Hoping for the Best, Preparing for the Worst: Employee Reactions to Automation at Work

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Automation is increasingly becoming a disruptive force in modern workplaces. For individual workers, the consequences of automation are varied; In some cases, employees may be harmed by automation (e.g., job loss), whereas in other cases employees may benefit from its implementation (e.g., enhanced performance). Importantly, the extent to which employees fear and disengage from, or eagerly anticipate and prepare for, automation may influence how they fare in the workplace. To this end, in this dissertation I present two essays across which I examine employees' psychological evaluations and subsequent attitudinal (Essay 1) and behavioural (Essay 2) reactions to automation at work. In Essay 1, I draw on appraisal theory to distinguish between employees' belief that technology can conduct their work (perceived automatability) from employees' appraisals regarding the implications of automation on their job prospects (job insecurity) and job performance (performance optimism). Given that control at work enables people to mitigate the possible harms of automation and harness the potential benefits of automation, I propose that control at work mitigates the relationship between perceived automatability and job insecurity, and strengthens the relationship between perceived automatability and performance optimism, with each appraisal having competing effects on downstream job attitudes. Using a survey (N = 500) and an experiment (N = 194), I found overall support for these predictions. In Essay 2, I examine people's preparatory responses to their job's objective likelihood of becoming automated (automatability), via their job insecurity. Given that skills-discrepancies may make people vulnerable to job loss during automation-related job restructuring or downsizing, I predict that people with a large skills-gap will be more likely to develop job insecurity in response to their automatability than people with a low skills-gap. I draw on control theories to suggest that job insecurity subsequently results in remedial actions to address the threat of unemployment, including developmental activities and career exploration, efforts which are further strengthened by organizational support for development (or the lack thereof). I found support for these predictions using a survey of 244 employees. Overall, this dissertation sheds light on employees’ perspectives on automation at work, with substantial practical implications for organizations and policymakers seeking to help employees transition to the future of work.

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CHAPTER 1: INTRODUCTION

Automation, defined as the process wherein technologies independently execute functions which previously relied on human labor (Parasuraman & Riley, 1997), is not a new phenomenon. Major advances in technological capabilities leading to economy-wide trends in automation have characterized several industrial revolutions since the 18th century. For example, during the first industrial revolution, mechanical technologies such as the steam engine, the cotton gin, and the spinning jenny replaced the need for humans to conduct various forms of physical labor. Today, technologies such as artificial intelligence (AI), machine learning, networks and cloud computing, and nano and additive manufacturing are driving the fourth industrial revolution (Schwab, 2017). It is predicted that these technologies will have a more significant impact on human labor than those of the previous revolutions (Brynjolfsson & McAfee, 2014; Cameron, 2017; Schwab, 2017). For one, the pace of technological innovation, likened to a "Cambrian explosion" (Pratt, 2015), is now exponentially faster than in previous centuries. Additionally, automation is now expanding into areas previously considered exclusively human domains, such as pattern recognition and complex communication (Brynjolfsson & McAfee, 2014).

Over the last several decades, the net effect of automation on economy wide unemployment has been null or even positive (Autor, 2015; Autor & Salomons, 2018; Mokyr et al., 2015). However, there is no guarantee this trend will continue (Brynjolfsson & McAfee, 2014; Cameron, 2017). Even if it does, millions of jobs will still be lost to automation in the transition (Arntz et al., 2017; Frey & Osborne, 2017). Therefore, at the *individual* level, the impacts of automation are likely to be complex and variable. Whereas some employees will gain employment opportunities, others will lose them.

Additionally, automation also has competing effects on individual employees' job quality. Depending on how automation is implemented, it may harm or improve important job characteristics such as job autonomy, skill variety, feedback, social interactions, and job demands (Parker & Grote, 2020, Smids et al., 2020). For example, automation may "deskill" a person's job by stripping them of their core job tasks, leaving them to monitor and remedy the errors of a machine. In contrast, automation can also replace "dull, dirty, and dangerous" tasks (Walsh & Strano, 2018, p. xix), which are associated with low job satisfaction (Gorny & Woodard, 2020), leaving behind tasks that require uniquely human capabilities such as creative and social intelligence (Frey & Osborne, 2017; Autor, 2014).

Finally, automation can be a double-edged sword in terms of its impact on employees' task performance. Automation can allow employees to be more efficient, less error prone, and can augment their capabilities (e.g., Asatiani et al., 2020; Brougham et al., 2019), thus allowing people to conduct safer, more productive, and more meaningful work. However, given automation's transformative effects on jobs and entire industries, the introduction of automation also necessitates that employees invest considerable time and effort into developing new knowledge, skills, and abilities (KSA) to remain employable (Brynjolfsson & McAffee, 2014; World Economic Forum, 2016).

In the face of these competing forces, employees' interactions with automation may, at least in part, influence how automation will impact them personally. Specifically, the extent to which employees prepare for, adapt to, and use automation, rather than ignore, reject, or even sabotage (e.g., the Luddites) automation may influence how well they fare at work. In this dissertation, I argue that one antecedent to employees' interactions with automation is the extent to which employees anticipate that automation will help or harm them.

To this end, in Essay 1, I distinguish between employees' appraisals regarding whether their job's automatability will help (automation-related performance optimism) or harm (automation-related job insecurity) their job prospects. I demonstrate that these appraisals have diverging effects on employees' job attitudes, and I elucidate the crucial role that control at work plays in the formation of employees' appraisals. I tested and found support for my model using a large-scale survey and an experiment. As such, this work contributes to the literature by differentiating between various automation appraisals, highlighting their competing effects on important workplace outcomes, and revealing the conditions under which they form.

In Essay 2, I examine employees' preparatory behaviours in reaction to their anticipation that automation will harm them. In particular, I examine people's preparatory behaviours in response to automation-related job insecurity, the personal factors (i.e., perceived skill-gaps) that contribute to the development of automation-related job insecurity, and the organizational factors (i.e., organizational support for development) that shape people's preparatory strategies. I tested and found support for my predictions in a survey of 244 employees. Thus, this work contributes to the literature by elucidating when, why, and how employees prepare for (or fail to prepare for) automation-related threats to their job security.

In combination, these two essays provide deeper insights into employees' perspectives on automation at work – insights that have been sorely lacking. My findings not only help advance theory, but also inform practice. By clarifying the conditions under which employees form various automation appraisals, and the conditions under which they act on them, we enable managers and policy makers to make informed decisions about how to help employees prepare for the future of work.

CHAPTER 2: FEAR OR EMBRACE? EMPLOYEES' DIVERGING APPRAISALS OF AUTOMATION, AND CONSEQUENCES FOR JOB ATTITUDES (ESSAY 1)

Since the first industrial revolution, modern work has followed a trajectory of ever-increasing automation (Schwab, 2017). Presently, technologies like AI, machine learning, and the internet of things, have accelerated the pace of automation, leading scholars to estimate that nearly 50% of U.S. occupations are at high risk of becoming redundant due to automation in the next few decades (Frey & Osborne, 2017). However, the impact of automation on individual workers is likely to be variable. In some cases, automation will be detrimental to workers, leading to poorer quality jobs (Parker & Grote, 2020; Smids et al., 2020) and loss of employment (Frey & Osborne, 2017). In other cases, employees will benefit from safer working conditions, enhanced productivity, and more meaningful occupations (Parker & Grote, 2020; Smids et al., 2020; Brynjolfsson & McAfee, 2014). To some extent, these outcomes will be determined by complex factors outside employees' control. However, employees' psychological evaluations and behavioural reactions to automation may also play a part in determining how automation will impact them. For instance, employees who fear and disengage in response to the implementation of new technologies will likely fare differently than employees who eagerly anticipate and embrace new technologies. Thus, the question becomes; what determines the nature of employees' perceptions and reactions to automation at work?

To date, research has not provided answers to this question. Instead, some studies have found that the fear of being replaced by automation is negatively related to well-being and favourable job attitudes (Brougham & Har, 2018; 2020; Vieitez et al., 2001). This focus on negative employee perceptions is perhaps unsurprising given that the anticipation of automation can be a stressful experience. Automation can threaten people's livelihood, and at the very least may require people to adapt to new workplace pressures, a process which can tax their limited resources. Nonetheless, given the variability in the impacts of automation (e.g., Parker & Grote, 2020), and given the variability in people's responses to stress (Lazarus & Folkman, 1984), we argue that employees' perspectives on automation are likely to be diverse. For one, it may be possible for employees to be aware of their job's automatability without fearing its negative impact. In addition, some people may appreciate the positive impacts of automation in the workplace (e.g., Brougham et al., 2019).

In the present paper we capture this diversity of evaluations by distinguishing between *perceptions* and *appraisals* of automation. To begin, we define *perceived automatability* as the degree to which an employee believes that the tasks comprising their job can be autonomously conducted by current technologies. We differentiate this perception from employees' *appraisals* of how automation will personally impact their well-being. Specifically, drawing on appraisal theory (Lazarus & Folkman, 1984), we suggest that the automatability of a person's job can be appraised as either a harmful, or beneficial. For example, perceived automatability is appraised as harmful when a person believes it will lead them to becoming redundant, and thus losing their job (e.g., Brougham & hear, 2018). We call this appraisal *automation-related job insecurity*. In contrast, an example of perceived automatability being appraised as beneficial is when a person believes it will allow them to work smarter, harder, or safer, and thus improve their job performance (e.g., Brougham et al., 2019). We call this appraisal *automation-related performance optimism*.

The nature of employees' appraisals will likely shape their affective and behavioural reactions to perceived automatability. Employees who appraise automation as a threat may believe that efforts to compete with the technology are futile and will likely disengage from their work and seek employment elsewhere. In contrast, employees who appraise automation with optimism may believe that efforts to engage with the technology will pay off and will likely attempt to reap the benefits of automation by becoming more engaged with their work and remaining committed to their organization. Importantly, we predict that the degree of control people experience at work will moderate automation appraisals. Control can help people navigate the ambiguities surrounding incoming automation; People who have a great deal of control at work can mitigate the harms, and also glean the potential benefits, associated with automation. As such, we suggest that perceived control will attenuate the relationship between perceived automatability and automation-related job insecurity, and also strengthen the relationship between perceived automatability and automation-related performance optimism.

In sum, we propose a model of employee perceptions and reactions to automation, as depicted in Figure 1. We tested our predictions across two complementary studies. In Study 1, we surveyed a diverse sample of U.S. employees to test the proposed effects in a naturalistic setting. In Study 2, we conducted an experiment to establish the causal relationships between the variables. By doing so, we make several contributions to the literature. For one, we go beyond previous research (Brougham & Haar, 2018; Coupe, 2019; Nam, 2019) to disambiguate perceived automatability from two distinct appraisals of automation. This allows us to demonstrate that perceived automatability has competing effects on downstream job attitudes depending on how employees appraise automation to affect their well-being. In addition, we reveal a key moderator of these appraisal pathways – control at work – demonstrating that contextual factors can strengthen or attenuate employees' perceptions of automation. As such, this research paves the way for managerial interventions to improve the success of automation implementation in the workplace.

Literature Review

A great deal of research across the fields of human-computer interactions, human factors, information technology, hospitality, management, and psychology have examined when and why people trust, and subsequently adopt technologies at work (for reviews see Glikson & Woolley, 2020; Hancock et al., 2011; Hoff & Bashir, 2015; Langer & Landers, 2021; Lee & See, 2004; Parasuraman & Riley, 1997; Schaefer et al., 2016). This research has identified the particular features of the technology (e.g., transparency, reliability, anthropomorphism), the user (e.g., self-confidence, expertise, mood, personality), and the situation (e.g., workload, task complexity) that interactively shape trust and use of technology. However, this research has not captured people's perceptions of broader technology-driven changes in the workplace, and the influence of these perceptions on general workplace attitudes and behaviours. For example, whereas the anthropomorphic features (e.g., eyes, voice) of a robot may influence a person's trust and use of that particular robot, these features may have less bearing on a person's belief that robots, in general, will steal their job, and their subsequent willingness to remain engaged with their job and their organizations.

To this end, a small body of research has sought to understand employees' perspective on general automation processes at work. Primarily, this research has focused on employees' fear that automation will threaten their job security. Automation-related job insecurity is related to diminished job attitudes, including lower career satisfaction, lower organizational commitment, and higher turnover intentions (Brougham & Haar, 2018; 2020). In addition, automation-related job insecurity is related to poorer employee well-being, including greater depression, cynicism, and anxiety (Brougham & Haar, 2018; Vieitez et al., 2001). This research is consistent with the broader literature on job insecurity, which has found that the "perceived threat to the continuity and stability of employment" (Shoss, 2017, p. 1914) is detrimental to job attitudes, mental and physical well-being, and job performance (Sverke et al., 2002).

Yet, research on employee perceptions of automation has frequently confounded automation-related job insecurity with perceived automatability. Perceived automatability is an evaluation regarding the *capabilities* of technologies, rather than an evaluation of the *impact* of technologies on an employees' personal outcomes. Evidence suggest that these two perceptions may be distinct. For example, various surveys have shown that although most people agree that automation will "do much of the work currently done by humans" and "will eliminate more jobs than in creates" in the coming decades, only a minority of people are worried about losing their own jobs to automation, with the majority believing that their own jobs will still exist in the coming decades (Gallup, 2018; Smith, 2016). Similarly, researchers have found no relationship between the objective likelihood that a person's job will be automated (Frey & Osborne, 2017) and their automation-related job insecurity (Brougham & Haar, 2017). Thus, perceived automatability and automation-related job insecurity may be distinct constructs with unique antecedents and consequences. Despite this, these variables have been consistently confounded in previous research, with automation-related job insecurity ("I am personally worried that what I do now in my job will be able to be replaced by smart technology, AI, robotics, and algorithms") being labelled automation awareness (i.e., perceived automatability; Brougham & Haar, 2018), and perceived automatability ("Overall, how likely do you think it is that, in the next 50 years, robots and computers will do much of the work currently done by humans?") being labelled concern about job loss (i.e., automation-related job-insecurity; Coupe, 2019; Nam, 2019).

Furthermore, research on employee perceptions of automation has primarily focused on negative perceptions of automation (Brougham & Haar, 2017; 2018; 2020; Coupe, 2019; Erebak

& Turgut, 2021; Goethals & Ziegelmayer, 2022; Koen & Parker, 2020; Lingmont & Alexiou, 2020; Nam, 2019; Priyadarshi & Premchandran, 2020; Vieitez et al., 2001). Nonetheless, a handful of qualitative studies have noted that some employees expect that automation will improve their personal and organization's performance by increasing efficiencies, decreasing errors, enhancing technical capabilities, improving safety, and affording time to focus on value-add aspects of work (Asatiani et al., 2020; Brougham et al., 2019; Roskies et al., 1988; Schneider & Sting, 2020). Along these lines, AI performance expectancy – the belief that the use of AI improves accuracy, productivity, or speed – is positively related to people's willingness to use AI (Cao et al., 2021; Gursoy et al., 2019; Lin et al., 2020). Employees in high skilled or management positions are especially likely to espouse positive automation-related performance expectations (Chao & Kozlowski, 1986; Dekker et al., 2017; Gohmann et al., 2005; Fink et al., 1995). Nonetheless, research on employees' positive impression of automation has been limited, with much of the research in this area remaining domain specific (Abdullah & Fakieh, 2020; Cao et al., 2021; Gohmann et al., 2005; Gursoy et al., 2019; Lin et al., 2020), relying on *ad-hoc* single item measures (Rodriguez-Bustelo et al., 2020; Fink et al., 1992), or measures which capture broader economic or organizational productivity (Chao & Kozlowski, 1986; Herold et al., 1995; Zhang et al., 2019) which make it difficult to isolate employees' perceptions of how automation will positively impact them personally.

More importantly, none of the research reviewed above sheds light on the conditions under which people form positive and negative impressions of automation. In the present study we address these limitations. We draw on appraisal theory (Lazarus & Folkman, 1984) to propose two distinct psychological stages: First, employees perceive the likelihood that their jobs may be automated (i.e., their automatability), and second employees appraise the impact of automation on their ability to keep and perform well at their jobs. We further draw on appraisal theory to suggest that the degree of control people experience at work will determine the extent to which they feel threatened or empowered by impending automation. Before developing these hypotheses, we first review appraisal theory in more detail.

A Model of Employee Perceptions and Reactions to Automation

Theoretical Background – Appraisal Theory

Appraisal theory provides a framework for understanding why the same stressors might evoke diverging psychological reactions from different people (Lazarus & Folkman, 1984; Dewe et al., 2012). Namely, appraisal theory states that peoples' interpretations of their environment – rather than the environment itself – shapes people's emotional and behavioural reactions to their surroundings. During *primary appraisal*, people evaluate whether they believe a stressor is going to influence their well-being. If the stressor is anticipated to lead to harm or loss, it is appraised as a *threat*, and the person experiences negative emotions such as fear and anger. In contrast, if a stressor is anticipated to lead to gain or mastery, it is appraised as a *challenge*, and the person experiences positive emotions such as eagerness and excitement.

In tandem, people also engage in a *secondary appraisal* to evaluate their ability and resources to cope with the stressor. They may consider their physical (e.g., energy), social (e.g., support), or psychological (e.g., self-esteem) resources to handle the demands of the situation. However, a crucial factor in making this evaluation is whether people feel in *control* of their circumstances (Folkman, 1984; Spector, 1998). People are more likely to appraise that they can cope, when they feel they have influence over the outcomes of the situation – when they feel they can decrease the likelihood of potential harms and increase the likelihood of potential gains. The primary and secondary appraisals also inform one another. People are more likely to appraise a stressor as challenging and less likely to appraise a stressor as threatening when they feel in control compared to when they do not feel in control (Lazarus & Folkman, 1984).

Relationship between Perceived Automatability and Automation Appraisals

With appraisal theory as a backdrop, we propose a novel model of employee perceptions and reactions to automation. The automatability of a person's job is an environmental stressor that is anticipated to have a disruptive influence on their job functioning. However, analogous to the "threat" and "challenge" appraisals, we suggest that perceived automatability will be related to both pessimistic and optimistic appraisals regarding automation's impacts on employees' well-being. First, we predict many people will make the inferential leap that if their job tasks can be automated, their employment prospects will suffer because they will be displaced by automation technologies. This is not an unreasonable inference in today's volatile job markets wherein organizations regularly hire from external sources to meet organizational needs rather than maintaining existing arrangements with their current employees (Direnzo & Greenhaus, 2011). There may be precedence for employees' fears that if a machine is able to do their job more effectively and at a lower cost than them, that their organization will favour the machine. As such, we predict that:

H1: There will be a positive relationship between perceived automatability and automation-related job insecurity.

However, we also predict that, rather than seeing automation as a source of competition, some people will see automation as a tool that is instrumental for improving workplace performance. Indeed, the purpose of automation is often to enhance performance in some capacity – albeit not necessarily individual employee performance – whether by increasing efficiencies, decreasing errors, or augmenting capabilities. As such, it is unsurprising that research (previously reviewed in other sections of this paper) has found that people believe automation will enhance organizational and personal performance (e.g., Asatiani et al., 2020; Brougham et al., 2019; Schneider & Sting, 2020). Thus, we predict that:

H2: There will be a positive relationship between perceived automatability and automation-related performance optimism.

The Moderating Effect of Control

Drawing further on appraisal theory, we suggest that *control at work* will moderate the extent to which perceived automatability is related to automation-related job insecurity and to automation-related performance optimism. When considering the automatability of their jobs, people are often considering a possible future event rather than an event that has already materialized. As such, there is inherent uncertainty regarding how automation will impact them. Indeed, as previously reviewed, there are several possible ways that automation may impact individual workers. We suggest that control at work will shape people's perceptions of how likely it is that certain outcomes will befall them. People who have a great deal of control may feel they can *cope* – both proactively and reactively (Koen & Parker, 2020) – with the environmental stressor in tangible ways, and therefore feel like active participants in automation processes, rather than passive recipients of automation's impacts.

Concretely, we suggest that people who have a great deal of control at work have the means to counteract the potential negative outcomes of automation. For example, in anticipation that an automated system will soon replace their work tasks, people who have a great deal of control over their decisions and schedules, compared to people with little control, can schedule professional development opportunities to expand their skillsets. This may improve their employability and mitigate their job insecurity (Koen & Parker, 2020). In contrast, employees with comparatively little control at work may feel stuck in redundant work processes, exacerbating their feelings of job insecurity. In addition, people who have a great deal of control at work could reallocate their automation-afforded time to tasks or roles they believe will be "safe" from displacement. In contrast, people with little control may feel helpless to reposition themselves within the company. Therefore, we propose that a comparatively great deal of control at work will decrease the likelihood that people will feel threatened by the automatability of their job. Specifically, we hypothesize that:

H3: Control will moderate the relationship between perceived automatability and automation-related job insecurity, such that the positive relationship between perceived automatability and automation-related job insecurity will be weaker for people who experience high control at work compared to people who experience low control at work.

Likewise, we suggest that people who have a great deal of control at work can also harness the potential positive outcomes of automation. For example, when an automated system gets introduced, people with a comparatively great deal of control over their schedules could arrange for training to develop skillsets that will enable them to make the most of the automation technology. People with little control at work may have a harder time keeping their skills up to date with technological progress. Further, people with a great deal of control over their job tasks could use their automation-afforded time to engage in new, value-add work tasks, thereby improving their overall job performance. In contrast, people with comparatively little control may feel powerless to harness their automation-afforded time, weakening any perceived performance benefits. Therefore, we propose that a comparatively great deal of control will increases the likelihood that people will feel empowered by the automatability of their job. Specifically, we predict that:

H4: Control will moderate the relationship between perceived automatability and automation-related performance optimism such that the positive relationship between perceived automatability and automation-related performance optimism will be stronger for people who experience high control at work compared to people who experience low control at work.

Downstream Effects on Engagement and Turnover Intentions

Downstream, we predict that automation-related job insecurity and automation-related performance optimism will have competing effects on job attitudes. In particular, we predict that automation-related job insecurity will decrease positive job attitudes and increase negative job attitudes, whereas automation-related performance optimism will increase positive job attitudes and decrease negative job attitudes. Threat appraisals are typically associated with negative emotional reactions, whereas challenge appraisals are associated with positive emotional reactions (Lazarus & Folkman, 1984). These emotions may predispose people to negatively and positively valanced job attitudes, respectively. Consistent with this, meta-analyses have shown that stressors typically considered threatening (e.g., role ambiguity, role conflict, job security, organizational politics) are associated with negative job attitudes, whereas stressors typically considered challenging (e.g., time pressure, responsibility, workload, job scope) are associated with positive job attitudes (Podsakoff et al., 2007). Further, as previously reviewed, threat appraisals in the automation context (i.e., automation-related job insecurity) have been found to be negatively related to job attitudes (Brougham & Haar, 2018; 2020; Vieitez et al., 2001).

In this paper we are especially interested in the effect of appraisals on job attitudes that may influence people's ability to successfully adapt to automation. First, we are interested in people's willingness to remain at their job (i.e., *turnover intention*), because the choice to stay may indicate an employees' willingness (or lack thereof) to prepare for, use, and work alongside new technologies. In addition, we are interested in people's willingness to invest time and energy into their work (i.e., *job engagement*). This is because job engagement may be a necessary precursor to devoting energy and resources to adapting to automation-related disruptions. Consistent with appraisal theories we predict that people who fear automation will displace them from their job (i.e., people with a high compared to low automation-related job insecurity) will feel a variety of negative emotions, which will translate into a lack of a desire to remain engaged at their present organization, and a desire to seek employment elsewhere. Further, we predict that people who believe automation will benefit their performance (i.e., people with a high compared to low performance optimism) will feel a variety of positive emotions, which will fuel engagement with their job, and decrease their desire to seek employment elsewhere. In sum, we predict that:

H5: Automation-related job insecurity will be a) negatively related to engagement, and b) positively related to turnover intentions.

H6: Automation-related performance optimism will be a) positively related to engagement, and b) negatively related to turnover intentions.

In combination, we predict that perceived automatability will have conditional indirect effects on job attitudes via two competing pathways. First, perceived automatability will be negatively related to engagement and positively related to turnover intentions via job insecurity. However, these effects will be mitigated for employees who possess a great deal of control at work. Specifically, we predict that:

H7a: The negative indirect effect of perceived automatability on engagement via automation-related job insecurity will be weaker when control at work is high compared to low.

H7b: The positive indirect effect of perceived automatability on turnover intentions via automation-related job insecurity will be weaker for people who experience high compared to low control at work.

Second, perceived automatability will positively related to engagement and negatively related to turnover intentions via performance optimism. These effects will be strengthened for employees who possess a great deal of control at work. Specifically, we predict that:

H8a: The positive indirect effect of perceived automatability on engagement via automation-related performance optimism will be stronger for people who experience high compared to low control at work.

H8b: The negative indirect effect of perceived automatability on turnover intentions via automation-related performance optimism will be stronger for people who experience high compared to low control at work.

Study 1

Method

Participants

To test our hypotheses, we combined data across two independent samples collected in August (Sample A) and October (Sample B) of 2019. These samples were originally collected to test the present hypotheses, as well as other, unrelated hypotheses. However, given the considerable overlap between the methods and variables across the two samples, we combined them to increase the power of our analyses.

Participants were 593 employees recruited via Amazon's Mechanical Turk (MTurk). To qualify for the study, participants had to be employed. We did not place restrictions on whether participants were employed through an organization or self-employed, or whether they worked full- or part-time hours. Additional eligibility criteria were that participants had to be U.S. residents, had to have previously completed 100 MTurk "Human Intelligence Tasks" (HITs) and had to have earned an approval rating of greater than 90% on those HITs. To improve data quality, we removed participants who answered one or more of three instructed-answer attention checks (e.g., "please answer strongly disagree") incorrectly (*n* = 93). Thus, the final sample consisted of 500 employees (255 from Sample A and 245 from Sample B). Participants were primarily White (77.6%), male (56.4%), and were on average 36.74 years old (*SD* = 10.37). They were mostly employed full-time at an organization (86.2%), working on average 38.05 hours per week (*SD* = 9.16), and had been employed at their organizations for 6.86 years (*SD* = 4.83). Participants came from a variety of sectors, including marketing, sales, and service (14.4%,), information technology (11.6%) and health science (10.2%).

Procedure

We spread participation across three surveys collected on three consecutive workdays to minimize participant fatigue and to reduce common method variance (Podsakoff et al., 2003). The procedure was similar across both samples, with deviations noted throughout this section. The steps of the procedure are also summarized in Figure 2. Each survey was either 20 (Sample A) or 10 (Sample B) minutes long. Participants received $2.00 USD (Sample A) or $1.00 USD (Sample B) per survey with an additional $2.00 USD (Sample A) or $1.00 USD (Sample B) bonus for completing all three surveys. A notable difference was that participants reported control at different times. Namely, participants reported control at Time 1 in Sample A and at

Time 2 in Sample B. However, consistent across both samples, participants reported perceived automatability, automation-related job insecurity, and automation-related performance optimism at Time 2, and job attitudes (engagement and turnover intentions) at Time 3. The automation-related variables (perceived automatability, automation-related job insecurity, automation-related performance optimism) were presented in counterbalanced order, as were the job attitudes (engagement and turnover intentions). All the participants in the final sample provided complete responses on all three surveys.

Measures

On all measures, participants responded to items on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Reliabilities are reported in Table 1. All scales are presented in their entirety in Appendix A.

Perceived Automatability. We measured perceived automatability using a nine-item scale developed for the present study. Items were written to capture the extent to which people believe that aspects of their job are susceptible to automation, devoid of any appraisal regarding the consequences of the automatability on their job security or job performance (e.g., "Some of the tasks performed on this job can be automated"). However, in hindsight, three of the items likely tapped job insecurity (e.g., "Automation will reduce the need for humans to perform this job"). Thus, these items were removed from the scale, resulting in six total items. Confirmatory Factory Analysis (CFA) confirmed that the six-item version of the scale (Cronbach's $\alpha = .87$, $\chi2(9) = 55.239$, $p < .001$, CFI = .969, RMSEA = .101, SRMR = .034) was a significantly better fit ($\Delta\chi2(18) = 250.549$, $p < .001$) for the data than the nine-item scale (Cronbach's $\alpha = .92$, $\chi2(27) = 305.788$, $p < .001$, CFI = .909, RMSEA = .144, SRMR = .060), lending empirical support to our rationale for removing the three items.

Automation-related Job Insecurity. We measured automation-related job insecurity with a 4-item scale, called the "Smart Technology, Automation, Robotics, and Artificial-Intelligence (STARA) awareness scale" (Brougham & Haar, 2018). This scale captures the extent to which people are worried that their job will be lost to STARA technologies (e.g., "I am personally worried that what I do now in my job will be able to be replaced by STARA"). As such, we believe this construct is more appropriately labelled automation-related job insecurity, because it refers to an appraisal regarding the impact of automaton on a person's job prospects, rather than simply an awareness of the automatability of one's job. We replaced all instances of the acronym "STARA" with the word "automation" to keep the terminology consistent across our measures.

Automation-related Performance Optimism. We developed a six-item scale to assess people's beliefs that automation will improve their ability to perform their job. An example item is, "Automation will enable me to perform my job better."

Control at Work. One common source of control at work is job autonomy – the freedom and independence employees are provided over their schedules, decisions, and work methods (Spector, 1986, Spector 1998, Rauvola & Rudolph, 2022). In particular, job autonomy provides employees with agency over their time and actions at work, which may enable them to actively shape how they interact with and are impacted by automation at work.

Control was assessed with Morgeson and Humphrey's (2006) job autonomy scale. This scale has three subdimensions capturing employee's level of control over various work procedures: scheduling autonomy ("The job allows me to make my own decisions about how to schedule my work"), decision-making autonomy ("The job provides me with significant autonomy in making decisions"), and methods autonomy (e.g., "The job allows me to make decisions about what methods I use to complete my work"), each assessed with three items.

Given that we did not specify different hypotheses by subdimension, the subdimensions were combined into a global measure of control. However, the methods autonomy subscale was not included in Sample B due to an error. Thus, for roughly half of the participants, control scores are based only on the scheduling and decision-making subscales[1].

Engagement. We measured engagement using Rich and colleagues' (2010) 18-item scale. This measure includes three subdimensions: physical engagement (e.g., "I work with intensity on my job"), emotional engagement (e.g., "I am enthusiastic in my job"), and cognitive engagement (e.g., "At work, my mind is focused on my job"). However, given that we did not make hypotheses by subdimensions, we combined the items into a global measure of engagement, as recommended by the original authors of the scale.

Turnover Intentions. We measured turnover intentions using Kelloway and colleagues' (1999) 4-item scale. An example item is "I am planning to look for a new job."

Analysis Plan

First, to ensure our scales measured distinct constructs, we tested a measurement model using CFA with all measured items loading onto their respective constructs. We compared this hypothesized model against two alternate measurement models. We tested a model in which the perceived automatability and automation-related job insecurity items loaded onto the same factor, because it is possible that people do not make a clear distinction between the technical possibility of their job's automatability and the consequence of their job's automatability on their job security. Further, we also tested a model in which all automation-related variables (perceived automatability, automation-related job insecurity, and automation-related performance optimism) loaded onto the same factor, because it is possible that people's automation-related beliefs are

[1] We reran all hypothesis tests with control at work calculated based on only the two subscales that were present in the entire sample. The results were unchanged.

indistinguishable. We used parcelling to reduce item-specific random errors (Little et al., 2002). We created three parcels each for engagement and control at work[2] corresponding to the subdimensions of these scales. For all other constructs we created two parcels per construct containing the even and odd items of the scales, respectively.

Next, we tested our hypothesized model using structural equation modeling (SEM). The SEM approach provides several advantages over traditional OLS regression approaches, including the ability to test all hypothesized relationships at once and testing the overall fit of the model (Bollen, 1989). We used observed, rather than latent variables. Doing so allowed us to obtain conventional fit indices, which is otherwise impossible in models containing latent interactions terms (Sardeshmukh & Vandenberg, 2017). We specified the model such that the automation appraisals (automation-related job insecurity and automation-related performance optimism) could covary. The dependent variables (engagement and turnover intentions) were also allowed to covary. Finally, we allowed the interaction term (perceived automatability x control at work) and its components to covary with one another, as these terms are necessarily interrelated. The predictor variables (perceived automatability and control at work) were mean centered to facilitate interpretation of the main effects (Cohen et al., 2003).

To test H1 and H2, we examined the paths from perceived automatability to automation-related job insecurity and automation-related performance optimism, respectively. To evaluate H3 and H4 we examined the interaction terms between perceived automatability and control predicting each automation appraisal. Significant interactions were plotted, and the simple slopes were calculated to understand the pattern of the interactions. To test H5 and H6, we examined

[2] Recall that for half the sample, we did not collect the "methods-autonomy" subscale of the control at work scale. Therefore, we also reran the measurement model using two parcels for the control at work construct (with even-odd parcelling). The measurement model results were unchanged.

the paths from the automation appraisals to each dependent variable. Finally, to test H7 and H8, we specified conditional indirect effects from perceived automatability to the dependent variables via each automation appraisal at high and low levels of control (±1SD above and below the mean of control) and calculated the difference between the high and low indirect paths. To account for the nonnormality of indirect effect sampling distributions (MacKinnon et al., 2002; MacKinnon et al., 2004), we used bootstrapping to create bias-corrected 95% confidence intervals around the estimates. Confidence intervals that excluded 0 were interpreted as significant.

Results

Means, standard deviations, and intercorrelations between all study variables are presented in Table 1. The hypothesized measurement model fit the data well ($\chi^2(62) = 255.213$, $p < .001$, CFI = .969, RMSEA = .079, SRMR = .046), indicating that the scales appropriately distinguished between the constructs. The alternate model in which perceived automatability and automation-related job insecurity loaded onto the same factor was a significantly worse fit for the data ($\Delta\chi^2(5) = 334.771$, $p < .001$; $\chi^2(67) = 589.984$, $p < .001$, CFI = .916, RMSEA = .125, SRMR = .074). Similarly, the alternate model in which all three automation-related constructs loaded onto the same factor was also a significantly worse fit for the data ($\Delta\chi^2(9) = 1532.724$, $p < .001$; $\chi^2(71) = 1787.937$, $p < .001$, CFI = .723, RMSEA = .220, SRMR = .123).

Next, we tested the structural model (Figure 3). The SEM indicated that the hypothesized structural model was only a fair fit for the data ($\chi^2(6) =65.297$, $p < .001$, CFI = .912, RMSEA = .141, SRMR = .062). Thus, we decided to test an alternate model wherein we freed the paths from control to the dependent variables, as control at work has been shown to be related to job attitudes in previous research (Spector 1986) and was also significantly related to engagement (*r*

= .37, $p < .001$), and turnover intentions ($r = -.24$, $p < .001$) in the current study. The resulting model was an excellent fit for the data ($\chi^2(4) = 11.614$, $p = .021$, CFI = .989, RMSEA = .062, SRMR = .020), and was a significant improvement from the originally hypothesized model ($\Delta\chi^2(2) = 53.683$, $p < .001$). Thus, we proceeded with the revised model.

Supporting H1 and H2, perceived automatability was significantly positively related to both automation-related job insecurity ($B = .74$, $SE = .04$, $p < .001$), and automation-related performance optimism ($B = .41$, $SE = .06$, $p < .001$). In H3, we predicted that control would moderate the relationship between perceived automatability and automation-related job insecurity such that the relationship would be weaker when control at work was high. In line with these predictions, control moderated the relationship between perceived automatability and automation-related job insecurity ($B = -.07$ $SE = .03$, $p = .017$, $\Delta R^2 = .01$). This interaction is plotted in Figure 4a. Simple slopes indicated that perceived automatability had a weaker positive relationship with job insecurity for people with high ($B = .67$, $SE = .05$, $p < .001$) compared to low control ($B = .81$, $SE = .04$, $p < .001$). Thus, H3 was supported.

Similarly, H4 predicted that control would moderate the relationship between perceived automatability and automation-related performance optimism such that relationship would be stronger for people with a comparatively great deal of control at work. In line with this, control significantly moderated the relationship between perceived automatability and performance optimism ($B = .13$, $SE = .05$, $p = .012$, $\Delta R^2 = .02$). This interaction is plotted in Figure 4b. Simple slopes showed that the positive relationship between perceived automatability and performance optimism was stronger for people with high ($B = .55$, $SE = .08$, $p < .001$) compared to low control ($B = .28$, $SE = .08$, $p < .001$). Thus, H4 was also supported.

Downstream, we predicted that job insecurity would be negatively related to engagement (H5a) and positively related to turnover intentions (H5b). In contrast, we predicted that performance optimism would be positively related to engagement (H6a) and negatively related to turnover intentions (H6b). These hypotheses were largely supported. Job insecurity was significantly negatively related to engagement (H5a; $B = -.09$, $SE = .03$, $p = .004$), and significantly positively related to turnover intentions (H5b; $B = .20$, $SE = .05$, $p < .001$). Further, performance optimism was significantly positively related to engagement (H6a; $B = .09$, $SE = .03$, $p = .006$). However, contrary to H6b, performance optimism was not significantly related to turnover intentions ($B = -.05$, $SE = .06$, $p = .347$).

Lastly, we tested the conditional indirect effects of perceived automatability on each dependent variable via each automation appraisal at high and low levels of control (Table 2). The negative indirect effect of perceived automatability on engagement via job insecurity was significant at both high (IE = -.060, 95% CI [-.103 -.020]) and low (IE = -.073, 95% CI [-.123, -.024]) levels of control. Further, in support of H7a, the negative indirect effect of perceived automatability on engagement via job insecurity was significantly *weaker* when perceived control was high compared to low (ΔIE = .013, 95% CI [.002, .032]). Next, the positive indirect effect of perceived automatability on turnover intentions via job insecurity was significant for people with both high (IE = .133, 95% CI [.062, .204]) and low (IE = .161, 95% CI [.076, .245]) control. Further, in support for H7b, the indirect effect was significantly *weaker* for people with high compared to low control (ΔIE = -.028, 95% CI [-.062, -.006]).

Next, the positive indirect effect of perceived automatability on engagement via performance optimism was significant for people with both high (IE = .047, 95% CI [.014, .089]) and low (IE = .024, 95% CI [.008, .050]) levels of control. Further, the positive indirect effect was significantly *stronger* when control was high compared to low (ΔIE = .023, 95% CI [.005, .058]). Thus, H8a was supported. Finally, contrary to H8b, there was no significant indirect effects from perceived automatability to turnover intentions via performance optimism for people with high (IE = -.029, 95% CI [-.097, .028]) or low (IE = -.015, 95% CI [-.054, .013]) levels of control, and the difference in the indirect effects across levels of control was also not significant (ΔIE = -.014, 95% CI [-.062, .011]).

Auxiliary Analyses

People may derive control from a variety of sources at work. Control over their schedules, decisions, and work methods is just one of these sources. People may also vary in their natural disposition to feel in control at work. Along these lines, among the variables we collected in the original surveys (Sample A and Sample B), *work locus of control* was a plausible alternate operationalization of the control at work construct. *Work locus of control* is an individual difference that describes the extent to which people believe that outcomes at work are controlled by their own action (internal locus of control), or by external forces (external locus of control; Spector, 1988). Therefore, we also conducted our hypotheses tests with work locus of control as the moderator variable. The conclusions were identical to when we used control at work as the moderator. The details of these analyses are reported in Appendix B.

Discussion

In this study we found support for many of our hypotheses. For one, we successfully distinguished between perceived automatability and automation-related job insecurity, constructs which had been previously confounded in the literature. Perceived automatability was found to be related to both negatively valanced (i.e., automation-related job insecurity) and positively valanced (i.e., automation-related performance optimism) automation appraisals. These relationships were further moderated by control at work. For people who experienced a comparatively great deal of control at work, the relationship between perceived automatability and automation-related job insecurity was weakened. In contrast, for people who experienced a comparatively great deal of control at work, the relationship between perceived automatability and automation-related performance optimism was strengthened.

Downstream, automation appraisals had competing effects on job attitudes. Namely, automation-related job insecurity was negatively related to engagement and positively related to turnover intentions whereas automation-related performance optimism was positively related to engagement. Therefore, via diverging appraisals, perceived automatability also had competing indirect effects of job attitudes. As such, we demonstrated that believing that a one's job is automatable does not necessarily have negative consequences on their job attitudes, but that appraisal processes determine the downstream consequences of this belief. We conducted this study in a naturalistic setting, with a large sample of employees who were employed in a wide variety of occupations. As such, we presented strong evidence for the generalizability of our findings.

However, in this study we were unable to establish the causal direction among the variables. One possible concern is that there may be reverse causality occurring among some of the variables. For instance, people who fear losing their job to automation may become hypervigilant to cues in the environment signalling automation, and thus perceive a greater likelihood that their job is automatable. Therefore, instead of perceived automatability leading to automation-related job insecurity, automation-related job insecurity may lead to perceived automatability.

Further, there may be plausible alternate explanations for some of our results. In particular, job type (high-skilled versus low-skilled), rather than control at work, may be the primary moderator between perceived automatability and automation appraisals. For one, people in comparatively high skilled jobs may be less likely to believe that automatability will lead to job loss, because high-skilled jobs are typically complex and variable, and as such, are less susceptible to being completely displaced by automation (Frey & Osborne, 2017; Brougham & Haar, 2017). Further, people in comparatively high-skilled jobs may be more likely to believe that automatability will lead to performance enhancements because employees in high skilled jobs typically receive more education in technology-relevant fields (e.g., science, technology, engineering, and mathematics), and thus may be more capable of utilizing the technology to their benefit. In line with this explanation, highly skilled, highly educated workers exhibit lower automation-related job insecurity compared to workers with lower skills and education (Chao & Kozlowski, 1986; Dekker et al., 2017; Morikawa, 2017). Given that high-skilled jobs are also typically associated with greater control at work, it is therefore possible that job type, rather than control at work was driving the effects in this study. Thus, in Study 2, we experimentally manipulated control, as well as automatability, to test their causal effects on automation appraisals.

Study 2

Method

Participants

In February 2021, we recruited 196 participants from MTurk to participate in an online experiment. To be eligible for the study, participants had to be U.S. residents, employed (full- or part-time, working at an organization or self-employed), and had to have previously completed 100 HITS with a minimum 90% approval rating on MTurk. The study was 20 minutes in duration and participants were remunerated $2.00 USD. We removed two participants who answered one or more of two instructed-answer attention check questions incorrectly. The final sample (*N* = 194) was primarily White (71.1%) and male (51.0%), with an average age of 38.29 years old (*SD* = 11.27). Participants were mostly employed full-time at an organization (76.8%), working on average 36.84 (*SD* = 11.12) hours per week, and had been tenured for 5.56 (*SD* = 4.84) years. They worked in various job sectors including marketing, sales, and service (16.0%), information technology (10.8%), and health science (8.7%).

Procedure

We conducted a 2 (automatability: high, low) by 2 (control: high, low), between-subjects experiment, with random assignment to conditions. We manipulated participants' perception of automatability and perception of control by providing false information about their jobs. To do so, we told participants we would be querying "academic and professional databases." First, we provided participants with detailed definitions of each construct. Automatability was defined as the likelihood that a job can be carried out by technologies, determined by factors such as 1) the tasks that make up the job, and 2) the ability of current technologies to conduct those tasks. Similarly, control was defined as an important work characteristic that encompasses factors such as "[employees'] developing their own methods to accomplish work, guiding themselves with little or no supervision, and making their own decisions."

Next, to create the impression that we would be accessing databases during the study, we asked participants to find their Standard Occupational Classification (SOC) code from O*Net (https://www.onetonline.org/) and copy it into the survey. Specifically, we provided participants with step-by-step instructions (Appendix C) on how to enter their job title into the O*Net search bar, where to look to identify their SOC code, and how to troubleshoot in case they were unable to immediately identify their SOC code. Using these instructions, nearly all[3] participants were able to successfully copy their SOC codes into the survey.

We anticipated that if we provided participants with exact information (e.g., your job has an 82% chance of becoming automated), it would likely to trigger suspicion. Instead, we told participants that it is difficult to determine the automatability and level of control of any job with exact certainty, and thus that we would only provide them with generalized information – "low, medium, or high" levels – regarding each variable. In reality, participants were randomly assigned to receive either the "low" or "high" levels of each variable. Specifically, in the high automatability condition participants read, *"Your job (Occupation Code = [piped text]) has a high risk of becoming automated. That is, your job is more automatable than 75% of all jobs."* In the low automatability condition they read, *"Your job (Occupation Code = [piped text]) has a low risk of becoming automated. That is, your job is less automatable than 75% of all jobs."* Likewise, in the high control condition they read, *"Your job (SOC code = [piped text]) has a high degree of control compared to other jobs. Concretely, your job has a greater degree of control than 75% of all jobs,"* whereas in the low control condition they read, *"Your job (SOC code = [piped text]) has a low degree of control compared to other jobs. Concretely, your job has a lower degree of control than 75% of all jobs." I*To increase the realism of the false information, the SOC codes participants entered earlier in the survey were piped into the messages.

The automatability and control manipulations were presented in counterbalanced order. Immediately after each manipulation, participants filled out manipulation checks. Following the

[3] The two participants who did not successfully copy their SOC codes still entered relevant text (i.e., job title, or URL containing the SOC code). Thus, later in the survey when their responses were piped into the automatability and control manipulation text, they received intelligible messages. Therefore, we retained their data.

manipulation checks, participants reported their automation appraisals (job insecurity and performance optimism), in counterbalanced order. Finally, participants reported their job attitudes (engagement and turnover intentions), in counterbalanced order.

At the conclusion of the study, we conducted an extensive debrief procedure, including an open-ended questionnaire asking participants to report the perceived purpose of the study and inquiring about suspicion[4]. Then, we explained to participants the true purpose of the study and directed participants to external resources containing true information about automatability (Frey & Osborne, 2017) and occupational control (National Center for O*NET Development), which they could visit on a voluntary basis.

Measures

The automation appraisals (job insecurity and performance optimism) and the dependent variables (engagement and turnover intentions) were measured with the same scales as in Study 1. Further, we used the perceived automatability scale and control at work scale from Study 1 as manipulation checks for the automatability and control inductions, respectively.

Analysis Plan

First, we specified the measurement model to test that our scales measured unique constructs. We included the measured variables in the model (job insecurity, performance optimism, engagement, and turnover intentions) but did not include the manipulation check variables (perceived automatability and control at work) in the measurement model. As such, we also did not test the analogous competing measurement models, as we did in Study 1, because

[4] Despite our efforts to enhance the realism of the manipulations, 12.4% of participants were distrustful of the automatability manipulation, and 6.70% were distrustful of the control manipulation. Given the potential impact of distrust on our results, we reran our hypotheses tests omitting individuals who expressed distrust about either manipulation. The results based on the reduced sample (N = 169) were largely unchanged, apart from H6a (the downstream effect of performance optimism on engagement) which was unsupported.

automatability was manipulated rather than measured in this study. Once again, we used parcelling: We created three parcels for engagement corresponding with the subdimensions of engagement (physical, emotional, and cognitive engagement). For all other constructs we created two parcels containing the even or odd numbered items.

Next, we tested our structural model. Perceived automatability was coded as 1 for the high automatability condition and -1 for the low automatability condition. Likewise, control was coded 1 for the high and -1 for the low control condition. To maintain consistency with Study 1, we specified the modified SEM model with additional paths from the moderator to the dependent variables. All other analytic procedures were identical to Study 1.

Results

Means, standard deviations, and intercorrelations between all study variables are presented in Table 3. The measurement model showed acceptable fit for the data ($\chi^2(21) = 77.063$, $p < .001$, CFI = .965, RMSEA = .118, SRMR = .057). Likewise, the structural model (Figure 5) also exhibited excellent fit ($\chi2(4) = 5.016$, p < .001, CFI = .990, RMSEA = .036, SRMR = .020).

Manipulation Check

We first sought to determine the efficacy of our manipulations (Table 4). As expected, people in the high automatability condition reported significantly higher perceived automatability than people in the low automatability condition ($t(192) = 5.49$, $p < .001$, $d = .79$). Also, in line with expectations, people in the high automatability condition did not report significantly different levels of perceived control than people in the low automatability condition ($t(192) = .29$, $p = .770$, $d = .04$). Similarly, people in the high control condition reported significantly higher perceived control compared to people in the low control condition ($t(192) =

4.16, p <.001, d = .60). Yet, people in the high control condition did not significantly differ from people in the low control condition in terms of perceived automatability (t(192) = .065, p = .515, d = .09). Thus, both manipulations were effective at inducing the intended perceptions, without influencing the perceptions they were not intended to influence.

Hypothesis Testing

First, in support for H1 and H2, automatability was significantly positively related to both automation-related job insecurity (B = .40, SE = .09, p < .001) and automation-related performance optimism (B = .23, SE = .09, p = .007). In support for H3, the automatability and control interaction significantly predicted job insecurity (B = -.21 SE = .09, p = .017, ΔR^2 = .03). This interaction is plotted in Figure 6. Simple slopes indicated that there was a significant positive relationship between automatability and job insecurity when control was low (B = .61, SE = .13, p <.001), but no significant relationship when control was high (B = .19, SE = .12, p = .10). Thus, H3 was supported. In contrast, there was no significant interaction between automatability and control in predicting performance optimism (B < .001, SE = .09, p = .972, ΔR^2 = .00), meaning that H4 was not supported.

Downstream, job insecurity was significantly negatively related to engagement (H5a; B = -.13, SE = .05, p = .003), and significantly positively related to turnover intentions (H5b; B = .34, SE = .08, p < .001). In contrast, performance optimism was not significantly related to engagement at the p < .05 level (B = .07, SE = .04, p = .097). Yet, given that we had posed directional *a priori* hypotheses, and given that the effect was consistent with the patten observed in Study 1, we interpret these results as supportive of H6a. However, performance optimism was not significantly related to turnover intentions (B = -.04, SE = .08, p = .593), failing to support H5b.

Finally, we tested the conditional indirect effects. As shown in Table 5, the negative indirect effect of automatability on engagement via job insecurity was significant in the low control condition (IE = -.081, 95% CI [-.155, -.032]) but not in the high control condition (IE = -.026, 95% CI [-.068, .002]). Supporting Hypothesis H7a, that the negative indirect effect was *weaker* when control was high compared to low (ΔIE = .056, 95% CI [.010, .137]). Next, the positive indirect effect of perceived automatability on turnover intentions via job insecurity was significant when control was low (IE = .208, 95% CI [.103, .350]) but not when control was high (IE = .066, 95% CI [-.007, .161]). The positive indirect effect was significantly *weaker* in the high compared to low control condition (ΔIE = -.143, 95% CI [-.317, -.028]), supporting H7b.

Given that the interaction between control and automatability on performance optimism (H4) was unsupported, the downstream conditional indirect effects on engagement and turnover intention (H8a and H8b) were also unsupported. Instead, we tested the unmoderated indirect effects from automatability to the dependent variables via performance optimism. The indirect effect of automatability on engagement via performance optimism was not significant (B = .016, SE = .012, 95% CI [-.001, .047]), although the 90% confidence interval did not intersect 0 (90% CI [.002, .042]). The indirect effect of automatability on turnover intentions via performance optimism was also not significant (B = -.009, SE = .019, 90% CI [-.057, .022]).

Discussion

The purpose of Study 2 was to constructively replicate the findings of Study 1 and to determine the causal direction among the focal variables. To this end, we replicated most of findings from Study 1. Namely, we found that perceived automatability predicted both types of automation appraisals – automation-related job insecurity and automation-related performance optimism. As in Study 1, control moderated the relationship between perceived automatability and automation-related job insecurity, such that in the high compared to low control condition, the relationship was attenuated. We also replicated the pattern of downstream effects of automation appraisals on job attitudes. Namely, automation-related job insecurity was negatively related to engagement and positively related to turnover intentions, whereas automation-related performance optimism was positively related to engagement.

However, unlike in Study 1, control at work did not moderate the relationship between perceived automatability and automation-related performance optimism. It is possible that the control manipulation was not strong enough to induce the interaction effect on performance optimism. Specifically, to induce perceived control, we told participants information about their job's *relative* level of control compared to other people (e.g., "Your job has a high (low) degree of control compared to other jobs). Although this manipulation may have induced thoughts about a person's level of job control relative to their peers, it may have failed to make salient the ways in which a person can exercise control in their day-to-day work lives – thoughts which would have helped employees reflect on the tangible ways in which they could harness automation for their benefit at work. Nonetheless, the manipulation check indicated that people perceived greater control in the high compared to low control condition. Thus, this explanation cannot fully account for the inconsistent results. Alternatively, it is possible that the population level interaction effect is small, and that therefore, although we were able to detect the effect with a large sample size in Study 1, we were unable to detect the effect in Study 2.

General Discussion

Automation has already and will continue to transform workplaces (Brynjolfsson & McAfee, 2014; Cameron, 2017; Schwab, 2017). Although the implications of automation on net employment trends have been extensively studied (e.g., Acemoglu & Restrepo, 2017; Autor et al., 2003; Autor & Salomons, 2018; Goos & Manning, 2007; Webb, 2019), individual employee perceptions and reactions to automation are not well understood. Instead, research in this area has often emphasized people's fearful evaluations of automation (e.g., Brougham & Haar, 2018, 2020; Koen & Parker, 2020; Nam, 2019), while also confounding perceptions and appraisals of automation. Further, no research has examined the conditions under which employees might form positively and negatively valanced evaluations of automation. To this end, the present research adopted appraisal theory as a theoretical framework to understand employees diverging appraisals of their automatability, and the consequences of these appraisals on their workplace attitudes. We tested our predictions using a mixed methods approach using two complementary studies – a large scale survey (Study 1) and an experiment (Study 2) – providing both an externally and internally valid test of our hypotheses. Below we explicate our major findings.

First, we successfully distinguished between perceived automatability and two appraisals: automation-related job insecurity and automation-related performance optimism. We found that perceived automatability was positively related to automation-related job insecurity, indicating that for some people, automatability is seen as a bad omen that signals that job loss is on the horizon. However, we also found that perceived automatability was also positively related to automation-related performance optimism, indicating that for some people, automatability is a positive signal which suggests the possibility of improved performance. Yet, consistent with the adage, "losses loom larger than gains," we also found that the bivariate correlations between perceived automatability and job insecurity were consistently stronger than the bivariate correlations between perceived automatability and performance optimism (Study 1 $z = 6.88$ $p < .001$; Study 2 $z = 2.60$, $p < .001$). Thus, the threat of job loss may be more salient than the opportunity to improve performance.

Importantly, we also found that control at work played a key role in shaping people's appraisals. We had suggested that having control at work may help employees engineer solutions to the potential threats posed by automation and orchestrate opportunities from the potential benefits offered by automation. In line with this, we found that people with a comparatively great deal of control at work exhibited a weaker relationship between perceived automatability and job insecurity (in both studies) and stronger relationship between perceived automatability and performance optimism (in Study 1). We also replicated this same pattern of results with a different operationalization of control (work locus of control) in Study 1. Therefore, there is converging evidence that control, whether derived from the workplace context or from people's general tendency to feel in control, may enable people to feel they can cope with automation adaptively.

Downstream, the effects of automation-related job insecurity and automation-related performance optimism were divergent. Automation-related job insecurity was detrimental to job attitudes by being negatively related to engagement and positively related to turnover intentions. In contrast, automation-related performance optimism was beneficial to job attitudes by being positively related to engagement. Thus, via diverging appraisals, perceived automatability also has diverging effects on job attitudes. Therefore, in contrast to the prevailing empirical findings (e.g., Brougham & Haar, 2018; 2020; Vieitez et al., 2001), we found that employees' awareness of their job's automatability does not exclusively have negative consequences at work, but that its effect depends on how it is appraised.

Theoretical Implications

With this research, we introduced theoretical clarity between perceptions and appraisals of automation. In particular, we drew on appraisal theory to explicate that people's recognition of their job's automatability is distinct from their evaluations of how automatability will impact their job prospects. Doing so allowed us to disambiguate previous research – which had often treated perceived automatability and automation-related job insecurity as one and the same. Instead, we found that these two variables are indeed distinct, with sometimes competing consequences on downstream outcomes. In particular, whereas job insecurity is detrimental to job attitudes (in line with previous research; Brougham & Haar, 2018; 2020; Vieitez et al., 2001), perceived automatability can have both positive and negative indirect effects on job attitudes. Therefore, conceptualizing perceptions and appraisals of automation as unique variables is crucial for moving this line of research forward.

Further, this research also reorients the literature to a more balanced perspective on employee reactions to automation. Research to date has leaned negative, with a focus on employees' fear of becoming displaced by technology (e.g., Brougham & Haar, 2018, 2020; Koen & Parker, 2020; Nam, 2019), among other more general threat perceptions (e.g., Cao et al., 2021; Erebak & Turgut, 2021; Herold et al., 1995). Our model, on the other hand, elevated the importance of appraisals in the process of employee reactions, thereby shifting the emphasis away from automation as a threat and towards automation as a stressor (Lazarus & Folkman, 1984). With this shift, automation is conceptualized as the source of multiple possible effects, and therefore, the source of multiple plausible employee reactions. This model led us to the nuanced finding that perceived automatability has both positive and negative indirect effects on job attitudes via competing appraisal pathways – a conclusion that contends with current empirical findings that employee awareness of automatability is related to primarily negative attitudes and well-being outcomes (e.g., Brougham & Haar, 2018; 2020; Vieitez et al., 2001).

With this more balanced perspective, new findings may emerge regarding the positive impacts of perceived automatability.

Finally, this paper contributed to our understanding of which employees adopt various automation appraisals, and why. Although previous research had examined the correlates of automation-related job insecurity (e.g., Brougham & Haar, 2018; 2020; Vieitez et al., 2001) and the correlates of some positive automation perceptions (Cao et al., 2021; Gursoy et al., 2019; Lin et al., 2020; Rodriguez-Bustelo et al., 2020), this study was to first to seek to understand the conditions under which employees might adopt these appraisals. We argued from an appraisal theory perspective that control is instrumental to shaping people's appraisal because it determines whether people have influence over their automation-related outcomes. Consistent with this argument, we found that both situational control (control at work) and dispositional control (work locus of control) moderated the relationships between perceived automatability and automation appraisals. Therefore, we provided insight into which occupations and which employees may be most susceptible to pessimistic or optimistic automation appraisals, and also how to intervene to influence people's appraisal.

Practical Implications

When automation is implemented at work, it may be crucial to ensure that employees' attitudes are not harmed in the process. To that end, managers can help employees foster optimistic appraisals and combat pessimistic automation appraisals by promoting employee control at work. For example, mangers could give employees control over their time and resources – by giving them flexible work schedules or discretionary professional development budgets – to enable them to prepare to take on new roles when automation replaces their current tasks. Employees are often highly motivated to maintain their job security (Shoss, 2017) and are willing and capable of engaging in such preparatory behaviours. For example, during an informational interview with the first author, an employee working at a university admissions office explained that she began taking evening classes towards a psychology degree when she learned that her workplace was implementing an automated admissions algorithm system, because she feared that the system would displace most of her work in the next few years (anonymous, personal communication, February, 2020). She believed that a psychology degree would equip her for new roles that were less likely to become automated. Not only would giving employees control tangibly help them prepare for automation, but our research suggests that it improves employees' psychological appraisals of automation and thus their downstream job attitudes.

Similarly, many people are highly motivated to perform well at work and will make use of their resources, including the technologies at their disposal, to perform to the best of their ability. Thus, giving employees control at work may enable and motivate them to make the best use of automation to achieve their peak performance. For example, employees may even be motivated to *automate their own job* (e.g., create computer programs that more efficiently conduct some of their work tasks), if they know that they will have autonomy over the automation-afforded time they gain by doing so. Thus, giving people control – such as by involving them in decisions over how automation-afforded time is reallocated– may enable employees to make the best use of automation, and simultaneously boost their automation appraisals and job attitudes.

However, as part of a larger strategy to prepare the workforce for automation, promoting employee control should only be one piece of a multi-pronged approach. Ultimately, employees may not be able to foresee ideal strategies to prepare for automation. For example, employees may not know *which* skills to develop if they do not know which technologies the company will implement or what new roles they are likely to transition into. Instead, management may have a better birds-eye view of employees' developmental needs and thus be in a better position to direct training and re-employment initiatives. Nonetheless, even if managers are at the helm of employee retraining efforts, the results of the present study suggest that maintaining high levels of employee perceived control is key to ensuring that employees continue to remain engaged and committed during the transition.

Limitations

The present research is not without limitations, and our results should be interpreted in light of the following. First, in our discussion of Study 1 we raised the concern that job type may be a plausible alternate explanation for our results. In particular, employees in high-skilled compared to low-skilled jobs likely appraise automatability differently. Employees in comparatively high-skilled occupations may believe that automatability is less likely to displace them, because their jobs are typically less automatable (i.e., their jobs are complex and less repetitive). Similarly, employees in comparatively high-skilled occupations may also believe that automatability is more likely to improve their performance because they may be in better positions to make use of the automation (i.e., they may have more relevant educational backgrounds). Thus, job type, rather than control at work, may be the primary driver of the observed interaction effect. We ruled out the possibility of job type being the *sole* explanation of our findings by conducting Study 2 and replicating the effects with an experimental induction of control at work. Nonetheless, job type may still be an important driver of the observed effects, and one that future research should consider more thoroughly.

Second, throughout the paper we argued that the construct of interest was *actual* control at work. Yet, we measured and manipulated people's *perceived* control at work, which may not be a perfect approximation of actual control due to various perceptual biases. Nonetheless, we believe this was a reasonable operationalization of control. Alternate operationalizations may have been to use objective ratings of occupational level control. For instance, O*Net categorizes occupations based on "independence" (defined as the job requiring employees to "develop one's own ways of doing things, guide oneself with little or not supervision, and depend on oneself to get things done") and "freedom to make decisions" (defined as the extent to which the job involves "decision making freedom, without supervision" National Center for O*NET Development). These operationalizations captures aggregate levels of control experienced by multiple employees within a particular occupation. Yet, employees' actual experiences of control may be idiosyncratic to them, determined by a variety of factors including company policies, individual differences, and employee-supervisor relationships. Thus, we argue that self-reported control provides a better approximation of actual control than objective, occupation-level ratings of control. In line with this, neither "independence" nor "freedom to make decisions" significantly moderated the relationship between perceived (Study 1) or manipulated (Study 2) automatability and automation-related job insecurity or automation-related performance optimism.

Finally, in the present studies we were unable to determine the causal direction among automation appraisals and job attitudes. One possible concern is that there may be reverse causality occurring. People with generally positive job attitudes may view automation through a rosy lens and thus believe it will enable them to perform their jobs better. In contrast, people with overall negative job attitudes may have a bias against any new organizational initiatives, and thus interpret automation as more threatening. Although the experimental design of Study 2 was able to establish the causal direction from perceived automatability to job attitudes, we nonetheless cannot rule out the reverse causal directions between the automation appraisals and job attitudes. Thus, future research is needed to verify these relationships.

Future Directions

There is a great deal about employee perceptions of automation that remains to be explored. For one, employees' evaluations regarding the impacts of automation on their job performance is likely multifaceted. Qualitative studies have identified that people believe automation will increase their efficiency, allow them to redirect their time, ease their workload, enhance their safety, augment their capabilities, and decrease errors (e.g., Asatiani et al., 2020; Brougham et al., 2019; Roskies et al., 1988; Schneider & Sting, 2020). In the current research we attempted to capture many of these sentiments under the board umbrella of "performance optimism." However, future work may attempt to develop a multidimensional scale to assess the complexity of people' evaluations because these nuances may have important consequences. For example, people's beliefs may be at odds across different dimensions, such as when they believe automation enhances their safety, but decreases their efficiency. It is unclear how these competing beliefs might translate into appraisals and subsequent job attitudes.

Automation appraisals are also likely to have additional important workplace consequences beyond those examined in the present study. For example, previous research has found that automation-related job insecurity is positively related to depression (Brougham & Haar, 2018) and anxiety (Vieitez et al., 2001). In contrast, we submit that automation-related performance optimism is likely to be negatively related to these and other indicators of poor well-being. Specifically, enhanced performance may increase people's workplace resources (Bakker & Demerouti, 2017), and fulfill people's basic needs (Deci & Ryan, 2012) – all of which could improve their well-being.

Additionally, automation appraisals may have both indirect and direct effects on performance such as organizational citizenship behaviours (OCBs), counterproductive work behaviours (CWBs), and task performance. Indirectly, automation appraisals may influence job attitudes and well-being which would have downstream effects on performance (Judge et al., 2001). In terms of direct effects, employees may withhold “good” performance (OCBs, task performance) and the enact “bad” performance (CWBs; e.g., Griep & Vantilborgh, 2018) in retaliation for company behaviours that they believe led to their automatability (e.g., organizational investment in technologies designed to replace employees).

Across both studies we found that performance optimism was unrelated to turnover intentions. We speculate this may be because the effect of performance optimism on turnover intentions was overshadowed by other factors that may shape turnover intentions, including financial and family obligations, career opportunities, and job satisfaction (Direnzo & Greenhaus, 2011). Nonetheless, certain contextual factors might heighten the impact of performance optimism on turnover intentions. For example, in companies with a comparatively high performance-oriented culture, automation-driven performance improvements may be seen as instrumental to obtaining rewards, and thus be more likely to incentivize employee to stay at the organization (i.e., reducing turnover intentions). Future research is needed to test these boundary conditions.

Conclusion

Automation is one of the major forces of change challenging today’s workforce. Despite this, research on employees’ perceptions of automation has thus far been limited. The present research sought to add nuance to the literature on employee perceptions of automation by disambiguating between perceptions and appraisals of automation. By doing so we demonstrated that varying appraisals of automation have diverging effects on downstream job attitudes. Importantly, we revealed that control at work is key to understanding the direction of employees' appraisals. Therefore, control may be lever by which managers could influence employees' reactions to automation in the future. In sum, this research provided insights that may help employees better prepare for the future of work.

Table 1

Means, Standard Deviations, Reliabilities, and Intercorrelations between Study 1 Variables (Essay 1)

	M	*SD*	1	2	3	4	5	6
1 Perceived Automatability	2.96	1.00	(.87)					
2 Automation-related Job Insecurity	2.12	1.16	.66 ***	(.96)				
3 Automation-related Performance Optimism	3.32	1.13	.33 ***	.04	(.97)			
4 Control at Work	3.82	1.02	-.14 **	-.25 ***	.13 **	(.97)		
5 Engagement	4.10	.81	-.18 ***	-.20 ***	.15 ***	.37 ***	(.96)	
6 Turnover Intentions	2.36	1.32	.17 ***	.22 ***	-.06	-.24 ***	-.53 ***	(.96)

Notes. $N = 500$. ** $p < .01$, *** $p < .001$. Reliabilities (Cronbach's alpha) are reported on the diagonal in parentheses.

Table 2

Conditional Indirect Effects of Perceived Automatability on Each Dependent Variable via Each Automation Appraisal at High and Low Levels of Control at Work (Study 1, Essay 1)

		95% CI		90% CI	
	IE	LB	UB	LB	UB
Perceived Automatability → Job Insecurity → Engagement					
Hypothesis 7a					
High Control at Work	-.060	-.103	-.020	-.096	-.028
Low Control at Work	-.073	-.123	-.024	-.116	-.033
Difference (High - Low)	.013	.002	.032	.003	.028
Perceived Automatability → Job Insecurity → Turnover Intentions					
Hypothesis 7b					
High Control at Work	.133	.062	.204	.072	.194
Low Control at Work	.161	.076	.245	.089	.231
Difference (High - Low)	-.028	-.062	-.006	-.057	-0.01
Perceived Automatability → Performance Optimism → Engagement					
Hypothesis 8a					
High Control at Work	.047	.014	.089	.019	.081
Low Control at Work	.024	.008	.050	.010	.046
Difference (High - Low)	.023	.005	.058	.006	.052
Perceived Automatability → Performance Optimism → Turnover Intentions					
Hypothesis 8b					
High Control at Work	-.029	-.097	.028	-.085	.020
Low Control at Work	-.015	-.054	.013	-.046	.008
Difference (High - Low)	-.014	-.062	.011	-.053	.006

Notes. N = 500. IE = indirect effect, LB = lower bound and UB = upper bound, CI = confidence interval.

Table 3

Means, Standard Deviations, Reliabilities, and Intercorrelations between Study 2 Variables (Essay 1)

	M	*SD*	1	2	3	4	5	6	7	8
1 Automatability Manipulation	-.01	1.00								
2 Control Manipulation	.01	1.00	.07							
3 Perceived Automatability	3.04	1.03	.37 ***	-.05	(.85)					
4 Perceived Control	4.03	.98	.02	.29 ***	-.20 **	(.95)				
5 Automation-related Job Insecurity	2.13	1.27	.31 ***	-.10	.62 ***	-.22 **	(.95)			
6 Automation-related Performance Optimism	3.31	1.18	.19 **	.03	.44 ***	.12	.23 **	(.97)		
7 Engagement	4.23	.74	-.00	-.02	-.21 **	.29 ***	-.20 **	.06	(.96)	
8 Turnover Intentions	2.39	1.29	.02	-.04	.19 **	-.25 ***	.33 ***	.04	-.45 ***	(.95)

Notes. N = 194. ** p < .01, *** p < .001. Reliabilities (Cronbach's alpha) are reported on the diagonal in parentheses.

Table 4

Means of Perceived Automatability and Perceived Control based on Experimental Condition (Study 2, Essay 1)

	Condition						Condition					
	High Automatability (N = 96)		Low Automatability (N = 98)				High Control (N = 98)		Low Control (N = 96)			
	M	*SE*	*M*	*SE*	t-test	*d*	*M*	*SE*	*M*	*SE*	t-test	*d*
Perceived Automatability	3.43	1.04	2.67	.88	5.49 ***	.79	3.00	1.03	3.09	1.05	.07	.09
Perceived Control	4.05	.94	4.01	1.02	.29	.04	4.30	.79	3.74	1.08	4.16 ***	.60

Note. *** $p < .001$

Table 5

Conditional Indirect Effects of Automatability on Each Dependent Variable via Each Automation Appraisal at High and Low Levels of Control (Study 2, Essay 1)

		95% CI		90% CI	
	IE	LB	UB	LB	UB
Automatability → Job Insecurity → Engagement					
Hypothesis 7a					
High Control	-.026	-.068	.002	-.061	-.004
Low Control	-.081	-.155	-.032	-.143	-.039
Difference (High - Low)	.056	.010	.137	.017	.120
Automatability → Job Insecurity → Turnover Intentions					
Hypothesis 7b					
High Control	.066	-.007	.161	.007	.144
Low Control	.208	.103	.350	.118	.328
Difference (High - Low)	-.143	-.317	-.028	-.282	-.046
Automatability → Performance Optimism → Engagement	.016	-.001	.047	.002	.042
Automatability → Performance Optimism → Turnover Intentions	-.009	-.057	.022	-.048	.016

Notes. N = 194. IE = indirect effect, LB = lower bound and UB = upper bound, CI = confidence interval.

Figure 1

Hypothesized Model (Essay 1)

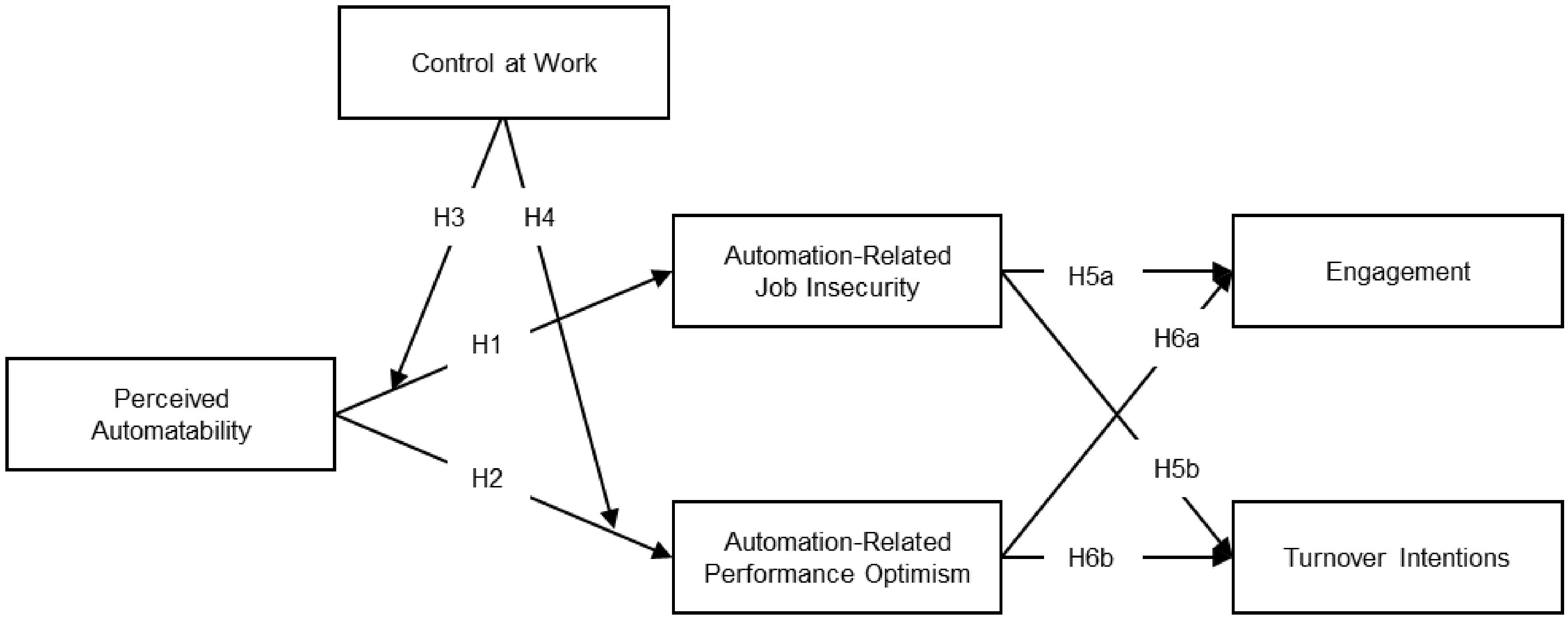
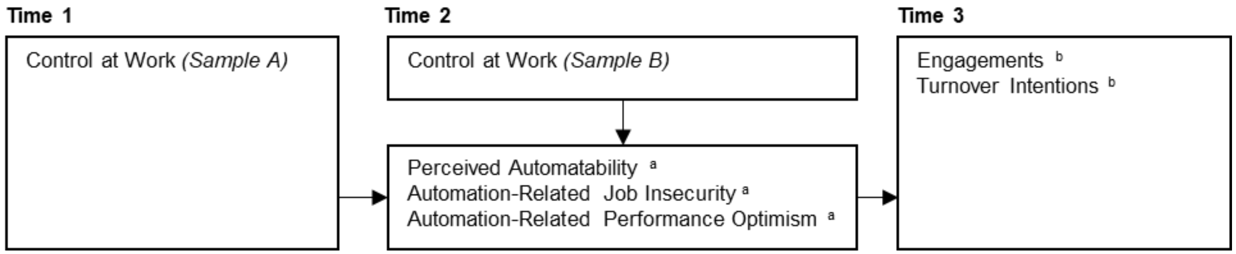


Figure 2

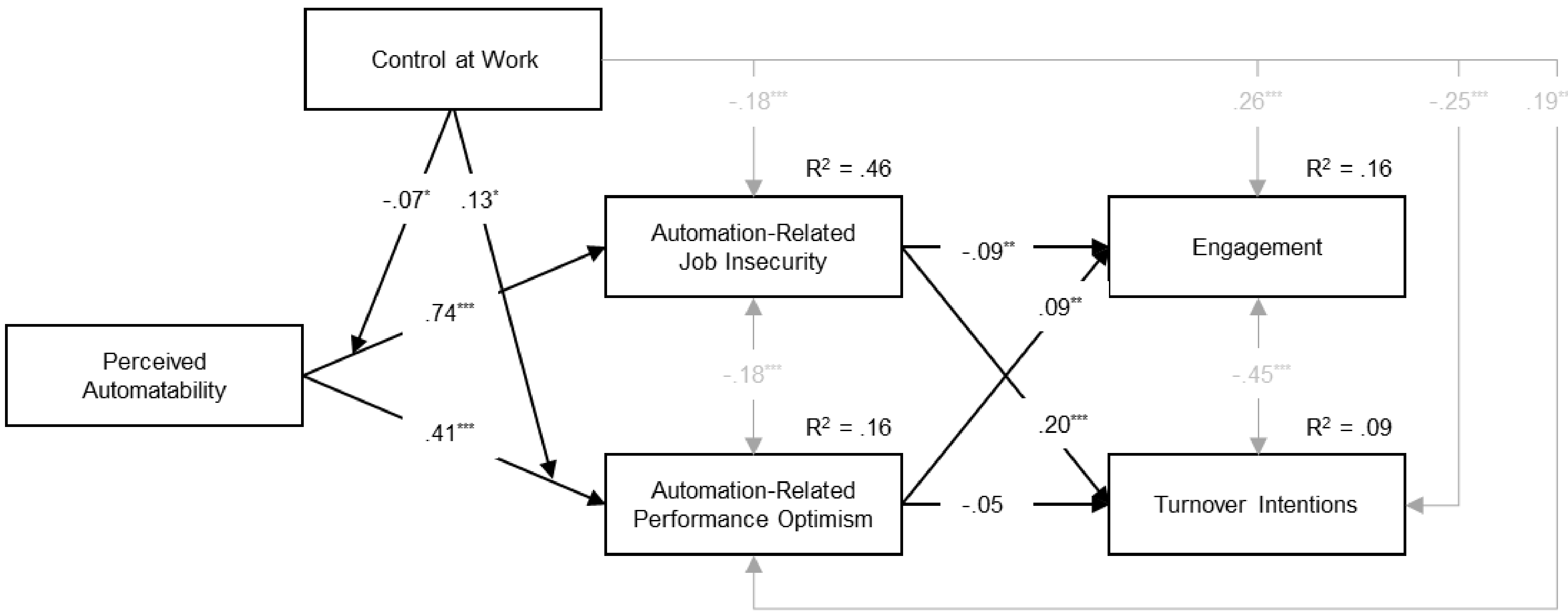
Summary of Procedures (Study 1, Essay 1)



Notes. Control at work was measured at different times across Samples A and B (denoted by the parentheses). a = variables counterbalanced with one another. b = variables counterbalanced with one another.

Figure 3

Structural Equation Model Results (Study 1, Essay 1)



Notes. * p < .05, ** p < .01, *** p < .001. Dark lines denote hypothesized paths and light lines denote additional paths in the structural model. The covariance paths between the interaction term and its components are not depicted for clarity.

Figure 4

Interactions Between Perceived Automatability and Control at Work Predicting (a) Job Insecurity And (b) Performance Optimism (Study 1, Essay 1)

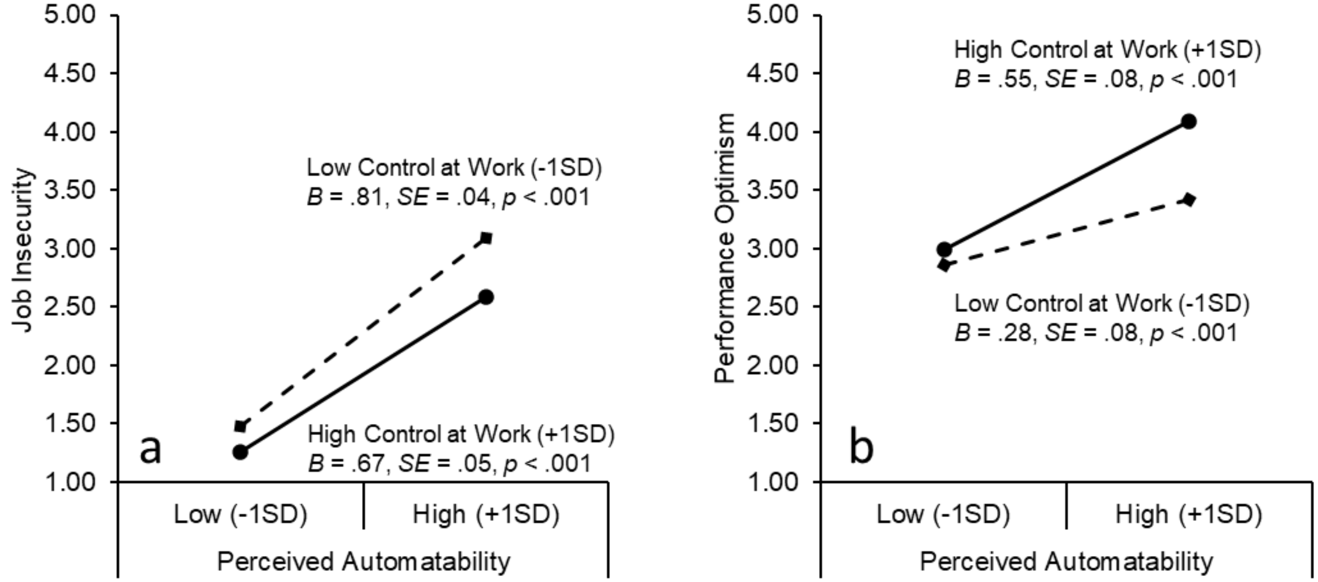
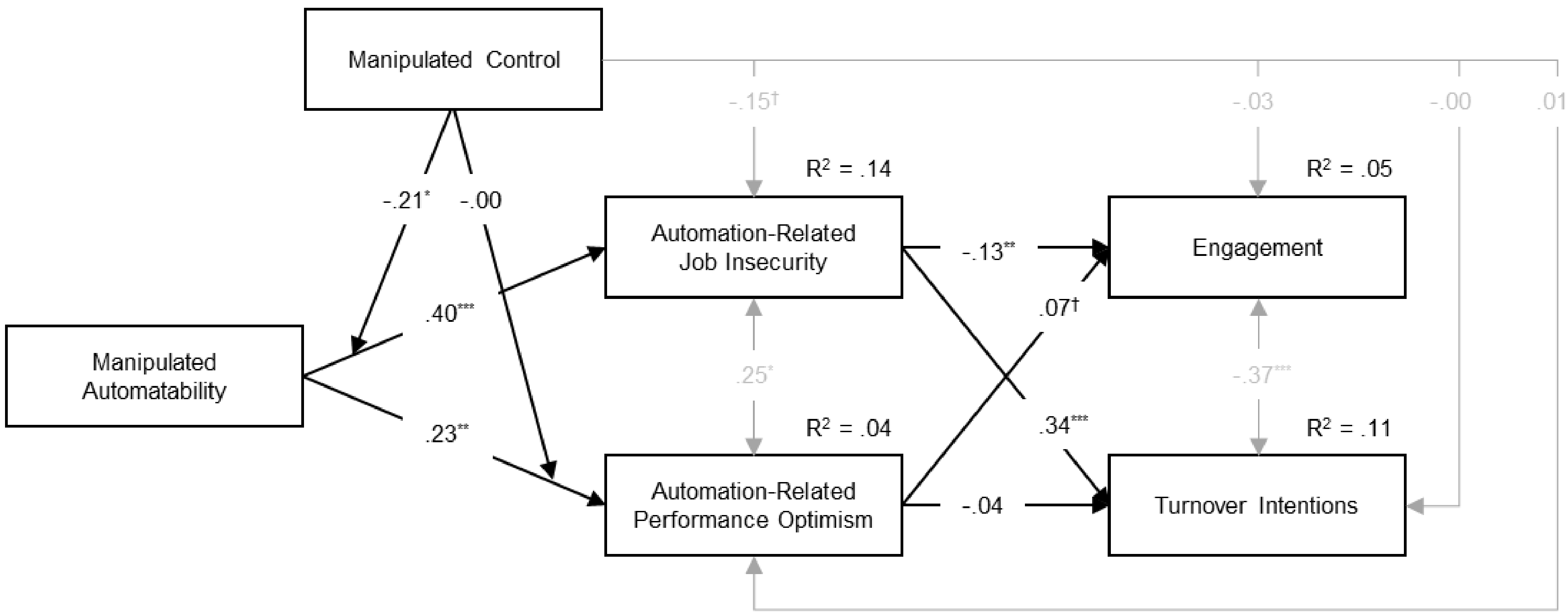


Figure 5

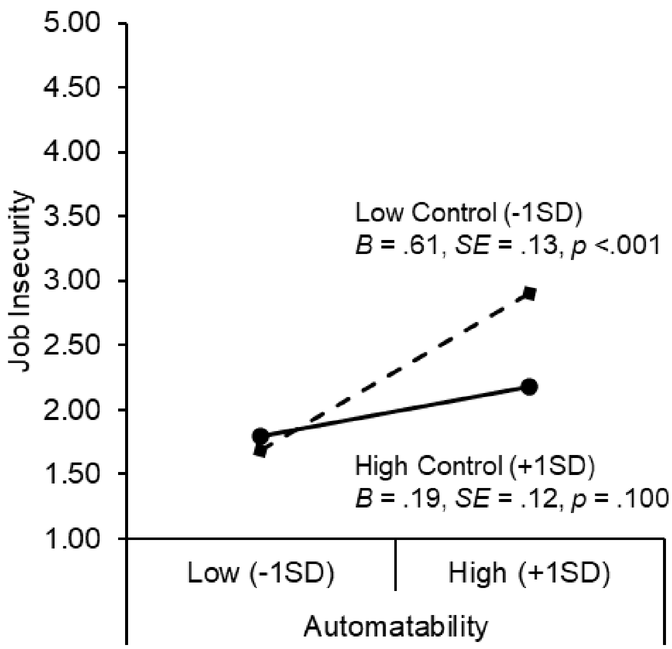
Structural Equation Model Results (Study 2, Essay 1)



Notes. * p < .05, ** p < .01, *** p < .001, † p < .10. Dark lines denote hypothesized paths and light lines denote additional paths in the structural model. The covariance paths between the interaction term and its components are not depicted for clarity.

Figure 6

Interaction Between Automatability and Control Predicting Job Insecurity (Study 2, Essay 1)



CHAPTER 3: HOLD ON TO YOUR DAY JOB: EMPLOYEE PREPARATIONS FOR AUTOMATION AT WORK

Labour economists estimate that between 9%-47% of US occupations are at high risk of becoming automated in the coming decades (Arntz et al., 2017; Frey & Osborne, 2017). Even if the lower end of these estimates turns out to be accurate, that still equates to 14 million lost jobs (U.S. Bureau of Labour Statistics, 2022). Techno-optimists are quick to point out that automation also creates jobs, possibly even more jobs, than it destroys. Indeed, the net effect of automation on employment over the last few decades has been null or positive (Autor, 2015; Autor & Salomons, 2018; Mokyr et al., 2015). However, this is likely little consolation to individual workers who bear the transition costs. That is, as automation takes over tasks and jobs which previously relied on human labour (Parasuraman & Riley, 1997), displaced employees often need to shift to new tasks and new jobs to remain employed. This transition requires preparation (Brynjolfsson & McAfee, 2014; Gekara & Snell, 2020; World Economic Forum, 2016). In particular, employees who are in high-risk occupations may need to develop their knowledge, skills, and abilities (KSAs) to equip themselves for future roles or may need to seek new career opportunities to replace their current, at-risk occupations.

To this end, we suggest that *automation-related job insecurity* – the belief that automation will displace a person from their job – may be a key motivator of preparatory behaviours (Carver & Scheier, 1998; Shoss, 2017). Specifically, in this paper we draw on control theories (e.g., Carver & Scheier, 1998) to suggest that job security is a key goal for many people, and that therefore, perceived discrepancies in job security (i.e., automation-related job insecurity) will motivate remedial actions aimed at enhancing job security – such as *developmental activities* and *career exploration*). Nevertheless, we also identify two problems: First, people may not experience sufficient automation-related job insecurity to motivate preparatory behaviours. There is some evidence to suggest that people are overly optimistic about their job security, even when their jobs are objectively automatable (Brougham & Haar, 2018; Koen & Parker, 2020). However, this evidence is ambiguous because it does not account for individual differences in vulnerability to job loss. Automation is not equally detrimental to all employee's job prospects (Parker & Grote, 2020; Smids et al., 2020) – thus, some people may not be afraid of losing their job to automation because they do not *need* to be afraid.

Second, automation-related job insecurity may not be sufficient to motivate people to prepare for automation. On the one hand, drawing on control theories (e.g., Carver & Scheier, 1998) we predict a positive relationship between automation-related job insecurity and preparatory behaviours (see also Shoss, 2017). However, experiencing job insecurity is highly stressful, and has been found to have negative implications for employees' mental and physical health, as well as their effort, performance, and cognitive functioning (Cheng and Chan, 2008; De Witte et al., 2015; Gilboa et al., 2008; Jiang and Lavaysse, 2018; Koen & van Bezouw, 2021; Sverke et al., 2002). As such, previous research has found competing evidence regarding the impacts of job insecurity on job preservation behaviours (e.g., developmental activities and job search; Kamphuis & Glebbeek, 2020; Lebert & Antal, 2016; van Hootegem et al., 2018; Zhang et al., 2019). In the present research we seek to address both these problems to gain a clearer understanding of *who* experiences automation-related job insecurity in response to the automatability of their job, and *under what conditions* automation-related job insecurity leads to various preparatory strategies .

To address the first problem, we suggest that people's perceptions of their skills will shape the extent to which people experience job insecurity proportional to their objective automatability. Employees' skills may shape whether they are vulnerable to job loss during automation-related organizational downsizing or restructuring. Employees whose skills are found to be mismatched with the job requirements, or below that of their peers' – whether because they possessed lower qualifications to begin with, or because automation has transformed the skill-requirements of their jobs (Autor et al., 2003; Spitz-Oener, 2006) – may be at greater risk of job loss. Therefore, we hypothesize that employees who perceive their skills to be subpar (i.e., employees who perceive a large *skills-gap*) compared to employees who perceive a small skills-gap will be more likely to respond to the automatability of their job with automation-related job insecurity.

To address the second problem, we suggest that the organizational context will shape people's preparatory strategies in response to automation-related job insecurity. In particular, we suggest that *organizational support for development* (hereafter referred to simply as *support for development*) will inform people's beliefs regarding the organization's commitment to retraining and retaining their employees – and thus people's desire to choose preparatory behaviours that will increase their job security either *within* (when support for development is high) or *outside* (when support for development is low) the organization. Given that developmental activities frequently involve investing resources within organizations, we hypothesize that people who experience high support for development will exhibit a stronger positive relationship between automation-related job insecurity and developmental activities than people who experience low support for development. Further, given that career exploration is typically a company "exit strategy", we hypothesize that people who experience low support for development will exhibit a stronger positive relationship between automation-related job insecurity and career exploration than people who experience high support for development.

We tested our model (Figure 7) using a survey of 244 US employees. In doing so we make several contributions to the literature. First, we guide research on employee fears of automation, by demonstrating that rather than people being overall "ignorant" of their automatability, people's fears may instead be tailored to their situation. Specifically, we suggest that, as the automatability of people's jobs increases, people whose skills make them vulnerable to jobs loss (i.e., people with a large skills-gap) will be more likely to develop job insecurity compared to people whose skills make them resistant to job loss (i.e., people with a small skills-gap). Second this research also contributes to the job insecurity literature by providing a theoretical framework (via control theory) and empirical test of the relationship between job insecurity and job preservations behaviours – a relationship which has previously been proposed but scarcely tested (Shoss, 2017; Kamphuis & Glebbeek, 2020). We also go one step further by identifying a boundary condition for this effect. In particular, we identify support for development as a situational context that influences whether people pursue preparatory behaviours, and which preparatory behaviours people pursue in response to job insecurity. By doing so we lay the groundwork for future research to explain the inconsistent findings between job insecurity and job preservation behaviours (e.g., Kamphuis & Glebbeek, 2020; Lebert & Antal, 2016; Zhang et al., 2019). Finally, our research identifies several levers (skills-gap, automation-related job insecurity, support for development) via which organizations may be able to manage employee preparatory responses to automation at work.

Impending Automation and the Need to Prepare

The past few decades have been characterized by breakthroughs in machine learning, artificial intelligence, and nanotechnology, as well as massive expansions in the availability of big data, computing power, and interconnectivity (Brynjolfsson & McAfee, 2014; Cameron, 2017; Schwab 2017). These technological advances have had undeniable impacts on employment, particularly via the replacement of human labour – a process known as automation (Parasuraman & Riley, 1997). Labour economists continue to debate whether "this time will be different" – that is, whether in the coming decades the net effect of automation on employment will remain neutral or positive, or whether automation will lead to large scale unemployment, as has been predicted for nearly a century (Cameron, 2017; Keynes, 1930; Mokyr et al., 2015). Nonetheless, at the micro-level, some individual employees have already, and will continue lose their jobs (Acemoglu & Restrepo, 2017; Arntz et al., 2019; Frey & Osborne, 2017), or experience significant changes in their job roles and job characteristics (Parker & Grote, 2020; Smids et al., 2020) due to automation related disruptions. In other words, automation threatens employees' quantitative job security (loss of the job itself) as well as their qualitative job security (loss of valued job features; Sverke et al., 2002).

As such, some employees may need to take action to ensure the stability and continuity of their employment (Shoss, 2017; Brynjolfsson & McAfee, 2014; Gekara & Snell, 2020; World Economic Forum, 2016). For one, employees may need to develop new KSAs to meet the changing demands of their jobs. Automation frequently transforms the skills-requirements of occupations (Spitz-Oener, 2006; Tschang & Almirall, 2021; Parker & Grote, 2020). In the last two decades, occupations have experienced a shift in task composition away from routine manual (e.g., operating and controlling machinery) and routine cognitive (e.g., calculating, correcting, measuring) tasks towards non-routine cognitive tasks (analyzing, evaluating, designing; Autor et al., 2003; Spitz-Oener, 2006). As an example, prior to the introduction of the automated teller machines (ATMs), a sizable percentage of bank tellers' jobs was to process client transactions. However, as ATMs took over this task, bank tellers' roles shifted towards customer relations and sales (Autor, 2015) – roles which rely on a different set of skills. Thus, depending on how well employees' skills overlap with their newly transformed job requirements, employees may need to engage in various developmental activities to ensure they can maintain their *current* job.

Alternatively, employees may also prepare for automation-related disruptions by seeking *new* employment. Automation has already, and will continue to displace many employees from their jobs (e.g., Acemoglu & Restrepo, 2017; Arntz et al., 2017; Frey & Osborne, 2017). By gathering information about jobs and organizations, investigating alternate career opportunities, and initiating networking connections (e.g., Stumpf et al., 1983) employees could ease the transition to new employment should their current job be lost. A particularly effective strategy may be for employees to seek to transition to industries that are less susceptible to the impacts of automation (e.g., caring professions; Frey & Osborne, 2017). Additionally, if automation has changed the skill-profile of their current occupation, employees could seek alternate industries or jobs that offer a better match for their KSAs (Zhang et al., 2019). However, preparing for automation may be a costly endeavour in terms of employees' time, energy, and financial resources. To this end, job insecurity may be a key motivator of preparatory behaviours.

Automation-Related Job Insecurity and the Motivation to Prepare

According to control theories (Carver & Scheier, 1981, Direnzo & Greenhaus, 2011; Vancouver et al., 2010), motivation arises from people's desire to reduce discrepancies between their goals and their perceived current states. Therefore, we draw on control theories to explain how job insecurity may motivate preparatory behaviours. First, we suggest that the desire to maintain a secure job is a central goal for many employees. This is because jobs provide a source of income, social connection, social status, and identity, and as such, they fulfill a variety of fundamental human needs (Deci & Ryan, 2000; Shoss, 2017). By threatening the continuity and stability of employment, automation creates a discrepancy between people's goal (i.e., secure employment) and their current states (threatened employment). Employees' perceptions regarding this discrepancy – that is, employees perceptions regarding "threats to the continuity and stability of employment" is called *job insecurity* (Shoss, 2017). Job insecurity caused specifically by the impacts of automation is called *automation-related job insecurity* (Essay 1). Thus, based on control theories, we suggest that automation-related job insecurity will predict behaviours aimed at reducing the gap between the current state of insecurity and the goal state of secure employment. Specifically, we suggest that automation-related job insecurity may predict preparatory behaviours such as developmental activities and career exploration.

Nevertheless, in the remainder of this paper we demonstrate two potential problems: First, that employees may not feel automation-related job insecurity proportional to their risk of being displaced by automation. Second, that automation-related job insecurity alone may not be sufficient to motivate preparatory action. In the following sections we elucidate these problems and offer a model to explain *which* employees are likely to experience automation-related job insecurity, and *under what conditions* they are likely to prepare for disruptions.

Objective Automatability

We begin by establishing that the objective automatability of a person's job can be estimated. A job's automatability is dependent on the likelihood that the tasks that make up the job can be autonomously conducted by technologies. To date, Frey and Osborne (2017) have provided the most comprehensive estimates of the automatability of a variety of occupations (see also Brynjolfsson et al., 2018; Felten et al., 2020; Tolan et al., 2021; Webb, 2019). To do so they created an algorithm to classify 702 occupations ranging from 0 (not at all automatable) to 1 (completely automatable) based on the extent to which those jobs relied on creative intelligence, social intelligence, and perception and manipulation – skills which are presently difficult or impossible to automate. The authors trained the algorithm on a test dataset which included 70 subjectively coded occupations. The algorithm replicated the test dataset, and generated estimates for the remaining occupations. This dataset is published with the occupations identified by the U.S. Labour Department's Standard Occupational Classification (SOC) codes. Nonetheless, people's subjective evaluations of their job insecurity may not line up with their objective probability of job loss as determined by their automatability.

Is Job Insecurity in Short Supply?

On average, there is evidence to suggest that people underestimate their job insecurity. Surveys have found that the majority of US and European adults believe that automation will have profound impacts on jobs in general (European Commission, 2017; Gallup, 2018; Smith, 2016). Yet, the same surveys also found that only a minority of respondents believe that automation will pose a threat to their *own* jobs. For example, 65% of U.S. adults believed that "in the next 50 years, robots and computers will do much of the work currently done by humans" (Smith 2016; $N = 2001$). Similarly, 73% of U.S. adults agree that AI will "eliminate more jobs that it creates" (Gallup, 2018; $N = 3297$). Finally, 72% of European adults agreed that "robots and AI steal peoples' jobs," (European Commission, 2017; $N = 27,901$). Yet, 80% of U.S. adults believed that their jobs or professions will still exist in 50 years (Smith 2016; $N = 2001$), only 23% of U.S. adults were worried that they will lose their own job to new technology (Gallup, 2018; $N = 3297$), and 53% of Europeans reported that their current job could not be conducted by a robot or AI (European Commission, 2017; $N = 27,901$).

Further, on average, even employees who are objectively at risk of losing their jobs to automation (i.e., people with highly automatable jobs) only report slightly greater job insecurity. Specifically, Brougham and Haar (2018) found that automatability (Frey & Osborne, 2017) and automation-related job insecurity were unrelated. In contrast, Koen and Parker (2020) found significant, but weak relationships between automatability and general job insecurity (e.g., "I think I might lose my job in the near future"; $r = .19$, $p < .01$), and between automatability and employment insecurity ("[my] skills will be valued 5 years from now"; $r = .21$, $p < .01$). In Essay 1, Study 1 of this dissertation, we also found a significant, but weak relationship between automatability and automation-related job insecurity ($r = .17$, $p < .001$). In sum, there is not a strong association between people's actual risk of losing their job to automation, and their fear of losing their job.

However, it is possible that automatable jobs provoke greater job insecurity in some people than others. Automation affects people differently. Although in some cases technology replaces workers from their job, in other cases, technology can instead enhance people's performance by increasing their speed, augmenting their capabilities, improving their safety, or freeing up their time for other value-add work tasks (Asatiani et al., 2020; Brougham et al., 2019; Roskies et al., 1988; Schneider & Sting, 2020). Therefore, for some, an increase in automatability is an increase in opportunity rather than an increase in threat to job security (Essay 1). Further, even if automation replaces much of an employees' tasks, it does not mean that their job, as a whole, will be lost. Jobs are malleable and can transform to include new roles when old ones are replaced (Autor et al., 2003; Spitz-Oener, 2006). Therefore, it is possible that the relationship between automatability and automation-related job insecurity varies by how vulnerable people are to job loss. People who are in automatable jobs but who are not susceptible to job loss may be less likely to develop automation-related job insecurity than people who are in automatable jobs but who are susceptible to job loss. To this end, we predict that employees' *skills* are an important predictor of their vulnerability to job loss.

The Moderating Effect of Skills-Gaps

Skills are a crucial antecedent of employee task performance (Campbell et al., 1993). For one, employees with an appropriate match between their skills and the job's requirements perform better than those with a mismatch between their skills and the job's requirements. Further, employees whose skills rank above their peers likely outperform their peers. This is important because automation-related disruptions often force organizations into pseudo-selection situations. For example, if a job requires restructuring because automation has changed the occupations' skill-profile, current incumbents may need to be re-evaluated as potential "candidates" for the newly restructured roles. In the absence of any major retraining initiatives, organizations may be more likely to retain employees who have the necessary skills for the newly restructured jobs than employees who do not have the necessary skills. Similarly, automation frequently results in a scenario wherein fewer employees are needed to accomplish the same amount of work. This creates a pseudo-selection scenario wherein current incumbents become the applicant pool for a limited number of remaining positions. Organizations are likely to retain the best "candidates" for the position – in this case, employees with the highest ranked skills. Therefore, we suggest that employees whose skills are underdeveloped, or not well aligned with the skills needed to be successful at their organization (i.e., employees with a large *skills-gap*) will be more vulnerable to job loss than employees whose skills are well-developed, or well aligned with their organization's needs (i.e., employees with a small skills-gap).

Consequently, we predict that among people who perceive themselves to have a high skill-gap, we will observe a stronger positive relationship between automatability and automation-related job insecurity than among people who perceive themselves to have low skills-gap. This is because in highly automatable jobs, people who recognize that their skills are deficient will feel threatened by impending automation-related disruptions. In contrast, in low-automatability jobs, people are unlikely to feel vulnerable to job loss due to automation regardless of their skills-level. In line with this, previous research has found that employees with greater skills and education (i.e., people with presumably lower skills-gaps perceptions) tend to be less afraid of losing their jobs to automation than employees with lower skills and education levels (Chao & Kozlowski, 1986; Dekker et al., 2017; Morikawa, 2017). Nonetheless, this research had only examined the main effect between skills and automation-related job insecurity. In the current study we extend this research by examining the relationship between skills and job insecurity and various levels of automatability. In particular, we predict that:

H1: Skills-gap will moderate the relationship between automatability and automation-related job insecurity such that the positive relationship between automatability and automation-related job insecurity will be stronger for people who perceive a large skills-gap compared to people who perceive a small skills-gap.

Job Insecurity: A Double-Edged Sword

Even if employees feel a great deal of automation-related job insecurity, it is unclear whether job insecurity will motivate people to prepare for automation. This is because job insecurity has been found to be a double-edged sword when it comes to motivating action. On the one hand, multiple reviews and meta-analyses show that job insecurity is negatively related to employee motivation and performance (Cheng and Chan, 2008; De Witte et al., 2015; Gilboa et al., 2008; Jiang and Lavaysse, 2018; Koen & van Bezouw, 2021; Sverke et al., 2002). Along these lines, several studies have found that job insecurity and preparatory behaviours (i.e., developmental activities and career exploration) are also unrelated (e.g., Blau et al., 2008; Cavanaugh & Noe, 1999; Koen & van Bezouw, 2021; Sanders et al., 2011) or negatively related (Blau et al., 2008; De Cuyper et al., 2021; Kamphuis & Glebbeek, 2020; Klehe et al., 2012; Koen & Parker, 2020; Lebert & Antal, 2016; Rodriguez-Bustelo et al., 2020; Van Hootegem & De Witte, 2019). However, the reasons for these effects are unclear. One theory is that job insecurity, being a highly stressful experience, strains limited resources, preventing the allocation of additional time and energy to preparatory behaviours (Koen & van Bezouw, 2021). Others have taken a social exchange perspective to argue that people may be reciprocating for job insecurity by withholding positive workplaces behaviours (e.g., participating in training; Kamphuis & Glebbeek, 2020).

On the other hand, based on control theories (e.g., Carver & Scheier, 1998, Direnzo & Greenhaus, 2011 Vancouver et al., 2010) we predict that people will be motivated to maintain a secure job, and that therefore, discrepancies in job security (i.e., job *in*security) will motivate people to engage in remedial actions. Other theorists have triangulated on the same logic, arguing that people engage in job preservation behaviours (e.g., Shoss, 2017) and proactive coping behaviours (Koen and Parker, 2020; Koen et al., 2019) to counteract threats to their job security. In line with this, under certain circumstances, job insecurity has been found to be positively related to various job preservation behaviours, including employee effort (Brockner et al., 1992), performance (Probst et al., 2007; Koen et al., 2019), organizational citizenship behaviours (Lam et al., 2015), developmental intent and activities (Elman & O’Rand, 2002;

Kamphuis & Glebbeek, 2020; van Hootegem et al., 2018; Zhang et al., 2019), and intention to switch industries (i.e., career exploration; Zhang et al., 2019).

Given these mixed findings, there is strong indication that there are moderators at play between job insecurity and preparatory behaviours. In other words, job insecurity alone is not enough to predict preparation for automation. By adopting control theories, we provide insight into the conditions under which job insecurity might motivate behaviour.

The Conditions Under Which People Act on their Job Insecurity: The Role of Support for Development

According to control theories, people's motivation to engage in behaviours depends on, among other factors, people's anticipation that engaging in the behaviour will be successful, and people's desire to achieve the outcome (Sun et al., 2014; Van Eerde & Thierry, 1996; Vroom, 1964). Put simply, people are more likely to put resources towards endeavours that have a high likelihood of achieving desirable outcomes than towards endeavours that are unlikely to be successful, or for which the outcome is not particularly desirable. Applied to the present context, this means that employees may find a preparatory behaviour appealing when a) employees believe it has a high likelihood of leading to job security (e.g., Koen et al., 2019), and b) when employees highly value the job which they are attempting to secure.

To this end, we suggest that support for development influences both likelihood and desirability evaluations. *Organizational support for development* encompasses the resources, assistance, and rewards offered by the organization to support their employees' developmental activities (e.g., Maurer et al., 2003; Maurer & Tarulli, 1994; Maurer et al., 2002). Support for development may signal to employees that an organization intends to invest in retraining – and thus retaining – their current employees through any potential automation-related organizational restructuring or downsizing. Thus, in organizations where support for development is high, employees may expect that if they invest in preparatory behaviours related to maintaining their current job, they will see a return on that investment (i.e., high likelihood of achieving job security). Further, employees may have a greater desire to work for an organization that has a strong compared to weak culture of support for development (i.e., high value associated with achieving job security). This is because support for development may signal to employees that the organization values and is committed to them, which may foster a sense of mutual loyalty and commitment (Lee & Bruvold, 2003).

Applying these considerations to concrete preparatory behaviours, we examine the impact of job insecurity on two diverging preparatory strategies: developmental activities and career exploration. *Developmental activities* are employees' effort to enhance their KSAs (Maurer et al., 2003). These activities are often intimately tied to the employees' current job. For example, employees may develop their skills by asking their supervisors, coworkers, or subordinates for feedback, practicing new skills on the job, attending work-related workshops, or volunteering for new work-related projects (Maurer et al., 2003). Therefore, investing in developmental activities is often synonymous with investing resources in the employees' current job and organization. As such, job insecurity may be more likely to prompt developmental activities for people who believe that investing resources into their current job will be instrumental to keeping their current job, and for people who have a desire to stay at their current job. Given that we argued that high support for development prompts a high level of expectancy that investments in the organization will pay off, and a desire to stay at the organization, we therefore, we predict that job insecurity will be more likely to motivate developmental activities for people who experience high compared to low support for development. Concretely we hypothesize that:

H2: Support for development will moderate the relationship between automation-related job insecurity and developmental activities such that the positive relationship between automation-related job insecurity and developmental activities will be stronger for people who experience high support for development than for people who experience low support for development.

In contrast, *career exploration* – which involves gathering information about jobs and organizations – is typically a job-exit, or organization-exit strategy. The goal of this preparatory behaviour is to enhance job security by finding new employment, rather than attempting to maintain the current job. As such, people may be more likely to use this strategy when they feel that investments in their current organization are unlikely to pay off, or when they are uninterested in staying at their current job. Given that we argued that people who experience low support for development are unlikely to expect investments in the organization to lead to job maintenance, and are unlikely to desire to stay at their organization, we thus hypothesize that job insecurity will be more likely to motivate career exploration when support for development is low compared to when support for development is high. Formally, we predict that:

H3: Support for development will moderate the relationship between automation-related job insecurity and career exploration such that the positive relationship between automation-related job insecurity and career exploration will be stronger for people who experience low support for development than for people who experience high support for development.

Combining H1 with H2 and H3, we predict that the indirect effect of automatability on preparatory behaviours via automation-related job insecurity will be strongest under certain conditions. In particular, we hypothesize that:

H4: The conditional indirect effect from automatability to developmental activities via automation-related job insecurity will be strongest for people who perceive a large skills-gap and high support for development.

H5: The conditional indirect effect from automatability to career exploration via automation-related job insecurity will be strongest for people who perceive a large skills-gap and low support for development.

Method

Participants and Procedure

To test our hypotheses, we conducted an online survey of 302 employees recruited from Amazon's Mechanical Turk (MTurk). Data were collected in October 2019. To be eligible for the study, participants had to have previously completed a minimum of 100 MTurk "Human Intelligence Tasks" (HITs) on MTurk and had to have earned greater than 90% approval rating on those HITs. Further, participants had to be employed full or part-time (with an organization or self-employed) and be US residents.

We included three instructed-answer attention check questions in the survey (e.g., "please answer agree"). Participants who failed to answer any one of these questions correctly were removed from the data to improve data quality (n = 58). Thus, our final sample consisted of 244 participants. Participants were primarily White (80.3%) and male (52.9%). They were on average 36.38 years old (SD = 10.07). The majority of participants were employed full-time at an organization (84.43%). They worked on average 37.19 hours per week (SD = 10.96) and had been at their organizations 7.41 years (*SD* = 5.63). Participants worked in a variety of sectors, including marketing, sales, and service (12.7%,), information technology (12.3%) and science, technology, engineering, and math (9.43%).

The study was spread across three surveys collected on three consecutive workdays (Monday, Tuesday, Wednesday) to reduce participant fatigue and minimize common method variance (Podsakoff et al., 2003). Participants received $1.00 USD for completing each 10-minute survey, and a bonus $1.00 USD for completing all three surveys. All participants provided complete responses on all three surveys.

At Time 1, we asked participants to identify their SOC code. This information was collected so that we could later merge our data with Frey and Osborne's (2017) database to identify the automatability of the participants' occupations. We directed participants to O*Net's website (https://www.onetonline.org/) and provided participants with step-by-step instructions (Appendix C) to identify their SOC code on the website. Participants were asked to copy and paste the SOC codes into the survey. Using the instructions, every participant was able to successfully copy their SOC code into the survey. However, Frey and Osborne's database did not contain automatability estimates for every participant's SOC code. Therefore, we only obtained automatability estimates for 198 participants (81.15%). Rather than restricting the sample to participants for whom we were able to obtain automatability estimates, we conducted pairwise deletion to retain as much data as possible.

After identifying their SOC codes, participants reported their perceived support for development, and then their automation-related job insecurity. At Time 2, participants reported their perceived skills-gap. Finally, at Time 3, participants reported developmental activities and career exploration (in counterbalanced order).

Measures

We present the full scales in Appendix D. Scale reliabilities are presented in Table 6.

Automatability

We derived the automatability of each participants' current occupation from Frey and Osborne's (2017) database. Participants automatability scores ranged from 0 (not at all automatable) to 1 (completely automatable).

Skills-gap

We measured participants' perceived skills-gap using Maurer and colleague's (2003) three-item self-perceived need for skill improvement scale. An example item is, "One or more of my career related skills or knowledge have been in need of improvement." Participants rated their agreement with the items ranging on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree).

Automation-related Job Insecurity

Automation-related job insecurity was measured with Brougham & Haar's (2018) four-item scale called the Smart Technology, Automation, Robotics and Artificial Intelligence (STARA) awareness scale. An example item is, "I am personally worried that what I do now in my job will be able to be replaced by STARA." We modified the items by replacing all instances of the acronym "STARA" with the word "automation." Participants rated their agreement with the statements on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Organizational Support for Development

We measured support for development using Maurer and colleague's (2003) work related support for development scale. Participants rated their agreement with the items on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). Although the original scale was comprised of three subdimensions (coworker support, supervisor support, and resource and policy support), we decided to only use participants' responses on the eight-item resource and policy support subdimension of the scale, as this subdimension most closely aligned with our conceptualization of the support for development construct. In particular, the items in this subdimension captured the macro-level organizational policies (rewards structures, value systems, regulations, resources) in place to support employee development (e.g., "There are learning and skill development resources available to me through my employer that can help me improve my career skills"). These items are also most closely aligned with similar scales measuring the same construct (Kraimer et al., 2011). In contrast, the items in the coworker support subscale (e.g., "My peers/coworkers are supportive of learning activities") and supervisor support subscale (e.g., "My supervisor's behaviour facilitates my participation in learning activities") may have also captured interpersonal elements of support that were not relevant to the present hypotheses[5].

Developmental Activities

Participants reported their developmental activities using Maurer and colleagues' (2003) learning and development activities scale. Specifically, participants were presented with the statement "To learn something new for my career or to improve my career skills, I have...", followed by 19-items including items such as, "taken an optional college of continuing education course," "worked to learn a new skill on the job," and "asked for feedback and input from a supervisor at work." Participants were asked to respond to items on a frequency scale from 0

[5] We reran our hypotheses tests using the full support for developmental scale (including all three subdimensions). The results were largely unchanged, with the exception of our interpretation of the results for H3. When using the reduced support for development scale, the p-value for H3 was $p < .10$, which we interpreted as supportive of our prediction. However, when we ran the model with the full support for development scale, the p-value for H3 was $p > .10$, and therefore was not supportive of our prediction.

(never) to 6 (about six or more times). The original scale included eight additional items which referred to mandatory learning and developmental activities (e.g., “received mandatory coaching from a supervisor at work”). These items were omitted from the scale because we were interested in employees’ volitional behaviours.

Career Exploration

Career exploration was measured using six-items from Stumpf and colleague’s (1983) career exploration survey. Specifically, we measured frequency of career exploration behaviours, such as whether participants “obtained information on the labor market and general job opportunities in my career area” over the past three months on scale from 1 (a little) to 5 (a great deal).

Analysis Plan

Our first step was to test the measurement model to ensure that our scales assessed unique constructs. We created a latent factor for each construct with measured items loading onto their respective constructs. We used parcelling for any scale that used more than three indicator items to reduce item-specific error variance (Little et al., 2002). We created three parcels per construct, and assigned every third item to each parcel (e.g., parcel one contained items 1,4,7; parcel two contained items 2,5,8; parcel three contained 3,6,9, etc.) until all items were assigned to a parcel. The hypothesized model was also tested against two competing alternate models. First, we tested an alternate model in which all the items loaded onto one factor. Additionally, we tested a model in which the developmental activities items and the career exploration items loaded on to the same factor. This was done because some of the items in the developmental activities scale (e.g., “consulted with a career counselor”) overlapped with the career exploration scale (e.g., “investigated career possibilities”), potentially calling into question the distinctiveness of the two measures.

Next, we tested the hypothesized model using structural equation modeling (SEM). Doing so allowed us to test our hypotheses simultaneously while also testing the overall fit of the model (Bollen, 1989). All constructs were modeled as observed (rather than latent) variables. This allowed us to obtain conventional model fit indices in models that contained interaction terms, something that is not possible using latent variables (Sardeshmukh & Vandenberg, 2017). For each of the interaction terms (automatability x skills-gap and automation-related job insecurity x support for development) we included in the model the covariance between the interaction term and its components. We did this because these terms are necessarily related to one another, and their exclusion may have been detrimental to the fit of the model. All independent variables (automatability, skills-gap, automation-related job insecurity, and support for development) were mean centered to aid the interpretability of the main effects (Cohen et al., 2003).

To test H1, we examined the interaction term between automatability and skills-gap predicting automation-related job insecurity. Significant interactions were plotted, and simple slopes were further examined at ±1SD above and below the mean of the moderator variable to understand whether the pattern of the interaction lined up with H1. To test H2 and H3, we examined the interaction term between automation-related job insecurity and support for development predicting developmental activities (H2) and career exploration (H3). Significant interaction terms were followed up by plotting the interactions and calculating the simple slopes at ±1SD above and below the mean of the moderator variable to interpret the pattern of the interactions.

Finally, the test H4 and H5, we first calculated conditional indirect effects from automatability to each dependent variables via automation related job insecurity at high and low levels (±1SD above and below the mean) of each moderator variable (skills-gap and support for development). We used bootstrapping to create bias-corrected 95% confidence intervals around the estimates (MacKinnon et al., 2002; MacKinnon et al., 2004). We then identified the indirect effect we expected to have the strongest effect compared to the other indirect effects. For example, for H4, we expected the strongest indirect effect to occur when people reported a large skills-gap and high support for development. To calculate whether this indirect effect was stronger than the other indirect effects, we created a composite of the remining indirect effects by averaging them. We then calculated the difference between the indirect effect of interest and the average of the remaining indirect effects. We once again used bootstrapping to calculate a bias-corrected 95% confidence interval around the difference to test whether the difference was significant. We employed this approach to minimize the number of potential comparisons between indirect effects to keep family-wise error rate low.

Results

In Table 6, we report the means, standard deviations, and intercorrelations between all study variables. The hypothesized measurement model demonstrated acceptable fit for the data ($\chi^2(80) = 221.190$, $p < .001$, CFI = .952, RMSEA = .085, SRMR = .064). In contrast, competing models in which all items loaded onto a single factor ($\Delta\chi^2(10) = 1944.398$, $p < .001$; $\chi^2(90) = 2165.588$, $p < .001$, CFI = .299, RMSEA = .307, SRMR = .215), and in which the developmental activities and career exploration items loaded onto a single factor ($\Delta\chi^2(4) = 485.886$, $p < .001$; $\chi^2(84) = 707.076$, $p < .001$, CFI = .790, RMSEA = .172, SRMR = .125), demonstrated significantly worse fit for the data.

The hypothesized structural model did not meet the standards of acceptable fit (Hu &

Bentler, 1999; $\chi^2(6) = 27.551$, $p < .001$, CFI = .843, RMSEA = .121, SRMR = .056). Thus, we tested an alternate model in which we freed paths from skills-gap to developmental activities and to career exploration (Figure 8). We did this because perceived skills-gaps may directly predict preparatory behaviours. In particular, people who perceive their skills to be underdeveloped may attempt to rectify this by engaging in developmental activities and finding a new career that is better aligned with their current KSAs. We found that this revised model fit the data well ($\chi^2(4) = 4.568$, $p < .001$, CFI = .996, RMSEA = .024, SRMR = .021), and was a significantly better fit for the data than the hypothesized model ($\Delta\chi^2(2) = 22.983$, $p < .001$). Therefore, we proceeded with this revised model for all remaining hypotheses tests.

Hypothesis Testing

In support of H1, skills-gap significantly moderated the relationship between automatability and automation-related job insecurity ($B = .38$, $SE = .16$, $p = .016$, $\Delta R^2 = .03$). The interaction is plotted in Figure 9. In line with expectations, the simple slope between automatability and automation-related job insecurity was positive and stronger for people who perceived a large skills-gap ($B = 1.20$, $SE = .32$, $p < .001$) compared to people who perceived a small skills-gap ($B = .18$, $SE = .30$, $p = .561$). Therefore, H1 was supported.

Next, we found that support for development significantly moderated the relationship between automation-related job insecurity and developmental activities ($B = -.24$, $SE = .07$, $p = .001$, $\Delta R^2 = .05$). However, the pattern of the interaction was not in the expected direction (Figure 10). We expected that automation-related job insecurity would be more strongly positively related to developmental activities for people who experienced high compared to low support for development. Instead, automation-related job insecurity had a positive relationship with developmental activities for people who experienced *low* support for development ($B = .33$, *SE* = .10, *p* = .001) but not for people who experienced high support for development (*B* = -.23, *SE* = .13, *p* = .074). There was, however, a positive main effect of support for development on developmental activities, (*B* = .16, *SE* = .08, *p* =.048) such that people who experienced high levels of support engaged in high levels of developmental activities regardless of job insecurity. We speak to these findings in greater detail in the discussion section.

In examining H3, we found that support for development did not moderate the relationship between automation-related job insecurity and career exploration (*B* = -.10, *SE* = .06, *p* = .073, $\Delta R^2 = .02$) by traditional $p < .05$ cut-off criteria. Nonetheless, when plotting the interaction (Figure 11) we found that, consistent with our predictions, automation-related job insecurity was positively related to career exploration for people who experienced low support for development (*B* = .30, *SE* = .09, *p* < .001) but not for people who experienced high support for development (*B* = .06, *SE* = .10, *p* = .553). Given that tests of interactions are often underpowered (Cohen et al., 2003) and given that the pattern of the interaction lined up with our hypotheses, we decided to interpret this effect as supportive of H3.

To test H4, we intended to compare the indirect effect at large skills-gap/high support for development to the average of the remaining indirect effects. However, given that the second stage moderation (H2) exhibited a pattern reverse to our expectations, this comparison was no longer warranted. Instead, we compared the large skills-gap/low support for development indirect effect to the average of the remaining indirect effects. We chose this comparison because the large skills-gap/low support for development indirect effect was the only indirect effect which was significant (IE = .395, 95% CI [.149, .781]), whereas the other indirect effects were not significantly different from zero (Table 7). Nonetheless, given that this was a post-hoc comparison, we chose to use a conservative test by interpreting the 99% confidence interval. The difference between the indirect effects was significant (ΔIE = .481, 99% CI [.102, 1.095]), indicating that the positive indirect effect of automatability on developmental activities via automation-related job insecurity was strongest for people who perceived a large skills-gap and low support for development.

Finally, given that the H3 second stage interaction pattern was in the expected direction, we proceeded to test H5 using our a priori approach of comparing the large skills-gap/low support for development indirect effect to the average of the remaining indirect effects (Table 7). We found that the difference in these indirect effects was significant (ΔIE = .320, 95% CI [.062, .684]). Therefore, in support of H5, the positive indirect effect of automatability on career exploration via automation-related job insecurity was strongest for people who perceived a large skills-gap and low support for development.

Auxiliary Analyses

In this paper we proposed that people's perceptions of their skills would shape whether holding a more automatable job would translate into greater job insecurity. To this end, we measured people's perceptions of their skills-gaps. However, there may be multiple ways to operationalize people's perceptions of their skills. For example, another insight into people's perceptions of their skills is their perception of their employability. Perceived employability refers to the ease with which people believe they can find employment (Bernston & Marklund, 2007). This perception is shaped, in part, by people's perceptions of their job-relevant skills. (Vanhercke et al., 2013; Williams et al., 2016). Therefore, we checked the robustness of our model by rerunning our hypotheses tests with employability as the first stage moderator. The pattern of results were identical to when skills-gap was in the model (including the reverse interaction pattern observed in H2). Detailed analyses are reported in Appendix E.

Discussion

More than ever before, employees are "racing against the machines" in a metaphorical duel for their jobs (Brynjolfsson & McAfee, 2011). Further, automation is changing the playing field, transforming the skills required to conduct work and thus to remain competitive for jobs (Autor et al., 2003; Spitz-Oener, 2006). Therefore, employees need to be strategic to ensure their long-term job security. For instance, employees may need to "level up" their KSAs, or seek new playing fields (i.e., seek new career opportunities) when their current jobs are threatened. Yet to feel motivated to engage in these preparatory behaviours, it may be necessary for employees to first believe that their jobs are in danger. Paradoxically, research has found that employees in automatable jobs do not report much greater job insecurity. Further, even when employees feel job insecurity, it does not always motivate them to take action to preserve their job security. In the present study we sought to address both these potential barriers. Thus, we sought to understand for whom automatable jobs provoke feelings of automation-related job insecurity, and under what conditions people respond to automation-related job insecurity with preparatory behaviours.

To this end, we found that people who believed their skills to be lacking were more likely than people who believed their skills to be well-developed to respond to their automatability with fear of being replaced. Given that skills-gaps are likely related to people's actual vulnerability of job loss, this may indicate that people's responses to automation are adaptive. Specifically, from a resource allocation perspective, people who are likely to be impacted by automation-related disruptions *ought* to be more emotionally responsive to their job's automatability than people who are unlikely to be impacted.

In turn, we found that job insecurity can drive people to prepare for automation under certain circumstances. For one, we found that job insecurity was positively related to developmental activities for people who experienced *low* support for development. In contrast, people who experienced high support for development engaged in a great deal of developmental activities regardless of their job insecurity. In our view, this illustrates a typical strong versus weak situation. Specifically, in organizations where there is strong support for development, people's motivation to engage in development originates from the organizational context (i.e., rewards structures and policies) rather than from the employees' personal needs (i.e., job insecurity). As a result, job insecurity may only have a minimally motivating effect on developmental activities. In contrast, in organizations where support for development is weak, employees' personal needs (i.e., job insecurity) may have a stronger motivating role on behaviour, resulting in the observed positive effect of job insecurity on developmental activities.

In terms of the other preparatory behaviour, career exploration, we found that job insecurity was positively related to career exploration for people who perceived low support for development. These results suggest that when organizations fail to support their employees' development, employees will attempt to address their job insecurity by seeking employment alternatives *outside* the organization.

Together, our model suggests that people are most responsive to automatability under a certain combination of conditions. In particular, automatability had the strongest indirect effects on both preparatory behaviours via job insecurity for people who perceived a large skills-gap and low support for development. This may suggest that people are more likely to take initiative to prepare for automation when they feel they need to take action and are solely responsible for the continuity of their career (i.e., when organizations signal little investment in the development of their employees). In other words, people may take matters into their own hands when they feel they have no other choice. However, although we identified this combination as the most *reactive* condition under which people prepare for automation, it does not suggest that this is the *ideal* condition for adaptive responses to automation. For example, we do not advocate that organizations abstain from supporting their employees' development. Indeed, support for development also had a positive main effect on developmental activities – therefore, fear is not the only way to motivate developmental activities. We return to this point in the practical implications section.

Theoretical Implications

This study adds much needed nuance to the accumulating research on employees' fear of automation. To date, research has painted a picture that suggests that employees are inaccurate judges of their automatability (Brougham & Haar, 2018; European Commission, 2017; Gallup, 2018; Koen & Parker, 2020; Smith, 2016). Although in some cases employees may indeed be inaccurate (Brougham & Haar, 2017), our results nonetheless paint a different picture. We showed that rather than people being inaccurate in general, there is variability in people's fearful reactions, such that people who are vulnerable to being displaced automation (i.e., people with a large skills-gap) are more likely to be afraid of their automatability, whereas people who are not vulnerable to being displaced by automation (i.e., people with a small skill-gap) are less likely to be afraid of their automatability. This clarifies previous research by suggesting that the weak relationship between automatability and job insecurity (Brougham & Haar, 2018; Parker & Grote, 2020; Essay 1) may be an artifact of hidden moderators.

This research also fortifies the literature on job insecurity and job preservations behaviours. Namely, the antecedent effect of job insecurity on job preservation behaviours (such as developmental activities and career search) has been repeatedly proposed (Shoss, 2017) but scarcely theoretically reasoned for, or empirically tested (Kamphuis & Glebbeek, 2020). To this end, we adopted a control theory perspective to provide a theoretical rationale for why job insecurity may motivate job preservation behaviours. In addition, we contributed empirical evidence that automation-related job insecurity predicts developmental activities and career exploration.

Nonetheless, where the relationship between job insecurity and job preservation behaviours have been tested, the findings have been decidedly mixed (e.g., Kamphuis & Glebbeek, 2020; Lebert & Antal, 2016; Zhang et al., 2019). To this end, we also contributed by providing a theoretical framework for understanding the inconsistent effects. We argued from a control theory perspective that job preservation behaviours can be thought of as goal directed behaviours, and that as such, concepts such as likelihood of success and desirability, could be used to deduce whether people choose to engage in the behaviours. Our results provided partial support for these arguments (i.e., our predictions related to career exploration were supported). Importantly, we laid a theoretical groundwork that can be applied broadly beyond the automation context to understanding the competing relationships between job insecurity and job preservation behaviours.

Practical Implications

The aim of this research was to identify ways to foster employee preparations for automation. To this end, we recommend that organizations help employees' form accurate perceptions of their skills. Indeed, evidence suggests that people often believe they score above average on various attributes, including their vocational skills (Zell, et al., 2019), which would suggest that they likely underestimate their skills-gaps. In combination with evidence that people typically underestimate their automatability (Brougham & Haar, 2018; Koen & Parker, 2020), this might tempt organizations and policymakers to engage in scare tactics to overcompensate for employees' apparent apathy towards preparing for automation. However, blanket approaches designed to increase employees' perceived skills-deficiencies may miscalibrate employees' perceptions of their skills, potentially causing harm. Specifically, people may develop job insecurity that is disproportional to their *need* to feel insecure, causing undue stress. Therefore, we recommend that organizations strive to calibrate their employee perceptions of their skills with their actual skill level. To do so, organizations could offer regular feedback to their employees regarding how their skills measure up relative to their peers, or relative to the organization's future strategic needs.

Yet, encouraging high levels of all preparatory behaviours may not be the goal, if not all preparatory behaviours are equally beneficial from the perspective of the organization. Skills shortages are likely to plague organizations in the coming decades (Gekara & Snell, 2020; World Economic Forum, 2016) and employee turnover can be costly for companies (Park & Shaw, 2013). Therefore, organizations may be motivated to retain and retrain their current workforce – goal which are well served by employees engaging in developmental activities and *refraining* from career exploration. The findings of the present research suggest that supporting employee development may be a one size fits all approach to achieving both aims. We found that high support for development was associated with high levels of developmental activities (regardless of job insecurity), and high support for development attenuated the relationship between job insecurity and career exploration. Therefore, organizations could create policies and reward structures to support development, such as providing paid time off to participate in development, compensating for developmental initiatives, offering wage increases to employees who develop new KSAs (Kamphuis & Glebbeek, 2020), or fostering peer mentoring through job shadowing programs and job rotations. Organizations willing to make these investments may see considerable return from retaining and upskilling their workforce.

Limitations

As with any research, our study is not without limitations. For one, our use of a survey design precludes us from making claims about the causal direction among the variables. This is a notable limitation because previous research indicates the possibility of reverse causality between some of our variables. For example, whereas we suggested that job insecurity leads to developmental activities, research has also found that engaging in developmental activities reduces subsequent job insecurity (Koen & Parker, 2020; Koen & van Bezouw, 2021; Lebert & Antal, 2016; De Cuyper et al., 2021). Likewise, whereas we modelled a path from skills-gaps to developmental activities – suggesting that people who feel a larger skill-gap would be more likely to engage in development – the reverse path is also likely true; People who engage in developmental activities likely reduce their perceived skills-gaps. Indeed, we submit that many of the relationships outlined in our model are likely reciprocal and unfold over time. Skills-gaps and job insecurity interactively drive preparatory behaviours, but the purpose of preparatory behaviours is to address job insecurity, sometimes by addressing people's skills-gaps. Therefore, future research may employ longitudinal designs to capture these processes and verify the causal directions we hypothesized in this paper.

In a similar vein, another limitation of the present research is that our measures did not allow us to draw conclusions regarding the timeline of preparatory behaviours. This was particularly a problem in our measurement of developmental activities. We asked participants to report the frequency with which they engaged in various developmental behaviours without specifying the time frame over which they may have conducted these behaviours. Therefore, participants could have interpreted the question in a number of ways, including the total number of times they have engaged in a particular developmental activity over the course of their careers. Given that the upper limit on the response scale was “6 or more times” and the mean of this scale was 3.63 (SD = 1.37), we doubt that many people interpreted the question in such a way. Nonetheless, future research should be more precise regarding the time frame. In particular, given that we were interested in people’s developmental activities in response to automation-related job insecurity, future research could take a more targeted approach and sample developmental activities in the months prior to and after the implementation of an automated system in the workplace to gauge people’s responses to changes in their automatability.

Finally, in our discussion of career exploration, we assumed that career exploration is a company “exit strategy” – in other words, that career exploration involves seeking only career opportunities *outside* of one’s current organization. This was integral to our hypothesis about the interactive effect of support for development and job insecurity on career exploration. However, the items in the career exploration scale did not exclude the possibility that people may also seek career opportunities within their current organization. To the extent that employees seek career opportunities *within* the organization, we would expect a reverse interaction pattern than what we originally hypothesized, such that high support for development would strengthen the extent to which job insecurity positively predicts career exploration. This is because employees who feel high support for development may desire to stay with the company and may expect that the organization would offer retraining support if they found a new career within the organization. It is possible that these competing effects may have made it more difficult to find support for H3. Thus, future research with more specific operationalizations of career exploration (i.e., career exploration *outside* the organization and career exploration *within* the organization) may be needed to test the robustness of our theoretical rationale.

Future Directions

The model presented in this paper provides a springboard from which to launch several future research directions. For example, in this paper we argued that people's skills influence their vulnerability to job loss because we argued that in cases where automation leads to organizational restructuring or downsizing, organizations would engage in *merit-based* selection decisions. However, there may be multiple other factors that determine whether employees "get the boot" during times of automation-related disruptions. For example, contributing factors may include employees' political skill, employees' seniority (i.e., how expensive it is to retain the employee), government regulations, and union participation. As such, employees' perceptions of these factors may also moderate whether automatability provokes a sense of job insecurity. Further still, these factors may have competing effects and may need to be considered collectively to best understand how employees react to their automatability.

Future lines of research could also explore employees' perceptions of the concrete skills they may need to prepare for the future of work. Consensus is beginning to emerge that certain skills, such as creative intelligence, social intelligence, and technical skills will be in demand in the future, either because these skills remain difficult to automate (i.e., creative and social intelligence) or because these skills are needed to operate and further develop the technologies that permeate work (i.e., technical skills; Autor et al., 2003; Davies et al., 2011; Deming, 2017; Frey & Osborne, 2017; World Economic Forum, 2016). People's skills may vary across these domains, such that some of their skills may fall within the "future-proof" category, whereas other may fall within the "vulnerable" category. For example, a nurse may possess above average social intelligence but lack technical skills. With the introduction of robotic nursing aids, it is unclear how such an employee will perceive their automation-related job security. Specifically, future research is needed to understand how competing skills-gap perceptions may influence the relationship between automatability and job insecurity. If research finds that possessing "future-proof" skills in one area counteracts the job-insecurity enhancing effect of a large skills-gap in another area, interventions may be needed to encourage people to prepare for automation despite feeling secure. People's long term career success may depend on it.

Finally, automation-related job insecurity may also impact the preparatory behaviours of people entering the job market for the first time. In particular, students may weigh the potential impacts of automation on their desired careers when considering their options (Mbilini et al., 2019). Jobs that are perceived to be more automatable may be less desirable than jobs are perceived to be impervious to automation. To this effect, research has found that younger people tend to exhibit greater automation-related job insecurity than older people, and are also more sensitive to the negative impacts of automation-related job insecurity than older people (Brougham & Haar, 2018), possibly because young people anticipate that automation is more likely to impact them in their lifetime. Yet, a study of South African undergraduate students found that only 22% of students reported considering automation in their career decisions (Mbilini et al., 2019). Nonetheless, this research is in its infancy. Future research is needed to clarify to what extent students think about the longevity of their careers, possibly even before they pick their university degree.

Conclusion

Employees who prepare may be in a significantly better position to weather automation-related disruptions. To this end, in this paper we showed that job insecurity may drive people to prepare for automation – both by means of improving their KSAs and seeking alternate career opportunities. We clarified *for whom* an automatable job is likely to trigger job insecurity, and *under what conditions* job insecurity is likely to lead to preparatory behaviours. By doing so, we revealed key levers organizations could use to manage employees' reactions to automation. Further, we added nuance to previous research on the relationship between automatability and job insecurity – demonstrating that automatability is more likely to provoke fear in some people than others. Finally, we also enriched the job insecurity literature by lending a theoretical framework for understanding the inconsistent findings between job insecurity and job preservation behaviours.

Table 6

Means, Standard Deviations, Reliabilities, and Intercorrelations Between Study Variables (Essay 2)

	N	*M*	*SD*	1	2	3	4	5	6
1 Automatability	198	.49	.38						
2 Automation-related Job Insecurity	244	2.25	1.18	.19 **	(.93)				
3 Perceived Skills-Gap	244	4.73	1.36	-.14	.15 *	(.89)			
4 Organizational Support for Development	244	5.08	1.18	-.15 *	-.18 **	-.10	(.88)		
5 Developmental Activities	244	3.63	1.37	-.10	.05	.15 *	.17 **	(.93)	
6 Career Exploration	244	2.54	1.09	-.15 *	.24 ***	.32 ***	-.00	.48 ***	(.92)

Notes. * < *p* .05, ** *p* < .01, *** *p* < .001. Reliabilities (Cronbach's alpha) are reported on the diagonal in parentheses.

Table 7

Conditional Indirect Effects of Automatability on Each Dependent Variable via Automation-Related Job Insecurity at High and Low Levels of Each Moderator (Essay 2)

		95% CI		90% CI	
	IE	**LB**	**UB**	**LB**	**UB**
Automatability → Automation-related Job Insecurity → Developmental Activities					
Small Skills-Gap, Low Support for Development	.058	-.143	.274	-.098	.239
Large Skills-Gap, Low Support for Development	.395	.149	.781	.186	.723
Small Skills-Gap, High Support for Development	-.041	-.285	.070	-.227	.045
Large Skills-Gap, High Support for Development	-.278	-.729	.010	-.652	-.032
Automatability → Automation-related Job Insecurity → Career Exploration					
Small Skills-Gap, Low Support for Development	.053	-.139	.235	-.098	.209
Large Skills-Gap, Low Support for Development	.365	.138	.691	.173	.634
Small Skills-Gap, High Support for Development	.010	-.027	.155	-.015	.130
Large Skills-Gap, High Support for Development	.070	-.156	.327	-.107	.283

Notes. N = 244. IE = indirect effect, LB = lower bound and UB = upper bound, CI = confidence interval.

Figure 7

Hypothesized Model (Essay 2)

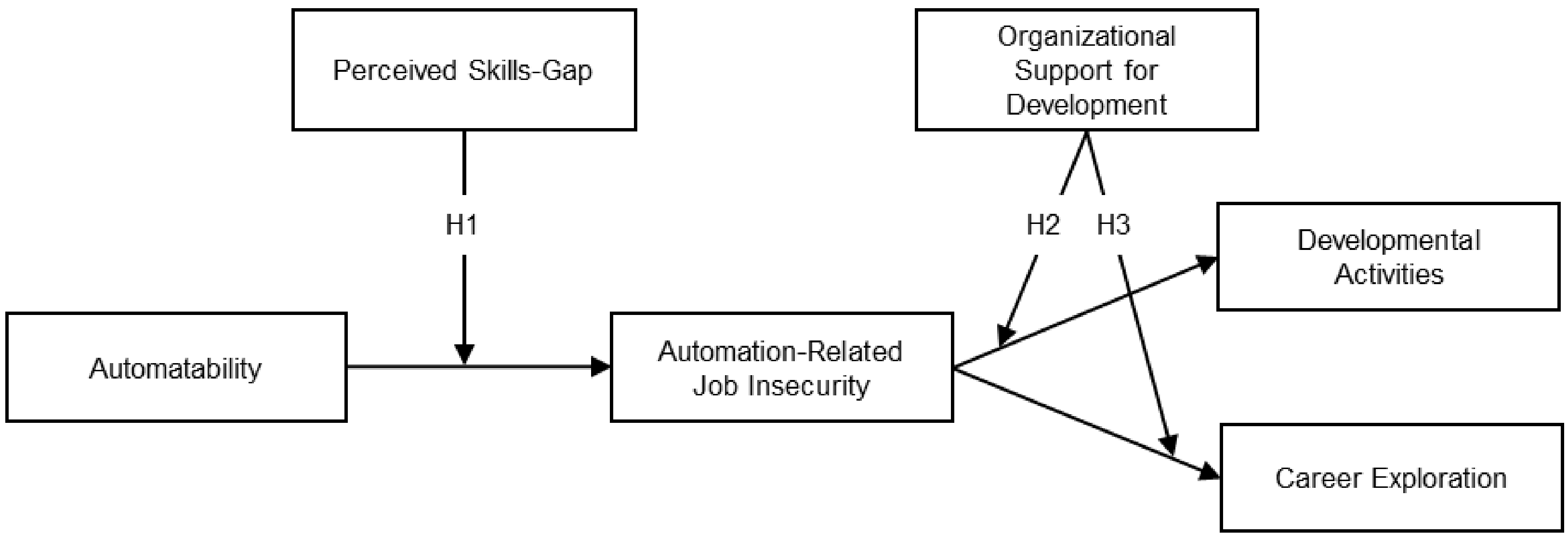
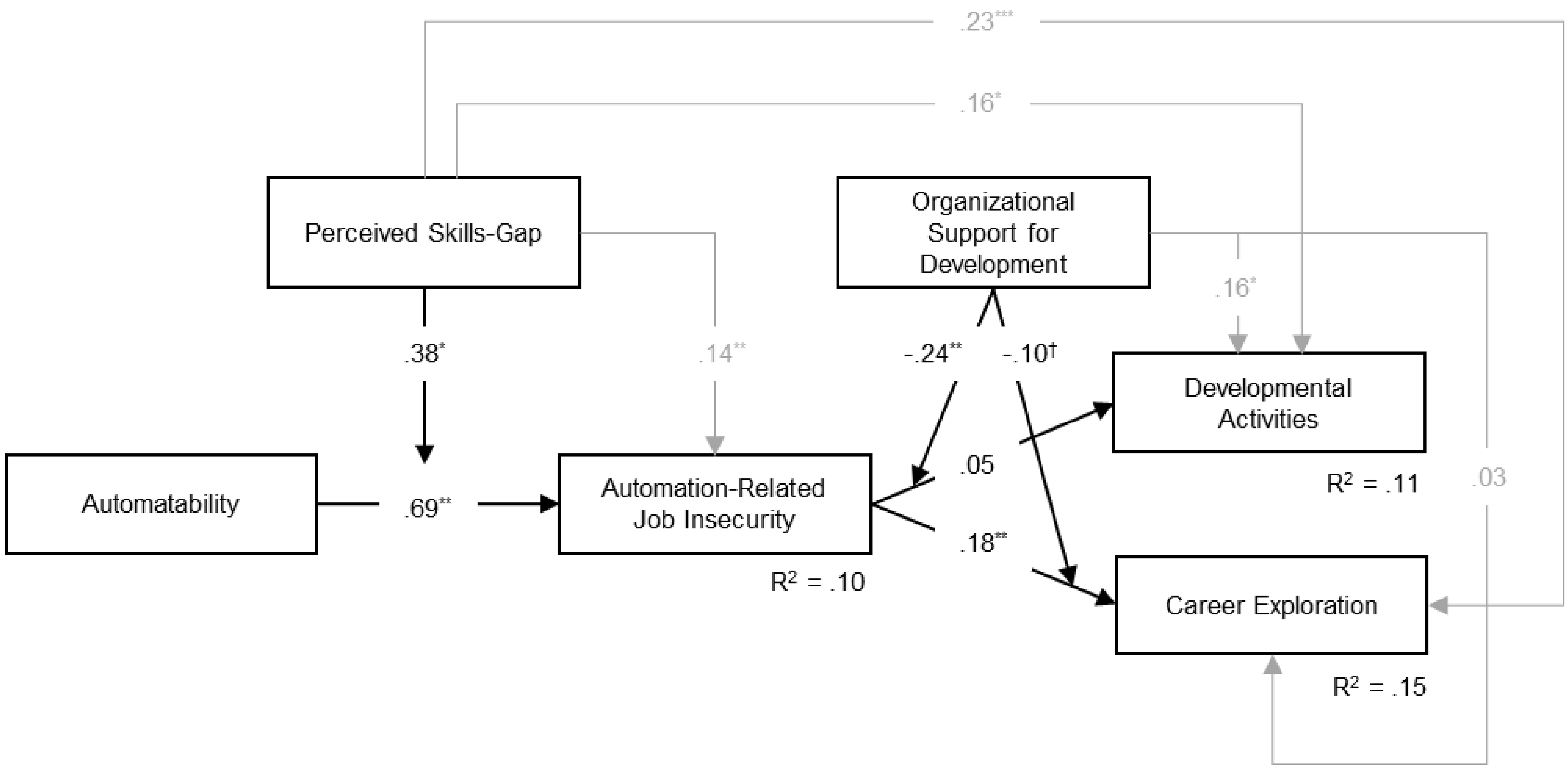


Figure 8

Structural Equation Model Results (Essay 2)



Notes. * p < .05, ** p < .01, *** p < .001, † p < .10. Dark lines denote hypothesized paths and light lines denote additional paths in the structural model. The covariance paths between the interaction term and its components are not depicted for clarity.

Figure 9

Interactions Between Automatability and Perceived Skills-gap Predicting Automation-Related Job Insecurity (Essay 2)

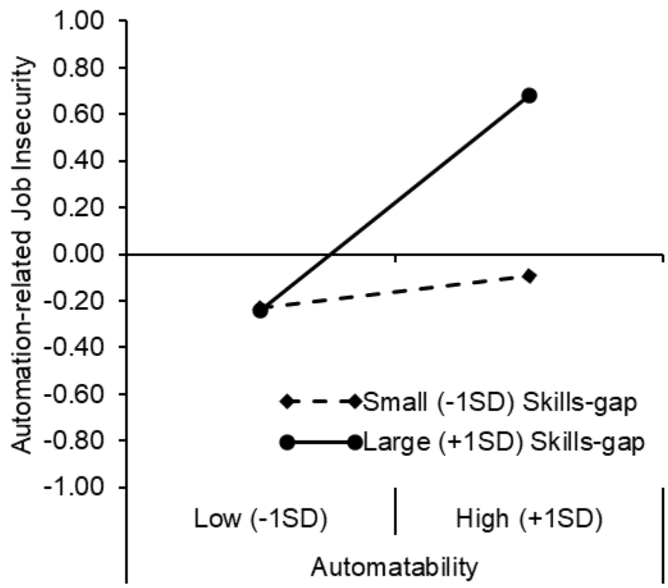


Figure 10

Interactions Between Automation-related Job Insecurity and Organizational Support for Development Predicting Developmental Activities (Essay 2)

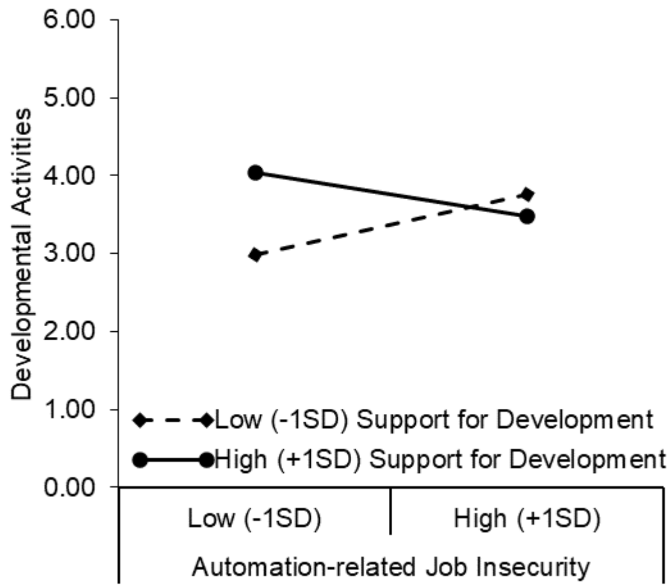
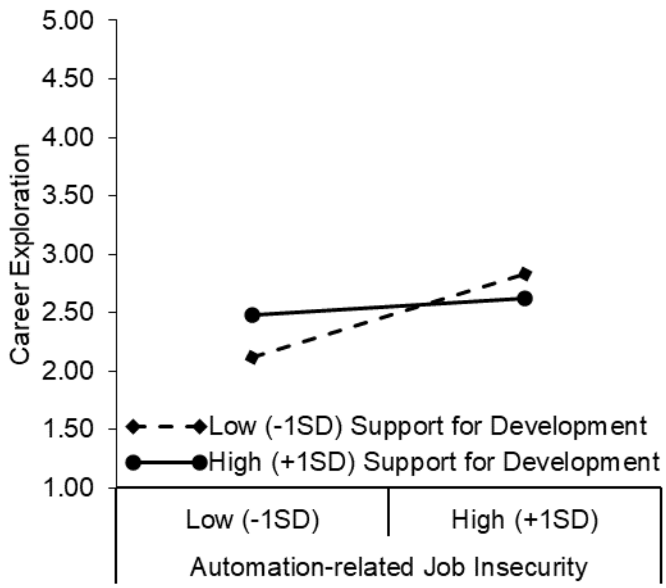


Figure 11

Interactions Between Automation-related Job Insecurity and Organizational Support for Development Predicting Career Exploration (Essay 2)



CHAPTER 4: CONCLUDING REMARKS

Automation is one of the top contributors to the changing landscape of work in the 21st century (Brynjolfsson & McAfee, 2014; Schwab, 2017; World Economic Forum, 2016). Despite this, little is known about employees' perspectives on automation in the workplace. To this end, this dissertation substantially expanded the literature on employee perceptions and reactions to automation at work. In particular, in Essay 1, I delineated different ways employees may psychological perceive their automatability and how these perceptions differentially affect workplace attitudes. In Essay 2, I demonstrated how personal and contextual factors shape employees' likelihood of engaging in preparatory reactions to their job's automatability.

Across these essays, I found that employees perspectives on automation are key to shaping employees' job attitudes (i.e., engagement, turnover intentions) and behaviours (i.e., developmental activities and career exploration). This means that there may be significant repercussions associated with neglecting to – or significant opportunities associated with choosing to – take into consideration employees' perspectives when implementing automation at work. To this end, I also identified several levers by which organizations could shape employees' perspectives (i.e., control at work, skills-gap) and subsequent behavioural responses (i.e., support for development) to automation at work. As such, this dissertation will serve as an important resource for organizations and policymakers seeking to prepare employees for the future of work.

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Appendices

Appendix A: List of Measures (Essay 1)

Perceived Automatability

1. Automation will change how this job is performed in the future.
2. A large percentage of the tasks performed on this job cannot be automated. (reverse)
3. In the future, this job will look very different because of automation.
4. Some of the tasks performed on this job can be automated.
5. Automation will not impact how this job is performed in the future. (reverse)
6. Many aspects of this job can be automated.

Automation-related Job Insecurity

(Brougham & Haar, 2018)

1. I think my job could be replaced by automation.
2. I am personally worried that what I do now in my job will be able to be replaced by automation.
3. I am personally worried about my future in my organisation due to automation replacing employees.
4. I am personally worried about my future in my industry due to automation replacing employees.

Automation-related Performance Optimism

1. Automation will enable me to perform my job better.
2. Automation will enhance my work performance.
3. Automation provides me with an opportunity to preform better at my job.
4. It will be easier to perform well on my job due to automation.
5. Automation will enable me to focus on the more important parts of my job.
6. Automation can complement my current skill set to enable me to work better.

Perceived Control

(Morgeson & Humphrey, 2006)

Work Scheduling Autonomy

1. The job allows me to make my own decisions about how to schedule my work.
2. The job allows me to decide on the order in which things are done on the job.
3. The job allows me to plan how I do my work.

Decision-Making Autonomy

4. The job gives me a chance to use my personal initiative or judgment in carrying out the work.
5. The job allows me to make a lot of decisions on my own.
6. The job provides me with significant autonomy in making decisions.

Work Methods Autonomy

7. The job allows me to make decisions about what methods I use to complete my work.
8. The job gives me considerable opportunity for independence and freedom in how I do the work.

9. The job allows me to decide on my own how to go about doing my work.

Engagement
(Rich, LePine, & Crawford, 2010)

Physical engagement
1. I work with intensity on my job.
2. I exert my full effort to my job.
3. I devote a lot of energy to my job.
4. I try my hardest to perform well on my job.
5. I strive as hard as I can to complete my job.
6. I exert a lot of energy on my job.

Emotional engagement
1. I am enthusiastic in my job.
2. I feel energetic at my job.
3. I am interested in my job.
4. I am proud of my job.
5. I feel positive about my job.
6. I am excited about my job.

Cognitive engagement
1. At work, my mind is focused on my job.
2. At work, I pay a lot of attention to my job.
3. At work, I focus a great deal of attention on my job.
4. At work, I am absorbed by my job.
5. At work, I concentrate on my job.
6. At work, I devote a lot of attention to my job.

Turnover Intentions
(Kelloway, Gottlieb, & Barham, 1999)

1. I am thinking about leaving this organization.
2. I am planning to look fora new job.
3. I intend to ask people about new job opportunities.
4. I don't plan to be in this organization much longer.

Appendix B: Auxiliary Analyses with Work Locus of Control as the Moderator (Study 1, Essay 1)

Locus of control was measured with Spector's (1988) 16-item scale. An example item is "promotions are usually a matter of good fortune" (reverse coded). Participants rated their agreements with the statements on a scale from 1 (disagree very much) to 6 (agree very much). Higher scores indicate internal locus of control, and lower scores indicated external locus of control.

The measurement model ($\chi^2(50) = 233.509$, $p < .001$, CFI = .969, RMSEA = .086, SRMR = .047) fit the data well. The structural model – including the same additional paths from the control moderator to the dependent variables as in Studies 1 and 2 – also fit the data well ($\chi^2(4) = 10.846$, $p = .028$, CFI = .990, RMSEA = .059, SRMR = .019). In support of H1 and H2, perceived automatability was significantly positively related to both automation-related job insecurity ($B = .74$, $SE = .04$, $p < .001$), and automation-related performance optimism ($B = .42$, $SE = .06$, $p < .001$). Supporting H3, work locus of control moderated the relationship between perceived automatability and automation-related job insecurity ($B = -.07$ $SE = .03$, $p = .024$) such that the relationship was weaker for people with internal ($B = .66$, $SE = .05$, $p < .001$) compared to external locus of control ($B = .78$, $SE = .04$, $p < .001$). Likewise, in support of H4 locus of control moderated the relationship between perceived automatability and automation-related performance optimism ($B = .13$, $SE = .05$, $p = .014$) such that the relationship between perceived automatability and performance optimism was stronger for people with internal ($B = .53$, $SE = .08$, $p < .001$) compared to external locus of control ($B = .31$, $SE = .07$, $p < .001$).

Downstream, job insecurity was significantly negatively related to engagement (H5a; $B = -.07$, $SE = .03$, $p = .030$), and significantly positively related to turnover intentions (H5b; $B = .13$, *SE* = .05, *p* = .015). Further, performance optimism was significantly positively related to engagement (H6a; *B* = .10, *SE* = .03, *p* = .003), but contrary to H6b, performance optimism was not significantly related to turnover intentions (*B* = -.05, *SE* = .05, *p* = .347).

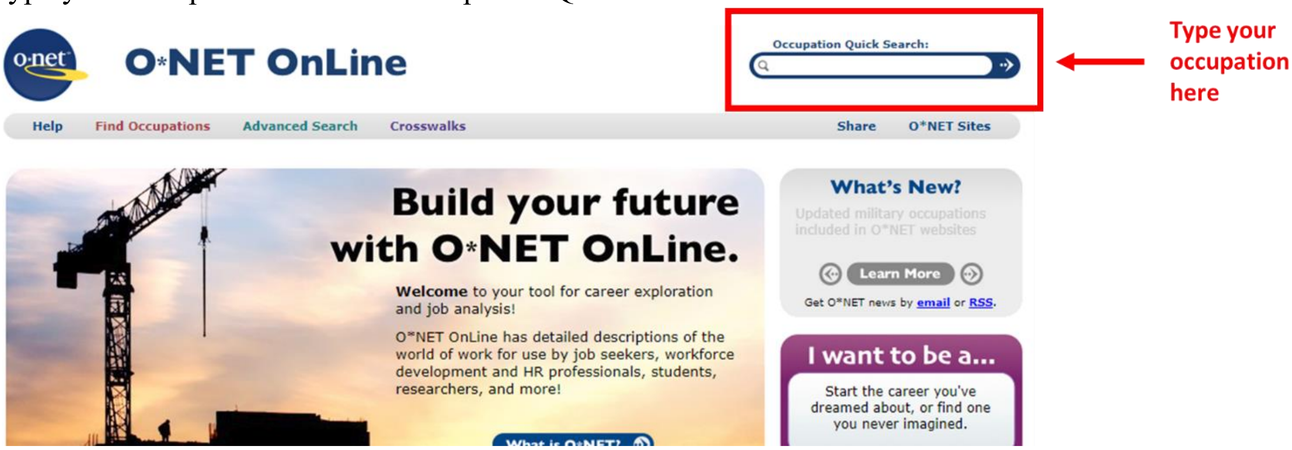
Finally, in support of H7a, the negative indirect effect of perceived automatability on engagement via job insecurity was significantly weaker for people with internal compared to external locus of control (ΔIE = .008, 95% CI [.001, .025]). Similarly, the positive indirect effect of perceived automatability on turnover intentions via job insecurity was significantly weaker for people with internal compared to external locus of control (ΔIE = -.014, 95% CI [-.038, -.002]). The positive indirect effect of perceived automatability on engagement via performance optimism was significantly stronger for people with internal compared to external locus of control (ΔIE = .021, 95% CI [.005, .052]), supporting H8a. However, contrary to H8b, there was no differences in the indirect effects from perceived automatability to turnover intentions via performance optimism across people with internal or external locus of control (ΔIE = -.011, 95% CI [-.045, .008]).

Appendix C: Instructions to Access Standard Occupational Classification Code

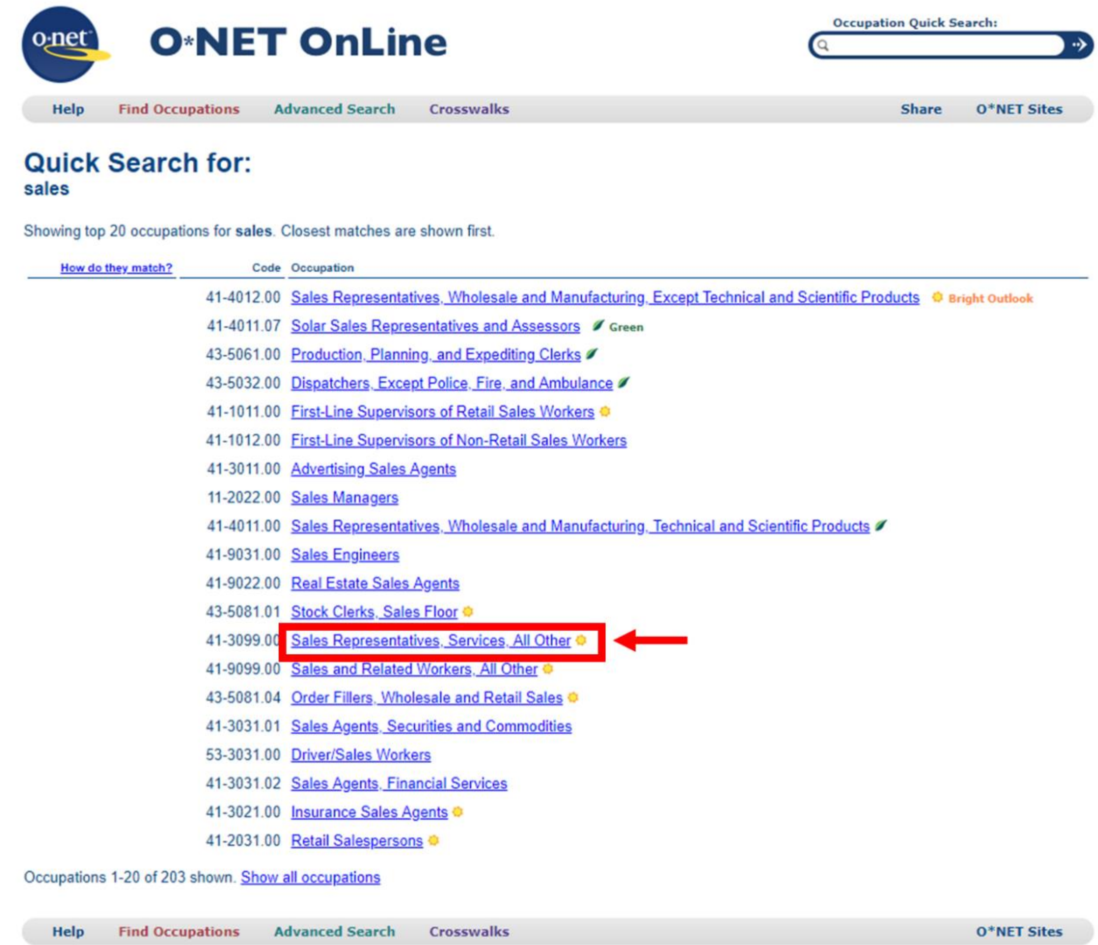
Please follow the instructions below to identify your occupation's code in the online dictionary of occupations.

STEP 1
Open this link in a **new tab**: https://www.onetonline.org/
If the link does not work, please type in "www.onetonline.org" into your web browser.

STEP 2
Type your occupation into the "Occupation Quick Search" bar

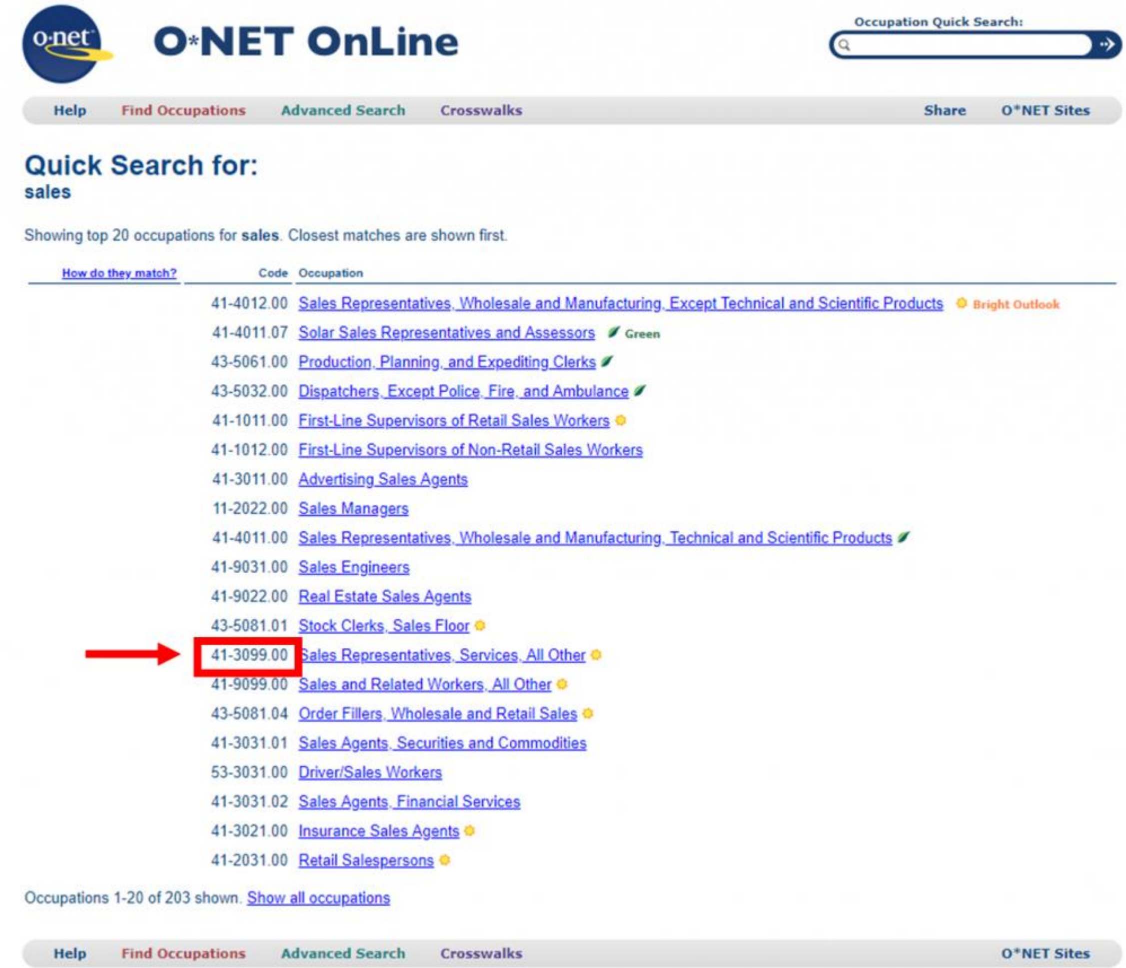


STEP 3
Find the occupation that most closely aligns with your current job.



STEP 4
If no relevant search results appear, try searching again with different keywords.

STEP 5
Find the code appearing on the left side of your occupation here:



O*NET OnLine

Occupation Quick Search:

Help | Find Occupations | Advanced Search | Crosswalks | Share | O*NET Sites

Quick Search for:
sales

Showing top 20 occupations for **sales**. Closest matches are shown first.

How do they match?	Code	Occupation
	41-4012.00	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products Bright Outlook
	41-4011.07	Solar Sales Representatives and Assessors Green
	43-5061.00	Production, Planning, and Expediting Clerks
	43-5032.00	Dispatchers, Except Police, Fire, and Ambulance
	41-1011.00	First-Line Supervisors of Retail Sales Workers
	41-1012.00	First-Line Supervisors of Non-Retail Sales Workers
	41-3011.00	Advertising Sales Agents
	11-2022.00	Sales Managers
	41-4011.00	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products
	41-9031.00	Sales Engineers
	41-9022.00	Real Estate Sales Agents
	43-5081.01	Stock Clerks, Sales Floor
	41-3099.00	Sales Representatives, Services, All Other
	41-9099.00	Sales and Related Workers, All Other
	43-5081.04	Order Fillers, Wholesale and Retail Sales
	41-3031.01	Sales Agents, Securities and Commodities
	53-3031.00	Driver/Sales Workers
	41-3031.02	Sales Agents, Financial Services
	41-3021.00	Insurance Sales Agents
	41-2031.00	Retail Salespersons

Occupations 1-20 of 203 shown. Show all occupations

Help | Find Occupations | Advanced Search | Crosswalks | O*NET Sites

STEP 6
Copy and paste the code of your occupation here:
[text entry box]

Appendix D: List of Measures (Essay 2)

Skills-gap
(Maurer, Weiss, & Barbeite, 2003)

1. One or more of my career related skills or knowledge have been in need of improvement.
2. I have seriously thought that my job abilities should be increased in certain areas.
3. I have been in real need of career related skill or knowledge improvement.

Automation-related Job Insecurity
(Brougham & Haar, 2018)

5. I think my job could be replaced by automation.
6. I am personally worried that what I do now in my job will be able to be replaced by automation.
7. I am personally worried about my future in my organisation due to automation replacing employees.
8. I am personally worried about my future in my industry due to automation replacing employees.

Organizational Support for Development
(Maurer, Weiss, & Barbeite, 2003)

1. There are learning and skill development resources available to me through my employer that can help me improve my career skills.
2. Skill development options or learning materials can be obtained by me that will assist in improving my job/career skills.
3. There are no effective development options or resources available that can help me improve my career skills. (reverse)
4. The policies and work rules where I am employed make it possible to participate in career related learning and development activities.
5. Regulations, reward policies and time constraints where I work make it difficult to participate in career-related learning and development activities. (reverse)
6. Our company places much value on employee learning and development activities.
7. My employer emphasizes employee learning to its employees.
8. My employer does not have an employee learning orientation. (reverse)

Developmental Activities
(Maurer, Weiss, & Barbeite, 2003)

1. Taken an optional college or continuing education course.
2. Used pre-recorded audio/video tapes that were optional (not required for my job).
3. Taken an optional/voluntary career-related training class, workshop, or seminar.
4. Read a book that was optional/voluntary reading.
5. Consulted with a career counselor.
6. Worked on or practiced a specific skill "on the job".
7. Worked to learn a new skill on the job.
8. Tried to improve a specific attribute of myself while I was doing the work required of my job.
9. Asked for feedback and input from coworkers.

10. Asked for feedback and input from a supervisor at work.
11. Asked for feedback and input from subordinates at work.
12. Voluntarily participated in a special project, task, or committee assignment.
13. Received optional/voluntary coaching from a supervisor at work.
14. Voluntarily taken a different job assignment on a temporary basis.
15. Worked on a career/professional development plan.
16. Participated in an optional/voluntary assessment at work which provided formal feedback on my strengths, weaknesses, or style.
17. Relied on a special or close relationship of some kind to get career-related advice or suggestions.
18. Acted as a job/career-related coach, mentor, or teacher to someone else.
19. Attended an organized event which focused on future career issues.

Career Exploration

(Stumpf, Colarelli, & Hartman, 1983)

1. Investigated career possibilities.
2. Went to various career orientation programs.
3. Obtained information on specific jobs or companies.
4. Initiated conversations with knowledgeable individuals in my career area.
5. Obtained information on the labor market and general job opportunities in my career area.
6. Sought information on specific areas of career interest.

Appendix E: Auxiliary Analyses with Perceived Employability as the Moderator (Essay 2)

Employability was measured using Berntson and Marklund's (2007) five-item scale. Participants rated their agreement with items such as, "My competence is sought-after in the labour market" on a scale from 1 (strongly disagree) to 5 (strongly agree).

The hypothesized measurement model demonstrated acceptable fit ($\chi^2(80) = 208.861$, $p < .001$, CFI = .956, RMSEA = .081, SRMR = .064). Next, we tested the structural model. We freed paths from employability to developmental activities and to career exploration to ensure consistency with the main study analyses. This structural model fit the data well ($\chi^2(4) = 7.807$, $p =.989$, CFI = .978, RMSEA = .062, SRMR = .028).

Given that employability and skills-gaps are inversely related (i.e., the higher a person's perceived skills-gap, the lower their perceived employability), our hypotheses regarding employability are also reverse of our hypotheses regarding skills-gap. For example, for H1, we expect that the positive relationship between automatability and automation-related job insecurity will be *stronger* for people with low employability compared to people with high employability. In support of this, employability significantly moderated the relationship between automatability and automation-related job insecurity ($B = -.58$, $SE = .27$, $p = .032$), such that the positive simple slope between automatability and automation-related job insecurity was stronger for people who perceived low employability ($B = 1.09$, $SE = .31$, $p < .001$) than for people who perceived high employability ($B = .09$, $SE = .34$, $p = .79$).

Next, support for development significantly moderated the relationship between automation-related job insecurity and developmental activities ($B = -.24$, $SE = .06$, $p = .001$). As in the main analyses, the pattern of the interaction was opposite to the expected direction. Automation-related job insecurity had a stronger positive relationship with developmental activities for people who experienced *low* support for development (B = .42, SE = .08, p < .001) than for people who experienced high support for development (B = -.16, SE = .13, p = .192).

Also like the main analyses, support for development did not moderate the relationship between automation-related job insecurity and career exploration (B = -.10, SE = .06, p = .08) at the p < .05 cut-off criteria. However, simple slopes indicated that automation-related job insecurity was more strongly positively related to career exploration for people who experienced low support for development (B = .37, SE = .08, p < .001) than people who experienced high support for development (B = .12, SE = .10, p = .252). Given that the pattern of results was consistent with our hypotheses, we decided to interpret this effect as supportive of our hypotheses.

Based on the unexpected second stage interaction pattern on developmental activities, we decided to revise our approach to testing H4. We compared the significant indirect effect at low employability/*low* support for development (rather than the originally planned indirect effect at low employability/*high* support for development) to the average of remaining indirect effects (all of which were not significantly difference from 0). This difference was significant using the more conservative α = .001 (ΔIE = .511, 99% CI [.126, 1.051]). Therefore, the positive indirect effect of automatability on developmental activities via automation-related job insecurity was strongest for people who perceived low employability and low support for development.

As planned, we compared the indirect effect at low employability/low support for development to the average of the remaining indirect effects. This difference was significant (ΔIE = .348, 95% CI [.092, .710]). Therefore, the positive indirect effect of automatability on career exploration via automation-related job insecurity was strongest for people who perceived low employability and low support for development.