UNIVERSIDADE CATÓLICA PORTUGUESA

INFORMAL LEARNING IN THE FACE OF CONTENT OCCUPATION INSECURITY: THE INFLUENCE OF OCCUPATIONAL SELF-EFFICACY AND FUTURE FOCUS

Dissertation to Universidade Católica Portuguesa to obtain a Master's Degree in Psychology in Business and Economics

By

Ciara Nolan

Faculty of Human Sciences

October 2024

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Abstract

Artificial intelligence applications are emerging in industries across the board, from healthcare and finance to marketing and education. Trends signify that these applications will cause economic disruption for years to come and rapidly overhaul how organisations operate. Worries about changes to the tasks and important features of one's occupation are emerging, coined content occupation insecurity. The idea of informal learning to keep up with the occupational changes often associated with occupation insecurity is gaining prominence. This study consequently investigated if content occupation insecurity is associated with lower levels of informal learning, and whether this relationship is mediated by a decline in occupational self-efficacy and future focus. To assess the direct effect of content occupation insecurity on informal learning and the parallel mediation effects of occupational self-efficacy and future focus, a mediation analysis was conducted. The findings showed that the relationship between content occupation insecurity and informal learning is dictated by competing mediating pathways that result in contradictory directional effects. Both negative and positive effects were uncovered resulting in an insignificant total effect and suggesting that the impact of content occupation insecurity on informal learning is highly context dependent. Academic and managerial implications, as well as future recommendations, are offered based on these findings.

Keywords: Artificial Intelligence, Occupation Insecurity, Content Occupation Insecurity, Job Insecurity, Informal Learning, Occupational Self-Efficacy, Temporal Focus, Future Focus, Attitudes Toward Change, Resilience

Resumo

As aplicações de inteligência artificial estão a emergir em várias indústrias, desde a saúde e as finanças até ao marketing e à educação. As tendências indicam que estas aplicações causarão uma disrupção económica nos próximos anos e revolucionarão rapidamente o modo de funcionamento das organizações. Estão a surgir preocupações relativamente às mudanças nas tarefas e nos atributos centrais de uma ocupação, conceito este designado por insegurança ocupacional de conteúdo. A ideia da aprendizagem informal como forma de acompanhar as mudanças ocupacionais associadas à insegurança ocupacional tem ganho destaque. Consequentemente, este estudo investigou se a insegurança ocupacional de conteúdo está associada a níveis mais baixos de aprendizagem informal, e se esta relação é mediada por um declínio na autoeficácia ocupacional e no foco no futuro. Para avaliar o efeito direto da insegurança ocupacional de conteúdo na aprendizagem informal e os efeitos de mediação paralela da autoeficácia ocupacional e do foco no futuro, foi conduzida uma análise de mediação. Os resultados mostraram que a relação entre a insegurança ocupacional de conteúdo e a aprendizagem informal é influenciada por vias de mediação concorrentes, que resultam em efeitos direcionais contraditórios. Foram identificados tanto efeitos negativos como positivos, resultando num efeito total insignificante e sugerindo que o impacto da insegurança ocupacional de conteúdo na aprendizagem informal depende fortemente do contexto. Com base nestes resultados, são oferecidas implicações académicas e gerenciais, bem como recomendações para futuros estudos.

Palavras-chave: Inteligência Artificial, Insegurança Ocupacional, Insegurança Ocupacional de Conteúdo, Insegurança no Trabalho, Aprendizagem Informal, Autoeficácia Ocupacional, Foco Temporal, Foco no Futuro, Atitudes em Relação à Mudança, Resiliência

Dedication

To my mam, who taught me the power of education.

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Table of Contents

Abstract ii
Resumo iii
Dedication iv
Acknowledgements v
List of Figures ix
List of Abbreviations x
1. Introduction 1
1.1. Topic presentation 1
1.2. Relevance of the topic 3
1.3. Problem Statement and Research Objective 4
1.4. Structure of the Dissertation 6
2. Theoretical Background 7
2.1. Artificial Intelligence 7
2.1.1. Brief history of Artificial Intelligence 7
2.1.2. Definition of AI 7
2.1.3. Categorisation of AI technologies 9
2.2. The Influence of AI on Occupations 10
2.2.1. AI within the labour market 10
2.3. Occupation Insecurity 14
2.3.1. Characteristics of occupation insecurity 15
2.3.2. Theoretical grounding of insecurity 17
2.3.3. Consequences of occupation insecurity 20
2.4. Informal Learning 22
2.4.1. Overview of informal learning 22
2.4.2. Importance of learning in the face of occupational change 24
2.4.3. Content occupation insecurity and informal learning 25
2.5. Occupational Self-Efficacy 27

2.5.1. Overview of self-efficacy 27
2.5.2. Introduction to occupational self-efficacy 28
2.5.3. Occupational self-efficacy in the face of insecurity 30
2.5.4. Importance of occupational self-efficacy for participation in informal learning behaviours 31
2.6. Future Focus 32
2.6.1. The concept of temporal focus 32
2.6.2. Future focus and occupation insecurity 34
2.6.3. Future focus and informal learning behaviour 34
3. Methodology 38
3.1. Research Design 38
3.2. Participants and Data Cleaning 39
3.3. Measures 39
3.4. Ethical Considerations 42
3.5. Procedure 42
3.6. Data Analysis Plan 43
4. Results 44
4.1. Data Preparation 44
4.2. Scale Reliabilities 44
4.3. Prevalence of Content Occupation Insecurity 45
4.4. Hypotheses Testing 45
5. Discussion 49
5.1. Research Findings 49
5.2. Academic Implications 50
5.3. Managerial Implications 52
5.4. Methodological Strengths 53
5.5. Limitations and future research 53
6. Conclusion 55

Bibliography 56
Appendices 85
Appendix A Descriptive Statistics 85
Appendix B Content Occupation Insecurity Scale 88
Appendix C Informal Learning Behaviours Scale 89
Appendix D Temporal Focus Scale – Future Focus 90
Appendix E Occupational Self-Efficacy Scale 91
Appendix F Attitudes Toward Change Scale 92
Appendix G Brief Resilience Scale 93
Appendix H Pre-Registration Form 94
Appendix I Information Sheet 97
Appendix J Artificial Intelligence Definition 98
Appendix K Survey Closing and Debriefing 99
Appendix L Scale Reliabilities 100
Appendix M Content Occupation Insecurity Frequency Table 101
Appendix N Parallel Mediation Analysis Summary Table with Resilience Included as a Covariate 102

List of Figures

Figure 1 Learning spectrum diagram.....23
Figure 2 A visual overview of the conceptual model for this thesis.....37
Figure 3 Parallel Mediation Model.....48

List of Abbreviations

AI	Artificial intelligence
b	Regression coefficient
BootSE	Bootstrap standard error
CI	Confidence interval
F	F-Statistic
M	Mean
N	Total number of cases
p	p-value
R^2	Coefficient of determination
SD	Standard deviation
t	t-statistic

1. Introduction

Artificial intelligence (AI) is an emerging, almost mysterious field of technology, with Stephen Hawking famously quoted as saying "…the rise of powerful AI will be either the best, or the worst thing, ever to happen to humanity. We do not yet know which" (Cellan-Jones, 2016).

1.1. Topic presentation

AI has the power to disrupt the labour market to an extent never experienced. It possesses impressive, wide-ranging abilities and is advancing at an exponential rate. Its applications have grown rapidly in the past number of years, with the technology cropping up in industries such as healthcare, finance, business, customer service, and marketing (Zhou et al., 2023). Trends indicate that AI tools will cause major economic disturbances for years to come and completely overhaul how companies operate (Xu et al., 2018). There are many incentives for organisations to implement AI, including for efficiency and productivity gains. Machines can already outperform humans in various intelligence dimensions, for instance storage, throughput efficiency, and computational efficiency (Zhou et al., 2023). With much of the developed world having grappled with poor productivity in recent years, the arrival of this innovative technology could be perceived as perfectly timed (see Bergeaud et al., 2015; Clifton et al., 2020; Hazan et al., 2024).

Despite its potential benefits, concerns have arisen about the impact AI implementation will have on professionals. Fears were initially raised that AI could trigger mass replacement across industries, pushing hundreds of millions of employees out of work in years to come (Frey & Osborne, 2017; Zhou et al., 2019). However, specialists have increasingly recognised that rather than only equipping AI driven machines with human-like capabilities, allowing them to function independently, AI also has the power to augment and advance human intelligence, performance, and capacity (Zhou et al., 2021). AI augmentation will trigger changes to occupational roles as specific tasks are replaced, with others demanding the professional to work alongside an AI system. In fact, Vrontis et al. (2021) proposed that human-AI collaboration is an unavoidable situation that professionals will face as AI is implemented across industries. This appears to be a generally accepted reality. Ott and

Spichiger (2024) reported that an average of 65% of respondents across nine European countries expected AI to take over components of their work and redefine their professional profiles.

Looming work-related changes can leave professionals feeling worried and insecure about the continuity of their work-related future (Greenhalgh & Rosenblatt, 1984). A recent Ernst and Young report involving data from 1000 Americans who work in an office job found that 75% expressed worries about AI making certain jobs obsolete, 72% were concerned about AI having a negative impact on their salary or career growth, with 66-67% anxious about losing out on promotions for not knowing how to use AI technology or falling behind if they do not use it in the workplace (Barrington et al., 2024). Past research has mainly concentrated on job insecurity, relating to the subjective fear of losing one's current job (quantitative job insecurity) or valued features thereof (qualitative job insecurity; De Witte, 2005; Hellgren et al., 1999; Roll et al., 2023). However, a novel and unexplored concept has recently emerged – occupation insecurity (Roll et al., 2023). A 'job' is a specific position within a specific organisation, whereas an 'occupation' is the profession an individual has been trained in and thus identifies with (i.e., a range of jobs with similar characteristics; Miles, 2019; Roll et al., 2023). Occupation insecurity refers to individual's worries about the future of their occupations and is thus a far broader term which the researchers propose is necessary to account for the scale of change unleashed by AI.

The concept of occupation insecurity consists of two dimensions – content occupation insecurity (like qualitative job insecurity) and global occupation insecurity (like quantitative job insecurity; Roll et al., 2023). Qualitative job insecurity, relating to the perceived threat of losing valued features of one's job has been identified as most applicable during times of rapid organisational alterations, with many fearing that their job will change rather than completely disappear (Hellgren et al., 1999; Van Hootegem & De Witte, 2019). This trend initially appears to extend to occupation insecurity, with Roll et al. (2023) finding that the percentage of those experiencing content occupation insecurity (46.7%) were almost treble compared to individuals experiencing global occupation insecurity (16.5%).

1.2. Relevance of the topic

In the face of changes to the features of one's occupation, individuals must enhance their skillset to adapt (Davenport & Dreyer, 2018, Jaiswal et al., 2021; Yuan et al., 2021). Brown et al. (2024) emphasised that changes will be all-encompassing, and vastly alter what employees need to thrive in their various occupations, as well as the general labour market. The days of training for one occupation and being "set" for life are disappearing. Occupational models are becoming increasingly flexible, making it essential for individuals to continue learning throughout their working lives (Kyndt & Baert, 2013). As stated in a recent IBM report, AI won't replace people—but people who use AI will replace people who don't" (Goldstein et al., 2023, p. 2). Thus, it is vital for professionals to continuously develop the skills and competencies required to thrive in their changing occupation, with Stephen Covey highlighting that "unless you're continually improving your skills, you're quickly becoming irrelevant" (Covey & Merrill, 2008, p. 104).

Informal learning has been identified as an important means for professionals to continuously update their knowledge and skills to adjust to changing professional environments, and adopt modern technologies (Noe et al., 2013). It typically occurs outside of formal, structured educational settings and can involve learning from oneself, learning from others, and learning from non-interpersonal resources. Examples include cognitive activities and behaviours such as experimenting, interacting with other experienced individuals in the workplace, asking questions, reflecting, and observing (Kodom-Wiredu et al., 2022). Informal learning enables professionals to accumulate new skills and remain relevant as new tasks and challenges arise in their current surroundings, rather than limiting their learning to formal settings. It can offer a method for employees to enhance their employability and adjust to changing occupational demands (Froehlich et al, 2014; Van Der Heijden et al., 2009). A study on Cedefop's European Skills and Jobs Survey 2014 on 28 European countries concluded that workers who engaged in informal learning showed grater skill enhancement than those who did not engage (Ferreira et al., 2017). They noted that its effect appeared to be greater than that of training participation. Further, previous research has indicated that the acquisition of novel skills and knowledge can protect against the stressful effects of a changing professional

situation (Niklova et al, 2014). Partaking in informal learning behaviours can evidently contribute to skill adoption, particularly vital in the face of rapid occupational change.

Although beneficial, engagement in informal learning during times of change is not guaranteed. Worries about the future of one's occupation can be rampant as AI is unleashed across the labour market (see Roll et al., 2023), potentially impacting an individual's behaviours, including whether they are engaged in informal learning. To the best of my knowledge, there is not yet any research exploring the relationship between content occupation insecurity and informal learning. However, when drawing upon literature surrounding qualitative job insecurity and informal learning, those experiencing job insecurity appear to be less likely to engage in learning and development activities (De Cuyper et al., 2022; Van Hootegem and De Witte, 2019; Van Hootegem et al., 2023). The exploration of the relationship between content occupation insecurity and other variables is presently restricted to burnout and work engagement (see Roll et al., 2023). In the presence of looming occupational changes due to AI, informal learning has been identified as an important adaptational strategy. With only one study to date exploring the novel concept of occupation insecurity, important questions remain about its prevalence, as well as its influence on adaptational strategies such as informal learning (Roll et al., 2023).

I, therefore, propose investigating the impact of content occupation insecurity on informal learning behaviours. As previous literature indicates the largely negative effects of insecurity on employee behaviours, I suggest that content occupation insecurity could be negatively related to informal learning.

1.3. Problem Statement and Research Objective

Driven by this gap in the literature and growing worries surrounding AI induced changes, this thesis strives to contribute to the presently sparse literature on occupation insecurity, specifically content occupation insecurity. Further, I plan to explore the relationship between content occupation insecurity and informal learning. This will expand the literature between occupation insecurity and other relevant variables. Research is currently limited to burnout and work engagement (Roll et al., 2023). Whilst some studies have explored the potential relationship between insecurity (specifically job insecurity) and informal learning (see Van

Hootegem and De Witte, 2019; Van Hootegem et al., 2023), further studies are required, particularly relating to the underlying pathways of any such relationship. Therefore, I employ measures for occupational self-efficacy and future focus, both of which can theoretically relate to informal learning and insecurity.

Occupational self-efficacy and future focus can be considered personal resources within the framework of the Conservation of Resources Theory (Hobfoll, 1989), which puts forth that individuals aim to retain and protect their personal resources and that these resources can be at risk of depletion when faced with external stressors such as occupation insecurity (Hobfoll, 2001). Occupation self-efficacy, referred to as a person's belief in their ability to carry out work-related tasks successfully, has been identified as a possible buffer against the impact of work stressors (Schyns & von Collani, 2002). Similarly, future focus, pertaining to an individual's tendency to focus on what is to come; imagining and considering the steps required to attain their future goals, has been linked to proactive career behaviours (Shipp et al., 2009). Both constructs can consequently be seen as protective factors that might mitigate the negative effects of occupation insecurity whilst also facilitating informal learning, a topic which will be explored throughout this thesis. Additionally, as Van Hootegem and De Witte (2019) noted, it might be important to investigate the impact of job insecurity (or in this case, occupation insecurity) on informal learning in light of the specific circumstances causing said insecurity, rather than utilising a more general insecurity scale as was the case in previous studies. As such, my focus is on AI induced content occupation insecurity.

A final aim of this research is to validate the Occupation Insecurity Scale, more specifically the content occupation insecurity subscale by sampling a broader range of professionals. Thus far, the scale has only been employed in the United Kingdom and Belgium (Roll et al., 2023). Roll et al. (2023) noted that the scale is equipped to "follow up on current events," including how the increased use of technology impacts professionals, with AI being a major technology type at present. By gaining deeper insights into the incidence of content occupation insecurity, we as a society are in a better position to support those affected, as well as to inform policy change. This thesis subsequently aims to answer the following research questions:

Research Questions (RQs)

1. How does content occupation insecurity impact informal learning?

2. What mediating roles do occupational self-efficacy and future focus play in the relationship between content occupation insecurity and informal learning?

To explore these research questions, a quantitative research design was utilised, comprising a cross-sectional survey to examine the relationships between content occupation insecurity, informal learning, and the mediating roles of occupational self-efficacy and future focus. This thesis strives to extend our knowledge surrounding underlying mechanisms which might influence the relationship between occupation insecurity and professionals' informal learning behaviours. This study will also offer practical insights for organisations and policymakers striving to ensure professionals' skills remain up to date as occupational tasks change and expand because of AI implementation. This is becoming increasingly relevant as the importance of the different aspects of informal learning are highlighted across the literature (Beausaert et al., 2021; Crans et al., 2022; Froehlich et al., 2014; Froehlich et al., 2015; Froehlich & Messmann, 2017; Froehlich et al., 2019; Leiß et al., 2022; Van Der Heijden et al., 2009; Van der Rijt et al., 2013). The findings of this study also aim to add to the limited literature surrounding occupation insecurity, by further validifying the content occupation insecurity subscale of the novel Occupation Insecurity Scale, exploring the prevalence of content occupation insecurity across a varied European and industry wide sample.

1.4. Structure of the Dissertation

Following on from this introduction, Chapter 2 builds the theoretical basis for this thesis by exploring the impact of AI across the labour market, as well as delving into literature surrounding the concepts of occupation insecurity and informal learning. A parallel mediation model was conducted to explore the research questions, with the methodology and results described in Chapters 3 and 4 respectively. Chapter 5 discusses the findings of this thesis in relation to existing literature, finishing with an overview of managerial and academic implications. Finally, Chapter 6 concludes the thesis.

2. Theoretical Background

The following chapter begins with an overview of AI, delving into its history, a definition, a categorisation of its technology types, and the impact of associated advancements within the labour market. The novel concept of occupation insecurity is explored, with particular emphasis placed on content occupation insecurity, along with informal learning, occupational self-efficacy and future focus. An overview is provided for each, providing solid theoretical background information for this thesis. The concepts are subsequently combined, offering insights into the potential relationship between content occupation insecurity and informal learning, as well as the mediating impact of occupational self-efficacy and future focus.

2.1. Artificial Intelligence (AI)

2.1.1. Brief history of AI

AI is a broad field of computer science focused on developing systems capable of carrying out tasks that once relied solely on the cognitive abilities of humans (Minsky, 1969; Signorelli, 2018). The technology first began to emerge as a research field in the 1950s, appearing at a similar time as the first computers (Tan & Lim, 2018). Minsky and McCarthy, along with fellow academics are widely considered to be the "founding fathers" of AI research in 1955, when they coined the term "Artificial Intelligence" whilst preparing their proposal for the "Dartmouth Summer Research Project on Artificial Intelligence" (Haenlein & Kaplan, 2019). Nevertheless, the area of AI is likely to even have predated this project (Tan & Lim, 2018). The first artificial neuron was described in the early 1940s, whilst speech recognition began to be explored in 1952 (Davis et al., 1952; McCulloch & Pitts, 1943). AI has garnered widespread attention in recent years, labelled a "second renaissance" by Tan and Lim (2018). The topical emergence of AI as an everyday topic is largely due to rapid progression in computer power and other technologies (including machine learning and natural language processing), as well as an "explosion" of data readily accessible to train AI algorithms (Bornet et al., 2021; Mariani et al., 2021).

2.1.2. Definition of AI

Definitions of AI can be rather vague, largely due to an imprecise understanding of the concept of ‘intelligence’ within the scientific world and beyond (High-Level Expert Group on Artificial Intelligence, 2018). Researchers typically consider the notion of rationality when referring to AI, whereby it can select the elite action to reach a specific goal, when provided with criteria to be optimised and other resources. They highlighted that whilst rationality is not the only “ingredient” in the concept of intelligence, and as such AI, it plays an important role. AI achieves rationality by interacting with its environment via sensors, interpreting what it perceives, choosing the best course of action, engaging in said action, which might result in the alteration of its environment (High-Level Expert Group on Artificial Intelligence, 2018).

To reduce misunderstandings, the High-Level Expert Group on Artificial Intelligence (2018, p. 7) strived to expand and clarify the definition of AI, during which they decided upon the following definition: "systems designed by humans that, given a complex goal, act in the physical or digital world by perceiving their environment, interpreting the collected structured or unstructured data, reasoning on the knowledge derived from this data and deciding the best action(s) to take (according to pre-defined parameters) to achieve the given goal. AI systems can also be designed to learn to adapt their behaviour by analysing how the environment is affected by their previous actions." These superior abilities differentiate AI from more traditional algorithms (Sheikh et al., 2023). For clarity, this thesis will utilise the definition of AI developed by the European Commission going forward.

AI encompasses a wide range of advanced technological systems (Ali et al., 2022). A major subset of AI is machine learning (Microsoft, 2024). It uses techniques (including deep learning) that allow machines to improve task performance along with experience. The learning process of this technology involves “feeding” the algorithm with data, using this data to train the model, testing and deploying the model, followed by utilising the model to complete a chosen task. A well-known subset of machine learning is deep learning (Microsoft, 2024). It is grounded in artificial neural networks, and contains multiple layers, each of which possess units capable of translating input data into readable and utilisable information for the layer that follows, enabling it to carry out a task (Microsoft, 2024; Tschang & Almirall, 2021). This technology type is valuable for analysing vast swaths of data and is increasingly capable

of managing more multifaceted data. Deep learning allows systems to interact with their surroundings, identify new features and adapt accordingly (Tschang & Almirall, 2021). A distinct difference between machine and deep learning techniques is that in machine learning, the algorithm must consume more data to accurately predict, whilst in deep learning, the algorithm can teach itself to make predictions because of its artificial neural network structure (Microsoft, 2024). Generative AI is another branch of AI that involves using techniques such as deep learning to "generate" novel content such as text, audio, and images, for which vast amounts of data are required.

AI technologies built using machine and deep learning techniques can work with vast swathes of data in both a structured and unstructured manner, allowing for the widespread scaling of data driven processes (Kasowaki & Kooper, 2024). Potential use cases involve but are not limited to language usage, image caption generation, concept formation, problem solving, prediction making, pattern recognition, object detection, and text analytics (Acemoglu & Restrepo, 2019; Kasowaki & Kooper, 2024; Microsoft, 2024). AI powered tools can automate an extensive range of data-driven tasks, such as data transformation, data cleaning, and data normalisation (Adadi, 2021). (Automating these tasks can reduce errors and enhance efficiency, reducing the risk caused by humans' subjective interpretation of data (Silberg & Manyika, 2019). AI algorithms can also analyse levels of historical data, reaching previously unused datasets in the process, and allowing for accurate future predictions, upon which more accurate decisions can be made (Königstorfer & Thalmann, 2020). Further, due to AI's capacity to analyse large volumes of data, it can create personalised user experiences, for example product or content recommendations (Kasowaki & Kooper, 2024). In general, AI technologies can draw conclusions, generate predictions, automate various tasks, and enhance efficiency (Adusumalli, 2016; Kasowaki & Kooper, 2024).

2.1.3. Categorisation of AI technologies

AI technologies can generally be divided into three categories - super, general, and narrow AI (Hidalgo et al., 2021). General and super AI could think, reason, learn, and make judgements without the need for human training (IBM Data & AI Team, 2023). Super AI would additionally have the capacity to take on uniquely human traits, such as understanding

human sentiments to experience emotions and desires. Although a goal amongst certain researchers, general and AI remain mere theoretical concepts for now (Vincent, 2018). Both would necessitate capabilities such as common-sense reasoning, self-awareness, and the ability of the aptitude of the machine to outline its own objective, without human interference (High-Level Expert Group on Artificial Intelligence, 2018). Debates are ongoing about whether this level of AI will (or should) ever be reached (Vincent, 2018). Therefore, all of today's AI applications fall into the "narrow" category which this thesis will limit its focus to. Narrow AI can be defined as a form of intelligence that has been programmed and trained to complete a specific task (Clifton et al., 2020). Everyday examples of narrow AI include voice recognition systems such as Siri, recommendation algorithms used by the likes of Netflix, autonomous cars, and OpenAI's generative AI ChatGPT model which partakes in text-based chat (IBM Data & AI Team, 2023).

2.2. The Influence of AI on Occupations

2.2.1. AI within the labour market

AI technologies offer massive potential across the labour market because of their widespread abilities. Trends indicate that AI will cause major economic disturbances in the years to come and alter how companies operate (Xu et al., 2018). To highlight how extreme its impact is likely to be, Bristol et al. (2024) stated that "what steam was to the First Industrial Revolution is what AI will be to the fourth." For context, steam revolutionised industries and completely altered how humans worked (Mohajan, 2019). The scale of change unleashed is likely to equate to or surpass the massive shift from farmwork to manufacturing brought about by the First Industrial Revolution (Illanes et al., 2018). However, earlier workplace transformations occurred over many decades, allowing for a 'gentle' transition. AI induced labour changes are likely to be much quicker. A consensus exists that we will experience dramatic structural changes to the labour market and the way we work because of AI implementation (Hirschi, 2018).

Two opposing viewpoints have emerged about the effects AI implementation is likely to have on employment – the views of "replacement" and "augmentation" (Tschang & Almirall, 2021). Scholars standing by the replacement viewpoint believe that AI technologies will

replace human employees outright by automating all components of their occupations. For example, Zhou et al. (2019) concluded that 278 million employees in China would be replaced by AI by 2049. Moreover, Frey and Osborne (2017) estimated that 47% of total United States employment is at high risk, seeing potential for related occupations to be automated over the one to two decades that followed. On the other hand, the augmentation stance is gaining traction. Associated researchers propose that automation could lead to more employee transitions than mass unemployment (Bessen et al., 2020). Scholars holding this view expect that AI will automate non-core tasks, achieving human-machine collaboration and offering synergic advantages, rather than pushing humans out of their occupations (Daugherty & Wilson, 2018). An optimistic viewpoint posits that the automation of various occupational tasks would enable colleagues to work more efficiently and free up time for them to focus on other "more complex" tasks (Chui et al., 2015).

Nevertheless, scholars accept that AI augmentation across the labour market will nonetheless unleash widespread changes which will have significant repercussions for humans and their occupations. Therefore, it is unlikely to be a simple transition. As occupational roles are augmented, professionals must enhance their skillset to adapt to the changes within their work environment (Daugherty & Wilson, 2018; Davenport & Dreyer, 2018; Jaiswal et al., 2021). Brown et al. (2024) additionally emphasised that changes will be all-encompassing, and vastly alter what employees need to thrive in their various occupations, as well as the general labour market. To survive and thrive within a rapidly changing "AI augmented" working world, professionals must continuously adopt new skills and work processes. AI will likely reduce the need for human input for a range of occupational tasks, whilst simultaneously generating new ones. As Davenport and Dreyer (2018) stated, employees who have learned how to work effectively alongside AI are most likely to be succeed. With AI's potential to replace and create tasks, widescale shifts have already begun across occupations.

2.2.2. The impact of AI on occupations

Occupations within the healthcare sector are being transformed by AI, with technologies already demonstrating widespread potential in medical imaging, diagnostics, and data analysis. AI can be successfully utilised for early detection and diagnostic (Sunarti et al.,

2021). It functions by comparing data from patients, with the independent learning system detecting an association and proposing a diagnosis. An AI driven breast cancer screening tool led to 1.2% fewer false positives and 2.7% fewer false negatives in the United Kingdom, when compared with results from human radiologists (McKinney et al., 2020). Similarly, Ardila et al. (2019) concluded that a deep learning model using a patient's computer tomography (CT) images to screen for lung cancer outpaced six human radiographers (with an average of 8 years' experience) providing an 11% reduction in false positives and 5% in false negatives when neither group had access to past CT images. With access to these images, the capabilities of both parties were on par. Typical screening for atrial fibrillation necessitates prolonged monitoring by cardiologists, which is time-consuming and costly (Attia et al., 2019). An AI model accurately differentiated between those with and without atrial fibrillation in 87% of instances. Finally, an AI system, namely Complementarity-Driven Deferral to Clinical Workflow has been developed which learns when to rely on AI tools for medical image interpretation and when to instead defer to a human clinician, allowing for streamlined AI-human collaboration (Dvijotham et al., 2023). These use cases highlight AI's promising abilities within the healthcare industry, freeing up time for healthcare professionals to focus on other aspects of patient care. Nevertheless, as AI technologies advance, medical workers might worry that AI could devalue their occupational expertise, whilst creating a need to continuously adapt to the new tools.

In the business and financial sectors, AI is expected to take over a selection of core functions, offering cost savings and enhanced efficiencies (Meena, 2020). Several possibilities have been identified in tasks associated with fraud detection, risk management, and data analysis. Ernst & Young integrated AI into its audit services, using an AI system that can quickly analyse and review documents and contracts (Sahota, 2024). In the banking industry, AI is changing lending processes (Königstorfer & Thalmann, 2020). AI tools can enhance the credit risk assessments of loan applicants, making more accurate predictions due to their ability to reach previously unused datasets. Utilising novel data, for example from social media can enable the bank to gain an in-depth overview of the "riskiness" of their clients. Moreover, due to its pattern recognition abilities, AI systems can detect fraudulent behaviour

in online banking and money laundering in transactions (Jadhav et al., 2016). AI also offers potential advantages in the business area of recruiting, automating the time-consuming task of screening curriculum vitaes, leaving human recruiters with extra time to spend on strategy design (Upadhyay & Khandelwal, 2018). AI can support human professionals, building upon their analytical abilities and enabling them to turn their focus to other complex or more strategic tasks (Huang & Rust, 2018). A shift from data aggregation and risk analysis to AI literacy skills and data-driven decision making could become the new norm for those in financial and business occupations.

Occupations which once relied heavily on human creativity and input are also being affected. Artistic and creative occupations are already experiencing changes as the development of novel AI tools continues, with Thapliyal and Thapliyal (2024, p. 40) referring to AI as a "powerful creative partner". Further, AI can support humans in overcoming the creative limitations of the human brain (Elfar & Darwood, 2023; Zhou & Lee, 2024). Creative tasks were traditionally considered to be "intrinsically human," translating unique human experiences, sentiments, and thoughts into physical matter (Thapliyal & Thapliyal, 2024). However, as narrow AI systems continue to advance, they are now capable of producing numerous types of creative content, including literature, artwork, and musical compositions. The implementation of AI within the creative sector offers benefits. For instance, Zhou and Lee (2024) noted that text-to-image generative can support humans in almost doubling their production of creative artifacts. Not only that, but these artifacts were reviewed 50% more favourably than human-produced content by fellow human beings. AI tools are causing changes within specific creative occupations. For example, AI tools can be utilised by user experience designers to determine the context of use and user requirements, support with solution design, review said designs, and support with solution creation (Stige et al., 2023). As outlined in Haleem et al. (2022) review of the impact of AI in marketing, incorporated technologies can support marketing professionals by analysing large amounts of data to make predictions and support with decision making. Marketers can utilise AI to segment clients based on certain criteria and generate AI-powered content. AI can also be used by marketing

professionals to tweak communicational content and generate superior customer suggestions (Brobbey et al., 2021; Neuhofer et al., 2020; Varsha et al., 2021).

Professionals within the educational sector are also likely to experience profound changes to their occupations because of AI advancements. AI driven technologies including intelligent tutoring, automated grading systems, and predictive analytics can offer unique learning experiences by personalising content and providing live feedback to students (Luckin et al., 2016; Holmes et al., 2019). Although offering the potential to enhance efficiency, they may also contribute to job insecurity as more traditional tasks are replaced, particularly those which are repetitive in nature such as grading (West, 2018). This raises questions about how the integration of AI across the educational sector might change occupational expectations and necessitate educators to gain new skills and digital competencies to remain competitive (Ng et al., 2023).

2.3. Occupation Insecurity

As outlined, AI technologies are transforming occupations across the labour market. Professionals must learn to work alongside new tools and complete a variety of new tasks, whilst also potentially experiencing the "loss" of various occupational tasks which AI can now take over. Insecurity concerns about one's place in this rapidly advancing market are surfacing. In the literature, numerous concepts are utilised to measure insecurity across employees. A well-researched insecurity-related concept is job insecurity. Job insecurity can be defined as "the perception of potential threat to continuity in his or her current job" or a worry about its existence going forward (Heaney et al., 1994, p. 1431; Rosenblatt & Ruvio, 1996). A novel concept - occupation insecurity has recently emerged and remains largely unexplored. Occupation insecurity refers specifically to "people's fears about the future of their occupations due to technological advancements" (Roll et al., 2023, p. 2).

For clarity, a 'job' is defined as a specific position within a specific organisation, whereas an 'occupation' is the profession an individual has been trained in and thus identifies with (Miles, 2019; Roll et al., 2023). An occupation thus involves a range of jobs with similar characteristics and defines a person's "role" within society (Roll et al., 2023). Roll et al. (2023) provided the example of a job as an administrative employee working at a certain

company. This employee can change jobs and find a highly similar position at another organisation. However, if the tasks associated with this occupation are automated, the occupation either disappears or is dramatically altered. Instead of simply switching to a different company, individuals might need to learn a different occupation, or acquire the skills and competencies required to adapt to the changing occupation.

Based upon these definitions, occupation insecurity diverges from job insecurity. Job insecurity involves employee worries about losing their current job or important features thereof (Roll et al., 2023). Occupation insecurity instead focuses on the wider, and potentially deeper concern that an individual's full occupation or related occupational tasks might become redundant. Roll et al. (2023) highlighted that if an individual loses their job or prominent features thereof, they can look for a similar job in another workplace to utilise their current skills. However, if one's whole occupation is expected to change or be replaced, the effects run much deeper and they might need to learn a full new occupation (Roll et al., 2023).

2.3.1. Characteristics of occupation insecurity

Roll et al. (2023) noted that similarities exist between the theoretical bases of job and occupation insecurity and confirmed convergent and divergent validity with job insecurity. Firstly, both are subjective in nature, inferring that the feeling of insecurity can vary between humans who are objectively in the exact same situation (Greenhalgh & Rosenblatt, 1984). Nevertheless, Roll et al. (2023) confirmed that objectively more insecure individuals are more likely to experience occupation insecurity compared to objectively secure individuals. This aligns with job insecurity, with De Witte et al. (2012) having noted that perceived job insecurity appeared to match the objective circumstances. Thus, whilst subjective in nature, occupation insecurity likely aligns with the objective situation. Further, not all potential changes to one's job or in this instance, occupation induce insecurity, only those which might trigger harm or loss for the individual at hand (Boswell et al., 2014). Therefore, the examination of occupation insecurity focuses on how individuals perceive and react to envisaged changes to or loss of their occupation, with this varying across the professional population. Secondly, the concepts imply an element of involuntariness with perceived changes occurring because of external factors (such as AI implementation) rather than

personal decisions, such as for example voluntary choosing to leave one's occupation (Roll et al., 2023). Thirdly, the concepts of insecurity explore perceived upcoming situations (Huang et al., 2013). They are future focused phenomena as they relate to negative changes which may occur going forward (Schoss, 2017). For example, those who experience occupation insecurity are still working within their occupation, but the perception of the future existence of one's occupation in general or in its present form is unclear. The threats have not yet come to fruition, thus indicating that insecurity involves uncertainty (Sverke et al., 2002).

Finally, occupation insecurity can be divided into two dimensions –global and content insecurity (Roll et al., 2023). Global occupation insecurity relates to people's fear of their full occupation disappearing. On the other hand, content occupation insecurity refers to individual's worries about their occupational tasks and responsibilities changing significantly. It encompasses concerns about aspects of their occupation being automated or outsourced, leaving them with less fulfilling work, or novel tasks for which they have not been trained. This falls in line with much research on job insecurity which differentiates between quantitative and qualitative job insecurity. Quantitative job insecurity refers to perceived threats to the job itself or to its continued existence, thus relating to a fear of job loss (De Witte, 1999; Hellgren et al., 1999). Conversely, qualitative job insecurity is not directly linked to job loss. Instead, it relates to undesirable variations within one's role or the elimination of valued features (Hellgren et al., 1999). This can include the worsening of employment conditions, demotion, absence of career prospects, worsening salary development, or the declining ability to utilise one's current skillset (Hellgren et al., 1999; Nikolova et al., 2023; Sverke & Hellgren, 2002). Employees might expect that they will retain their job but going forward, it might not resemble the position they once enjoyed.

Based upon this idea, Roll et al. (2023) separated occupation insecurity into global and content occupation insecurity. Global occupation insecurity can be linked to quantitative job insecurity. It relates to one's fear of their whole occupation disappearing, thus indicating a "more extreme" version of quantitative job insecurity (Roll et al., 2023). It refers to subjective worries that a person's entire line of work will no longer be relevant going forward. For instance, a lorry driver might worry that their occupation will be fully replaced if autonomous

lorries become more mainstream (Brynjolfsson & McAfee, 2014). Content occupation insecurity is related to qualitative job insecurity. Content occupation insecurity incorporates fears that the tasks and responsibilities of one's occupation will be significantly altered (Roll et al., 2023). As such, components of their job could be automated, perhaps leaving them with tasks which do not fulfil them or that they have not been trained for. Although global occupation insecurity poses a concern for employees within particular industries, it is likely to be a more long-term challenge compared to content occupation insecurity, which reflects the numerous occupational feature and task changes that many professionals are already facing. Therefore, it is likely to pose a more immediate threat.

Although limited research has explored the prevalence of occupation insecurity across the professional population to date, Roll et al. (2023) found in their initial analysis of the concept that 46.7% of their 1373 participants from across the United Kingdom and Belgium reported experiencing perceived content occupation insecurity. Approximately 16.5% of employees reported the perception of global occupation insecurity. With further occupation insecurity research not yet available, I will point to research by Laine et al. (2009) and Lee et al. (2018) who stated that qualitative job insecurity (similar to content occupation insecurity) can be even more widespread than quantitative job insecurity, particularly during periods of rapid change. Blotenberg and Richter (2020) emphasised the importance of gaining a deeper understanding of qualitative job insecurity across the labour market allowing for the identification and development of tools and strategies to equip the labour force to adapt to changes, and to reduce the negative outcomes associated with insecurity. If the worries associated with global occupation insecurity are to materialise, one's occupation will be fully lost. However, with content occupation insecurity, the opportunity to effectively adapt to potential upcoming changes to one's occupation remains. Further, as I highlighted previously, many occupations will experience shifts in the near future due to AI implementation, rather than complete elimination. As such, this thesis will narrow its focus to content occupation insecurity.

2.3.2. Theoretical grounding of insecurity

Before going further, I will explore the theoretical basis of insecurity concepts. Numerous theoretical models have been utilised as a basis for understanding perceptions of insecurity.

These can be applied to investigate the deeper worries of occupation insecurity in the face of AI induced changes. Whilst job insecurity is a relatively stable construct, evidence indicates that it can fluctuate over time (Kinnunen et al., 2014; Klug et al., 2019). The Conservation of Resources Theory (Hobfoll, 1989) posits that humans intrinsically place greater emphasis on resource loss compared to resource gain (Hobfoll et al., 2018). It details that individuals endeavour to hold onto, guard, and build resources, and are threatened by the prospect of resource loss. De Cuyper et al. (2012) emphasised that job insecurity could be understood from a resource-based perspective, with employees prioritising holding onto their job or important job features when feeling insecure. This notion can also be applied to occupation insecurity. If a professional perceives a threat to their valued resources, including for example their skills, knowledge, or occupational tasks, they would, according to the theory, experience a stress response. The Conservation of Resources Theory views stable employment and professional features as valued resources. Thus, the existence of perceived insecurity about losing these, especially when related to one's full occupation, can likely be considered stressful (Van Hootegem et al., 2022). In line with the Conservation of Resources Theory, if one was to face occupation insecurity, one would likely enter "survival mode." Their priorities would be expected to shift to retaining resources, rather than allocating energy to acquiring additional resources.

Similarly, Cognitive Appraisal Theory (Lazarus & Folkman, 1984) can be applied to understand insecurity. The theory proposes that stress is observed as the imbalance between the demands placed on a person, along with the resources they possess to cope. Thus, Lazarus (1991) claimed that stress experiences fluctuate greatly between humans contingent on their interpretation and appraisal of the situation. In essence, cognitive appraisal relates to the one's subjective evaluation of a situation that impacts the degree to which the situation is considered to be stressful (Campbell et al., 2013). There are two important stages in the appraisal process (Adekiya, 2024). Firstly, a primary appraisal is conducted. In this stage, humans determine if a situation is pertinent to their wellbeing, and thus if it can be perceived as threatening. In the context of occupation insecurity, professionals might consider if potential changes to their full occupation or internal tasks pose a threat to their future within their occupation. If a threat is

recognised, a secondary appraisal follows, whereby the individual evaluates their capacity to cope with the situation (Adekiya, 2024). When relating to occupation insecurity, this could be, for example, one's perceived capacity to learn or adapt. Thus, if one believes they can cope, the occupation insecurity could be alleviated. If not, the negative personal and professional consequences associated with insecurity are more likely to be unleashed. By interpreting occupation insecurity through the lens of Cognitive Appraisal Theory, a more in-depth understanding of how professionals psychologically process AI induced occupational changes and how these could materialise into a sense of insecurity. The theory offers insights into why certain professionals could experience greater levels of occupation insecurity than others, despite working in the same occupation.

An additional well-known theory of relevance is the Job Demand-Control Model (Karasek, 1979; Karasek, 1990). The model assumes that a professionals' working conditions can be separated into two general groups - job demands and job resources, both of which are related to certain outcomes (Demerouti et al., 2001). Demands relate to physical, psychological, or social aspects of the job which require continuous physical and/or psychological exertion or skills (Bakker & Demerouti, 2007). These demands are consequently associated with physical or psychological costs to the individual. Bakker and Demerouti (2007) listed high work pressure and unfavourable work environment as examples of demands. Adapting to a changing occupation due to AI induced changes is likely to fall into this category. Bakker and Demerouti (2007) highlighted that demands are not automatically negative. Rather, they might develop into stressors if an employee cannot sufficiently recover (Meijman & Mulder, 1998). On the other hand, resources denote physical, social, psychological, or organisational components which support with achieving professional goals, decrease job demands and their associated costs, or stimulate personal growth and development (Bakker & Demerouti, 2007). Resources are not only necessary to cope with job demands but are also valuable by themselves, aligning with Hobfoll's (1989) Conservation of Resources Theory which, as I discussed above, states that a major human motive is the maintenance of resources (Bakker & Demerouti, 2007). Resources can be utilised as a method

of achievement or allow one to protect their other resources. For instance, occupation security, autonomy, flexibility, task significance, identity, and control, to name but a few.

In general, the theory posits that professionals experience strain when faced with high levels of demands and have limited control or autonomy over their occupational situation and/or possess insufficient resources to cope. Research has previously indicated that persons experiencing perceptions of high demands and low control are most likely to report low workplace engagement and high levels of burnout (Belkic et al., 2004; de Lange et al., 2003; Gameiro et al., 2020; Häusser et al., 2010; Van der Doef & Maes, 2010). The Job Demand-Control Model can be employed in the context of AI induced occupation insecurity. As AI technologies become the norm within one's occupation, professionals might experience intensified demands due to their need to develop new skills, keep up with exponentially advancing technological systems, and adapt to new tasks. Resources such as control could diminish concurrently as professionals' tasks change. This combination of high demands for new skills and low control over occupational tasks they once managed independently could contribute to an amplified sense of occupational insecurity. The aforementioned models, namely the Conservation of Resources Theory, Cognitive Appraisal Theory, and the Job Demand-Control Model can contribute to clarify why AI induced occupational changes might trigger occupation insecurity, and why such insecurity can be considered stressful.

2.3.3. Consequences of occupation insecurity

To date, limited research has explored the consequences of occupation insecurity. Previous job insecurity studies have however linked the concept with a range of negative outcomes. For instance, qualitative job insecurity (most closely linked to content occupation insecurity) was found to be related to decreases in job performance (Callea et al., 2016; Niesen et al., 2018; Stynen et al., 2013), organisational commitment (Vander Elst et al., 2014a), employee wellbeing (Callea et al., 2019; De Witte et al., 2010), and career satisfaction (Otto et al., 2011). Further, job insecurity is associated with increased counterproductive work behaviours, directed towards the organisation and other individuals in the workplace (Van den Broeck et al., 2014), greater turnover intentions (Hellgren et al., 1999), and higher absenteeism (Chirumbolo & Areni, 2005; De Witte et al., 2010; Jiang & Lavaysse, 2018). Guarnaccia et al.

(2016) concluded that job insecurity was negatively related to job satisfaction, general health, and work engagement for both private and public sector employees. Experiences of job insecurity can also contribute to low levels of work engagement (Park & Ono, 2016), increasing anxiety (Cheung et al., 2018), and reduced emotional wellbeing (Vander Elst et al., 2014b). For those experiencing job insecurity, threat and uncertainty form major components of how they perceive their environment (He et al., 2022; Shoss, 2017; Wang et al., 2015).

Roll et al. (2023) posited that the impact of occupation insecurity may go above and beyond that of job insecurity. However, limited research has explored the relationship between the novel concept of occupation insecurity and other variables. To the best of our knowledge, research is limited to the initial exploration conducted by Roll et al. (2023) when developing the concept of occupation insecurity and an applicable scale. They explored the relationship between occupation insecurity and both burnout and work engagement, finding that occupation insecurity was positively related to burnout, with global occupation insecurity showing incremental validity beyond job insecurity. Further, a significant negative relationship was also found between occupation insecurity and work engagement (Roll et al., 2023). These findings support the notion that occupation insecurity can unleash a range of negative outcomes on employees. However, a significant gap in the literature is evident, with additional studies required to examine any potential relationships between occupation insecurity and additional work-related variables. Moreover, as preliminary analyses of occupation insecurity were restricted to participants from the United Kingdom and Belgium, this thesis will strive to gather a more representative Europe wide sample.

Despite the widespread negative connotations associated with job insecurity, it might also lead to several positive consequences under certain conditions. For some professionals, it might foster adaptability, driving them to grasp new skills or find innovative solutions in response to their current uncertain work situation (Jahoda, 1982). In this sense, it could encourage proactive behaviour, for instance networking or personal development, as professionals strive to increase their value in the labour market (Swerke et al., 2002). Furthermore, the uncertainty can stimulate a heightened willingness to learn, as persons recognise the importance of expanding their skills and knowledge to remain competitive

within their occupation. Probst et al. (2007) found that job insecure individuals were in fact more productive than their job insecure counterparts, albeit less creative. Additionally, Staufenbiel and König (2010) concluded that job insecurity can encourage employees to enhance their performance to avoid being laid off. Nevertheless, they concurrently uncovered that job insecurity can also lead to a decrease in work attitudes, thus negatively impacting job performance, turnover intentions, and work attitudes. These contradictory findings emphasise the complexity of the impact of job insecurity, with both negative and positive effects comprehendible. Although by no means guaranteed, professionals who respond positively to job insecurity, particularly by viewing it as a catalyst to grow their occupation relevant skills and knowledge can reap the benefits of remaining relevant in a changing professional climate.

2.4. Informal Learning

2.4.1. Overview of informal learning

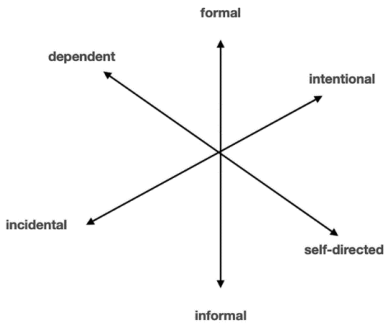
Informal learning could offer a solution for professionals to remain relevant in the labour market. It is a broad term that involves the acquisition of skills or knowledge outside of formal, structured educational and learning environments (Watkins & Marsick, 1992). Although related, it can differ from formal learning which typically refers to the acquisition of skills or knowledge solely through organised programmes such as workshops, training courses, or formal education (Cerasoli et al., 2018). Informal learning can be identified by a range of characteristics. Dron and Anderson (2022) characterised it as typically self-directed and self-regulated. Further, they emphasised that this type of learning can be incidental, with Watkins and Marsick (1992) highlighting that incidental learning is a subset of informal learning. Although Watkins and Marsick (1992) stated that it can be planned or unplanned, learning is not normally the main goal but rather a byproduct of doing something else.

Informal learning does not typically contain rules. It can take place in non-educational settings and does not demand systematic support to encourage such learning (Tannenbaum et al., 2009). It is open-ended and can take place at any time and any place, including for instance within a formal learning event (Dron & Anderson, 2022). Whilst Dron and Anderson (2022) accepted that any of these characteristics can also occur in a formal learning setting, they stated that if enough of them are present, it can enable us to describe the type of learning

as informal. Dron and Anderson (2022) did note that both informal and formal learning lie on a spectrum, with the existence of a certain level of indistinctiveness. However, for clarity, they developed a learning spectrum (see Figure 1), within which informal is characterised as largely incidental and self-directed, whilst formal is dependent and intentional (Dron & Anderson, 2022).

Figure 1

Learning spectrum diagram



Various studies of informal learning noted that it encompasses behaviours and cognitive activities that are other-focused or self-focused (Cerasoli et al., 2018; Doornbos et al., 2008; Lohman, 2005). Noe et al. (2013) divided these behaviours and actions into three dimensions, namely learning from oneself, learning from others, and learning from non-interpersonal resources. Learning from oneself involves trialling new methods of performing and reflecting upon one's own performance (Noe et al., 2013). It is often driven by reflection which enables employees to develop a better understanding of their work. It allows professionals to connect past work experiences and current tasks at hand, making past experiences accessible for future actions (Froehlich et al., 2023; Kolodner, 1992). Reflecting enables one to self-regulate their work processes by connecting actions, plans, and the results of their professional performance. It also allows individuals to link their own perspectives with those of their colleagues.

Learning from others encompasses interacting with colleagues and superiors to gain feedback and develop performance improvement strategies. Crans et al. (2022) and Leiß et al. (2022) emphasised the importance of consulting with or seeking feedback from colleagues. Learning from others has also been shown to have positive consequences for careers

(Froehlich et al., 2019), mental health (Beausaert et al., 2021), and innovation processes (Froehlich & Messmann, 2017). Finally, Noe et al. (2013) defined learning from non-interpersonal resources as involving reading various publications or searching the internet for information and resources. With podcasts becoming increasingly popular, they are likely to fall into this latter category, allowing listeners to acquire up-to-date knowledge and information across a wide range of professional topics (Kelly et al., 2022; Kocak & Alagozlu, 2021; Riddell et al., 2020). Prior literature has concluded that partaking in these activities is associated with improvements in a range of professional and general competencies, thus evidencing their relevance (Froehlich et al., 2015; Van Der Heijden et al., 2009). Moreover, these dimensions have previously been noted as important components of informal learning, with relationships found between them and other significant professional variables such as employability and perceived career development (Froehlich et al., 2014; Van der Rijt et al., 2013). For this thesis, Noe et al.'s (2013) three dimensions: learning from oneself, learning from others, and learning from non-interpersonal resources will be utilised to define informal learning behaviours.

2.4.2. Importance of learning in the face of occupational change

With occupations and related tasks and required skills changing due to AI implementation, continuous adaptation is required in the workplace. As Falconer et al. (2013) mentioned, we are occupying a world where knowledge and work are changing so quickly that individuals must continuously learn (Falconer et al., 2013). Strack et al. (2021) highlighted that an adaptable workforce that is prepared to continuously learn over time as the demand for different skills evolves is essential. Although formal learning certainly has its place, it more often takes place episodically, earlier in life, and can be removed from its "context of application" (Dron & Anderson, 2022). It can also be largely driven by extrinsic factors such as getting good grades or receiving a certificate, rather than from intrinsic interest or motivation (Dron & Anderson, 2022; Ryan & Deci, 2017). Dron and Anderson (2022) explained that informal learning, whether chosen or incidental to actions or behaviours that are occurring regardless that can take place at any time or place is fundamentally motivating, thus meeting needs for autonomy, competence, and generally relatedness which form major

elements of intrinsic motivation (Ryan & Deci, 2017). As such, informal learning enables professionals to accumulate new skills and remain relevant as new tasks and challenges arise in their current surroundings, rather than limiting their learning to formal settings. Informal learning can offer a method for employees to enhance their employability and adjust to changing occupational demands (Froehlich et al., 2014; Van Der Heijden et al., 2009). Dron & Anderson (2022) noted that informal learning offers many benefits, compounded due to its accessibility and low cost. It can be driven by and allow individuals to adapt according to immediate professional needs. As well as not being defined by an "end goal" such as a grade or certificate, particularly as said goal is likely to adjust rapidly, informal learning can offer the potential for more meaningful learning experiences within one's own workplace compared to those which formal training allows for (Benson, 1997; Tannenbaum et al., 2009). Overall, informal learning can offer a plethora of professional benefits, particularly in terms of allowing workers to adapt quickly in the face of change.

2.4.3. Content occupation insecurity and informal learning

Nevertheless, and despite their apparent importance, partaking in informal learning behaviours is largely at the discretion of the individual (Noe et al., 2013). They are not initiated by others, somewhat like organisational citizenship behaviours which are viewed as being more "optional" in the workplace. It is determined by an individual's own decision and motivation to partake in the dimensions of informal learning identified by Noe et al. (2013), i.e., "to interact with others, reflect on their experiences, and seek information." Secondly, informal learning does not necessarily happen when it is required, such as when the task or features of one's occupation are changing due to AI implementation (Noe et al., 2013). Internal and external factors can influence such participation. As stated previously, occupation insecurity is negatively related to work engagement, and positively related to burnout. However, studies have not yet explored any possible connection between occupation insecurity and informal learning behaviours. Professionals experiencing content occupation insecurity might benefit the most from participation in informal learning behaviours to acquire the necessary skills to adapt to potential occupational feature changes. The lack of research

investigating the relationship between content occupation insecurity and informal learning behaviours highlights an open research area which this thesis will begin to explore.

Whilst content occupation insecurity has not yet been researched in relation to any form of learning, one can turn to several studies surrounding job insecurity and learning behaviours. For example, De Cuyper et al. (2022) concluded that higher qualitative job insecurity led to reduced participation in formal work-related learning. Van Hootegem et al. (2023) noted that job insecurity had a direct effect on participation in development activities, with increases in job insecurity related to decreases in participation in development activities. Moreover, Van Hootegem and De Witte (2019) concluded that professionals who are qualitatively insecure (in line with content occupation insecurity) are less likely to partake in informal learning, a relationship which was found to be mediated by a decrease in occupational self-efficacy and an increase in psychological contact breach. Research is not however fully conclusive yet, with concurring evidence also existing. For instance, Cheng (2022) attained results indicating that employees experiencing higher levels of job insecurity were more likely to partake in formal learning programmes organised by their organisation. Important to note, however, is that this study only explored firm-organised formal learning, rather than self-initiated informal learning. Nevertheless, studies exploring the relationship between job or occupation insecurity and informal learning are in their infancy.

Although due to the novelty of the construct of occupation insecurity, limited research has explored its effects, the experience of job insecurity with its similar underlying characteristics appears to induce a state of relative passivity (Shoss, 2017; Van Hootegem et al., 2022). This falls in line with the Conservation of Resources Theory which emphasised that heightened levels of stress related to the perceived potential loss of resources (for example, valued aspects of one's occupation) trigger a defensive position to conserve remaining resources, with conservation outlined as more important than the acquisition of new resources (Hobfoll, 1989; Van Hootegem et al., 2022). Therefore, as Van Hootegem et al. (2022) pointed out, humans would reduce their investments in engaging in behaviours and activities, such as informal learning behaviours which could put remaining resources under further pressure (Hobfoll,

2001; König et al., 2010). As informal learning involves resource gain, those experiencing occupation insecurity would not be expected to partake in such activities.

This view can be further cemented using Cognitive Appraisal Theory, whereby perceived changes to one's occupation could be considered threatening. If the individual believes that they are unable to cope, they would be expected to be more likely to withdraw and focus on directing their remaining resources toward immediate survival rather than investing in the long-term. Thirdly, according to the Job Demand-Control Model, persons experiencing perceptions of high demands and low control could be considered less likely to partake in productive behaviours like informal learning. In line with previous research and the theoretical background outlined, I hypothesise the following:

Hypothesis One (H1): Content occupation insecurity is negatively associated with informal learning.

2.5. Occupational Self-Efficacy

2.5.1. Overview of self-efficacy

Self-efficacy "refers to beliefs in one's capabilities to organise and execute the courses of action required to produce given attainments" (Bandura, 1997). It essentially highlights the significance of one's own perceptions of their capabilities as central factors contributing to successful outcomes (Gallagher, 2012). The construct of self-efficacy stems from Bandura's (1977) Social Cognitive Theory. Self-efficacy highlights the significance of one's own perceptions of their capabilities as central in contributing to successful outcomes (Gallagher, 2012). The theory of self-efficacy focuses on how humans can be empowered with a sense of agency that will enable them to achieve their goals. It is a malleable concept that indicates a person's subjective confidence in their capacity to perform and succeed, rather than offering an objective appraisal of their abilities or skills (Gist & Mitchell, 1992; Ryan, 1999).

Bandura (1977, 1986) posited that self-efficacy impacts an individual's selection of persistence, effort, and activities, with Bandura (1977) also highlighting that one's own beliefs normally have a greater impact on decision-making outcomes, motivation levels and outcomes than what is objectively true. Self-efficacy impacts almost every aspect of an individual's life.

These beliefs establish the basis for human motivation, well-being, and personal achievement (Bandura, 1997). If one believes that they cannot succeed in the task put in front of them, they are less likely to even try. Thus, humans lean towards performance when they are confident in their abilities and avoidance when they are not (Pajares, 2002). Bandura (1977) posited that self-efficacy beliefs influence effort expended, persistence, and activity selection. Persons with high self-efficacy are more likely to challenge themselves, allocate more energy to the attainment of their goals, and persevere for longer in the face of adversity (Bandura, 1997; Bandura, 2012). Doubting one's own abilities can lead to negative outcomes.

The information utilised to form self-efficacy beliefs is derived from four sources, i.e., mastery experiences, vicarious experiences, verbal persuasion, and physiological and affective states (Pfitzner-Eden, 2016). Mastery experiences refer to information about one's own past achievements and failures, with achievements typically enhancing self-efficacy beliefs, whilst failures can trigger the opposite effect. Vicarious experiences involve witnessing another attain, for instance a peer. Verbal persuasion involves being convinced by important individuals in one's life of one's capabilities, strongly swayed by the perceived credibility, trustworthiness, and expertise of the persuader (Bandura, 1977). Finally, a person's interpretation of their physiological and affective cues when judging their own capabilities impacts their self-efficacy. It should be noted that the information obtained from these sources does not independently impact self-efficacy (Schunk, 1996). Instead, the information is cognitively appraised by the individual (Bandura, 1986). When an individual appraises a situation, they evaluate the demands of the situation, their available resources, and their individual capacity to meet those demands. Persons with high self-efficacy are theorised to be more likely to persevere, and recover quickly from setbacks, as they trust in their ability to control outcomes. Conversely, those with low self-efficacy might appraise the exact same situation as overwhelming and are more likely to give up when faced with difficulties (Bandura, 1997).

2.5.2. Introduction to occupational self-efficacy

Self-efficacy has been widely divided into two concepts, i.e., domain-specific self-efficacy and generalised self-efficacy (Arenius & Minniti, 2005; Baum et al., 2001; Markman et al.,

2005; Shang et al., 2022; Zhao et al., 2005). Occupational self-efficacy is a domain-specific type of self-efficacy (Füllemann et al., 2015). Although distinct, it was found to be closely related to generalised self-efficacy (Schyns & Von Collani, 2002; Sherer et al., 1982). Occupational self-efficacy can be defined as a personal resource that relates to one's beliefs in their own abilities to perform successfully within their occupational domain; a definition that will be utilised in this research paper (Abele & Spurk, 2009; Spurk & Abele, 2014).

Füllemann et al. (2015) stated that extremely narrow, task-specific measures of self-efficacy, for instance a person's capacity to prepare for and conduct a sales call, would allow for the highest predictive and explanatory power due to its elevated level of specificity. However, its applicability would be extremely limited as only the segment of the population partaking in sales activities would be accounted for (Füllemann et al., 2015). On the other hand, Füllemann et al. (2015) emphasised that although occupational self-efficacy is of intermediate specificity, it nevertheless remains exclusively relevant to the occupational setting, rather than solely measuring generalised self-efficacy. Further, in comparison to task-specific measures of self-efficacy, occupational self-efficacy can be utilised to compare a range of occupations, organisations, and industries, offering far more versatility (Bandura, 1997; Füllemann et al., 2015; Schyns & Von Collani, 2002). Due to its wider applicability, occupational self-efficacy will be utilised in this thesis.

Occupational self-efficacy is a valuable personal resource, particularly in the rapidly changing modern labour market (Füllemann et al., 2015). Professionals who possess stronger occupational self-efficacy beliefs are likely to perceive the demands of adjusting to change as less stressful and more stimulating. More, they are likely to consider additional resources to be more plentiful and to handle demanding situations in a more problem-oriented manner, thus leading to less stress and greater professional engagement and performance (Cifre et al., 2011; Füllemann et al., 2015; Salanova et al., 2006). It should be noted that Cifre et al. (2011) and Salanova et al. (2006) did not directly explore occupational self-efficacy, but rather 'professional self-efficacy,' another domain-specific form of self-efficacy which is nonetheless deemed comparable to occupational self-efficacy.

Prior research has also found significant positive relationships between occupational self-efficacy and work performance, as well as work engagement, general health, and job satisfaction (Çetin & Aşkun, 2018; Guarnaccia et al., 2016; Paggi & Jopp, 2015). Further, Liu and Huang (2019) discovered that occupational self-efficacy directly impacted organisational commitment, whilst also indirectly affecting work engagement. Onyishi et al. (2018) highlighted the protective qualities of occupational self-efficacy, demonstrating that it moderated the relationship between quantitative job demands (in this instance, quantitative job demands were measured by asking participants various questions surrounding how fast and hard they must work) and psychological well-being. In general, self-efficacy can also buffer against the negative effects of burnout (Shoji et al., 2016; Wallin et al., 2023).

2.5.3. Occupational self-efficacy in the face of insecurity

In line with the Conservation of Resources Theory, those who are in stressful situations, for instance due to perceived occupation insecurity will focus on conserving their other resources (Hobfoll, 2001; Van Hootegem et al., 2022). Thus, professionals experiencing insecurity might be less likely to further enhance their occupational self-efficacy, particularly as self-efficacy necessitates time and effort investments (Bandura, 2000; Van Hootegem et al., 2022). Further, if employees withdraw from the professional situation so as not to place stress on their remaining resources, Van Hootegem et al. (2022) considered that they are less likely to experience positive occupational occurrences, including positive affect or feelings of mastery. As these experiences are valuable sources of self-efficacy, it can induce a cycle of self-efficacy depletion (Bandura, 1977).

Although no research to date has explored the relationship between content occupation insecurity and occupational self-efficacy, prior studies have examined the relationship between job insecurity and self-efficacy. Many studies reported a negative connection between the two variables. For instance, König et al. (2010) noted a strong negative correlation between job insecurity and general self-efficacy. Etehadi and Karatepe (2018) found that job insecurity negatively impacts generalised self-efficacy. Additionally, Guarnaccia et al. (2016) concluded that insecure contract types are linked with lower occupational self-efficacy. They also observed a significant partial mediation effect by occupational self-efficacy for the

relationships between job insecurity, work engagement, job satisfaction and general health (Guarnaccia et al., 2016). In a longitudinal study, Alisic and Wiese (2020) reported that increases in career insecurity predicted decreases in occupational self-efficacy. Van Hootegem et al. (2022) also supported these findings, noting in their study that changes in both qualitative and quantitative job insecurity were linked with changes in occupational self-efficacy. I consequently put forth that content occupation insecurity is negatively associated with occupational self-efficacy:

Hypothesis Two (H2): Content occupation insecurity is negatively related to occupational self-efficacy, in that higher levels of content occupation insecurity will be associated with lower levels of occupational self-efficacy.

2.5.4. Importance of occupational self-efficacy for participation in informal learning behaviours

If professionals want to participate and succeed in informal learning behaviours, they must believe that they can do so (Maurer & Tarulli, 1994). Thus, professionals possessing higher levels of occupational self-efficacy might be better equipped to deal with occupational changes through informal learning behaviours and the associated acquisition of relevant skills and knowledge. Previous research has already illustrated that self-efficacy plays an important role in employee development (Bandura, 1997; Ryan, 1999; Van Hootegem et al., 2022). It was identified as a valuable initial step in the learning process (Zimmerman, 2000). Alisic and Wiese (2020) additionally highlighted that self-efficacy is a crucial cognitive and behavioural resource for personal development and change. In their meta-analysis on self-regulated learning, Sitzman and Ely (2011) discovered that self-efficacy showed a strong correlation with learning (Van Hootegem et al., 2022).

Further, another form of self-efficacy, memory self-efficacy seems to be a critical antecedent to professionals' participation in training and development activities (Schulz & Roßnagel, 2010). Kyndt et al. (2011) found that self-efficacy was a significant positive predictor of formal learning intentions in low-qualified employees. Similarly, Renkema (2006) related self-efficacy to formal learning intentions. Maurer et al. (2003) found that self-efficacy for development significantly affected attitudes towards development. It also had an indirect

effect on participation in learning and development activities as employees with higher self-efficacy not only had more favourable attitudes towards development but also cultivated more robust intentions to participate in learning activities. These intentions consequently led to actual participation (Maurer et al., 2003).

From a theoretical perspective and in line with our base theories, specifically the Conservation of Resources Theory (Hobfoll, 1989), I expect that occupational self-efficacy could act as a personal resource. Resources can help to buffer against the negative effects of stressful experiences and support with coping when faced with perceived "demands", e.g., partaking in informal learning behaviours to more positively deal with the changes brought about to one's occupation by AI. Therefore, I propose that occupational self-efficacy is positively related to informal learning behaviours:

Hypothesis 3 (H3): Occupational self-efficacy is positively related to informal learning, in that lower occupational self-efficacy will be associated with reduced informal learning behaviour.

Finally, considering the proposed mediating role of occupational self-efficacy, it is hypothesised that:

Hypothesis 4 (H4): Content occupation insecurity negatively influences informal learning through occupational self-efficacy.

2.6. Future Focus

2.6.1. The concept of temporal focus

Future focus refers to an individual's tendency to focus on what is to come; imagining and considering the steps required to attain their future goals (Shipp et al., 2009). The concept stems from the idea of temporal focus which comprises thinking about the past, present, or future without stating the specific attitudes or thoughts involved (Shipp et al., 2009). Bluedorn (2002) referred to temporal focus as a means through which humans can mentally 'time travel,' encompassing past, present, and future experiences and expectations into their behaviour, attitudes, and cognitions. Shipp et al. (2009) noted that the distinct multidimensional nature of the concept allows individuals to direct their attention across three

periods of cognitive focus in varying degrees. However, although an individual might direct much of their attention towards one of the dimensions, this does not prevent them from simultaneously paying attention to the other dimensions. For instance, a human could experience a high degree of future focus, without neglecting the past and present.

Shipp et al.'s (2009) conceptualisation of temporal focus, from which I base the 'future focus' variable differs from related time-related concepts such as temporal and time orientation. For context, temporal orientation refers to cognitive preoccupation in the past, present, or future (Shipp et al., 2009; Zimbardo et al., 1997; Zimbardo & Boyd, 1999), with Holman and Silver (1998) positing that an individual can become trapped in any one of these time periods. Similarly, time orientation involves a person's thoughts and behaviours mainly aimed at the past, present, or future (Nuttin, 2014). These concepts thus consider time perception as existing on a continuum. On the other hand, the concept of temporal focus posits that the past, present, and future are distinct frames, and can occur concurrently in differing degrees. Shipp et al., 2009 noted that boxing an individual into one of the three dimensions was simplistic, and hinders a balance between past, present, and future.

Shipp et al. (2009) posited that each individual is in possession of a unique 'temporal focus profile,' to which future focus belongs, depicting the extent to which a person focuses their attention on the past, present, and future in differing intensities. A person's temporal focus profile is comprised of stable and fluctuating elements - a stable element (i.e., dominant temporal focus) and a fluctuating element which can be altered by external factors such as personal experiences and education (i.e., events dependent). Dominant, or stable temporal focus is rooted in a person's cultural and childhood experiences (Shipp & Aeon, 2019). The degree to which one generally focuses on the past, present, and future can be influenced by culture and childhood experiences. For example, Ji et al. (2009) found that Chinese participants focused on the past to a greater extent than Canadian participants. More, Yau (1988) concluded that Chinese participants were normally brand loyal, indicating strong levels of past focus. In relation to childhood experiences, Van Gelder et al. (2018) found that exposure to harsh and inconsistent parenting practices leads to the development of "short-sighted" or present focus as an adaptive measure, with less attention paid to the future. Despite

this stable aspect, fluctuations do occur, for example due to ageing or life events, particularly those which question values and priorities (Koen & van Bezouw, 2021; Shipp & Aeon, 2019). To illustrate, the 9/11 terrorist attacks initially triggered a greater present focus, with a stronger past focus still lingering a year on (Holman & Silver, 2006; Holman et al., 2016).

2.6.2. Future focus and occupation insecurity

As major events can trigger a fluctuation in future focus (see Koen & van Bezouw, 2021; Shipp & Aeon, 2019), it is not unrealistic to anticipate that global AI induced changes and their anticipated impact on individual occupations could alter one's temporal focus profile. In line with the Conservation of Resources Theory, those in precarious situations tend to focus more on maintaining the resources that they do have. Their focus shifts to short-term solutions, rather than future planning (Koen & van Bezouw, 2021). This implies a potential reduction in future focus. To date, limited research has explored the impact of insecurity on future focus. One initial exploration by Koen and van Bezouw (2021) concluded that one type of job insecurity – affective job insecurity, was unrelated to future focus. Nevertheless, their data was collected during the Covid-19 pandemic, with the researchers highlighting that the "temporary" nature of perceived pandemic related insecurity could have influenced results. This insecurity was unlike the more permanent insecurity unleashed by AI. In a similar line, Lam et al. (2019) found that job insecurity led to a reduction in the future time perspective of casino employees. I consequently propose a deeper exploration into the effects of perceived insecurity with long-term consequences, i.e., content occupation insecurity on future focus:

Hypothesis 5 (H5): Content occupation insecurity is negatively related to future focus, in that higher levels of content occupation insecurity will be associated with lower levels of future focus.

2.6.3. Future focus and informal learning behaviour

Each temporal focus dimension – past, present, and most importantly for the purpose of this study – future, can impact what information is relevant for individuals (Shipp et al., 2009). Further, they affect a person's current attitudes, behaviours, and decisions (Shipp & Aeon, 2019; Shipp et al., 2009). A strong past temporal focus can make one more likely to dwell on

times gone by, seeing fewer motives to change (Shipp et al., 2009; Zimbardo & Boyd, 1999). Individuals with a strong present focus tend to pay attention to the "here and now." This temporal focus has been linked with spontaneity and the act of grasping immediate opportunities (Shipp et al., 2009). Finally, and perhaps most relevant for this study, those with high levels of future focus place more emphasis on thinking about what is to come, imagining and considering the steps necessary to attain their future goals (Shipp et al., 2009). This falls in line with the idea that goals are future-oriented, thus individuals with a higher degree of future focus might direct a greater amount of their cognitive attention towards their objectives.

The extent to which a person focuses on the future might reflect the degree to which they take immediate versus more distant consequences into account (Parker & Collins, 2010; Strathman et al., 1994). Individuals with higher levels of future focus are more inclined to set objectives and act in a proactive manner and are less likely to procrastinate (Alberts & Dunton, 2008; Ferrari & Díaz-Morales, 2007; Lasane & Jones, 1999; Seijts, 1998; Shipp & Aeon, 2019). Future focus is related to a long-term outlook and the consideration of potential future outcomes of one's actions. Shipp and Aeon (2019) noted that by paying more attention to potential future consequences, those with a greater future temporal focus were more likely to exercise and eat healthily, oftentimes offering long-term benefits rather than immediate pleasure. Strobel et al. (2013) demonstrated that future focus positively influences the organisational citizenship behaviours of altruism, civic virtue, and courtesy. From a professional standpoint, future focus could act as a personal resource, with those possessing a high level of future focus found to be more likely to actively plan for their professional future (Zacher, 2014). He et al. (2022) noted that future work self-salience can act as a "compass," navigating professionals towards consistent focus on and investment in behaviours that help them to achieve their future work goals, for example accumulating skills in their current position.

Strauss et al. (2012) found that the more salient one's 'future work self' is (i.e. the extent to which an individual has a clear and accessible mental image that reflects their aspirations for their future work self), the more likely they were to proactively develop their skills and attain career-relevant resources. It can act as a source of motivation for professionals as they

strive to identify and attain goals to fill the gap between their current self and the one present in the image that they have manifested (He et al., 2022). More, Koen and van Bezouw (2021) found that future focus was a necessary determinant of proactive career behaviours (i.e., building resources to master or change one's career, for example developing new technical skills or building one's network), whereby those with a higher level of future focus were more likely to partake in such proactive activities. Similarly, future work self-salience – a similar concept, was linked to positive outcomes such as proactive career behaviours, work engagement, and career adaptation (Guan et al., 2014; He et al., 2022; Taber & Blankemeyer, 2015). More, He et al. (2022) concluded that future work self-salience moderated the negative impact of job insecurity on proactive career behaviours. I propose that a high level of future focus is the most relevant temporal dimension for preparing oneself for a changing occupation, comprised of novel requirements and tasks:

Hypothesis 6 (H6): Future focus is positively related to informal learning behaviour, in that lower levels of future focus will be associated with reduced informal learning behaviour.

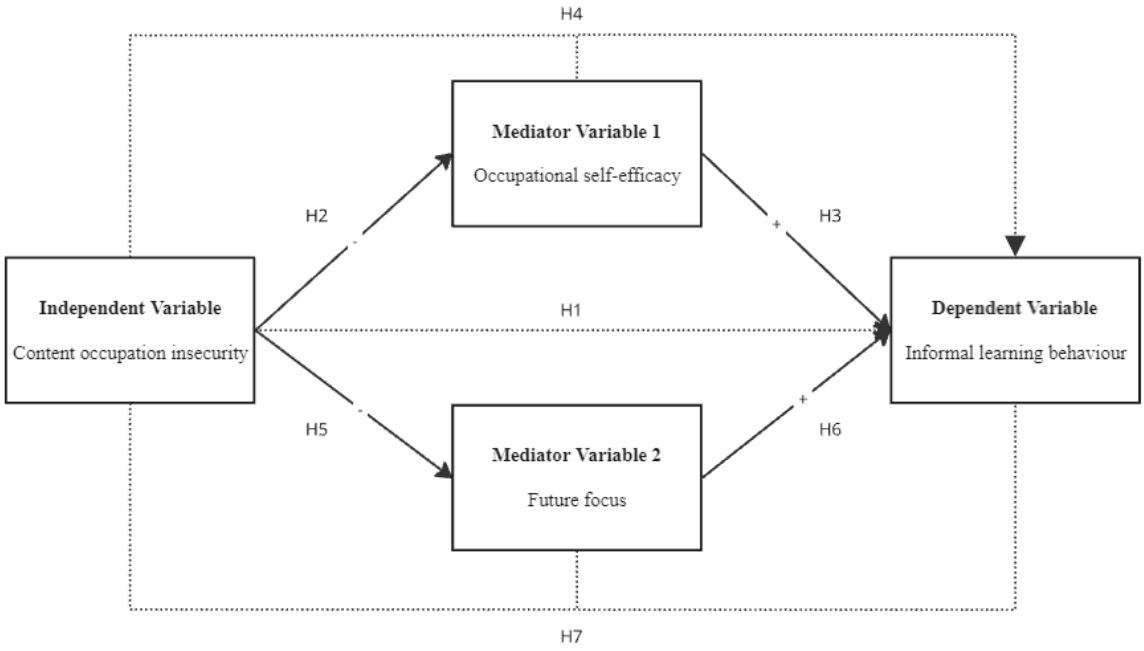
Considering the proposed mediating role of future focus, it is hypothesised that:

Hypothesis 7 (H7): Content occupation insecurity negatively influences informal learning through future focus.

The conceptual model for this study is visualised in Figure 2.

Figure 2

A visual overview of the conceptual model for this thesis



3. Methodology

3.1. Research Design

A quantitative research design was utilised, comprising a cross-sectional survey to examine the relationships between content occupation insecurity, informal learning, and the mediating roles of occupational self-efficacy and future focus. The main goal was to examine the direct effects of content occupation insecurity on informal learning, as well as the indirect effects via occupational self-efficacy and future focus using a parallel mediation model. By exploring these relationships concurrently, the study aimed to offer insights into the ways through which content occupation insecurity might affect informal learning. The thesis also included attitudes toward change and resilience as covariates. The study took place online through the Qualtrics platform (Qualtrics, 2004). Online surveys are low cost and can open the study to a wider potential sample as participants do not need to be in one place at once (Evans & Mathur, 2005). Confidentiality and anonymity can additionally be assured. The survey was designed to be completed within 8 minutes, ensuring that the associated time-related burden was limited for those taking part, whilst still allowing for broad data collection.

A cross-sectional design is an observational study design (Setia, 2016). It does not necessitate the manipulation of participants nor the study environment, allowing for the examination of real-world phenomena as they naturally happen without changing conditions (Simkus, 2023). A cross-sectional study involves the collection of data at one point in time, enabling the exploration of associations among variables. Data relating to all variables can be collected at once. The design is typically inexpensive and not time consuming, thus useful for gathering data from a larger population within a short period of time (Wang & Cheng, 2020). Whilst the design does not allow for the identification of causal relationships, it is particularly helpful for providing a snapshot into current correlations, which can also advise later longitudinal studies. Further, as AI is rapidly altering the labour market, a cross-sectional study can offer a valuable snapshot into how individuals currently perceive its impact on their occupation, as well as their current informal learning behaviours. The efficiency of this design can quickly inform organisations and policy makers.

3.2. Participants and Data Cleaning

167 responses were obtained. 21 responses were removed from analyses due to incomplete data, i.e., they did not fill the scales required for the mediation analysis. After elimination, a valid sample size of 146 participants remained. Participants ages ranged 19 to 69 (M=37, SD=14.3). Overall, 97 identified as female, 48 as male, and 1 as other. Participants were employed in a range of European countries, namely the United Kingdom (43.2%), Ireland (32.2%), Germany (18.5%), Switzerland (3.4%), the Netherlands (1.4%), Austria (0.7%), and Portugal (0.7%). Data relating to the industry of participants were also collected, with most participants employed in the education sector (18.5%), followed by the business and financial sector (15.1%) and as healthcare practitioners (13.7%). Most participants had completed a bachelor's degree (49.9%), followed by an equal number of participants having graduated from high school (19.9%) and completed a master's degree (19.9%). See Appendix A for a full overview of descriptive statistics. All participants were engaged in permanent employment for at least twenty hours per week. Participants did not receive compensation for participating.

3.3. Measures

Content Occupation Insecurity The Occupation Insecurity Scale, developed by Roll et al.'s (2023) was used to measure content occupation insecurity. The scale contained two subscales, each measuring a separate dimension of occupation insecurity, i.e., global (6 items) or content (5 items). For this thesis, the 5 insecurity items were used. In line with the original scale, a differentiation between "occupation" and "job" was provided prior to scale commencement, including definitions and a relevant example. Participants were asked to consider each statement in relation to AI, leading to slight tweaks in the wording of scale items, i.e., the replacement of the word "technology" with "artificial intelligence." All items were rated on a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree." Examples of items included "I expect that my occupation will undergo significant changes due to AI developments." See Appendix B for scale items used in this thesis. Items were randomised, and reverse-scored when required. Roll et al.'s (2023) determined that reliability for the content occupation insecurity subscale was good, standing at $\alpha = 0.83$.

Informal Learning Behaviours Noe et al.'s (2013) informal learning scale was utilised to measure informal learning behaviours. The scale was based on prior research on informal learning by Bear et al. (2008), Lohman (2005), and Lohman and Woolf (2001). The measure included three items each to represent learning from non-interpersonal resources, oneself, and others, totalling nine items. Noe et al. (2013) chose to combine these three factors due to their level of intercorrelations. Participants were asked to reflect upon the past three months and specify how often they partook in a selection of informal learning behaviours in an average working week ("Consider the past three months. How often during a typical work week have you engaged in the activities below in order to learn and help you better perform your job?"). Slight tweaks were made to four scale items to ensure clarity and relevance for today's workforce (see Appendix C for a list of scale items used). A five-point Likert style response scale was provided, with response options ranging from "never" to "all the time." Items were randomised. This measure has been used to explore informal learning behaviours, with good reliability reported. Noe et al. (2013) reported $\alpha = .86$ in their initial use of the scale items.

Future Focus The Temporal Focus Scale, created by Shipp et al. (2009) was used in this study. The full scale comprises three subsections, consisting of four items each for past, present, and future focus. To measure future focus in this thesis, the four future focus items were utilised in their existing form (see Appendix D). Participants were told that the following statements related to their thoughts about the future and asked to indicate how often they experienced these thoughts on a 7-point Likert scale, ranging from 1 (never) to 7 (constantly). An example item was "I focus on my future." Shipp et al. (2009) reported $\alpha = .86$ for the four future focus items. This measure has been utilised in previous studies (e.g., Koen & van Bezouw, 2021).

Occupational Self-Efficacy A short version of the Occupational Self-Efficacy Scale, adapted by Rigotti et al. (2008) was used to measure occupational self-efficacy. This six-item scale was based upon a long version of the Occupational Self-Efficacy Scale, first designed by Schyns and von Collani (2002) and containing 20 items. The original scale was formed using four different scales which were reformulated for the work context, namely the General Self-Efficacy Scale (Scherer et al., 1982), the Generalised Self-Efficacy Scale (Schwarzer, 1994),

the Heuristic Competence Scale (Stäudel, 1998), and the Hope Scale (Snyder et al., 1991). Schyns and Von Collani (2002) also released a shortened eight item version, further reduced to six items by Rigotti et al. (2008). Slight tweaks were made to ensure that responses were related to one's occupation rather than their job, i.e., the word "job" was replaced with "occupation." A sample item included "I can remain calm when facing difficulties in my occupation because I can rely on my abilities." Participants were asked to rate the items on a 6-point Likert scale, ranging from 1 (not at all true) to 6 (completely true). See Appendix E for a list of scale items. High values indicate high occupational self-efficacy. Rigotti et al. (2008) reported high reliability for the scale, ranging from $\alpha = 0.85$ to 0.90 across five country samples.

Attitudes toward Change – Covariate Attitudes toward change are comprised of "a person's cognitions about change, affective reactions to change, and behavioural tendency toward change" (Dunham et al., 1989, p. 5). It serves as a key construct, or conceptual state that impacts employees' support of organisational change and was included as a covariate in this study (Choi, 2011). The short version of Dunham et al.'s (1989) Attitude Toward Change Instrument was utilised. The initial measure contained 52 items and was comprised of three dimensions – cognitive, affective, and behavioural intent. The developers selected 18 items for a shorter version of the scale, containing 6 items for each of the three dimensions (see Appendix F). A sample item was "I find most changes to be pleasing." Participants were provided with the following information, "The following statements relate to various aspects of change at work. Please read each statement carefully and indicate the extent to which you agree or disagree with it." They were asked to rate items on a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree." The coefficient alpha reliability for a single 18-item scale was reported as 0.90 (Dunham et al., 1989).

Resilience – Covariate Resilience can be defined as one's ability to bounce back from or recover from stress (Smith et al., 2008). It has been recognised as a salient psychological construct for employees in dealing with workplace difficulties (Bardoel et al., 2014; Le & Le, 2024). Thus, it was thus included as a covariate in this study. Smith et al.'s (2008) Brief Resilience Scale was utilised. There were 6 items in this measure (see Appendix G), for

example “I tend to bounce back quickly after hard times.” Participants were asked to respond to each statement on a 5-point Likert scale, with answer options ranging from “strongly disagree” to “strongly agree.” Items were randomised and reverse scored when necessary. Good internal consistency and test-retest reliability has been reported for the measure, with the Cronbach’s alpha ranging from 0.80-0.91 across four samples (Smith et al., 2008). Highlighting its widespread usage, Smith et al. (2023) noted that by mid-2022, the Brief Resilience Scale had been cited over 3800 times in Google Scholar, translated into over twelve languages, and employed around the world in more than twenty-four countries.

3.4. Ethical Considerations

Potential ethical issues were identified prior to the commencement of data collection. This study involved a degree of intransparency as participants were not fully aware of the study aims. However, full disclosure was provided at the conclusion of the study when participants were debriefed. We also invited participants to contact the researcher, should any queries arise. This study dealt with the potentially triggering topic of occupation insecurity. We thus reminded participants that they were free to leave the study at any stage without consequences. Moreover, data collected were fully anonymous.

3.5. Procedure

We pre-registered the hypotheses and research design with the Catholic University of Portugal School of Psychology (see Appendix H). This study took place via Qualtrics. Participants were recruited through convenience sampling, specifically word of mouth with snowball sampling also taking place, and by posting in various Microsoft Teams channels at the main researcher’s current workplace, diconium GmbH (Goodman, 1961). Before the study commenced, participants viewed an information sheet (see Appendix I). A brief definition of AI was provided to ensure that all participants understood the technology (see Appendix J). Participants then completed the informal learning scale (Noe et al., 2013), the content subscale of the Occupation Insecurity Scale (Roll et al., 2023), the Brief Resilience Scale (Smith et al. (2008), the Occupational Self-Efficacy Scale (Rigotti et al., 2008), the Future Focus subscale from the Temporal Focus Scale (Shipp et al., 2009), and the Attitudes Toward Change Scale (Dunham et al., 1989). After completing the scales, participants were asked to provide

demographic information, specifically their age, gender, country of employment, highest level of education or training completed, and occupational category. They were then thanked for their participation, debriefed, and advised that they could reach out to the main researcher in case of any queries (see Appendix K for an overview). We transferred data into the IBM Statistical Package for the Social Sciences for Macintosh, Version 29.0 (IBM Corp., 2023).

3.6. Data Analysis Plan

Data were cleaned and prepared, items were reverse scored where necessary, composite variables were formed, and scale reliabilities were measured. To test the hypotheses, I employed a parallel mediation model to explore the relationships between content occupation insecurity and informal learning behaviours. This enabled the assessment of the direct effect of content occupation insecurity on informal learning behaviours and the indirect effects through occupational self-efficacy and future focus. I explored how self-perceived content occupation insecurity impacted both occupational self-efficacy and future focus respectively, and how these variables influenced informal learning behaviours. Attitudes toward change and future focus were included as covariates. A Monte Carlo Power Analysis for Indirect Effects (Schoemann et al., n.d.) was utilised to assess the power of detecting indirect effects in the model with two parallel mediators. This Power Analysis has been identified as a best practice for assessing the required sample size in mediation models (Muthén & Muthén, 2002; Schoemann et al., 2017; Thoemmes et al. 2010). The model included content occupational insecurity impacting occupational self-efficacy and future focus, which then influenced one's informal learning behaviours. The analysis incorporated a correlational design whereby content occupational insecurity was negatively correlated with both occupational self-efficacy and future focus, occupational self-efficacy and future focus had no correlation with each other, and both were positively correlated with informal learning behaviours. The four variables were standardised with a standard deviation of 1. The aim was to attain a target power of 0.8. I initially varied the sample size between 100 and 250, with increments of 5 participants per step. The analysis involved 1000 replications, each with 2000 Monte Carlo draws, a confidence interval of 95%, and a random seed of 1234. I identified the required sample size to be 145.

4. Results

4.1. Data Preparation

Open-ended age information was translated into numerically measurable data. 1 age response was deleted as it included the year of birth rather than the age. The 9 items from the informal learning scale were summed to form a single composite score. The maximum score was 45, with higher scores indicative of greater informal learning behaviours. Content occupation insecurity items were combined to created one composite score. The maximum score was 25. Higher scores denoted more content occupation insecurity. Items 2, 4, and 6 were reverse coded in the Brief Resilience Scale. The mean of the six items was calculated to form a singular score. Higher mean scores implied higher resilience. Occupational self-efficacy items were summed to form a single composite score. The highest score possible was 36, with higher scores indicative of greater occupational self-efficacy. Future focus items were summed to form a composite score. The maximum score was 28, with higher scores being indicative of a greater focus on the future. Items from the attitudes toward change scale were summed to form one composite score. Although the scale comprises three dimensions, i.e., cognitive, affective, and behavioural intent, Dunham et al. (1989) emphasised the reliability of measuring the items together, reporting $\alpha = 0.89$ for the total 18-item scale. Items 2, 7, 8, 10, and 15 were reverse scored. The 18 scale items were summed, allowing for a maximum score of 90. This score was consequently divided by 18 to compose a final mean score. Higher scores signified more positive attitudes toward change, with the maximum possible score being 5.

4.2. Scale Reliabilities

Reliability has previously been demonstrated for the six scales utilised in this study, as outlined above. However, as certain items were slightly tweaked in the Informal Learning Scale (Noe et al., 2013), the content subscale of the Occupation Insecurity Scale (Roll et al., 2023), and the Occupational Self-Efficacy Scale (Rigotti et al., 2008), reliability analyses were performed. Hair et al. (1998) recommended an alpha cut-off point of 0.55, with “good” reliability typically standing at 0.7 or above. The Cronbach’s Alpha values exceeded 0.7 for all our scales - the Informal Learning Scale ($\alpha = 0.810$), the Content Occupation Insecurity

Subscale (α = 0.867), the Brief Resilience Scale (α = 0.886), the Occupational Self-Efficacy Scale (α = 0.906), the Future Focus Scale (α = 0.909); and the Attitudes Toward Change Scale (α = 0.928). The scale reliability results can be seen in Appendix L.

4.3. Prevalence of Content Occupation Insecurity

I analysed the prevalence of content occupation insecurity across the sample. Upon creating the Occupation Insecurity Scale, Roll et al. (2023) stated that a total score above the halfway point (in this case, 13, rounded to the nearest whole number) is considered indicative of "insecurity," with a score below the halfway point indicative of "security." A total of 73.8% scored 13 or higher on the content occupation insecurity scale (M = 16.19, SD = 5.09). In this study, content occupation insecurity scores ranged from a minimum of 5 to a maximum of 25. For a full overview of score frequencies, see Appendix M.

4.4. Hypotheses Testing

To assess the direct effect of content occupation insecurity on informal learning and the parallel mediation effects of occupational self-efficacy and future focus, a mediation analysis was carried out using Hayes' PROCESS macro for SPSS (Model 4; Hayes, 2023). This model is designed to test mediation hypotheses, including ones with multiple mediators. The macro allows for the conduction of regression-path analyses to study direct and indirect effects (Hayes, 2018). Attitudes toward change and resilience were incorporated into the study as covariates to control for potential confounding variables. To test the hypotheses, 5000 bootstrap samples were drawn, and a 5% significance level was selected. The model explored the indirect effect of content occupation insecurity on informal learning through the potential mediators of occupational self-efficacy and future focus, thus implying a parallel mediation. As reliance was not found to be significantly related to any other variable in the model, it was excluded from the final analysis (see Appendix N for an overview of results when resilience was included in the model).

4.4.1. Total effect of content occupation insecurity on informal learning

The total effect model, which predicted informal learning from content occupation insecurity, with attitudes toward change included as a covariate (but excluding mediators),

accounted for 17% of the variance in informal learning, $R^2 = .17$, $F(2, 143) = 14.23$, $p < .001$. The linear regression analysis indicated that the total effect of content occupation insecurity on informal learning (Path c) was not significant, $b = -.05$, $t(143) = -.53$, $p = .59$, 95% CI [-.23, .13], suggesting that content occupation insecurity was not directly associated with informal learning when examined without considering the mediators, occupational self-efficacy and future focus. Thus, H1 which proposed that content occupation insecurity is negatively associated with informal learning was not supported.

4.4.2. Direct effect of content occupation insecurity on informal learning

However, the direct effect of content occupation insecurity on informal learning was significant (Path c'), $b = .20$, $t(141) = 2.30$, $p = .02$, 95% CI [.03, .37], revealing a significant suppressed positive effect, such that when content occupation insecurity, informal learning also increased.

4.4.3. Indirect effects through occupational self-efficacy

The model predicting occupational self-efficacy from content occupation insecurity and attitudes toward change explained 27% of the variance in occupational self-efficacy, $R^2 = .27$, $F(2, 143) = 26.88$, $p < .001$. The effect of content occupation insecurity on occupational self-efficacy (Path a1) was negative and significant, $b = -.39$, $t(143) = -4.69$, $p < .001$, 95% CI [-.55, -.22], indicating that higher levels of content occupation insecurity were associated with lower levels of occupational self-efficacy, thereby supporting H2. Further, the effect of occupational self-efficacy on informal learning was positive and significant (path b1), $b = .44$, $t(141) = 5.26$, $p = .00$, 95% CI [.28, .61], implying that higher levels of occupational self-efficacy were related to higher levels of informal learning. Thus, H3 was also supported. Thirdly, the indirect effect of content occupation insecurity on informal learning through occupational self-efficacy was significant, $b = -.17$, BootSE = 0.06, 95% CI [-.3, -.07], supporting H4, such that occupational self-efficacy mediates the relationship between content occupation insecurity and informal learning, specifically that content occupation insecurity negatively influences informal learning through occupational self-efficacy.

4.4.4. Indirect effects through future focus

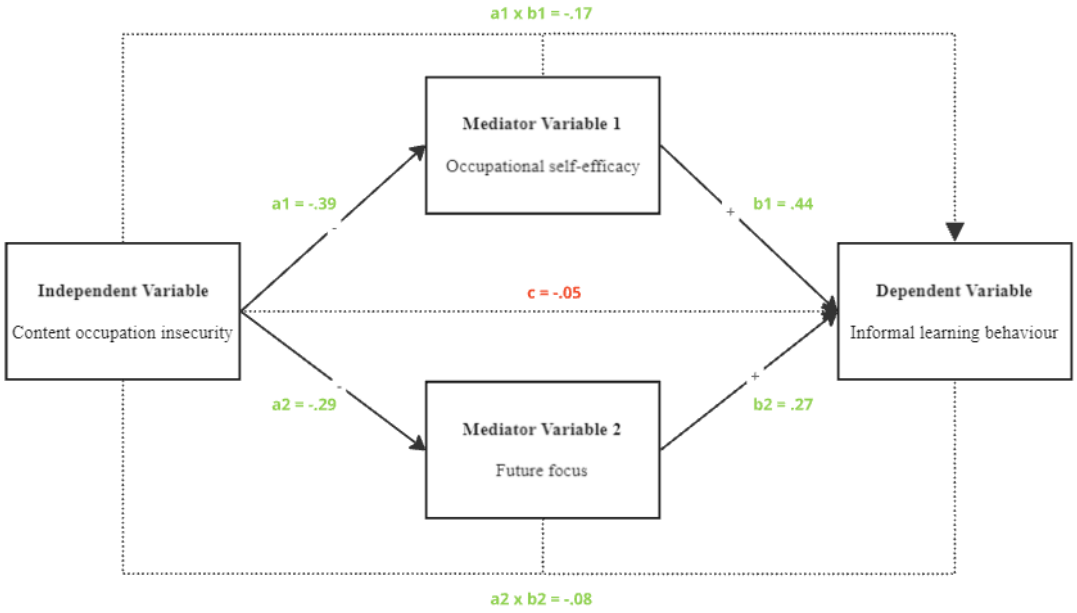
The model predicting future focus from content occupation insecurity and attitudes toward change explained 25% of the variance in future focus, $R^2 = .25$, $F(2, 143) = 23.26$, $p < .001$. Firstly, the effect of content occupation insecurity on future focus (Path a2) was significant, $b = -.29$, $t(143) = -3.92$, $p < .01$, 95% CI [-.44, -.15], showing that higher levels of content occupation insecurity were associated with lower levels of future focus, supporting H5. The effect of future focus on informal learning was positive and significant (Path b2), $b = 0.27$, $t(141) = 2.85$, $p = 0.01$, 95% CI [.08, .45], whereby lower levels of future focus were related to lower levels of informal learning. Thus, H6 was supported. The indirect effect of content occupation insecurity on informal learning through future focus was also significant, $b = -.08$, BootSE = .04, 95% CI [-.17, -.01], suggesting a significant negative mediation effect which supports H7, such as a negative indirect effect exists between content occupation insecurity and informal learning via future focus.

4.4.5. Total indirect effect (through occupational self-efficacy and future focus)

The total model predicting informal learning, including content occupation insecurity, occupational self-efficacy, future focus, and attitudes toward change explained 38% of the variance in informal learning, $R^2 = .38$, $F(4, 141) = 21.79$, $p < .001$. The total indirect effect of content occupation insecurity on informal learning through both occupational self-efficacy and future focus was significant, $b = -.25$, BootSE = .07, 95% CI [-.4, -.12]. This suggests that, combined, occupational self-efficacy and future focus significantly mediate the relationship between content occupation insecurity and informal learning. Although the direct effect of content occupation insecurity was positive, the total indirect effect was negative, creating a competitive mediation pattern.

Figure 3

Parallel Mediation Model



5. Discussion

5.1. Research Findings

This primary aim of this thesis was to explore the relationship between content occupation insecurity and informal learning, and to investigate whether this relationship was mediated by occupational self-efficacy and future focus. Further, I strived to gain insights into the prevalence of the novel concept of content occupation insecurity during this period of rapid change. Within the model, I focused on measuring four variables, i.e., informal learning, occupational self-efficacy, future focus, and content occupation insecurity. Resilience and attitudes toward change were controlled for in each analysis, however resilience was removed due to its lack of relationship with all main variables. All participants filled out a series of scales, allowing for the determination of a score for each main variable and covariate.

The findings of this thesis uncover a complex set of interactions between content occupation insecurity and informal learning that are not immediately apparent when only examining the total effect. The nuanced relationship between content occupation insecurity and informal learning was distinguished by a non-significant total effect but significant indirect effects through the mediators - occupational self-efficacy and future focus. The total effect of content occupation insecurity on informal learning was not significant, highlighting that overall, content occupation insecurity does not have an effect on informal learning. Nevertheless, there were two significant indirect pathways through occupational self-efficacy and future focus, each contributing to a decrease in informal learning. Intriguingly, the direct effect of content occupation insecurity on informal learning was positive, illustrating the complex presence of competing mediating pathways that produce conflicting directional effects.

The competitive mediation pattern can be interpreted as content occupation insecurity negatively impacting informal learning through decreased occupational self-efficacy and future focus. This finding builds upon previous research demonstrating a negative relationship between job insecurity and learning through occupational self-efficacy (see Van Hootegem and De Witte, 2019), as well as studies which found that job insecurity and insecure contract types can negatively affect occupational self-efficacy (see Alisic & Wiese, 2020; Guarnaccia et al.,

2016; Van Hootegem et al., 2022), and those which demonstrated that self-efficacy plays an important role in employee development (for example, Bandura, 1997; Ryan, 1999; Van Hootegem et al., 2022). It also adds future focus as a significant mediator in the relationship between content occupation insecurity and informal learning, falling in line with base research highlighting the negative impact of job insecurity on future time perspective (see Lam et al., 2019), and studies outlining the importance of future focus for proactive career behaviour participation (see Koen & van Bezouw, 2021; Guan et al., 2014; He et al., 2022; Taber & Blankemeyer, 2015).

However, there appears to be an additional positive pathway that counterbalances these negative effects. The presence of these competing pathways signifies that content occupation insecurity might have a dual impact, concurrently undermining informal learning through occupational self-efficacy and future focus, but with a positive direct effect also existing which was not captured by mediators included in the present model. A similarly conflicting finding was demonstrated by Staufenbiel and König (2010) who concluded that job insecurity could both positively and negatively impact employee performance. In general, the positive direct effect found in this thesis implies the presence of a suppressed effect, in which the true relationship between content occupation insecurity and informal learning is hidden when only looking at the total effect. The positive effect also indicates that there might be other unmeasured mediators or compensatory processes that have a positive influence on informal learning in the presence of content occupation insecurity, counterbalancing the negative pathways through occupational self-efficacy and future focus.

5.2. Academic Implications

The growing body of literature on the effects of job insecurity, as well as its relationship with informal learning in recent years indicates the increasing importance of both variables. Informal learning has been identified as a strategical way to adapt to the professional changes which could be triggering job insecurity. However, to date, limited research has directly explored the relationship between these two variables. Furthermore, the concept of occupation insecurity has emerged. Although stemming from job insecurity, it encompasses the fear of losing or experiencing significant changes to one’s full occupation, rather than only to their

job. Considering the exponential growth of AI technologies across industries, it can be assumed that whole occupations are now exposed to change. Despite its timely relevance, I could not find any literature exploring the concept of occupation insecurity, beyond Roll et al.'s (2023) study which developed the concept and associated scale. A research gap was consequently noted in relation to occupation insecurity. Due to its likely relevance in the face of significant AI changes, it was explored in lieu of job insecurity for its relationship with informal learning.

The findings of this thesis contribute to the academic literature surrounding the relationship between occupation insecurity and informal learning, including potential mediating variables, building upon prior research which focused on job insecurity. The existence of conflicting directional pathways complicates the relationship between content occupation insecurity and informal learning. The conflicting findings fall in line with job insecurity research by Staufenbiel and König (2010), who found that insecurity can simultaneously have positive and negative effects on employee performance, as outlined in the literature review of this study. Although limited occupation insecurity research exists, the base concept of job insecurity has typically been seen as an adverse factor, linked with a range of negative psychological and behavioural outcomes. Further, this falls in line with the Conservation of Resources Theory (Hobfoll, 1989) which posits that individuals will not seek to gain further resources when in a state of stress.

Alas, the positive direct effect found in this thesis suggests that content occupation insecurity might also act as a motivational source under certain conditions. In specific currently unexplored instances, professionals could recognise the benefits of learning informally to cope with their occupationally insecure situation and act accordingly. Additionally, in line with the Job Demand-Control Model (Karasek, 1979), the positive effect of content occupation insecurity could be attributed to control resources such as autonomy or flexibility which protect the individual from the negative effects of insecurity. Although comparatively rare, certain studies have concluded that job insecurity can have positive outcomes (see Jahoda, 1982; Probst et al., 2007; Swerke et al., 2002). In general, this thesis emphasises the importance of considering the complex nature of stressors like content

occupation insecurity, which can operate through competing mediators that must be unravelled to fully comprehend their effect on informal learning.

Furthermore, this is the first empirical study that explores the relationship between content occupation insecurity and informal learning, and only the second to the best of my knowledge which adopts the novel concept of occupation insecurity for research purposes. This thesis builds upon previous work investigating the relationship between job insecurity and informal learning, further highlighting the importance of occupational self-efficacy and future focus as mediating variables. Additionally, and as far as I am aware, this is the first study to focus on one specific cause of insecurity, i.e., AI induced, with previous job insecurity studies not differentiating between different causes. This study also served to further validate the content occupation insecurity dimension of the Occupation Insecurity Scale, expanding its usage in countries beyond Belgium and the United Kingdom and highlighting its reliability. Finally, this thesis uncovered that content occupation insecurity is a prevalent issue across employees working in a range of industries and countries.

5.3. Managerial Implications

The pattern of opposing effects uncovered in this thesis suggests that targeted interventions aimed at modifying the mediators might considerably influence the overall impact of content occupation insecurity on informal learning. For example, efforts to increase occupational self-efficacy and future focus amongst employees could reduce the negative indirect effects of the fear of changes to important features of one's occupation, enabling the positive residual effect to dominate. Due to the malleable nature of occupational self-efficacy and future focus, organisations could focus on workshops to enhance the strength of both variables across workers. More, employees could be encouraged to participate in occupational activities which allow them to prove their worth, offering a potential natural boost to their occupational self-efficacy. Enhancing these mediators could buffer against the negative effects of content occupation insecurity. Furthermore, the results of this thesis highlight that there might be other positive pathways still to be found that could be utilised in future interventions. For instance, and in line with the Job Demand-Control Model (Karasek, 1979), where autonomy and flexibility act as resources that protect against the negative effects of job

insecurity, training programmes that promote autonomy and flexibility might activate the positive effects of content occupation insecurity. However, further research is required before implementing any programmes apart from those targeting occupational self-efficacy and future focus.

5.4. Methodological Strengths

A strength of this present study the fact that it did not sway from the hypotheses that were pre-registered with the Catolica Faculty of Human Sciences. Following the pre-registered plan increased the integrity of this thesis and prevented the 'file drawer effect,' whereby non-significant results remain unreported (Nagarajan et al., 2017). Moreover, following the pre-registered hypotheses eradicated the risk of HARKing (hypothesising after the results are known), which has been connected to a jump in false positive results, and significantly decreases the replicability of a scientific study (Kerr, 1998). Overall, this thesis offers full transparency to the reader. Furthermore, the sample size of 146 allowed us to reach the 145 participants required to reach 80% power, as calculated in the Monte Carlo Power Analysis for Indirect Effects which was run prior to study commencement (Schoemann et al., n.d.). This increased the likelihood of detecting significant results.

5.5. Limitations and future research

Despite the theoretical, practical, and methodological strengths of this study, certain limitations must be considered. Firstly, convenience sampling was used in this thesis. Although reasonable due to time and monetary constraints, a non-representative sample can result (Vehovar et al., 2016). Most participants were recruited via individual WhatsApp and Microsoft Teams messages, as well as through various group chats on both applications. As a result, many participants were employed in the United Kingdom, Ireland, or to a lesser extent Germany. Future studies could consider incorporating a wider range of participants, thus likely further enhancing the generalisability of results.

Secondly, participation was limited to full-time professionals with permanent contracts. This allowed for more straightforward survey creation and interpretation of results as all individuals belonged to the same group. However, widening the participation pool to include

persons with temporary contracts could boost the generalisability of results. Temporary workers are typically more vulnerable to job insecurity due to the unstable nature of their employment (De Cuyper et al., 2008). This finding might also extend to occupation insecurity. More, dividing participants based on their level of tenure could also offer further insights as Cheng and Chan (2008) for instance, found that persons with longer tenure were more exposed to the negative repercussions of job insecurity. To improve the external generalisability of this study and to gain a more nuanced understanding of how content occupation insecurity is perceived and managed across diverse employment situations, I propose future studies measure length of tenure, as well as comparing participants based on employment type.

Thirdly, the existence of a significant positive effect alongside significant negative indirect effects in this thesis indicate that there were unmeasured mediators not included in this model. Future research could add additional mediators such as those identified as job resources within the Job Demand-Control Model, which can help to buffer the negative effects of insecurity (Karasek, 1979; Karasek, 1990). Examples include autonomy and flexibility. Such exploratory studies might help to clarify the positive residual effects found in this thesis. More, psychological contract breach was previously explored as a mediator in the relationship between job insecurity and training (see Van Hootegem & De Witte, 2019). Going forward, it could be worthwhile to explore it as a mediator in relation to content occupation insecurity and informal learning, in addition to occupational self-efficacy and future focus. Further, this study explored only one type of self-efficacy – occupational self-efficacy. Future studies could extend this to include other self-efficacy variables which have been highlighted as important precedents for learning, for example memory self-efficacy (see Schulz, M & Roßnagel, 2010), and self-efficacy for development (see Maurer et al., 2003).

Furthermore, although practical for offering initial insights, the cross-sectional design of this study limits the ability to draw causal conclusions. Longitudinal research could be a wise next step to explore how the relationship between AI induced content occupation insecurity and informal learning evolves over time, particularly as AI continues to be implemented across occupational sectors, and professionals potentially become more accustomed to insecurity.

6. Conclusion

As AI applications spread exponentially across industries, concerns about its impact on occupations are arising, leading to the conceptualisation of occupation insecurity. This thesis focused specifically on content occupation insecurity. Ensuring that professionals can adapt to AI induced changes within their field of expertise is of paramount importance to ensure a smooth transition, with informal learning previously identified as an effective means to keep up with work-related changes. This thesis has contributed to the novel research field of occupation insecurity, building upon previous job insecurity studies which explored the effect of insecurity on informal learning, and highlighting occupational self-efficacy and future focus as potential mediators of this relationship. The findings signal that the relationship between content occupation insecurity and informal learning is dictated by competing mediating pathways that result in contradictory directional effects. Whilst content occupation insecurity has a negative effect on informal learning through occupational self-efficacy and future focus, there is another positive effect that materialises once these pathways are considered, indicating the existence of additional mediators which were unaccounted for that contribute positively to informal learning. The negative and positive effects combined result in an insignificant total effect, suggesting that that impact of content occupation insecurity on informal learning is highly context dependent. Understanding and targeting these mediators through training programmes and workshops could allow the positive effect to dominate, promoting an adaptable workforce actively engaged in informal learning.

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Appendices

Appendix A

Descriptive Statistics

Descriptive statistics for age

	N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
Age	145	19	69	37.46	14.26
Valid N (listwise)	145				

Frequency table for gender

	N	*%*
Male	48	32.9%
Female	97	66.4%
Other	1	0.7%

Frequency table for education

	N	*%*
Elementary school graduate or equivalent	3	2.1%
High school graduate or equivalent	29	19.9%
Bachelor's degree	68	46.6%
Master's degree	29	19.9%

PhD or higher	5	3.4%
Trade/Technical/Vocational school	12	8.2%

Frequency table for industry

	N	*%*
Business and Finance	22	15.1%
Technology	12	8.2%
Engineering	3	2.1%
Science and Research	5	3.4%
Education	27	18.5%
Legal	16	11.0%
Social Services	3	2.1%
Arts and Media	2	1.4%
Healthcare Practitioners	20	13.7%
Service	9	6.2%
Sales and Marketing	3	2.1%
Customer Support	1	0.7%
Office and Administrative Support	6	4.1%
Farming, Fishing, and Forestry	1	0.7%

Installation, Maintenance, and Repair	3	2.1%
Transportation and Logistics	3	2.1%
Other	10	6.8%

Frequency table for country of employment

	N	*%*
Austria	1	0.7%
Germany	27	18.5%
Ireland	47	32.2%
Netherlands	2	1.4%
Portugal	1	0.7%
Switzerland	5	3.4%
United Kingdom	63	43.2%

Appendix B

Content Occupation Insecurity Scale

The following questions ask you about the future of your **occupation** in light of artificial intelligence (AI) advancements.

What is an occupation?

An **'occupation'** is a trade or profession that has been learned in training or through experience. An occupation, therefore, requires a certain professional knowledge. When we talk about the disappearance of an occupation in this questionnaire, we mean that the 'business line' disappears.

An **example** of this is a food server at a restaurant. The occupation is "food server", which has been learned and trained through experience. If this food server loses their *job at Restaurant X*, they can find a new *job* at another restaurant and continue working as a food server. However, if restaurants become automated and the *occupation "food server"* disappears, they will never be able to work as a food server again in the future, and they will have to learn another occupation.

Keep this in mind as you read the following statements. Please take your time to indicate your level of agreement with them.

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I expect that my occupation will undergo significant changes due to AI developments.	○	○	○	○	○
Certain tasks of my occupation will no longer be relevant in the future.	○	○	○	○	○
I am certain that my occupational responsibilities will change significantly due to AI before my retirement.	○	○	○	○	○
I will need to perform tasks in my occupation in the future, for which I am not well trained at the moment.	○	○	○	○	○
I need additional training in AI in order to be able to continue working in my occupation.	○	○	○	○	○

Appendix C

Informal Learning Behaviours Scale

Consider the past three months. How often during a typical work week have you engaged in the activities listed below in order to learn and help you better perform in your occupation?

	Never	Rarely	Sometimes	Often	All the time
Reflecting about how to improve my performance.	○	○	○	○	○
Experimenting with new ways of performing my work.	○	○	○	○	○
Using trial and error strategies to learn and better perform.	○	○	○	○	○
Interacting with a mentor.	○	○	○	○	○
Interacting with my supervisors.	○	○	○	○	○
Interacting with my colleagues.	○	○	○	○	○
Reading professional magazines and industry publications.	○	○	○	○	○
Searching the Internet for occupation relevant information.	○	○	○	○	○
Consuming content such as books, articles, or podcasts related to my work.	○	○	○	○	○

Appendix D

Temporal Focus Scale – Future Focus

The following statements relate to your thoughts about the future. Please read each statement carefully and indicate how often you experience these thoughts on a scale from 1 (never) to 7 (constantly):

	1 (Never)	2	3 (Sometimes)	4	5 (Frequently)	6	7 (Constantly)
I think about what my future has in store.	○	○	○	○	○	○	○
I think about times to come.	○	○	○	○	○	○	○
I focus on my future.	○	○	○	○	○	○	○
I imagine what tomorrow will bring for me.	○	○	○	○	○	○	○

Appendix E

Occupational Self-Efficacy Scale

More than halfway there! Please rate the following statements about your occupational experiences on a scale from 1 to 6, where 1 means "Not at all true" and 6 means "Completely true":

	1 (Not at all true)	2	3	4	5	6 (Completely true)
I can remain calm when facing difficulties in my occupation because I can rely on my abilities.	○	○	○	○	○	○
When I am confronted with a problem in my occupation, I can usually find several solutions.	○	○	○	○	○	○
Whatever comes my way in my occupation, I can usually handle it.	○	○	○	○	○	○
My past experiences in my occupation have prepared me well for my professional future.	○	○	○	○	○	○
I meet the goals that I set for myself in my occupation.	○	○	○	○	○	○
I feel prepared for most of the demands in my occupation.	○	○	○	○	○	○

Appendix F

Attitudes Toward Change Scale

Final question! The following statements relate to various aspects of change at work. Please read each statement carefully and indicate the extent to which you agree or disagree with it.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I look forward to changes at work.	○	○	○	○	○
I usually resist new ideas.	○	○	○	○	○
I am inclined to try new ideas.	○	○	○	○	○
Change usually benefits the organisation.	○	○	○	○	○
I usually support new ideas.	○	○	○	○	○
Most of my co-workers benefit from change.	○	○	○	○	○
I don't like change.	○	○	○	○	○
Change frustrates me.	○	○	○	○	○
Changes tend to stimulate me.	○	○	○	○	○
Most changes at work are irritating.	○	○	○	○	○
I often suggest new approaches to things.	○	○	○	○	○
Change often helps me perform better.	○	○	○	○	○
I intend to do whatever possible to support change.	○	○	○	○	○
Other people think that I support change.	○	○	○	○	○
I usually hesitate to try new ideas.	○	○	○	○	○
Change usually helps improve unsatisfactory situations at work.	○	○	○	○	○
I find most changes to be pleasing.	○	○	○	○	○
I usually benefit from change.	○	○	○	○	○

Appendix G

Brief Resilience Scale

Please indicate how much you agree or disagree with the following statements on a scale from 1-5, where 1 means "Strongly Disagree" and 5 means "Strongly Agree".

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
I tend to bounce back quickly after hard times.	○	○	○	○	○
I have a hard time making it through stressful events.	○	○	○	○	○
It does not take me long to recover from a stressful event.	○	○	○	○	○
It is hard for me to snap back when something bad happens.	○	○	○	○	○
I usually come through difficult times with little trouble.	○	○	○	○	○
I tend to take a long time to get over set-backs in my life.	○	○	○	○	○

Appendix H

Pre-Registration Form

CATÓLICA
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LISBOA

Inscrição do Tema da Dissertação | Registration of Dissertation Topic

MESTRADO EM | MASTER'S DEGREE IN **Psychology Applied to Business and Economics**

Nome do aluno | Student name

Ciara Nolan

Número de aluno | Student number

139722020

Endereço de correio eletrónico | Email address

s-cnolan@ucp.pt

Número de Telemóvel | Mobile no.

+353867219016

Tema | Topic

The Impact of Content Occupation Insecurity on Informal Learning Behaviour: The Mediating Roles of Occupational Self-Efficacy and Future Focus.

Tipo de trabalho | Type of work

Dissertação / Dissertation	x
Relatório de Estágio / Report	
Projeto / Project	

Orientador(es) | Supervisor(s)

Professor Filipa de Almeida

Descrição sumária do objeto e metodologia | Brief description of object and methods

Artificial intelligence (AI) is rapidly transforming the modern workforce. Bristol et al. (2024) highlighted that "what steam was to the First Industrial Revolution is what AI will be to the fourth," with steam having revolutionised industries and overhauling how individuals worked (Mohajan, 2019). AI is replacing and augmenting the tasks that humans need to complete (Green, 2024). As a result, occupations are likely to be overhauled.

In response to these rapid changes, the construct of 'occupation insecurity' has emerged (Roll et al., 2023). It refers to the subjective threat to the continuation of one's occupation. It is comprised of two dimensions – global occupation insecurity (the fear of the whole occupation disappearing) and content occupation insecurity (the fear of the occupation becoming significantly different, even if the whole occupation might not disappear).

Although not yet widely explored, Roll et al. (2023) found that 46.7% of their participants were experiencing content occupation insecurity, compared to 16.5% reporting global occupation insecurity. Due to its apparent prevalence, this thesis will focus on content occupation insecurity, deepening the associated understanding.
Informal learning has been identified as an important way for employees to acquire new skills and knowledge, thus enabling them to remain employable and adapt to new occupational demands (Tannenbaum et al., 2010). However, previous research suggests that those experiencing job insecurity (a concept related to occupation insecurity) are less likely to engage in work-related learning.
This study thus aims to explore the impact of 'content occupation insecurity' on informal learning behaviours, whilst investigating which psychological variables are at play.

Research Questions

How does content occupation insecurity affect informal learning behaviour, and what mediating roles do occupational self-efficacy and future focus play in this relationship?

Hypotheses

Direct effect of content occupation insecurity on informal learning

Hypothesis 1 (H1): Content occupation insecurity is negatively associated with informal learning behaviour.

Indirect effect via occupational self-efficacy

Hypothesis 2 (H2): Content occupation insecurity is negatively related to occupational self-efficacy, in that higher levels of content occupation insecurity will be associated with lower levels of occupational self-efficacy.

Hypothesis 3 (H3): Occupational self-efficacy is positively related to informal learning, in that lower occupational self-efficacy will be associated with reduced informal learning behaviour.

Hypothesis 4 (H4): Occupational self-efficacy mediates the relationship between content occupation insecurity and informal learning, such that higher content occupation insecurity leads to lower occupational self-efficacy, which in turn leads to reduced informal learning behaviour.

Indirect effect via future focus

Hypothesis 5 (H5): Content occupation insecurity is negatively related to future focus, in that higher levels of content occupation insecurity will be associated with lower levels of future focus.

Hypothesis 6 (H6): Future focus is positively related to informal learning behaviour, in that lower levels of future focus will be associated with reduced informal learning behaviour.

Hypothesis 7 (H7): Future focus mediates the relationship between content occupation insecurity and informal learning, in that negative indirect effects will exist between content occupation insecurity and informal learning behaviour via future focus.

Indique até 5 obras fundamentais para a sua pesquisa | Please name up to 5 works relevant to your research.

Bristol, H., de Boer, E., de Kroon, D., Shahani, R., & Torti, F. (2024, February 21).

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Adopting AI at speed and scale: The 4IR push to stay competitive. McKinsey & Company. https://www.mckinsey.com/capabilities/operations/our-insights/adopting-ai-at-speed-and-scale-the-4ir-push-to-stay-competitive

Green, A. (2024). Artificial intelligence and the changing demand for skills in the labour market. *OECD Artificial Intelligence Papers*, 14, OECD Publishing. https://doi.org/10.1787/88684e36-en

Mohajan, H. (2019). The first industrial revolution: Creation of a new global human era. *Journal of Social Sciences and Humanities*, *5*(4), 377-387.

Roll, L. C., De Witte, H., & Wang, H.-J. (2023). Conceptualization and Validation of the Occupation Insecurity Scale (OCIS): Measuring Employees' Occupation Insecurity Due to Automation. *International Journal of Environmental Research and Public Health*, *20*(3), 2589. https://doi.org/10.3390/ijerph20032589

Tannenbaum, S. I., Beard, R. L., McNall, L. A., and Salas, E. (2010). "Informal learning and development in organizations," in *Learning, Training, and Development in Organizations*. eds. S. W. J. Kozlowski and E. Salas (New York, United States: Routledge/Taylor & Francis Group), 303-331.

Data | Date
26/07/2024

Assinatura do Mestrando | MA Student Signature
CIARA NOLAN

Data | Date
26/07/2024

Assinatura do(s) Orientador(es) | Supervisor Signature

Appendix I

Information Sheet

Informal Learning Behaviours, Influences, and Perceptions of Artificial Intelligence

I would like to invite you to take part in this research study exploring informal learning behaviours, their determinants, and perceptions of artificial intelligence. I, Ciara Nolan, am conducting this experiment as part of my master's thesis at the Católica University of Portugal, under the supervision of Prof. Filipa de Almeida.

Any individual **aged between 18 and 70** who is **permanently employed** (not including self-employed) **for at least 20 hours per week** is invited to take part in this study.

The study consists of filling out a series of questionnaires regarding your informal learning behaviours, their determinants, and your artificial intelligence (AI) perceptions.

The survey is fully anonymous and should not take longer than **8 minutes** to complete. This study is undertaken for educational purposes and will form part of the requirements for my Master in Psychology with Business and Economics at the Católica University of Portugal. It will also add to current research around informal learning and artificial intelligence.

Please answer as honestly as possible. You will not be asked at any stage to disclose personal or identifying information such as your name or date of birth, ensuring that data remains anonymous. The data collected will be used for research purposes only and may be presented in my thesis or disseminated in academic journals in an aggregated and fully anonymous form.

We ask you to take the study in one go, without interruptions.

There are no expected side effects of participating in this study beyond those associated with looking at a computer screen for circa 8 minutes. You are free to leave the survey at any time, and this will not result in any negative consequences. Should you decide to withdraw, the data that has been collected up until this point cannot be retrieved due to the anonymity of responses.

I can be contacted at any time, prior to, during, or upon completion of the questionnaire, at s-cnolan@ucp.pt.

By continuing you agree to participate, confirm that you are aged between 18 and 70, and are permanently employed for at least 20 hours per week.

Thank you!

Appendix J

Artificial Intelligence Definition

What is Artificial Intelligence (AI)?

Artificial intelligence (AI) can be defined as "systems designed by humans that, given a complex goal, act in the physical or digital world by perceiving their environment, interpreting the collected structured or unstructured data, reasoning on the knowledge derived from this data and deciding the best action(s) to take (according to pre-defined parameters) to achieve the given goal. AI systems can also be designed to learn to adapt their behaviour by analysing how the environment is affected by their previous actions" (AI HLEG, 2018, p7).

AI is becoming an increasingly important part of modern workplaces. For example, virtual assistants like Microsoft Cortana and Google Assistant help manage schedules and carry out tasks autonomously based on voice commands. AI-driven chatbots answer customer queries. Recruitment systems use AI to screen applications, and run initial interviews by analysing interviewee responses (Upadhyay, 2018). In healthcare, AI systems can identify diseases, and offer treatment recommendations (Sumit et al., 2019; Sunarti et al., 2021). AI tools can be utilised for data analytics, forecasting trends, identifying patterns, and recommending actions.

Appendix K

Survey Closing and Debriefing

Thank you for your participation in this research study. For this study, it was important that some information was withheld from participants. Now that you have completed the study, I will describe the withheld information to you, why it was important, and answer any questions that you may have.

Participants were requested to complete surveys which measured insecurity about the content of one's occupation due to AI, as well as work-related informal learning behaviours. Occupational self-efficacy and future focus were measured as they might explain how or why occupation insecurity impacts informal learning behaviours. Finally, we controlled for resilience and attitudes toward change.

The aim of this study was to examine the relationship between content occupation insecurity due to AI and work-related informal learning behaviours.

The main researcher conducting this study is Ciara Nolan, a student at the Católica University of Portugal, who can be contacted with any queries at s-cnolan@ucp.pt.

Appendix L

Scale Reliabilities

	Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
Informal Learning	.81	.82	9
Content Occupation Insecurity	.87	.87	5
Brief Resilience	.89	.89	6
Occupational Self-Efficacy	.91	.91	6
Future Focus	.91	.91	4
Attitudes Toward Change	.93	.93	18

Appendix M

Content Occupation Insecurity Frequency Table

Score	N	%
5	2	1.4
6	2	1.4
7	1	0.7
8	5	3.4
9	6	4.1
10	11	7.5
11	6	4.1
12	5	3.4
13	6	4.1
14	6	4.1
15	19	13.0
16	6	4.1
17	8	5.5
18	9	6.2
19	6	4.1
20	17	11.6
21	5	3.4
22	10	6.8
23	5	3.4
24	5	3.4
25	6	4.1

Appendix N

Parallel Mediation Analysis Summary Table with Resilience Included as a Covariate

Path	b	SE	t	p	95% CI
Model 1: Content Occupation Insecurity → Occupational Self-Efficacy					
$R^2 = .28$, $F(3, 142) = 18.21$, $p < .001$					
Content Occupation Insecurity → Occupational Self-Efficacy	-.39	.08	-4.66	< .001	[-.55, -.22]
Resilience → Occupational Self-Efficacy	.55	.58	.95	.34	[-.59, 1.69]
Attitudes Toward Change → Occupational Self-Efficacy	3.38	.82	4.15	< .001	[1.77, 5.00]
Model 2: Content Occupation Insecurity → Future Focus					
$R^2 = .25$, $F(3, 142) = 15.43$, $p < .001$					
Content Occupation Insecurity → Future Focus	-.29	.08	-3.92	< .001	[-.44, -.15]
Resilience → Future Focus	-.15	.52	-.28	.777	[-1.19, .89]
Attitudes Toward Change → Future Focus	3.5	.74	4.72	< .001	[2.03, 4.96]
Model 3: Informal Learning					
Content Occupation Insecurity → Informal Learning	.2	.09	2.29	.023	[.03, .37]
Occupational Self-Efficacy → Informal Learning	.45	.09	5.28	< .001	[.28, .62]
Future Focus → Informal Learning	.26	.09	2.81	.006	[.08, .45]
Resilience → Informal Learning	-.33	.56	-.6	.550	[-1.44, .77]
Attitudes Toward Change → Informal Learning	1.86	.87	2.15	.033	[.15, 3.58]

Indirect Effects					
Total indirect effect	-.25	.07	-	-	[-.4, -.12]
Content Occupation Insecurity → Occupational Self-Efficacy → Informal Learning	-.17	.06	-	-	[-.31, -.07]
Content Occupation Insecurity → Future Focus → Informal Learning	-.08	.04	-	-	[-.17, -.01]