing on physical robots in manufacturing tasked with routine and hazardous duties (Turja et al., 2022). However, this paper adopts a broader definition of automation, focusing on digital automation technologies (DAT) aimed at automating processes and decision-making across all industries:
    a. **Robotic Process Automation (RPA)** employs web-based robots (bots) to mimic rule-based human actions step-by-step (Sobczak, 2021), to automate back-office 'doing work' (Filgueiras et al., 2022; IEEE, 2017; Siderska, 2021).
    b. **Machine Learning (ML)** refers to a system using algorithms to detect and learn from data patterns to predict future scenarios (Spring et al., 2022).
    c. **Artificial Intelligence (AI)** combines with other DAT technologies to learn from external data (Sobzcak, 2021) and mimic human intelligence to perform cognitive functions (Raisch and Krakowksi, 2021). Humans interact with data and conduct tasks such as problem-solving (Raich and Krakowski, 2021), visual analysis and speech recognition (Kumar et al., 2023) to achieve tasks.
    d. **Generative AI (GAI)** is an emerging phenomenon rising in prominence since the release of ChatGPT in November 2022 (McKinsey, 2023). GAI applications are built using artificial neural networks inspired by the neurons connecting the human brain and can process extremely large sets of unstructured data to perform tasks and generate content (McKinsey, 2023).

2. **Augmentation** refers to a pattern of work where human workers coexist alongside DATs, by utilising automation to increase the productivity of tasks (Tschang and Almirall, 2022). Well-designed augmentation aims at leaving tedious and repetitive work for DATs, and creative task-solving for humans (Furendal and Jebari, 2023).

3. **Work design** refers to the processes of how work is structured, organised, and experienced (Waschull et al., 2020). It is a crucial tool for re-adjusting job attributes to focus on employee needs and abilities, with the goal of implementing a stronger focus on creative and innovative activities (Hernaus and Maric, 2019).

4. **Skills** refer to an employee's accumulated knowledge (Rinta-Kahila et al., 2023) and their ability to learn new tasks and technologies (Sony and Mekoth, 2022). This includes declarative knowledge (information people know, and their ability to apply expertise), and procedural knowledge (an understanding of how to perform a task) (Rinta-Kahila et al., 2023).

The remaining chapters of this paper present an overview of a semi-systematic literature review conducted on the research topic, whilst then progressing to present a synthesis of the academic literature and associated research gaps. This paper concludes with two recommendations for organisations to help boost productivity with workplace automation, as well as suggesting several future research agendas.

2. Methodology

The systematic literature review first emerged from the field of medical science, in an effort to improve the quality of journal literature reviews (Tranfield et al., 2003). The systematic approach enables a reproducible and transparent synthesis of literature, whilst also establishing a comprehensive audit trail encompassing procedures and conclusions (Snyder, 2019). Since its conception, the systematic approach has evolved into the golden standard for literature reviews (Snyder, 2019), addressing the challenges prevalent in traditional methodologies, such as selectivity bias, singular outputs, and unreliable findings (Snyder, 2019; Tranfield et al., 2003). However, scholars note that a full-scale systematic approach may not be suitable for studies which are time-bound (Papaioannou et al., 2009; Snyder, 2019) or those which cover diverse disciplines (Papaioannou et al., 2019). For such studies, scholars recommend following a semi-systematic approach (Snyder, 2019). Snyder notes how this less rigid approach enables authors to search literature themes with predefined conditions, subsequently enabling a thematic synthesis of the literature. Due to the predefined search terms identified thus far, the semi-systematic approach has been adopted for this paper.

2.1 Conducting the Search

Following the method recommended by Snyder (2019), scholars should first define the research question or subject. Based on the gaps highlighted from the author's previous semi-systematic review (Murphy, 2024), several research questions were defined:

RQ 1 – Does workplace automation lead to job displacement?
RQ 2a – Does augmentation alongside automation positively influence employment?
RQ 2b – Does augmentation alongside automation positively influence productivity?
RQ 2c – What successful approaches are being followed to enable augmentation?

The review was then conducted through searching the 3 inter-related terms of automation, work design and employee skills. In parallel, a PRISMA was implemented to monitor and organise the process, similar to those conducted in other systematic literature reviews (Borges et al., 2021; Shirmohammadi et al., 2022). Figure 1 documents the PRISMA process followed in this paper, by adopting the official template from the PRISMA Statement Organisation (Page et al. 2020).

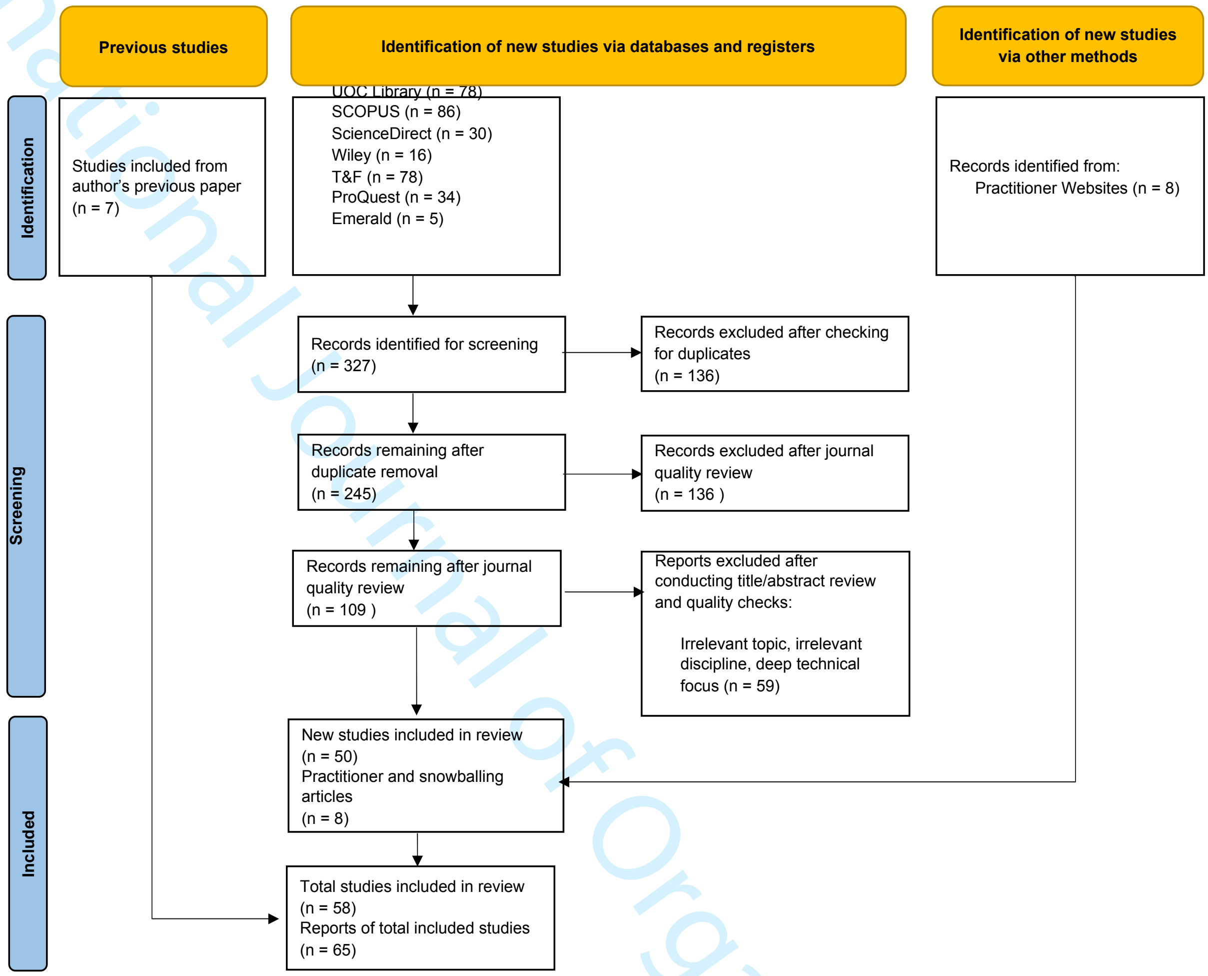

Figure 1. PRISMA for Semi-Systematic Review (Adapted from Page et al. 2020).

Step 1: Academic databases were researched for inclusion. Previous automation literature reviews consistently leverage SCOPUS (Bankins et al., 2023; Borges et al., 2023; Filippi et al., 2023) and Science Direct (Trenerry et al., 2021), leading to their inclusion. The author's prior semi-systematic review (Murphy, 2024) also suggested Wiley and Taylor and Francis for their subject area coverage. A dearth of organisational-level automation research (Murphy, 2024) prompted the inclusion of Emerald and ProQuest, for a broader perspective.

Database	Search String
UOC Library	((Automation) OR (RPA) OR (AI) OR ("robotic process automation") OR ("artificial intelligence")) AND (("job design") OR ("Employee skills") OR ("worker skills") OR ("people skills") OR ("work design") OR (augmentation))
SCOPUS	((automation) OR (rpa) OR (ai) OR ("robotic process automation") OR ("artificial intelligence")) AND (("job design") OR ("employee skills") OR ("worker skills") OR ("people skills") OR ("work design") OR (augmentation))
WILEY	(Automation OR "artificial intelligence") AND ("job design" OR "work design" OR "people skills" OR "worker skills" OR "employee skills" OR augmentation)

ScienceDirect	1. (Automation OR RPA OR AI OR "robotic process automation" OR "artificial intelligence") AND ("augmentation") 2. (Automation OR RPA OR AI OR "robotic process automation" OR "artificial intelligence") AND ("job design" OR "work design" OR "employee skills" OR "worker skills")
Taylor and Francis	[[All: automation] OR [All: ai]] AND [[All: "employee skills"] OR [All: "worker skills"] OR [All: "job design"] OR [All "work design"]] AND [Article Type: Article] AND [Publication Date: (01/01/2021 to 12/31/2023)]
ProQuest	Noft((Automation OR "Artificial intelligence") AND ("job design@ OR "work design" OR "employee skills" OR "worker skills"))
Emerald	1. Automation OR "artificial intelligence" AND "job design" OR "work design" 2. Automation OR "artificial intelligence" AND "worker skills" OR "people skills" OR "employee skills" 3. Automation OR "artificial intelligence" AND augmentation

Table 1. Final search strings (created by the author).

Step 2: Search strings focusing on the outlined terms were created and refined through iterative tests on each database (Table 1). Notably, the inclusion of 'computer science' yielded technically orientated articles, resulting in refinements to exclusively target articles within business domains. Given the evolving nature of automation, search strings were filtered to retrieve articles published post- October 2020. The searches prioritised peer-reviewed journal articles, to ensure quality. Search string consistency was prioritised, only deviating when variations appeared in database filtering capabilities.

Step 3: Search results from each database were compiled into EndNote and categorised. Duplicates were eliminated.

Step 4: Articles were screened for quality based on their journal ranking. Only journals published in 3-4* CABS journals, or Q1 SJR journals, were retained.

Step 5: Title and abstracts were reviewed to confirm scope relevance. Articles covering irrelevant topics (e.g., surgical automation) or possessing an overly technical focus (e.g., solution design and coding) were excluded.

Step 6: Relevant studies from the author's previous work were included (Murphy, 2024), alongside practitioner insights from strategic consultancy reports.

3. Results

Following the searches, this paper presents a review of the academic literature retrieved. After grouping articles based on research aims and scope, two themes were formed: Automation and Employment, Automation and Augmentation. Each theme is synthesised in the following sub-chapters.

3.1 Automation and Employment

Recent scholarly articles have examined the conflicting views of automation's impact on employment through the debates of job displacement, or job creation/enhancement.

3.1.1 The Automation Displacement Debate

In their review of 102 papers, Filippi et al. (2023) found the literature investigating how automation affects employment to be extremely complex and immature. They found publications focusing on distinct levels of analysis and applying different approaches, often with inconsistent results. For example, Filippi et al. found scholars in Asia and Oceanic regions to be estimating the automatability of jobs at a mere 9%, whilst other scholars suggested 49% of jobs globally could be automated. Further contradictions can be seen throughout the literature. In the USA, Sampson (2021) suggested that 47% of jobs were at risk of being automated, but one year later Toshav-Eichner and Bareket-Bojmel (2022) estimated only 25% of jobs were at risk. Dogan and Yilidirim (2022) then proposed 40% of global jobs will be automated by 2023. However, whilst many papers discuss the demise of jobs, scholars such as Wang et al. (2023) continue to validate the findings from CIPD (2018), that organisations are not achieving the performance benefits of automation, often seeing no positive business outcomes.

McGuiness et al. (2023) contributed a different perspective to the argument, by focusing on skill displacement rather than job displacement. McGuiness et al. (2023) concluded that 16% of EU and UK workers have experienced skillset displacement events via technology over the past 5 years, and 23% believed they would lose their job over the next 12 months due to skills displacement. Such data has led scholars to suggest that skills shelf-life is waning (Goal and Kovacs-Ondrejkoviv, 2023).

Scholars note this fear of technological displacement is not a new phenomenon, and we have seen periodic warnings throughout the past two centuries of technology substituting labour (Mondolo, 2021). These fears became more prominent in the surge of the industrial revolution (Toshay-Eichner and Bareket-Bojmel, 2022), and the rapidly improving capabilities of automation are once again renewing the discourse about the future of work (Filippi et al., 2023; Furendal and Jebari, 2023). However, DAT are expected to disrupt the labour market more than previous automations (Guimaraes and Gil, 2022). New automations developed in Google can beat the Turing test (Ozkazanc-Pan, 2021), and using automation to replace human tasks is becoming increasingly more common in retail, customer services, operations, medicine, and aerospace (Dogan and Yildirim, 2022). Scholars note that whilst industrial automations used to manage the dirty, dull, or dangerous work, current advances in technology look to automate more human-centred work (Turja et al. 2022). For example, new ML techniques are enabling Unilever to use AI to support talent acquisition, Netflix for personal film recommendations, and Pfizer for drug recovery (Johnson et al., 2022).

Sampson (2021) discusses how in the service sectors we saw telephone operators reduce by 90% in 2001-2017, telemarketers by 61% and medical transcriptionists by 47%, all through automation. However, a 2-year study in the maritime industry contrastingly found that organisations are still in the preliminary stages of automation adoption, utilising tools such as RPA and conversational chatbots (Gronsun and Aanestad (2020). Even in these initial stages, Sobczak's (2021) Polish multi-sector study found only 13% of organisations have managed to scale their RPAs, with most companies tweaking small projects or piecemeal tasks. Building on Sobczak's findings, Flechsig et al.s (2022) later Europe-wide study found that RPA projects in supply chain and purchasing showed a failure rate of up to 50%. Gronsun and Aanestad (2020) advised that more advanced AI and ML algorithmic automations continue to be rare in organisations. Nevertheless, McGuiness et al. (2023) discuss how this is creating a concept called technological alarmism, resulting in a creation of moral panic across workers (Turja et al., 2022), and the 'work displacement' theory (Dogan and Yildirim, 2022; Furendal and Jebari, 2023).

3.1.1.1 Displacement Examples from the Field

Guimaraes and Gil (2022) used historic literature to propose that employment will reduce overall due to automation. In their simulations, they proposed an automation shock whereby it becomes profitable to replace workers with automation technologies, and thus resulting in job destruction. They propose that the automation of widespread work will result in leftover tasks which do not require full-time workers, contributing to the rise of a gig economy. Guimaraes and Gil (2022) also propose that widespread automation will accelerate employee de-skilling, creating further unemployment. However, their study is based on hypotheses, and does not factor empirical evidence or consider the new tasks which will be created through automation (Dellermann et al., 2021).

In a challenge to the hypotheses of Guimaraes and Gil (2022), several scholars argue that whole occupations are rarely automatable (Cimini et al., 2022; Dellermann et al., 2021) and only 5-9% of the tasks inside jobs are automatable (Sampson, 2021). In fact, scholars from work design theory advise that work is not designed into static jobs but is formed of dynamic tasks which change as technology advances (Murphy and Turnbull, 2024; Waschull et al., 2020). Whilst automation is accelerating the movement from traditional ways of working, we will still operate in a task-based system (Boudreau and Donner, 2021; Murphy and Turnbull, 2024). This led Sampson (2021) to call out a research gap in that most literature focuses on job automation, and not task automation. Sampson advises that as one task falls to automation, others become more prominent, and thus employees may need to be willing to relinquish some tasks to automated solutions, enabling them to focus on higher-order work.

Some scholars worry that the job displacement view of automation may lead to ethical and diversity inequalities. In a viewpoint paper, Ozkazanc-Pan (2021) discussed how scholars theorise an ultra-low wage, precarious workforce, will emerge due to job and skills displacement. Ozkazanc-Pan suggested racial inequalities would grow due to job displacement, since reports show how African Americans are over-represented in support positions (e.g., assistants, administrative), which automation will disproportionately impact. This led Ozckazanc-Pan to suggest diversity and gender topics will be at the forefront of future workplace automation discussions. Yet, the literature remains inconclusive on which employee populations are more at risk of automation. Whilst Toshav-Eichner's and Bareket-

Bojmel's (2022) evidence of a study in Israel validated Ozkazanc-Pan's hypotheses to suggest blue-collar work is most at risk of automation, they also noted that there is scant research comparing the impacts on blue versus white-collar workers. Thus, Toshav-Eichner and Bareket-Bojmel advised that the evidence is too undeveloped to make conclusions.

Other topics arising from the view of displacement due to automation are the impact on employee wellbeing. In a survey of 2,434 educational professionals, Turja et al. (2022) found that employee expectations of how automation might impact their work created a negative association with employee wellbeing, in the form of burnout symptoms and less meaningful work. Turja et al. found that employees who find their work meaningless were optimistic for automation, whilst those who find their work meaningful have less hope and more anxiety about automation replacing labour. Whilst this study was limited in its hypothetical nature, and being focused only in the educational sector, the author's previous literature review (Murphy, 2024) found comparable results. The author's paper found workplace automation led to new employee wellbeing needs around self-efficacy, workplace isolation, social cohesion, autonomy, and trust.

3.1.2 The Automation Enabling Debate

Turja et al. (2022) reference a phenomenon whereby people are evaluating the risk of automation much higher than it is, due to a constant media hype on AI. Bankins et al. (2023) suggested that societal narratives often offer science-fiction based portrayals of automation, and thus mischaracterising it. In an Amazon case-study, Furendal and Jebari (2023) concluded that it is a mistake to believe there is a fixed amount of work in the economy. They hypothesised that as jobs become superfluous to automation, the increases in productivity will create economic growth, resulting in higher labour demands overall. This hypothesis was supported by Filippi et al. (2023), who noted that short-term job loss would be temporary, and new emerging occupations from automation would result in longer-term employment. For example, Sampson (2021) found that whilst USA manufacturing employment declined by 5.6 million jobs between 2000- 2010, predominantly through automation, we saw a similar sized increase in jobs in the service sector. This led Sampson to suggest that as productivity increases in one sector, employment shifts to another.

Supporting the aforementioned viewpoints, Furendal and Jebari (2023) argue that scholars focusing on the concept of labour replacement due to automation are flawed in their thinking, and that discontent would force governments into political and social obstructions of technological progress. For example, Coombs (2020) argued that after the mass-unemployment spikes caused by the COVID pandemic, governments are not likely to support mass automation that further disrupts employment and strains welfare systems.

Filippi et al. (2023) also raised the point that high price of automation, regulatory aspects, and ethical considerations, can hinder it from widespread adoption. Such viewpoints led to Filippi et al. concluding that the probability of workplace automation may be impacted by market structures, such as the education of workers, work councils and local labour laws. Findings from Toshav-Eichner's and Bareket-Bojmel's (2022) study of 539 workers in Israel partly validate Filippi et al.s (2023) and Furendal and Jebari's (2023) propositions. Toshav-Eichner and Bareket-Bojmel found that workers in unionised jobs do not fear job loss, regardless of how automation may impact their jobs. In their study, they found that whilst 74% of public sector blue-collar workers described automation as simplifying their work, they also saw it as a replacer. In comparison, Toshav-Eichner and Bareket-Bojmel found that only 53% of white-collar workers saw automation as a replacer. However, both sets of employees did not fear job displacement due to union support.

Some academic studies have found automation to result in rapid growth of jobs at the top and bottom of the wage distribution (McGuiness et al. 2023) due to new task creation to oversee automations such as RPA, or creative occupations working alongside GAI. Thus, scholars note how it is important to understand the re-instatement effects of automation (McGuiness et al., 2023), since labour-enabling technology has historically been more accepted by workers than labour-replacing technologies (Furendal and Jebari, 2023). After navigating the conflicting evidence in their systematic literature review, Filippi et al. (2023) concluded that, in general, the consensus is changing towards the viewpoint that automation adoption does not necessarily imply job loss. This led Sampson (2021) to assert that instead of talking about which jobs will exist in future, scholars should instead be asking which tasks are more conducive to automation, and redesigning jobs to leverage employees' creative expertise. Filippi et al. (2023) also suggested that workers can adjust to protect themselves from displacement, via the acquisition of new skills and transitioning to new work activities. For example, in their paper Toshav-Eichner and Bareket-Bojmel (2022) found that companies such as AT&T and Amazon were announcing major re-skilling initiatives to prepare their employees for working alongside automation and avoiding displacement. This led to scholars suggesting policies and studies should now focus on how to improve human capital, and produce skills that are complemented by automation, versus substituted (Mondolo, 2021; Toshav-Eichner and Bareket-Bojmel, 2022). However, the author's previous systematic literature review (Murphy, 2024) found the topic of how to up-skill to work alongside automation continues to be a gap in the literature.

One research area scholars are calling for more attention on is augmentation alongside automation (Furendal and Jebari, 2023). In their literature review Tschang and Almirall (2022) found that recent studies suggest that the displacement theory is not materialising, and thus leading scholars in the field are advocating for human and machine augmentation (Raisch and Krakowski, 2021), in a way that leaves tedious and repetitive work for automation, and creative task-solving for humans (Furendal and Jebari, 2023). The scholarly debate of automation augmentation is further discussed in the subsequent chapter.

3.2 Automation and Augmentation

Tschang and Almirall (2022) describe augmentation as a pattern of work where human workers coexist alongside automation technologies, by utilising automation to increase the productivity of tasks. Scholars note how this co-existence of humans and automations offers exciting potential to augment human capabilities (Raisch and Krakowski, 2021; Ren et al., 2023) often increasing the productivity of higher skilled work, whilst offloading lower skilled tasks to bots (Tschang and Almirall, 2022). Scholars such as Enola and Khoreva (2023) argue that there can be no such thing as automation without augmentation. They argue that augmentation is a necessity of every organisation, and automation cannot be separated from augmentation in the workplace.

Bankins et al. (2023) furthered the views of Enola and Khoreva (2023), stating that the productivity and efficiency benefits of automation can only be achieved through close collaboration, rather than human displacement. Raisch and Krakowski (2021) found that a one-sided focus on automation without augmentation can lead to de-skilling, and poorer performance compared to companies who focus on augmentation.

In recent a literature review (Garibray et al., 2023) and editorials (Dellermann et al., 2021; Ren et al. 2023) assessing the co-existence of humans and automation, scholars highlighted the complementary benefits that an augmentation approach can achieve. Whilst Ren et al. (2023) noted that automation improves efficiency, speed, consistency and reliability of certain tasks, scholars found that humans excel at logical reasoning, language processing, and creativity and emotion (Garibray et al., 2023), and can be flexible and adaptable (Dellermann et al., 2021). Both sets of scholars suggested that we can achieve better performance by combining human and machine intelligence, to leverage the strengths of both and mitigate weaknesses (Ren et al. 2023), with humans remaining at the centre (Garibray et al., 2023). Raisch and Krakowski (2021) called this the transition to the second machine age, whereby humans will partner with automation bots to enable mutual learnings and multiply capabilities. In terms of practicalities, Ren et al. found several scholars suggesting that automation should start the structured work tasks (e.g., following scripts or codified processes), and then transition the less structured and more creative tasks to humans. This augmentation could be numbersome, and in the form of digital assistants, feedback loops, decision-making, and enhancing customer interactions and service offerings (Bankins et al., 2023). These benefits of augmentation have led to leading technology companies, such as Microsoft, announcing they will focus on building automations which leverage human skills, rather than replace them.

3.2.1 Success Stories with Augmentation

Wang et al.s (2023) study of 202 participants in the USA found a rise in employees augmenting alongside AI powered chatbots in the service sector. Wang et al. found that chatbots took the less desirable work away from employees, such as late night or weekend questions, reducing overall workload and enabling a more flexible work schedule. The chatbots increased predictive analytics to generate new insights, which led to human workers feeling they understood their customers better and were able to provide enhanced knowledge support. Spring et al. (2022) also found chatbot augmentation increasing in the law and accountancy sectors. Similar to the findings from Wang et al. (2023), Spring et al. found cashflow forecasting chatbots were being used to manage routing progress questions from clients, removing long hours and weekend work for junior staff, and augmenting with them when specialist decision-making or knowledge was needed. Spring et al. (2022) found this helped to release employees from repetitive tasks and provide more time for focusing on, and amplifying, professional expertise.

Similar to the author’s previous literature review (Murphy, 2024), Wang et al. found that trust was a crucial success factor in employee and automation augmentation. In a study on engineers in the USA and India, Tang et al. (2022) suggested that employee trust in automation can be influenced by the sense that the automations are less authentic, ethical, and decisions can be seen as unfair. This is evidenced in Tschang and Almirall’s (2022) literature review, whereby automation was found to be augmenting the work of doctors and radiologists by detecting patterns in scans. The humans augmented alongside technology to exercise ethical and human judgements or acquire more sensitive data from patient interviews. Thus, the ethical pieces of work in the medical sector appear to be reserved for humans, to build trust. Wang et al. (2023) also suggested that employees develop trust through improving the perception of functionality, reliability, and data protection of automation. However, Wang et al.s study was limited through a paid survey across separate companies, which could enable bias, and as the study was not longitudinal, it is unknown how employee perceptions of the chatbots evolved as new functionalities were developed.

In another dimension of trust, Wesche et al.s (2022) study of the German population found that people react negatively to decisions made by automation tools versus a human being. Wesche et al. found that decisions regarding redundancies, promotions and personnel selections made by automation tools were considered untrustworthy. Wesche et al. found studies showing automation tools have not yet matched humans in skillsets of subjective judgment and emotional abilities. This led Wesche et al. (2022) to suggest organisations manage some tasks with ‘human in the loop components’, to deliver a better experience for end-users. Human in the loop refers to human feedback and responsibility for performance management of the automation, including error handling and improvements (Gronsun and Aanestad, 2020).

In a small Finnish study of 37 media consultancy employees, Einola and Khoreva (2023) found differing experiences with augmentation across different employee profiles. They found managerial participants saw automation augmentation as an avenue to tap into human creativity, increase sales profits and customer satisfaction. Einola and Khoreva (2023) found that digital savvy employees took to augmentation with ease and expected it as part of the natural progression of automation. Some digital savvy employees even quoted automations as a close friend or colleague throughout their interviews. However, Einola and Khoreva found that employees with lower technology skillsets saw automation as a tedious, broken tool, and a friction maker in the workplace. These employees frequently criticised the bots for not being sufficiently intelligent and requiring too much supervision or control. Whilst this study was limited to one organisation and one national culture, these findings suggest that skillsets in technological fluency are a necessity for successful augmentation, a finding also validated in Ren et al.s (2023) literature review. Einola and Khoreva (2023) raised how one operator said augmentation can lead to energy burnout, and they enjoy spending a couple of hours in a day doing manual jobs without utilising high mental capacity, versus being creative all day. This finding led to Einola and Khoreva joining the rallying call for organisations and HR to design changes in jobs and skills to enable successful augmentation. Einola and Khoreva discussed how this is more important than ever, given that the type of work performed by humans and automation is changing every day, expanding the complexity of the ecosystem where humans and automation co-exist.

In another study in the service sector, Mingotto et al. (2020) assessed the success of a humanoid AI assistant deployed in the reception desk of a hotel. The hotel management had hoped to use the bot as a staff assistant, providing customers with access to fast information, and freeing up employees to offer more complex services. Through their longitudinal study, Mingotto et al. noted how employees were nervous at the start of deployment and feared displacement. However, as the bot learned from employees over time, moving from 51% to 75% accuracy of responses, management also updated information cards to advise the customers to speak to employees as a robot concierge if needed. These two changes were found to help employees feel closer to the technology, eventually leading them to become enablers and supporters of the strategy. The findings of this study suggest that Wang et al.s (2023) findings of the importance of trust in augmentation are accurate, but also there is a role for managers to support employees with feeling a part of the new work system involving automation. Mingotto et al. (2020) found that in general, the employees of the hotel needed trainings on automation basics, how to interact with and how to train the bot, which were eventually incorporated into standard operating procedures.

Gronsun and Aanestad (2020) built further on Migotto et al.s (2020) findings of the training needed for employees augmenting with automation. In their 2-year study in the maritime industry, they found employees being use as a human in the loop component. In this study, Gronsun and Aanestad found that to develop and train algorithms required considerable work, as well as the work needed to acquire and prepare data sets for training. This finding validates suggestions in the automation enabling debate, suggesting human work can evolve into management of automations, and new tasks can be created. In this case study, new roles emerged focusing on auditing and altering the results of the automation, to transform data into valuable insights. Dellermann et al. (2021) found that this augmentation approach can generate new knowledge for not just the automations, but for humans as well, enabling implicit knowledge transfer in both directions, which can create a sense of psychological ownership that increases trust. This fundamental role of feeding and supervising automation machines has existed for a long-time in industrial factories, and since human cognitive capabilities are currently unattainable by automations, this role will continue for the foreseeable (Villani et al., 2022). In this maritime scenario Gronsun and Aanestad (2020) hypothesised that the human in the loop role would remain necessary over the lifetime of the automation, to support with training and auditing as the bot evolved into new tasks or from changes to the external environment. This led Gronsun and Aanestad to suggest that humans will have roles in future as coaches who guide automation, and that skills in data science and domain expertise will be crucial distinguishers for future work.

While Gronsun and Aanestad's (2020) study was limited to the maritime industry, a later study by Colombo et al. (2023) in the purchasing domain produced similar findings. Colombo et al. conducted qualitative interviews across 8 companies who were looking to augment employees with automation to aggregate data for decision-making, increase process efficiency, and respond faster to risks and opportunities. Interviews across all companies suggested that augmentation with business intelligence automations (AI and ML) created an enlargement of tasks, enabling humans to concentrate more than before on contracting and negotiation activities, spending more time on higher value work. However, Colombo et al. (2023) suggested that companies could be even more successful in augmentation by improving employee skills in decision-making, data analysis and interpretation. Colombo et al. suggested that managers need to start work on transitioning employees from generalists and into specialised skill blocks to remain competitive with automation. Similar to the findings of Mingotto et al. (2020), Colombo et al. also found that moving from siloed automation to augmentation is not systematic and must be forced by managers who reduce resistance to change and promote new skills growth.

In addition to the elements of trust (Wang et al., 2023), and technological fluency (Einola and Khoreva, 2023; Ren et al., 2023), Bankins et al.s (2023) systematic literature review found additional elements that contributed to successful augmentation. Firstly, Bankins et al. found several fundamentals need to exist at the individual employee level. Bankins et al. found that high satisfaction with automations fit-to-task, and user needs, led to increased job satisfaction and productivity. Employees viewed a positive task-fit as the automation undertaking repetitive tasks and improving decision-making. So, similar to Wang et al.s (2023) findings, Bankins et al. (2023) suggested better augmentation occurs when workers trust the AI and understand its nature and purpose. Bankins et al. also found that the way automation alters a job design can affect augmentation success, with employees demonstrating enhanced innovation when automation supports job autonomy, complexity, and information processing. Ren et al. (2023) built on this to advise that employees must be able to use their domain and job expertise to complement automation skillsets. Scholars note how this domain knowledge is a crucial integrator into automation, as the automation needs to learn from, and sense organisational data with the human expert (Tschang and Almirall, 2022).

However, similar to the findings from Einola and Khoreva (2023), Bankins et al. (2023) found that augmentation can lead to increased mental strain, and increase the need for constant skills development, which can impede benefits. Bankins et al. (2023) also found workers who were resistant to automation negatively affected augmentation. An example was in workers with high domain experience, or long service experience, who trusted their own capabilities more than automation. Ren et al. (2023) suggested this was because humans have the tendency to overestimate our abilities, resulting in a reluctance to delegate to automation. In the same view as Raisch and Krakowski (2021) Ren et al. (2023) claimed this failed augmentation is one of the largest contributors to the lack of productivity we receive from automation, a statistic previously called out by several scholars in this review (CIPD, 2018; McKinsey Digital, 2023; Wang et al., 2023). Ren et al. (2023) advised this as an area organisations need to fix, as humans can often unlearn information as they gain new experiences and acquire new knowledge. Bankins et al. (2023) propose this might be remedied by allowing workers to incorporate their knowledge alongside automation output but retaining greater human input overall.

Another finding led Bankins et al. to suggest that employee performance levels can influence augmentation success. Findings showed that lower and higher ranked employees experienced fewer benefits from automation, due to information overload in lower-ranked employees, and algorithmic aversion is more experienced, higher-ranking employees. Middle performers who adopted augmentation achieved the strongest outcome and gained competitive advantage. However, these findings contrast with those of Parker and Grote (2022), seminal authors in work design theory, who referenced studies in the Netherlands which upskill lower-level service employees. However, Parker and Grote (2022) validated Bankins et al.s (2023) findings that higher-ranking employees were de-skilled due to the reduction of specialist knowledge and skills. Parker and Grote (2022) labelled this as unsensible work design, and Bankins et al. (2023) called for augmentation that focused on employee centred design. At the organisational level, Bankines et al. found that active role modelling by leaders of augmentation, and supportive HR practices, enabled a higher up-take. Whilst their paper was limited in the fact it did not call out specific HR policies for organisations to adopt, Bankins et al. (2023) suggested leaders should use positively framed messages which present automation as a benefit for improving the quality of work and employee wellbeing.

3.2.2 Negative Perceptions of Augmentation

While there are positive sides to the automation and augmentation model, challenges have been raised about how companies have implemented it. Furandel and Jebari (2023) discuss the risk of augmentation being designed in a way that leads to 'human stunting'. From their case study in Amazon, augmentation had been used in a way that resulted in humans focusing on specific singular tasks whereby they are superior to automations, manual dexterity. Furandel and Jebari found this to be leading to a job with a limited set of tasks, an increase in repetitive movements, and overall decreased satisfaction for employees. Thus, evidence suggests that organisations do not yet have a grasp on how best to implement automation from a perspective of good work design.

Another example of stunting was found in Garibray et al.s (2023) literature review, where studies suggested that the introduction of decision-making automations restricted employees' ability to apply their skills, knowledge, and expertise to substituted tasks. Garibray et al. found that decision-making automation tools empowered less qualified employees by enabling them to complete tasks they otherwise could not, and contrastingly deskilled highly qualified employees by reducing the skills needed for their jobs. Building on Garibray et al.s (2023) findings, Samiolo et al. (2023) found evidence of stunting across different employee seniority levels. Samiolo et al. (2023) found automations in the auditing sector to not consider the 'thought tasks' required by auditors, and instead increase 'box-ticking' which reduced mindfulness and promoted automatic habit. This resulted in trainee auditors becoming less attuned to what a usual transaction may look like, and lacking critical skill development opportunities for as and when complex scenarios arose.

Equivalent results were found in Leyer and Schneider's (2021) study in the services sector, whereby augmentation led to experienced resources 'un-learning', and over time struggling to validate the automations suggestions, in turn becoming dependent on the generated output. However, Leyer and Schneider's (2021) was limited to one sector, and analysed historic case-study info, rather than new empirical findings. Garibray et al.s (2023) findings are also in direct contrast to the findings from Ren et al., (2023) in the same year, who concluded that higher-skill workers benefit more from automation than lower-skilled workers. Garibray et al.s (2023) findings also differ from those of Bankins et al. (2023), who found that lower-ranking, less qualified employees did not benefit as highly from augmentation. Thus, three literature reviews in the same year have provided different findings. A possible source of conflicting results is that the automation literature is crowded with papers assessing distinct levels of DAT (e.g., RPA, AI, ML) across different levels of workers, but without explicitly specifying their differences (Murphy, 2024). However, regardless of differing results, the risk of de-skilling through augmentation and automation has been called out as a serious organisational challenge.

Rinta-Kahila et al. (2023) found evidence of organisations rushing to automate their processes, without catering for skills erosion, and thus receiving detrimental impact to quality of services. Examples Rinta-Kahila et al. presented from the health care, auditing and financial industries surrounded experiences whereby automations had malfunctioned or failed, and employees no longer had the skills to understand how to act in the process, resulting in financial losses and reduced competitive advantage. An example from a high-reliability context saw an advanced cockpit automation fail, which resulted in aircraft crashes due to pilots' reliance on the technology, and muted ability to respond (Rinta-Kahila et al., 2023). In the accounting sector, Rinta-Kahila et al. noted that automation can result in decreased awareness of task activities, and deteriorated motivation to maintain and improve their own domain competence. Employees were found to tune out of company trainings, as they thought the automation would manage any of the tasks being trained. Rinta-Kahila et al. (2023) concluded that skill erosion alongside information systems is the critical managerial challenge of our time, and we still do not know how to harness the transformative benefits of emerging IT whilst ensuring to maintain critical human skills. Rinta-Kahila et al. found a gap of existing empirical studies in the space and suggested for studies considering automation and augmentation in an organisational setting from socio-technical perspectives, to understand how to build the right interactions between humans and automation.

In an extreme example, Monod et al. (2024) assessed the success of an AI sales assistant implemented in a Chinese organisation to support workers with enhanced customer insights. Whilst originally sold to employees as a work-enabler, management quickly started using the AI as surveillance, monitoring employee work patterns, and then eventually using the AI to reduce headcount, without any upfront transparency to employees. Birnbaum and Somers (2023) have referenced similar findings of algorithmic surveillance, resulting in employees being de-humanised and defined as discrete pieces of data which can be deconstructed and monitored by algorithms. This demonstrates both ethical concerns and poor work design impacts of augmentation, which can remove autonomy.

Tang et al.s (2022) study of engineers in India and the USA found another detrimental aspect of augmentation. From their quantitative surveys, they found evidence that augmentation can heighten the perception of work goal progress, but also induce a self-esteem threat, resulting in reduced employee performance. Tang et al. found that augmentation can increase feelings of dependency on automations, resulting in employees no longer trusting themselves. To increase self-esteem when working in automations, Tang et al. (2022) recommended managers support employees in engaging positive self-affirmations or mindfulness practice to thrive at work. However, Tang et al.s recommendation could be seen as generalist, and does not tackle the underlying work design, or employee skillset needs in an augmentation model.

Whilst Tang et al.s study was conducted through paid surveys, which could reduce reliability of the results, a later study by Kumar et al. (2023) appears to validate Tang et al.s findings. In a study across mixed sectors in India, Kumar et al. (2023) found augmentation can lead to a sense of skill inadequacy, and thus reduced self-efficacy, in employees. This reduced self-efficacy then directly impacted a feeling of technostress, due to fear of job losses and role ambiguity in an augmentation model. This is an alarming finding, considering that Medici et al.s (2023) study across Germany and Switzerland found technological self-efficacy was the predominant factor which dictated whether individuals were capable of coping and adapting to the changing work environment. Medici et al. defined self-efficacy as a person's belief in their ability to successfully perform a particular behaviour or course of action. They found that employees who demonstrated higher self-efficacy were more able to adapt to the new skills requirements and work environment with automation. Employees with higher self-efficacy also demonstrated a stronger understanding of the critical need for constant skill development to face technological advancements. These findings are important contributions given the notable findings from previous studies on automation's ability to impact self-efficacy (Kumar et al., 2023; Tang et al., 2022). However, Medici et al.s study was limited in the fact that answers were self-reported, and it is not clear how generalisable they are across other national cultures. To combat the issues of self-efficacy, Kumar et al. (2023), suggested skill development and continuous learning will reduce technostress. However, Medici et al.s (2023) findings would suggest that self-efficacy is a precursor to being able to build new skills in a changing work environment.

4. Discussion

4.1 Findings

The findings of this paper are presented below while referring to the original research questions.

RQ 1 – Does workplace automation lead to job displacement?
Amid the different perspectives surrounding automation and employment, studies suggest that the true answers of whether automation leads to job displacement are still unknown due to scant research. This question is answered in two parts:

4.1.1 Literature Complexities

Bessen et al. (2020) and a following literature review by Mondolo (2021) found that empirical studies in automation at the firm level are scant, and most historic studies have been focused on robots and physical machines in the manufacturing or production sectors. This was later validated by Cimini et al. (2022), and Langer and Landers (2021) also suggested that most of our current understanding is driven by vignette studies. Mondolo noted how the increasing adoption of DAT had not yet been considered by scholars. In fact, Mondolo found that organisational-level data related to DAT had only started to be collected by the national statistics offices as of 2021 and were not yet in included in any major innovation surveys. In their seminal paper, Raisch and Krakowski (2021) argued that this was driven by an initial slow period of technological progress after AI was introduced as a concept in the 1950s, resulting in a liquidated discussion of AI use in organisations, and a heavy literature focus on the computer science, engineering, and robotics domains. Raisch and Krakowski explained that management scholars have consequently provided little insight into AI or wider automation topics from an organisational lens during the past few decades, with many automation scholars focusing on how to automate as far as possible, regarding humans as a disturbance in the work system that should be designed out.

Filippi et al.s (2023) systematic literature review examined 102 papers across leading journal databases to analyse how automation affects employment and validated Mondolo's and Raisch and Krakowski's finding. Filippi et al. (2023) found that only 18% of papers retrieved focused on DAT, with the remainder focusing on broader Information Technology (IT) or industrial robots. Most of these papers were quantitative and focused on the production and engineering sectors. Other scholars have found the automation in organisation literature to be heavily reliant on hypothetical or conceptual driven scenarios (Mingotto et al., 2020; Wesche et al., 2022), often leveraging anecdotes, assumptions, and heavily skewed to specific viewpoints (Tschang and Almirral, 2022).

4.1.2 Literature Review Examples

Building on the complexities referenced above which assert the complex and immature nature of the automation and employment literature, this literature review has contributed some answers to this question. The majority of studies from this review seem to suggest automation does not directly cause job displacement. In contrast, studies suggest organisations are still in their infancy and struggling to grasp automation (Sobczak, 2021), and that whole occupations are rarely automatable end-to-end (Cimini et al., 2022; Dellermann et al., 2021). Instead, experts suggest that new tasks will be created through automation, which in-turn crafts economic growth and could lead to new job creation and increased skillsets (McGuiness et al. 2023). Scholars also note a sense of over-inflation in media narratives, which often lack the interests of political, governmental, and union lenses.

RQ 2a – Does augmentation alongside automation positively influence employment?
This literature review would suggest that augmentation alongside automation does positively influence employment, and thus could negate the effects of displacement. Seminal scholars suggest that organisational focuses on automation without augmentation lead to de-skilling and poorer organisational performance (Raisch and Krakowski, 2021). In contrast, augmentation can lead to human-in-the-loop models which create new jobs such as automation coaches and trainers (Gronsun and Aanestad, 2020), and an enlargement of existing tasks (Colombo et al., 2023).

RQ 2b – Does augmentation alongside automation positively influence productivity?
This literature review suggests that productivity with automation can only be achieved through augmentation (Bankins et al., 2023). Studies showed that augmentation approaches can increase sales profits and customer satisfaction through enabling human creativity (Einola and Khoreva, 2023), and the removal of weekend work and long hours, leading to task expansion (Spring et al., 2022; Wang et al., 2023). However, this literature review has highlighted the importance in building employee skills to ensure successful augmentation (Einola and Khoreva, 2023), as well as facilitating strong work design. This literature review found that poor work design with automation augmentation is the largest contributor to reduced productivity (Ren et al., 2023).

RQ 2c – What successful approaches are being followed to enable augmentation?

1. Scholars found that building trust in automations is crucial for successful augmentation (Tang et al., 2022; Tschang and Almirall, 2022). Scholars found employees needed to have trust in automations capability for ethical considerations and decision-making skills. Organisations could build this by helping employees to see the reliability of automations (Wang et al., 2023) or by focusing on end-user design, centred on fit-to-task deployment and meeting user needs (Bankins et al., 2023). Another successful method of building trust is through human-in-the-loop approaches, which place humans in charge of the automation, and build new roles and tasks (Gronsun and Aanestad, 2020).

2. Scholars found augmentation enhanced innovation when it supported employee autonomy and work design (Bankins et al., 2023), again suggesting the need for strong work design considerations. Alarming trends were found whereby an absence of employee autonomy and strong work design can lead to human stunting (Kovacs-Ondrejkoviv, 2023). Organisations can navigate this by making workers feel a part of the augmented system and giving them responsibility for interacting with and training the automations (Mingotto et al., 2020).

3. Augmentation was found to be most successful when automation is not responsible for handling sensitive topics such as redundancy or promotion decisions, which fall better to human emotional judgement (Wesche et al., 2022).

4. Finally, scholars suggested that to truly benefit from augmentation organisations should seek to build skills in decision-making, data analytics, data interpretation and domain expertise (Colombo et al., 2023; Gronsun and Aanestad, 2020).

4.2 Limitations

This paper is limited in several ways. Firstly, the semi-systematic review focused only on peer-reviewed journal articles, and thus misses insights from other artefacts such as grey literature, book chapters and conference papers etc. The review was equally restricted by its search term limitations, which may have omitted relevant articles using different terminology. Finally, only articles in 3-4* CABS journals, or Q1 SJR journals, were included. This naturally omits high quality articles which may have been published in lower ranked journals, potentially leading to an incomplete representation of the literature.

4.3 Future Recommendations

Based on the academic findings of this paper, several recommendations can be made for the future.

1. Organisational recommendations:

a. Organisations looking to drive automation productivity should create strategies focusing on augmentation, in a way that promotes strong work-design, builds employee trust, and leverages human creativity alongside machine strengths.
b. Organisations should focus on rigid and continuous upskilling approaches, to combat the shortening shelf-life of skills and adapt to the constant change brought around by advances in automation. Skills are also a necessity to benefit from, and drive innovation through, augmentation.

2. Future research agendas:
    a. Future studies in augmentation should move away from the technical view of automation (Spring et al., 2022) and move towards a socio-technical approach (Kumar et al., 2023; Parker and Grote, 2022; Spring et al., 2022) in a way that enables continuous learning and improvement within the 'system' (Dellermann et al., 2021).
    b. Scholars are calling for new research into how DAT affects employment (Filippi et al., 2023) post the rise of GAI capabilities such as ChatGPT (Mondolo, 2021).
        i. Scholars have suggested new research focusing on how to enable successful augmentation with 'human in the loop' designs (Bankins et al., 2023; Cimini et al., 2022; Einola and Khoreva, 2023; Furendal and Jebari, 2023; Langer et al., 2021; Murphy, 2024; Sampson, 2021). Such studies are crucial, since we still lack a detailed understanding of how to successfully augment (Kumar et al., 2023; Spring et al., 2022).
        ii. Bankins et al. (2023) suggests such studies can focus on how to deploy automation in a way that enhances human thriving, with the author's previous literature review suggesting resilience to be an under-utilised lens in this area (Murphy, 2024).
        iii. The academic literature also suggest future studies are needed on how to upskill to remain relevant in the emerging work environment (Dellermann et al., 2021; Filippi et al., 2023; Rinta-Kahila et al., 2023; Vrontis et al., 2021) to support successful augmentation (Cimini et al., 2022; Murphy, 2024; Mingotto et al., 2020).
        iv. Kelan (2023) suggested future studies need to explore what these skills are, and how they manifest in the workplace.
        v. Scholars have requested future studies to employ qualitative measures (Filippi et al., 2023), through case studies in the social science domains (Samiolo et al., 2023), to enable detailed investigation and clarify the conflicting results to-date.

4.4 Contributions

This paper synthesised research in a sparsely covered area to add further clarity to the automation and job displacement debate. Firstly, this paper examines diverse literature to shed light on the nuanced relationship between automation and job displacement. The findings challenge the simplistic narrative by highlighting the complexities and suggesting that automation may create job growth vs displacement. Secondly, this paper emphasises the importance of augmenting employees alongside automation to boost productivity, enhance skills, and create task expansion. This paper also provides two recommendations for organisations to help them with employing augmentation.

Through an extensive review, this study also identifies key factors influencing productivity, such as trust in automation, employee autonomy, and strong work design.

Finally, this paper has continued the research agenda, outlining future avenues which emphasise the need for socio-technical and qualitative studies.

5. Conclusion

This paper has contributed to the sparsely researched field of automation in an organisational setting, its impact on employment and productivity, and the mediating role of augmentation. This paper has suggested that, despite limited empirical evidence, automation does not always lead to job displacement, but instead presents new opportunities for skills enhancement and task expansion/ new job creation. In answer to the global dearth of productivity gains being harnessed from automation, this paper suggests productivity hinges on effective automation strategies, through building trust in automation, employee autonomy and strong work design. The urgent need for employee upskilling and continuous improvement programs is also emphasised, providing organisations with recommendations for how to successfully prepare for, and leverage, automation.

Finally, this paper contributes to academia by providing several future research areas through recommended socio-technical approaches, to continue building our knowledge in this domain.

References

Bankins, S., Ocampo, A. C., Marrone, M., Restubog, S. L. D., & Woo, S. E. (2023). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. *Journal of organizational behavior*. https://doi.org/10.1002/job.2735

BCG. (2023). https://www.bcg.com/capabilities/artificial-intelligence/ai-for-business-society-individuals/working. *Boston Consulting Group*. Retrieved 18/11/2023, from https://www.bcg.com/capabilities/artificial-intelligence/ai-for-business-society-individuals/working

Bessen, J., Goos, M., Salomons, A., & van den Berge, W. (2020). Firm-Level Automation: Evidence from the Netherlands. *AEA papers and proceedings*, *110*, 389-393. https://doi.org/10.1257/pandp.20201004

Birnbaum, D., & Somers, M. (2023). Past as prologue: Taylorism, the new scientific management and managing human capital. *International journal of organizational analysis (2005)*, *31*(6), 2610-2622. https://doi.org/10.1108/IJOA-01-2022-3106

Borges, A. F. S., Laurindo, F. J. B., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*, *57*, 102225. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2020.102225

Boudreau, J., & Donner, J. (2021). Are You Ready to Lead Work Without Jobs? *MIT Sloan management review*, *62*(4), 1-5. https://www.proquest.com/scholarly-journals/are-you-ready-lead-work-without-jobs/docview/2528895037/se-2?accountid=14620

http://zh8wk8vq8w.search.serialssolutions.com/directLink?&atitle=Are+You+Ready+to+Lead+Work+Without+Jobs%3F&author=Boudreau%2C+John%3BDonner%2C+Jonathan&issn=15329194&title=MIT+Sloan+Management+Review&volume=62&issue=4&date=2021-07-01&spage=1&id=doi:&sid=ProQ_ss&genre=article

Cimini, C., Lagorio, A., Cavalieri, S., Riedel, O., Pereira, C. E., & Wang, J. (2022). Human-technology integration in smart manufacturing and logistics: current trends and future research directions. *Computers & Industrial Engineering*, *169*, 108261. https://doi.org/https://doi.org/10.1016/j.cie.2022.108261

CIPD. (2018). Automation and the future of work [Online]. 1-9. Retrieved 18th March 2023, from https://www.cipd.co.uk/Images/cipd-submission-to-hoc-business-select-committee-on-automation-and-the-future-of-work_tcm18-51802.pdf

Colombo, J., Boffelli, A., Kalchschmidt, M., & Legenvre, H. (2023). Navigating the socio-technical impacts of purchasing digitalisation: A multiple-case study. *Journal of purchasing and supply management*, *29*(3), 100849. https://doi.org/https://doi.org/10.1016/j.pursup.2023.100849

Company, M. (2023). The State of Organizations 2023: Ten shifts transforming organizations. *McKinsey & Company*. Retrieved 14th October 2023, from https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/the-state-of-organizations-2023

Coombs, C. (2020). Will COVID-19 be the tipping point for the Intelligent Automation of work? A review of the debate and implications for research. *International Journal of Information Management*, *55*, 102182-102182. https://doi.org/10.1016/j.ijinfomgt.2020.102182

Davenport, T. H., & Mittal, N. (2023). How companies can prepare for the coming “AI-first” world. *Strategy & leadership*, *51*(1), 26-30. https://doi.org/https://doi.org/10.1108/SL-11-2022-0107

Deloitte. (2023). Tech Trands 2023 [Online]. *Deloitte Insights*. Retrieved 11th March 2023, from https://www2.deloitte.com/content/dam/insights/articles/us175897_tech-trends-2023/DI_tech-trends-2023.pdf

Digital, M. (2023). The economic potential of generative AI: The next productivity frontier. *McKinsey & Company*. Retrieved 18/11/2023, from https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-AI-the-next-productivity-frontier#introduction

Dogan, M., & Yildirim, P. (2022). Managing automation in teams. *Journal of economics & management strategy*, *31*(1), 146-170. https://doi.org/10.1111/jems.12456

Einola, K., & Khoreva, V. (2023). Best friend or broken tool? Exploring the co-existence of humans and artificial intelligence in the workplace ecosystem. *Human resource management*, *62*(1), 117-135. https://doi.org/10.1002/hrm.22147

Filgueiras, L. V. L., Corrêa, P. L. P., Alves-Souza, S. N., Teodoro, S. M., Silva, M. S. P. d., Encinas Quille, R. V., & Demuner, V. R. d. S. (2022). Working with robotic process automation: User experience after 18 months of adoption. *Frontiers in Computer Science*, *4*. https://doi.org/10.3389/fcomp.2022.936146

Flechsig, C., Anslinger, F., & Lasch, R. (2022). Robotic Process Automation in purchasing and supply management: A multiple case study on potentials, barriers, and implementation. *Journal of purchasing and supply management*, *28*(1), 100718. https://doi.org/10.1016/j.pursup.2021.100718

Furendal, M., & Jebari, K. (2023). The Future of Work: Augmentation or Stunting? *Philosophy & Technology*, *36*(2), 36. https://doi.org/https://doi.org/10.1007/s13347-023-00631-w

Goel, S., & Kovacs-Ondrejkovic, O. (2023). Reskilling for a Rapidly Changing World. *Boston Consulting Group*. Retrieved 18/11/2023, from https://www.bcg.com/publications/2023/reskilling-workforce-for-future

Grønsund, T., & Aanestad, M. (2020). Augmenting the algorithm: Emerging human-in-the-loop work configurations [Article]. *Journal of Strategic Information Systems*, *29*(2), Article 101614. https://doi.org/10.1016/j.jsis.2020.101614

Group, B. C. (2023). Reaching New Heights in Uncertain Times. *Innovation Strategy and Delivery*. Retrieved 14th October 2023, from https://www.bcg.com/publications/2023/advantages-through-innovation-in-uncertain-times?utm_source=linkedin&utm_medium=social&utm_campaign=most-innovative-companies&utm_description=organic&utm_topic=marketing&utm_geo=global&utm_content=2023&linkId=215805232

Guimarães, L., & Mazeda Gil, P. (2022). Looking ahead at the effects of automation in an economy with matching frictions. *Journal of economic dynamics & control*, *144*, 104538. https://doi.org/10.1016/j.jedc.2022.104538

IEEE. (2017). IEEE Guide for Terms and Concepts in Intelligent Process Automation: IEEE 2755-2017. Retrieved 12th April 2023, from https://standards.ieee.org/ieee/2755/6893/

Jesuthasan, R. a. B., J. (2017). Thinking Through How Automation Will Affect Your Workforce [Online]. *Harvard Business Review*. Retrieved 10th March 2023, from https://hbr.org/2017/04/thinking-through-how-automation-will-affect-your-workforce

Johnson, P. C., Laurell, C., Ots, M., & Sandström, C. (2022). Digital innovation and the effects of artificial intelligence on firms' research and development – Automation or augmentation, exploration or exploitation? *Technological Forecasting and Social Change*, *179*, 121636. https://doi.org/https://doi.org/10.1016/j.techfore.2022.121636

Kelan, E. K. (2023). Automation Anxiety and Augmentation Aspiration: Subtexts of the Future of Work. *British journal of management*, *34*(4), 2057-2074. https://doi.org/10.1111/1467-8551.12679

KPMG. (2022a). KPMG Global Tech Report 2022 [Online]. *KPMG Insights*, *September 2022*, 1-26. Retrieved 25th March 2023, from https://kpmg.com/xx/en/home/insights/2022/09/kpmg-global-tech-report-2022.html

KPMG. (2022b). KPMG: The future of HR: Lessons from the Pathfinders [Online]. *KPMG Insights*, *September 2022*, 1-26. Retrieved 25th March 2023, from https://assets.kpmg.com/content/dam/kpmg/xx/pdf/2021/09/the-future-of-hr-lessons-from-the-pathfinders.pdf

Kumar, A., Krishnamoorthy, B., & Bhattacharyya, S. S. (2023). Machine learning and artificial intelligence-induced technostress in organizations: a study on automation-augmentation paradox with socio-technical systems as coping mechanisms [Article]. *International Journal of Organizational Analysis*. https://doi.org/10.1108/IJOA-01-2023-3581

Langer, M., König, C. J., & Busch, V. (2021). Changing the means of managerial work: effects of automated decision support systems on personnel selection tasks. *Journal of business and psychology*, *36*(5), 751-769. https://doi.org/https://doi.org/10.1007/s10869-020-09711-6

Langer, M., & Landers, R. N. (2021). The future of artificial intelligence at work: A review on effects of decision automation and augmentation on workers targeted by algorithms and third-party observers. *Computers in human behavior*, *123*, 106878. https://doi.org/10.1016/j.chb.2021.106878

Leyer, M., & Schneider, S. (2021). Decision augmentation and automation with artificial intelligence: Threat or opportunity for managers? *Business horizons*, *64*(5), 711-724. https://doi.org/10.1016/j.bushor.2021.02.026

McGuinness, S., Pouliakas, K., & Redmond, P. (2023). Skills-displacing technological change and its impact on jobs: challenging technological alarmism? [Article]. *Economics of Innovation and New Technology*, *32*(3), 370-392. https://doi.org/10.1080/10438599.2021.1919517

McKendrick, J. (2023). Time To Redesign Your Career For The Age Of Artificial Intelligence . *Forbes*. Retrieved 13th August 2023, from https://www.forbes.com/sites/joemckendrick/2023/08/13/time-to-redesign-your-career-for-the-age-of-artificial-intelligence/?sh=3b04d34f1a24

Medici, G., Grote, G., Igic, I., & Hirschi, A. (2023). Technological self-efficacy and occupational mobility intentions in the face of technological advancement: a moderated mediation model. *European journal of work and organizational psychology*, *32*(4), 538-548. https://doi.org/https://doi.org/10.1080/1359432X.2023.2197215

Mingotto, E., Montaguti, F., & Tamma, M. (2021). Challenges in re-designing operations and jobs to embody AI and robotics in services. Findings from a case in the hospitality industry. *Electronic markets*, *31*(3), 493-510. https://doi.org/10.1007/s12525-020-00439-y

Monod, E., Mayer, A.-S., Straub, D., Joyce, E., & Qi, J. (2024). From worker empowerment to managerial control: The devolution of AI tools' intended positive implementation to their negative consequences. *Information and Organization*, *34*(1), 100498. https://doi.org/https://doi.org/10.1016/j.infoandorg.2023.100498

Murphy, L. (2024) Wellbeing in the age of virtual teams and workplace automation - a systematic review and future research agenda. *International Journal of Organizational Analysis*, ahead-of-print, https://doi.org/10.1108/IJOA-08-2023-3938

Ozkazanc-Pan, B. (2021). Diversity and future of work: inequality abound or opportunities for all? *Management decision*, *59*(11), 2645-2659. https://doi.org/10.1108/MD-02-2019-0244

Ozmen Garibay, O., Winslow, B., Andolina, S., Antona, M., Bodenschatz, A., Coursaris, C., Falco, G., Fiore, S. M., Garibay, I., Grieman, K., Havens, J. C., Jirotka, M., Kacorri, H., Karwowski, W., Kider, J., Konstan, J., Koon, S., Lopez-Gonzalez, M., Maifeld-Carucci, I., . . . Xu, W. (2023). Six Human-Centered Artificial Intelligence Grand Challenges. *International Journal of Human–Computer Interaction*, *39*(3), 391-437. https://doi.org/10.1080/10447318.2022.2153320

Page, M. J., McKenzie, J. E., Bossuvt, P. M., Boutron, I., Hoffman, T. C., & Mulrow, C. D. (2020). The PRISMA 2020 Statement: An updated guideline for reporting systematic reviews. . *BMJ 327*(71). https://doi.org/10.1136/bmj.n71

Papaioannou, D., Sutton, A., Carroll, C., Booth, A., & Wong, R. (2009). Literature searching for social science systematic reviews: consideration of a range of search techniques. *Health Information & Libraries Journal*, *27*(2), 114-122. https://doi.org/10.1111/j.1471-1842.2009.00863.x

Parker, S. K., & Grote, G. (2022a). Automation, Algorithms, and Beyond: Why Work Design Matters More Than Ever in a Digital World. *Applied psychology*, *71*(4), 1171-1204. https://doi.org/10.1111/apps.12241

Parker, S. K., & Grote, G. (2022b). More than 'more than ever': Revisiting a work design and sociotechnical perspective on digital technologies: International Review of Applied Psychology. *Applied psychology*, *71*(4), 1215-1223. https://doi.org/https://doi.org/10.1111/apps.12425

Raisch, S., & Krakowski, S. (2021). Artificial Intelligence and Management: The Automation–Augmentation Paradox. *The Academy of Management Review*, *46*(1), 192-210. https://doi.org/10.5465/amr.2018.0072

Ren, Y., Deng, X. N., & Joshi, K. D. (2023). Unpacking Human and AI Complementarity: Insights from Recent Works [Article]. *Data Base for Advances in Information Systems*, *54*(3), 6-10. https://doi.org/10.1145/3614178.3614180

Samiolo, R., Spence, C., & Toh, D. (2023). Auditor judgment in the fourth industrial revolution. *Contemporary accounting research*. https://doi.org/10.1111/1911-3846.12901

Sampson, S. E. (2021). A Strategic Framework for Task Automation in Professional Services. *Journal of service research : JSR*, *24*(1), 122-140. https://doi.org/https://doi.org/10.1177/1094670520940407

Siderska, J. (2021). The Adoption of Robotic Process Automation Technology to Ensure Business Processes during the COVID-19 Pandemic. *Sustainability (Basel, Switzerland)*, *13*(14), 8020. https://doi.org/10.3390/su13148020

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333-339.

Sobczak, A. (2021). Robotic Process Automation implementation, deployment approaches and success factors – an empirical study. *Entrepreneurship and Sustainability Issues*, *8*(4), 122-147. https://doi.org/10.9770/jesi.2021.8.4(7)

Sony, M., & Mekoth, N. (2022). Employee adaptability skills for Industry 4.0 success: a road map. *Production & Manufacturing Research*, *10*(1), 24-41. https://doi.org/10.1080/21693277.2022.2035281

Spring, M., Faulconbridge, J., & Sarwar, A. (2022). How information technology automates and augments processes: Insights from Artificial-Intelligence-based systems in professional service operations. *Journal of operations management*, *68*(6-7), 592-618. https://doi.org/10.1002/joom.1215

Tang, P. M., Koopman, J., Yam, K. C., De Cremer, D., Zhang, J. H., & Reynders, P. (2022). The self-regulatory consequences of dependence on intelligent machines at work: Evidence from field and experimental studies. *Human resource management*. https://doi.org/10.1002/hrm.22154

Toshav-Eichner, N., & Bareket-Bojmel, L. (2022). Yesterday's workers in Tomorrow's world. *Personnel review*, *51*(5), 1553-1569. https://doi.org/10.1108/PR-02-2020-0088

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *British journal of management*, *14*(3), 207-222. https://doi.org/10.1111/1467-8551.00375

Trenerry, B., Chng, S., Wang, Y., Suhaila, Z. S., Lim, S. S., Lu, H. Y., & Oh, P. H. (2021). Preparing Workplaces for Digital Transformation: An Integrative Review and Framework of Multi-Level Factors. *Frontiers in psychology*, *12*, 620766. https://doi.org/10.3389/fpsyg.2021.620766

Tschang, F. T., & Almirall, E. (2021). Artificial Intelligence as Augmenting Automation: Implications for Employment. *Academy of Management perspectives*, *35*(4), 642-659. https://doi.org/10.5465/amp.2019.0062

Turja, T., Minkkinen, J., & Mauno, S. (2022). Robotizing meaningful work. *Journal of Information, Communication & Ethics in Society*, *20*(2), 177-192. https://doi.org/https://doi.org/10.1108/JICES-06-2021-0063

Villani, V., Sabattini, L., Żołnierczyk-Zreda, D., Mockałło, Z., Barańska, P., & Fantuzzi, C. (2021). Worker satisfaction with adaptive automation and working conditions: a theoretical model and questionnaire as an assessment tool. *International Journal of Occupational Safety and Ergonomics*, *27*(4), 1235-1250. https://doi.org/10.1080/10803548.2021.1899649

Wang, X., Lin, X., & Shao, B. (2023). Artificial intelligence changes the way we work: A close look at innovating with chatbots. *Journal of the Association for Information Science and Technology*, *74*(3), 339-353. https://doi.org/https://doi.org/10.1002/asi.24621

Waschull, S., Bokhorst, J. A. C., Molleman, E., & Wortmann, J. C. (2020). Work design in future industrial production: Transforming towards cyber-physical systems. *Computers & Industrial Engineering*, *139*, 105679. https://doi.org/https://doi.org/10.1016/j.cie.2019.01.053

Wesche, J. S., Hennig, F., Kollhed, C. S., Quade, J., Kluge, S., & Sonderegger, A. (2022). People's reactions to decisions by human vs. algorithmic decision-makers: the role of explanations and type of selection tests. *European journal of work and organizational psychology*, *ahead-of-print*(ahead-of-print), 1-12. https://doi.org/10.1080/1359432X.2022.2132940

Wright, D. P., Anastasiia; Schaefer, Gina; Thopalli, Kartik; Telfrod, Tanya. and Urbaniak, Tanya. . (2022). Automation with Intelligence [Online]. *Deloitte Insights*, 1-32. Retrieved 12th March 2023, from https://www2.deloitte.com/us/en/insights/focus/technology-and-the-future-of-work/intelligent-automation-2022-survey-results.html