Faculty of Business Economics

Master of Management

Master's thesis

Algorithmic Management Impact on Workers Performance and Well being

Sara Ouzian

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Business Process Management

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Preface

This master thesis is written as part of obtaining my Master's degree at the University of Hasselt, in Business Process Management.

I would like to express my deepest gratitude to my supervisor, promotor Professor Dr. Dave Stynen, for his invaluable guidance, expertise, and patience. His insightful feedback and mentorship have been critical in shaping the direction of my research and refining my academic skills. I am truly fortunate to have had the opportunity to work under his supervision.

I am also extremely grateful to my parents for their unconditional love and support throughout my journey as an international student far away from home. Their encouragements have been the driving force behind my accomplishments, and I am truly grateful for their constant presence in my life.

Lastly, I would like to thank all the individuals who have contributed to my research by participating and sharing my survey, which contributed to enriching my study and improving its overall quality.

Abstract

Algorithms are increasingly used in streamlining processes and automating decision making, aiding managers in covering different aspects of their functions such as monitoring, scheduling, and evaluating performance (Wood, 2021). This has raised many challenges within organizations in regulating the adoption of algorithmic management practices, as well as its effects on the working environment. The main purpose of this master thesis is to investigate the extent to which algorithmic management impacts employees' psychological well-being and job performance. Drawing on the literature, the job characteristics model (Hackman & Oldham, 1974) and the job demand-control model of Karasek (1979), a research model was developed to empirically examine the impact of algorithmic management practices in 'traditional' companies on workers' well-being and performance, through the mediating effect of job autonomy.

Conducted by collecting data from 125 employees from different countries and companies, our study reveals that algorithmic management is related to both workers' psychological well-being and job autonomy, but no association was found to job performance. While some of our hypotheses could not be validated by the results of our empirical study, statistical results of the regression analysis showed that job autonomy mediates the relationship between algorithmic management and their psychological well-being. We discuss the theoretical and practical implications of these findings.

Key words: algorithmic management; job autonomy; task performance; psychological well-being; job characteristics model, job demand control model.

Summary

Algorithmic management refers to the use of algorithm to support managers in their daily functions. Thanks to the emergence of new technologies (machine learning, artificial intelligence...), the scope of algorithmic management is constantly broadening in terms of organizational contexts. The aim of implementing algorithmic management systems is to aid managers in their responsibilities including monitoring, scheduling, and evaluating employees' performance, through streamlined processes and automated decision making, while also increasing value to companies, all of which has profound implications both for workers and organizations. This has raised new challenges within organizations in regulating the adoption of algorithmic management practices, especially since the impact on the workplace is quite complex, as well as its effects on employees, notably in terms of their performance and well-being. Since little research has addressed this topic, the main purpose of this master thesis is to discover the extent to which algorithmic management impacts employees' psychological well-being and job performance.

Drawing on the literature, the job characteristics model (Hackman & Oldham, 1974) and the job demand-control model of Karasek (1979), we examined whether the experience of core job characteristics mediates the relationship between, on one hand, algorithmic management and task performance and algorithmic management and psychological well-being on the other. Particularly, we have investigated the role of perceived job autonomy as a mediator, as it is considered one of the most fundamental job characteristics shaping the work experience, and one that could potentially be either undermined or enhanced by algorithmic management. Our primary research question was: To what extent does algorithmic management impact employee psychological well-being and job performance? To address our research topic, we chose to rely on a quantitative methodology, based on an online survey. We collected data from 125 employees from different countries and companies, who are exposed to different degrees of algorithmic management in their work. This allowed us to have a broad view of the practice of algorithmic management within 'traditional' companies and explore its future scope.

Based on our review from the literature, we established four hypotheses, and we developed a research model to empirically examine the effects of algorithmic management practices on workers' well-being and performance, through the mediating effect of job autonomy. While some of our hypotheses could not be validated by the results of our empirical study, statistical results of the regression analysis indicated that job autonomy only mediates the relationship between algorithmic management and employees' well-being. To further test the significance of the indirect effect of algorithmic management on employees' psychological well-being, we also undertook a Sobel test based on our regression analysis results, which confirmed the mediating role of job autonomy.

As such, our study supports the argument that algorithmic management significantly impacts job autonomy, which also significantly influences psychological well-being. Despite the literature being quite mitigated on algorithmic management effect on autonomy, as it can both foster autonomy by allowing more flexibility at work, and restrain it via algorithmic monitoring and control, our study revealed that algorithmic management has the potential to promote autonomy for employees, and could provide employees with more flexibility and independence in their work. Our findings highlight the importance of fostering algorithm management practices and providing

employees with a sense of job autonomy to enhance psychological well-being in the workplace, as algorithmic management can be used in ways that can promote feelings of autonomy, especially when it is presented as a support tool for employees that is time saving, and that allows greater accuracy.

Despite the positive relation to autonomy, no association was found between algorithmic management and job performance, which contradicts some of our hypotheses. The use of algorithmic management does not appear to have a positive or negative impact on employees' performance based on our study's findings. The absence of an association between algorithmic management and job performance may be attributed to several plausible factors rooted in the complexity of organizational dynamics, the specificity of the working context and the environment in which the practice is implemented, as well as the nature of tasks that are subjected to algorithms. Algorithms were set to optimize tasks involving routine and repetitive work (Brynjolfsson and McAfee, 2014), and were proven to be less impactful in creative or non-routine tasks (Meijerink & Bondarouk 2023), which require more innovation and human judgment. The different effects in terms of performance between routine and non-routine tasks might result in an overall null effect when aggregated across diverse job functions, which might explain the lack of association between algorithmic management and task performance found in our study.

By establishing the impact of algorithmic management in traditional working contexts, our work contributes to the literature in the management field exploring algorithmic management from workers' perspective, (as opposed to previous studies mainly focusing on managers and companies' incentives), by better understanding the degree to which they're exposed to algorithms in different aspects of their work life, and their experience being managed by algorithms. Our study extends the research on algorithmic management beyond the gig work and digital platforms' contexts which was largely addressed by the literature, and explores the use of algorithmic management within 'traditional' companies that are relying more and more on algorithm-based solutions to improve their operations and processes (recruitment, manufacturing, warehouse management...). We also contribute to the literature studying work autonomy in relation to algorithmic management practices. Our findings add to our understanding of the determinants of well-being and performance in algorithmic management settings, and provide valuable insights for future research on algorithmic management and its impact on workers' work outcomes.

In addition to contributing to the existing literature, our study provides deeper insights into the impact of algorithmic management on workers' well-being and performance, by revealing one mediating mechanism. The combination of two work outcomes provides a large perspective for understanding the diverse impacts of algorithmic management and sheds light on its duality in restraining and promoting different work outcomes. Although algorithmic monitoring has both positive and negative impacts on workers, the negative effects can be turned into opportunities. In this regard, our study provides pointers for the design of algorithmic management systems from workers' perspective. Our findings may contribute to understanding the challenges and opportunities of the practice and offer useful support for managers and companies when working with their newly implemented algorithmic management systems or trying to improve their already existing ones.

Our study has several limitations. Our model was based on state of the art of the actual knowledge and mainly on the previous work related to algorithmic management in the gig economy context. Future research can focus more on workers' attitudes towards algorithmic management in traditional working contexts and in various industries, especially since the practice is constantly growing. Further work outcomes and related variables could also be included in our model. For instance, future studies may investigate other moderators and mediators related to algorithmic management that might impact employees' psychological well-being. Future research could also incorporate other job characteristics into their framework to provide a comprehensive understanding of the impact of algorithmic management on employees and on different work outcomes. In the same vein, it is also important to address algorithmic management functions and additional components of the practice that might have an effect on work outcomes and might be important in the future. In the absence of a clear association between algorithmic management with task performance, future studies might also explore other mechanisms that might be related to algorithmic management, such as workers' motivation, job satisfaction, organizational support, task engagement, and feedback and training.

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1. Introduction

The rapid digitalization of the workplace and recent technological advances are increasingly transforming work environments and continuously influencing human tasks and job requirements (Parent-Rocheleau & Parker, 2022). In light of these rapid advancements, characterized by the use of artificial intelligence (AI), big data, and machine learning, many predict that most current jobs will likely transform in the future (Jarrahi, 2018; Raisch et al., 2021). Numerous researchers also expect a rise in new types of jobs (Pol & Reveley, 2017; West, 2018), which will completely transform working environments due to a shift towards human-machine interfaces (Unruh et al., 2022), where intelligent machines and software technologies will increasingly replace the human element of production and supplant workers (Benzell et al., 2015; Brynjolfsson & McAfee, 2014; Frey & Osborne, 2017). This is expected to result in new interactions and previously unforeseen complementarities between workers and digital systems (Bessen, 2015; Mokyr et al., 2015), which will require more extensive and continuous learning, in addition to high levels of teamwork and flexibility for the employees (Unruh et al., 2022). In addition to transforming jobs and work processes, the technological growth and fast-paced digital transformation in current organizations contribute to the automation of management functions (Jarrahi et al., 2021), resulting in more flexible work environments that transcend geographical and time constraints. Moreover, the Covid-19 pandemic has also accelerated flexibility and digitalization within the workplace (Unruh et al., 2022), all of which contributed to *"the extension of alternative, more automated management practices in traditional companies, including factories, offices, and wholesale warehouses"* (Baiocco et al, 2022, p.5). According to Cram et al. (2022), the pandemic has also occasioned an increase in tools used to monitor employees' home office activities. Consequently, researchers have begun to focus on the repercussions of technological advances for management practices, including algorithmic management (Kellogg et al., 2020; Raisch et al., 2021).

Algorithmic management can be defined as "the *large-scale collection and use of data on a platform to develop and improve learning algorithms that carry out coordination and control functions traditionally performed by managers*" (Möhlmann et al., 2021, p.2001; Benlian et al., 2022, p. 825). In this respect, the widespread use of algorithmic management has led the way for 'new' working environments characterized by more standardized working processes and procedures. As mentioned above, although algorithmic management "*carries out coordination and control functions traditionally performed by managers*", the practice does not intend to replace managers entirely. Instead, it provides them with technology-enabled tools (such as learning algorithms, machine learning, and AI) to assist them with supervising employees (Wiener et al. 2023). In this regard, algorithmic management is portrayed as a support tool (Toyoda et al., 2020), that can help managers in their decision-making, as the implementation of algorithmic decision-making is set to impact human lives positively (Benlian et al., 2022). Consequently, the practice has been linked to increased operational efficiency (Kellogg et al., 2020), thanks to the automated, standardized and streamlined working processes and procedures.

Despite its many advantages, algorithmic management can alter power dynamics in the workplace (Baiocco et al, 2022), leading to power imbalances between management and workers, which might impact negatively the working environment and create work tensions (Benlian et al., 2022). Given its transformative reach and societal and managerial impacts *(*Jabagi et al*.,* 2020), algorithmic management has stirred much interest among academics in the business and psychology research fields, especially since the practice is expected to continue to grow in the future (Benlian et al., 2022). As we transition into a period in which algorithms are contributing to organizational decision making (Lee et al.,2018), it is essential to understand algorithmic management practices and to what extent they impact workers. Nonetheless, the study of how algorithms affect human workers and workplace processes remains in its early stages, with most research on algorithmic management focusing on platform businesses, whereas more 'traditional' companies are shifting toward algorithmic management. Additionally, existing literature focuses more on managers and organizations, rather on employees, when addressing algorithmic management impacts on performance metrics, decision quality, and on whether or not algorithms yield a high return on investment. One underexplored area of study that we've noted in this regard, is the impact of algorithmic management on the well-being and performance of workers, especially in 'traditional' work settings, where algorithmic management continues to evolve (Wood, 2021). The current body of knowledge regarding the characteristics and impact of algorithmic management on workers in the gig-economy offers valuable insights to better comprehend the practice (Baiocco et al., 2022). However, further research is required to investigate how algorithmic management is implemented outside the realm of digital platforms, in order to have a better understanding of its impact on employees in various industries and work settings.

According to previous studies on the subject, algorithmic management often has a negative connotation (Parent-Rocheleau & Parker, 2022; Kinowska & Sienkiewicz, 2022), especially since it is associated with a reduction of human involvement and contributes to eliminating of the empathetic aspects of managing employees (Duggan et al.,2020; Veen et al., 2020). Consequently, algorithmic management practices can be associated with several risks and challenges, related to employees' well-being and performance. However, many studies noted that the implementation of algorithmic management can occasion potential benefits notably for organizations, in terms of cost-effectiveness and scalability (Tomprou & Lee,2022; Kinowska & Sienkiewicz 2022), and for decision makers regarding the efficiency and accuracy of their decisions (Lee, 2018). Moreover, studies have found that algorithmic management can improve task performance, particularly in tasks involving routine and repetitive work (Brynjolfsson and McAfee, 2014).

Therefore, we chose to investigate the relationship between algorithmic management and task performance- which is "*defined as the effectiveness with which job incumbents perform activities that contribute to the organization's technical core either directly by implementing a part of its technological process, or indirectly by providing it with needed materials or services*" (Borman & Motowidlo, 2014, p. 99). This conceptualization differs from contextual performance (i.e. performance not formally required as part of the job but that helps shape the social and psychological context of the organization (Borman & Motowidlo, 1993). Since algorithmic management is more focused on enhancing performance in the strict sense rather than extra-role performance, we chose to focus primarily on task performance, which refers to the specific tasks and responsibilities outlined in the job description. As for well-being, there is insufficient evidence of the potential impact of algorithmic management on workers' sense of well-being (Kinowska & Sienkiewicz, 2022). Parent-Rocheleau & Parker (2022) found that algorithmic management is indirectly related to employees' well-being, while other studies argue that the 'pressurized working environments' (Duggan et al.,

2020) resulting from algorithmic management practices might significantly reduce well-being (Wood et al., 2019). We chose to focus on psychological well-being in our study, which is regarded as the most critical well-being factor in the workplace (Johnson et al., 2018; Holman et al., 2018).

Since the impact of algorithmic management on employees' performance and well-being is complex, further research is needed to fully comprehend the potential mechanisms underlying the impact of algorithmic management on employees' performance and well-being. Using the job characteristics model (Hackman & Oldham, 1974) and the job demand-control model of Karasek (1979), we investigate whether the experience of core job characteristics mediates the relationship between, on the one hand, algorithmic management and performance and well-being on the other. We explore the role of perceived job autonomy, as it is considered one of the most fundamental job characteristics shaping the work experience and one that could potentially be either undermined or enhanced by algorithmic management. Our primary research question is: To what extent does algorithmic management impact employees' job performance and psychological well-being?

This study may contribute to understanding the challenges and opportunities of algorithmic management in various organizational contexts and structures. Our findings will add to the body of existing literature, as we study relationships with employee performance and well-being and investigate a potential mediating mechanism that centers on the experience of job characteristics. Additionally, our findings can be used to explore algorithmic management's potential benefits and challenges and develop recommendations for organizations looking to implement algorithmic management systems.

To address our research topic, we choose to rely on a quantitative methodology, based on an online survey, in order to collect our data from a sample of workers exposed to different degrees of algorithmic management in their work. The quantitative research design will help us collect a large number of responses that allows us to have a broad overview of the practice within 'traditional' companies in multiple countries, and explore algorithmic management's future scope.

The remainder of this paper is as follows. We first give an overview of the research on algorithmic management literature and introduce key related variables, while highlighting the importance of workers' well-being, performance, and autonomy, and developing hypotheses related to our research question. In the subsequent section, the data and methodology are presented. Section four describes the empirical results. Finally, the last section discusses recommendations, theoretical and managerial implications alongside limitations.

2. Literature review

2.1 Algorithmic management

Algorithms have been utilized in companies for quite some time now, notably for managerial purposes. The first mention of algorithms in the workplace can be traced back all the way to the 19th century, according to Wood (2021), when Max Weber discussed the "*step-by-step, distributed and nominally objective procedures for selection and sorting that characterized decision-making in modern bureaucracies*" (Fourcade & Healy 2017; p.2). The academic literature defines algorithms as "*computer-programmed procedures that transform input data into a desired output"* (Kellogg et al., 2020, p. 370). They can also indicate a finite sequence of precise instructions for performing a computation or solving a problem (Garey, 1997). According to Leicht-Deobald et al. (2019)

classification, there are three algorithm categories: descriptive algorithms, which can extract information and spot patterns from large datasets. The second category is predictive algorithms, that can predict future developments based on past or real-time data, and thirdly prescriptive algorithms, which recommend courses of action based on predictions and other data (Unruh et Al., 2022). Algorithmic management refers to the use of these software algorithms to automate decision making processes and work alongside human managers in the completion of their daily tasks (Wood, 2021). In that sense, "*algorithmic management is a managerial practice that replaces some of the tasks and processes that workers typically engage with, by using algorithms that are developed by the very same individuals' data on the platform"* (Duggan et al.,2020, p. 119), as opposed to 'traditional management', which solely relies on human-to-human interactions as can be seen in figure 1.

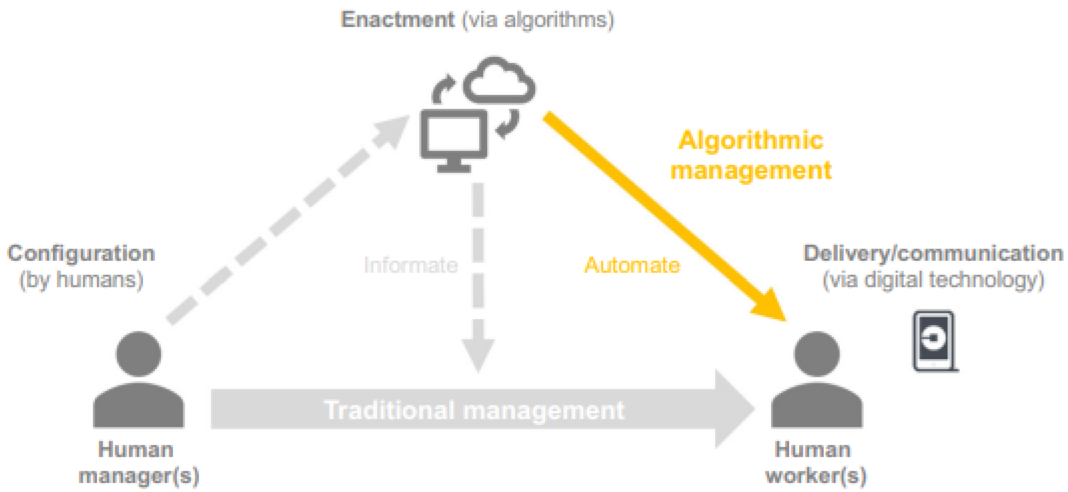

Figure 1. The difference between 'traditional' and algorithmic management (Wiener et al. 2023, p. 487; Cram & Wiener, 2020, p. 74)

The term algorithmic management was first developed by Lee et al. (2015), who defined it as "*technologies that support managerial decision-making and assume managerial functions*" (p. 1603). According to Mateescu and Nguyen's (2019) definition, algorithmic management can be considered "*a diverse set of technological tools and techniques that remotely manage workforces, relying on data collection and surveillance of workers to enable automated or semi-automated decision-making*" (Wood, 2021, p. 1). In the same line, Möhlmann et al. (2021, p.2001), refer to algorithmic management as "*the large-scale collection and use of data on a platform to develop and improve learning algorithms that carry out coordination and control functions traditionally performed by managers*". Parent-Rocheleau & Parker, 2022 identified areas where algorithmic management assists managers in performing several tasks, primarily when managing workers in the gig economy, such as: monitoring which relies on people analytics, goal setting by defining goals and targets, providing automated feedback, scheduling, calculating salaries and bonuses…

The widespread adoption of algorithmic management over the last decades is due to many factors, including the increasing use of data and the focus on data-driven decision-making, data mining, and machine-learning algorithms (Kellogg et al., 2020). Thanks to the availability of high computing power and digital data collection, organizations can gain new insights into their operations and optimize multiple processes and automate a new range of tasks, including human resource tasks such as recruiting, scheduling, measuring productivity, and evaluating performance (Unruh et al., 2022; Veen et al., 2020). Companies operating algorithmic management is prompting the development of new algorithmic occupations and is continuously contributing to the rapid growth of the practice (Zuboff, 2019), while also expanding the scale and the use of its processes and tools. Recent technological advances overtaking workplaces are also affecting the number of workers concerned by algorithms, due to the broadening of automated management decisions (Kinowska & Sienkiewicz 2022).

As the scope of algorithmic management has expanded over the years, the reach of these automated managerial decisions is also expected to grow, both in conventional settings and platform work. Algorithmic management was mainly present and first introduced in the context of gig economy platforms as a 'central' managerial practice. As Lee et al., (2015, p.1603)- who first introduced this concept- mentioned in their research paper, the use of algorithmic management in platform work enabled a "*companies to oversee myriads of workers in an optimized manner at a large scale*". This explains why empirical research has focused more on the platform economy, where algorithmic management is widely used, instead of exploring the use of algorithmic management in traditional working contexts (Parent-Rocheleau et al., 2021; Kinowska & Sienkiewicz, 2022). Algorithmic management has gained popularity and has reached beyond platform organizations, to include conventional employers (Delfanti & Frey, 2021). Many traditional companies started to rely on algorithm-based solutions to improve their operations and processes including, logistics (Lippert et al., 2023), warehouse management (Gent, 2018), and manufacturing (Briône, 2020). However, underlying differences remain between the use of algorithmic management in both contexts; as Lippert et al., (2023) explained, many specific algorithmic management mechanisms used in platform-based work contexts cannot be easily transferred to, and thus do not necessarily translate to traditional work contexts.

When algorithmic management technologies are introduced in traditional workplaces, they interact with their specific organizational structure and hierarchy, which are quite distinct from one work context to another (Unruh et al., 2022). In their research paper, Duggan et al., (2020) explain the major structural differences between algorithmic management in traditional and in platform organizations. In platform businesses, the practice is used to substitute managers, whereas in traditional organizations, algorithmic management is used along organizational hierarchies to complement managers (Jarrahi et al., 2021). In this context, it is unconceivable to have algorithmic management systems operating all by themselves, without the involvement or input of human managers (Wood, 2021). Another difference between platform organizations and traditional organizations is that workers in the former are usually freelancers (which are often considered as 'peripheral' workers), whereas the latter employ to a greater extent 'core' employees who more often hold permanent contracts (Duggan et al., 2020). Additionally, the relationship between workers and their managers in ‘traditional’ companies differs from that of their counterparts within gig economy platforms, where algorithmic control is more present to conceal the absence of human managers. According to Wiener et al., (2023, p. 485), algorithmic control refers to using intelligent algorithms to "*align worker behaviors with organizational objectives*". Algorithmic evaluation of workers, which is among the primary steps identified in the generic control process, alongside direction and discipline (Lippert et al., 2023), was more present in traditional companies (Wood, 2021), compared to gig economy platforms. Kellogg et al. (2020) introduced in their research six forms of algorithmic control (all starting with an "R"), which are called the "6 Rs" framework, that operates algorithmic control in the workplace through six main mechanisms, where employers can use algorithms to direct workers by Restricting and Recommending, evaluate workers by Recording and Rating, and discipline workers by Replacing and Rewarding them.

In sum, this section highlights that the scope of algorithmic management continues to expand, as more 'traditional' companies are adopting the practice. Algorithmic management includes more human resource managerial responsibilities, which were "*previously being the sole responsibility of managers"* (Kinowska & Sienkiewicz, 2022, p.26). These automated decision-making tools primarily involve employee performance monitoring and control, all of which have profound implications for workers and organizations.

2.2 Algorithmic management impacts on organizations and workers

Given its broad reach across multiple work contexts, there is a growing concern among the public and policymakers regarding the current and future impacts of algorithmic management practices (Wood et al., 2019). Algorithmic management has been explored and analyzed in the literature regarding its implications for the future of work (Lippert et al., 2023), benefits, drawbacks, as well as its impact on various organizational and managerial aspects (Wood, 2021; Parent-Rocheleau, et al. 2022). One advantage of algorithmic management is improved decision-making (Lee, 2018), algorithms can process large amounts of data and make predictions and decisions based on that same data. Algorithmic management can also help organizations make more fair and objective decisions, as it reduces the biases that may arise from human decision-making, which makes it easier to create a transparent and equitable work environment (Bernstein & Li, 2017). By relying on algorithms for their decisions, organizations can reduce the influence of personal biases, improving the objectivity of their decisions and increasing their fairness (Araujo et al., 2020). Thanks to their ability to process large amounts of data accurately, algorithms also provide organizations with insights that would otherwise be difficult to obtain. This helps companies make better decisions and improve their overall performance. In this regard, Wu & Shang (2020) found that algorithmic management can help organizations identify and prioritize opportunities more effectively, leading to improved decision-making and better outcomes. Scholars also suggest that data collection systems can lead to more efficient search and retrieval of information and better analyses of decisions that impact organizational performance (Kellogg et al., 2020). Additionally, algorithmic management can provide real-time insights and feedback on performance and productivity (Wiener et al. 2023), enabling managers to make informed decisions and adjust their strategies as needed.

In line with the above-mentioned, algorithmic management can be associated with increased efficiency. Algorithms automate and streamline many routine tasks, freeing time for managers and employees to focus on more meaningful and fulfilling tasks (Cram et al., 2022; Wiener et al., 2023). Furthermore, algorithmic management can help organizations reduce the chances of human error and allocate resources more effectively, ensuring that resources are directed toward the most critical tasks, which can lead to better outcomes for organizations, including efficiency, and reduced errors and inconsistencies (Liu et al., 2015). According to Oosthuizen (2022), algorithmic management can help organizations identify improvement areas, leading to increased accountability and a more data-driven approach to management, thanks to the detailed and accurate data provided. Algorithmic management can also improve transparency and accountability in the workplace, as algorithmic management systems often provide detailed logs of all actions and decisions, which can help reduce the risk of unethical behavior and promote fairness in decision-making processes (Kellogg et al.,2020).

Despite the many benefits of using algorithms for organizations and employees, notably improved efficiency, decision-making, and organizational learning, the decision fairness and accountability of algorithmic processes, and their impact on workers' well-being are still debatable. In this regard, Duggan et al., (2020) emphasize the need for more consideration of the consequences of algorithmic management on employees' collaboration and task execution, and its impact on management practices and on the working environment. Also, the 'invasive' role of algorithms raises ethical issues about transparency and data protection, especially regarding sharing personal employee data that serves as inputs to algorithms (Unruh et al., 2022, Duggan et al.,2020). Previous research on the subject found that the use of algorithms in management can have both positive and negative impacts on employees (see Table 1), with outcomes largely dependent on the specific context and how algorithmic management is implemented, and most importantly, employees' perceptions of algorithmic management which, regardless of its positive outcomes for organizations, can significantly influence the adoption of the practice.

Table 1. Algorithmic management (AM) positive and negative impacts on employees (adapted from Parent-Rocheleau & Parker, 2022)

AM positive impact	AM negative impact	References
Autonomy		Meijerink & Bondarouk (2023); Kinowska & Sienkiewicz (2022)
	Autonomy	Leicht-Deobald et al., (2019); Kellogg et al., (2020); Orlikowski & Scott (2015); Strohmeier (2020)
Feedback		Cram et al., (2022); Wiener et al., (2023), O'Neil, (2016)
role clarity and		Kittur et al., (2013)
task engagement		Toyoda et al., (2020)
well-being		Parker & Grote (2022)
	well-being	Möhlmann & Zalmanson (2017)
decision-making		Araujo et al., (2020); Kellogg et al., (2020); Lee, (2018) ; Wu & Shang (2020); Wiener et al. (2023)
performance		Liu et al., (2015); Cheng & Hackett (2021); Kinowska & Sienkiewicz, (2022)
	performance	Gagné et al, (2022); Stanton & Julian, (2002)
task allocation		Jarrahi et al., (2021); Kittur et al., (2013)

2.3 Algorithmic management in relation to well-being and performance

2.3.1 Employee well-being and performance and their determinants

Many authors have expressed their concern over the integration of employees' well-being aspects into the design of workplaces that implement new technologies (Lee et al, 2018). Well-being is a multidimensional term that implies a sense of balance, fulfillment, and satisfaction across multiple domains (Diener, 2009). *"According to Misselbrook (2014), well-being is the state of each employee where they understand their capabilities, cope with life stresses, work productively, and contribute to their community",* (Kinowska & Sienkiewicz 2022, p. 24).

Previous studies have covered different dimensions of well-being, such as occupational well-being, psychological, physical, and financial well-being. Workers' well-being has been linked to various outcomes such as job satisfaction, employee engagement, reduced absenteeism (Johnson et al., 2018). We chose to focus, in our study, on work-related psychological well-being, which is considered the most important factor of well-being in the work process (Kinowska & Sienkiewicz 2022). Psychological well-being can be defined as "*the combination of feeling good and functioning effectively*" (Huppert, 2009, p. 137). Our choice to focus on psychological well-being in our study is due to positive psychological states being associated with increased levels of work motivation and satisfaction (Snell & Bohlander, 2013; Cascio & Boudreau, 2010; Hackman & Lawler, 1971; Hackman & Oldham, 1975; Moorhead & Griffen, 2008). Conversely, stressful working environments impact negatively employees' mental health (Godin et al., 2005; Melchior et al., 2007), which impacts negatively levels of psychological well-being and leads to poor-quality work performance and higher turnover rates.

In addition to focusing on psychological well-being, our research also sheds light on employees' performance at work, namely job performance since it is considered one of the most important and studied variables in the field of management (Carpini et al 2017). Job performance refers to an employee's ability to perform the tasks required by their job effectively and to achieve the objectives set by the organization (Campbell & Wiernik, 2015). In this regard, performance is typically evaluated based on various criteria, such as task completion, quality of work, productivity, and customer satisfaction, to determine the extent to which an employee meets general organizational performance expectations (López-Cabarcos et al., 2022). The academic literature presents a broad conceptualization of job performance that brings together all the potential behaviors that positively contribute to the achievement of organizational goals (Griffin et al., 2007), which includes task performance (Williams & Anderson, 1991), contextual performance (Borman & Motowidlo, 1997; Organ, 1988), adaptative performance (Berg, et al., 2010), and proactive performance (Parker et al., 2006). Task performance refers to an employee's ability to perform the core job duties that are required in their job description. It is generally defined as the individual's effectiveness in carrying out their job's technical or functional aspects, such as completing assignments, meeting deadlines, and achieving quantitative goals (Borman & Motowidlo, 1997). On the other hand, contextual performance, refers to an employee's ability to perform duties that are not necessarily outlined in their job description but are essential for the functioning and success of the organization as a whole. This includes helping coworkers, improving work processes, and showing a positive attitude (Organ, 1988).

Employee performance and well-being have been widely studied in the literature and are recognized as critical and crucial factors for organizational success since they are linked to numerous organizational outcomes, such as productivity, profitability, increased competitiveness, innovation, and overall organizational success (Bakker & Demerouti, 2017; Bowling et al., 2010; Alfes et al., 2012; Nielsen et al., 2017). In the same way, the relationship between employee well-being and work performance has been a topic of interest for scholars for many years, as it was demonstrated by various studies that when employees feel a great sense of well-being, their work performance also improves (Wright & Cropanzano, (2004); Harter et al., 2003).

In the work context, many factors contribute to psychological well-being and performance, including personal work-related factors, such as job satisfaction, work-life balance, as well as work-environmental factors, like having a supportive organizational culture (Nurisman & Sampurna, 2020; Wilson et al., 2004). Additionally, different leadership styles were shown to influence well-being and performance (Akdere & Egan, 2020). For instance, transformational leadership, which involves inspiring and guiding employees to achieve their full potential, is a determinant of both employee job performance (Akdere & Egan, 2020), and well-being (Bass & Riggio, 2006). Influential leaders can foster a positive organizational culture that prioritizes employee well-being and provides opportunities for professional development, recognition, and feedback (Bass & Riggio, 2006). Conversely, autocratic leadership, which involves dictating to employees without considering their opinions and needs, is associated with higher levels of stress, burnout, and absenteeism (Bass & Riggio, 2006).

In addition to leadership and management styles, studies have shown that work design affects job performance and well-being (Humphrey et al., 2007; Parker et al., 2017). The job characteristics model (Hackman & Oldham, 1976) and job demand-control model (Karasek, 1979) are prominent frameworks for understanding work design and how it is related to employees' outcomes. These models suggest that positive job features or resources, such as task significance, autonomy, and feedback, together with the variety of skills and the identity of the task, can generate meaningfulness at work, which has been found to enhance overall job performance among workers (Grant, 2008; Humphrey et al., 2007). On the opposite side, job demands stated in these models have been identified as role stressors, such high work pressure, role ambiguity and role conflict, which can play a major role as a source of stress when not managed accordingly, and affect employees' well-being and performance negatively (Vandenberghe et al., 2011).

2.3.2 The relationship between algorithmic management, employee performance, and psychological well-being

Upon examining current studies on algorithmic management, there are two main contrasting perspectives that arise in regards to the impacts of algorithmic management. The integration of technology and automation in the workplace can impact employee well-being and performance in both positive and negative ways (Parker and Grote, 2022; Kinowska & Sienkiewicz 2022). While some research highlights the perceived advantages of employing algorithmic management methods, such as improved decision making and task allocation, which all lead to enhanced overall performance (Kellogg et al. 2020), other studies focus on the negative aspects, often referred to as the 'dark side' of algorithmic management, which are responsible for increased workload, stress, and burnout (Möhlmann et al., 2021; Ropponen et al., 2019; Benlian et al., 2022).

Concerning employee performance, research has shown that algorithmic management can significantly improve performance by streamlining processes and making them more efficient, leading to greater efficiency and objective decision-making for companies in scheduling, task allocation, and performance evaluation (Jarrahi et al., 2021). Moreover, algorithmic management can benefit workers in terms of developing their skills, thanks to the feedback provided by algorithms, and can grant them flexible working hours and schedules, due to the optimized task and resource allocation that the algorithms allow for (Benlian et al., 2022), all of which contributes to increasing employees' productivity, performance and job satisfaction (Kittur et al., 2013). In the same vein, algorithmic management can help create a more supportive work environment through automated coaching and real-time monitoring systems (O'Neil, 2016). These systems can help employees improve their skills and performance, leading to greater organizational accomplishments. Additionally, the data gathered through algorithms can be used to give personalized feedback and data-based development support (Cram et al., 2022; Wiener et al., 2023), that helps employees learn and improve, which then leads to more positive outcomes, including high levels of performance (Wells et al., 2007). Furthermore, algorithmic management can enhance other aspects of employee performance, such as accuracy and speed in completing tasks, due to the objective nature of algorithmic decision-making (Cheng & Hackett, 2021, Kinowska & Sienkiewicz 2022).

Algorithmic management can also increase efficiency and productivity by automating specific tasks, reducing the workload on employees, and enabling workers to focus on tasks that require more creativity and critical thinking (Morgan et al, 2020). In this regard, a study by Lee et al., (2019) found that using a real-time algorithmic scheduling system led to significant improvements in employee task completion time, task quality, and task allocation. Similarly, Wood (2021) found that the algorithmic management of employees' schedules can improve the predictability and stability of work schedules, which in turn can lead to better task performance and increased productivity. Moreover, integrating algorithms facilitates novel modes of workplace interactions that can be positively perceived by employees, as they receive automated input and feedback by algorithms (Wiener et al., 2023), guiding them towards high performance and achievements without enforcing any changes on them (Möhlmann et al., 2021). Thanks to their feedback, such tools may enrich and equip workers with extra skills, making them resilient in the face of challenges, and presenting them with better career perspectives (Cram et al., 2022).

However, algorithmic management may also hinder other aspects of employees' job performance, especially for tasks requiring creativity and innovation, such tasks call for human judgment and subjective decision-making. Other studies have found mixed or negative relationships between algorithmic management and core task performance. For example, a study by Barlage et al., (2019) found that algorithmic management was associated with higher performance for routine tasks, but lower performance for non-routine tasks. Additionally, a study by Stanton & Julian (2002), found that employee electronic monitoring and productivity data collection led to decreased task performance due to decreased job satisfaction and motivation. For their part, Berg et al., (2018) found that the algorithmic management of call center workers led to decreased task performance, due to high levels of stress and anxiety caused by algorithmic monitoring and feedback. Despite negative findings, most research thus far suggests positive effects on employee performance. In line, we hypothesize that:

Hypothesis 1.b: Algorithmic management is positively related to employees' task performance.

Regarding psychological well-being, the use of algorithms can lead to increased stress and burnout, as employees may feel pressure to constantly perform at a high level to meet the algorithmic systems' expectations. According to the literature, algorithmic management can also lead to feelings of isolation and a lack of autonomy, which impacts negatively employee mental health. A study by Brougham & Haar (2018) found that employees who perceived their work to be controlled by algorithms reported higher levels of job strain, and lower levels of job satisfaction and organizational commitment. Similarly, a study conducted by Duggan et al., (2022) found that using algorithmic management in gig economy work contexts, led to increased feelings of job insecurity and decreased levels of job satisfaction, which were associated with lower psychological well-being among workers. Additionally, using algorithms can also create feelings of disempowerment and job insecurity among employees, who may feel that their work is being micromanaged and undervalued.

According to Benlian et al., (2022, p. 833), "*algorithmic control is often perceived as overly controlling and intrusive and can lead to various adverse effects. The predominantly coercive control style resulting from algorithmic management is likely to cause emotional suffering and hinder well-being (Pregenzer et al., 2021)"*. Moreover, recent studies found that algorithmic management can lead to decreased job satisfaction and can also increase workload and stress among employees, particularly in situations where employees are required to constantly adapt to new algorithms and decision-making processes (Umer et al., 2019), which can lead to decreased motivation and job satisfaction, due to reduced autonomy and control among employees (Parker & Grote, 2022).

However, algorithmic management can enable more flexible work arrangements, such as remote work, which was found to increase job satisfaction and work-life balance (Sullivan, 2012). This can contribute to higher occupational and psychological well-being and allow employees to better balance their work and personal responsibilities. Algorithmic management can also help organizations understand their employees better and provide them with the resources and support they need to perform at their best. A study by Lee et al. (2015) found that algorithmic management can help organizations create more personalized work environments, leading to improved employee engagement and higher levels of job satisfaction.

On the other hand, research also shows that algorithms can lead to a lack of personal connection between managers and employees, which might impact job satisfaction and meaningfulness and motivation at work negatively (Roos & Eeden, 2008; Leicht-Deobald et al., 2019). Algorithmic opaqueness which refers to information asymmetries over how automated decisions are taken, is one of the major drawbacks of algorithmic management (Rosenblat & Stark 2016; Shapiro, 2018). This results in workplace situations where workers subjected to instructions from algorithms, can be prompted to feel uncertain and question the legitimacy of the given instructions and decisions taken, due to algorithmic opaqueness (Gal et al. 2020; Jarrahi et al. 2021).

Nevertheless, algorithmic management can help reduce the potential for bias and favoritism in decision-making, by creating a fairer and more equitable workplace for all employees (Davenport & Kirby, 2015), since humans may be prone to gender and racial biases (Benlian et al., 2022). This, in turn, can lead to greater trust in the organization and increased job satisfaction, leading to higher occupational and psychological well-being, since workers' well-being is associated with their perception of their supervisors' and companies' fairness. Accordingly, the more employees perceive management decisions to be ethical and fair, the more impact it has on their well-being (Sparr & Sonnentag, 2008).

Despite also positive findings, most research thus far suggests negative effects on employee well-being. In line, we hypothesize that:

Hypothesis 1.a: Algorithmic management is negatively related to employees' psychological well-being.

2.3.3 Complex explanatory mechanisms

Due to the nature of interactions between machine and humans, the impact of algorithmic management is deemed ambiguous (Faraj et al. 2018), and not easy to explain nor to predict (Benlian et al., 2022). This complexity is especially present when addressing the impact of algorithmic management on employees' well-being and performance, which can vary depending on various factors and the specifies of the implementation of algorithmic management. The design, implementation, and use of work decision algorithms, and thereby their effects on workers, depend on many factors, such as the organizational structure and culture, legal and institutional frameworks, and on-going trends in the industry and the economy (Unruh et Al., 2022), adding to that how algorithms are perceived by employees compared to humans (Lee et al, 2021).

In an attempt to explore perceptions of algorithmic management, Lee et al. (2018) measured the perceived fairness, trust, and emotional responses to decisions in an algorithmic management work context. They found that algorithmic and human-made decisions were perceived as equally fair and trustworthy and evoked similar emotions. However, human managers' fairness and trustworthiness were attributed to the manager's authority, whereas algorithms' fairness and trustworthiness were attributed to their perceived efficiency and objectivity. Their study also highlights that algorithms' perceived lack of intuition and subjective judgment capabilities contributed to lower fairness and trustworthiness judgments, which is similar to Waytz & Norton's (2014) findings, suggesting that people think that computers and robots have less emotional capability compared to humans. Algorithmic management was also found to restrict interpersonal relationships and presents a less empathetic approach to human resource management (Duggan et al, 2020), due to the lack of understanding of human emotions and navigating social nuances.

Furthermore, algorithmic management raises concerns about power imbalances (Fourcade & Healy 2017), and fairness (Duggan et al, 2020). There are also concerns over algorithms perpetuating existing biases and discrimination, leading to unfair decisions and outcomes, in addition to the lack of transparency and accountability in algorithmic decision-making, and the potential for algorithms to be manipulated or misused to serve personal interests. Moreover, algorithms can be biased in the sense where they can be based on flawed data, leading to unfair evaluations and decisions about employees' performance. This results in many concerns about the potential negative effects of algorithmic management on workplace well-being. The increased use of algorithms to manage and evaluate employee performance can create a more stressful work environment, as employees are under constant pressure to perform at a high level. The use of algorithms in performance management and surveillance can also lead to increased pressure and stress on employees, who might feel like their every move is being monitored and subject to being evaluated (Jarrahi et al., 2021), especially for workers in the gig economy.

Empirical studies also highlight that digitalization and work flexibility can intensify work by extending work activities and given tasks beyond the set working location and hours (Green ,2004; Wood et al, 2019). Longer working hours and higher work intensity, have all been found to be associated with remote working and algorithmic management, which were made possible by new digital technologies (Felstead & Henseke, 2017, Wood et al, 2019, Unruh et al., 2022). In addition to that, recommendations and feedback generated by algorithms can lead to work intensification (Mendonça et al, 2023), thereby increasing stress and pressure on employees. Work intensification is set to lower well-being and job satisfaction, just like the routinization and reduction of meaningful tasks occasioned by algorithms (Felstead et al., 2019). In this context, the implementation of algorithmic management might generate some form of resistance within employees (Wood, 2021), who might go against the changes set by the practice and perceive them negatively, which can further exacerbate negative outcomes for both employees and organizations. Despite having the potential to enhance certain aspects of employee performance and organization efficiency, algorithmic management also carries risks for employee well-being and performance.

2.3.4 Exploring one pathway: the mediating role of job autonomy

Research in the work design field continues to grab the attention of many scholars and practitioners, especially with the emergence of new technologies that support management practices and alter traditional work arrangements. One major theory to consider when examining algorithmic management within the context of job design research is the Job Characteristics Model (Hackman and Oldham, 1974). The Job Characteristics Model (JCM) has dominated the field of work design and has had an overall significant impact on research (Morgeson & Humphrey 2008), as the literature supports and presents many expansions of the model (Spector & Jex, 1991).

In their model, Hackman and Oldham (1974) suggest that outcomes, including job attitudes and behaviors (Spector & Jex, 1991), are affected by five core objective job characteristics: autonomy, skill variety, task identity, task significance, and feedback. In addition to these five characteristics, substantial work has been exploring new job characteristics (Parker et al. 2006). Since some attributes of work have become more important in recent times (algorithms, telework, digitalization…), additional variables have been suggested by several researchers (e.g., Oldham et al, 1996; Parker et al, 2001; Roberts et al, 1981), such as physical ease, work scheduling, work conditions. Similarly, Morgeson and Humphrey (2008) identified 21 distinct job characteristics categorized within four categories: task motivation, knowledge motivation, social, and contextual work characteristics. These characteristics have specific implications for human resource managers, as the model outlines the circumstances in which employees will perform in a positive and productive manner. By enhancing the five intrinsic job characteristics, worker motivation, satisfaction, and performance issues can be reduced, since the model enables managers to achieve an optimal fit between workers and their jobs (Boonzaier et al., 2001), through a better understanding of the critical factors that contribute to employees' motivation and enhance task performance, leading to higher levels of engagement and better overall performance.

In addition to performance, job characteristics also predict job satisfaction, stress, and depression (Parker et al., 2006), as there is considerable evidence that the said characteristics have effects on employees' mental health and psychological states, including major depression, burnout, and substance use (Iacovides et al., 2003; Williams & Cooper, 1998), which in turn influence personal and work outcomes (Snell & Bohlander, 2013; Cascio & Boudreau, 2010; Moorhead & Griffen, 2008).

Even though the five core job characteristics are all associated with positive outcomes, they were proven to have different impacts on job outcomes (Saavedra & Kwun, 2000), with specific outcomes associated only or primarily with some of these job characteristics rather than with others (Fried & Ferris 1987). Of the numerous work characteristics at the task level, autonomy is considered one of the most critical work characteristics (Parker & Grote, 2022), and remains both the most studied and the most influential among the five job characteristics (Morgeson & Humphrey, 2008), hence why we choose to focus our study on job autonomy as a predictor of job performance, and well-being.

On the other hand, Karasek (1979) emphasizes, in his Job Demand-Control Model, the role of autonomy in identifying how job characteristics (job control and job demands) impact employees' psychological well-being (Theorell et al., 1990). Karasek's job demands-control model is one of the most widely studied models of occupational stress (Kain & Jex, 2010; Ganster & Murphy, 2000; Shultz et al., 2010). It stipulates that having high job demands matched with low decision-making authority (job control), can lead to negative health outcomes like stress and burnout. Therefore, when employees perceive autonomy as being supportive of their work, and increasing their control over work, it enhances their job satisfaction, organizational commitment, and psychological well-being (Mijakoski et al., 2015).

"*According to Hackman and Oldham's definition of the characteristics, autonomy represents the extent to which the job allows the employee substantial freedom, independence, and discretion in scheduling the work and determining the procedures to be used in carrying it out"* (Boonzaier et al., 2001, p.12). In other words, autonomy refers to the degree to which an employee controls how they perform their work. In the literature, autonomy is conceptualized as a job resource, since it correlates negatively with emotional strains and positively with health (Adelmann, 1987; Spector et al., 1988; Spector & Jex, 1991). In line with Karasek's (1979) model, job demands which corresponds to elements that play an important role in increasing workers' stress (heavy workload, job complexity and ambiguity, time pressure…), can be balanced out by increasing job control. The Job Demand-Control model indicates that individuals that have a high level of autonomy and control over their work can manage high job demands (Theorell et al., 1990). In other words, when employees have high levels of job demands, they tend to experience high levels of work stress, which undermines their psychological well-being (Van der Doef & Maes 1999). As such, having high control with regard to one's job, autonomy in decision-making, and control over the way tasks are being performed, will help decrease the stress level caused by high job demands, which translates into lower work stress levels experienced by workers, and consequently, better well-being (Shultz et al., 2010; Gameiro et al., 2020).

In addition to its impact on occupational stress and employees' well-being, job autonomy is also set to influence performance positively (Parker and Grote, 2022). Results of a study by Humphrey et al., (2007) have shown that autonomy has been linked to both objective and subjective performance ratings, and to having a beneficial impact on key human resource indicators such as turnover and productivity (Humphrey et al., 2007; Torraco, 2005). Studies have also found that autonomy is a strong predictor of employees' organizational commitment, as it gives meaning to work (Martela & Riekki, 2018), and can intrinsically motivate employees (Parker & Ohly, 2008), making them feel less pressured and constrained (Kinowska & Sienkiewicz 2022), which promotes their psychological and physical health and decreases risks of absenteeism and turnover for companies (Spector et al., 1988).

According to Cooper and Barling (2008), providing employees with greater autonomy for their tasks may result in quicker problem-solving capabilities, as well as an improved ability to anticipate and resolve issues using their skills (Wall et al., 1992; Miller & Monge, 1986), resulting in higher performance levels (Hackman & Oldham, 1976) that yield positive outcomes such as higher employee satisfaction, well- being and motivation. Given earlier reasoning, we suggest the following 2 hypotheses:

Hypothesis 2.a: Job autonomy is positively related to employees' psychological well-being.
Hypothesis 2.b: Job autonomy is positively related to employees' job performance.

2.3.5 Algorithmic management's dual relationship with autonomy

Research has extensively examined the advantages of promoting worker autonomy in human-to-human interactions (Toyoda et al., 2020). However, with the increasing use of human resource management algorithms to enhance or automate decision-making in the workplace, scholars have turned their attention toward investigating the effects of algorithmic management on employees' autonomy (Meijerink & Bondarouk 2023). Algorithmic management systems can significantly influence job design aspects outlined by the job characteristics model, as they modify work processes and limit individual control over them (Kinowska & Sienkiewicz 2022). Analyzing how the use of technological advancements that rely on innovative ways for data generation, behavioral prediction, and organizing work, impact key elements such as job autonomy, is crucial as algorithmic management is expected to increase existing challenges for autonomy at work (Unruh et al.,2022).

Current research on software algorithms in the workplace has predominantly conceptualized algorithmic management as a method for managers to regulate employees, especially in the gig economy. Algorithmic management raises concerns regarding workplace control and autonomy, since it may intensify existing means of managers' supervision by allowing for widespread surveillance of workers via algorithms (Unruh et al., 2022). In the same vein, Kellogg et al., (2020) argue that algorithmic technologies constitute a 'novel' control mechanism. They argue that algorithmic control is more ambiguous and impersonal than previous control mechanisms, which can exacerbate feelings of injustice for employees (Kinowska & Sienkiewicz 2022). Moreover, many control-enhancing activities associated with algorithmic management come at the expense of job autonomy, limiting workers' ability to exercise authority over various work aspects (Meijerink & Bondarouk, 2023). Given that monitoring devices are frequently used to evaluate worker performance (Evans & Kitchin, 2018) based on collected data, individuals tend to prioritize monitored tasks while overlooking non-monitored ones (Tomczak et al., 2018). This results in employees working solely to meet objectives based on monitored tasks, at the expense of other potentially valuable aspects of their job (Schafheitle et al., 2020). Ultimately, this undermines worker's autonomy regarding their work methods, as demonstrated in previous studies in algorithmically-monitored contexts (Leclercq-Vandelannoitte, 2017).

Moreover, scholars argue that algorithmic management reduces autonomy and value for workers, by instilling discipline and leaving no room for workers to explore personal and professional growth (Kellogg et al., 2020), and creating information asymmetries (Rosenblat & Stark 2016; Shapiro, 2018), which occur when algorithms remain opaque or if workers lack control over data collection processes. On the other hand, the constant monitoring of various aspects such as employees' attitudes, behaviors, performance levels, and emotional states through tracking digital devices like browsers or cellphone apps has been seen as pervasive surveillance (Lee et al. 2015; Möhlmann & Zalmanson 2017), aimed at controlling personnel which in addition to reducing autonomy (Murray and Rostis 2007; Sewell and Taskin 2015), may result in emotional stress (Mateescu & Nguyen, 2019b; Parent-Rocheleau & Parker, 2022). Besides, work decision algorithms reduce the possibility for workers to exercise discretion over their work (Unruh et al.,2022), and limit workers' autonomy through excessive controls instilled by algorithms, and ultimately by managers (Meijerink & Bondarouk 2023).

However, despite limiting job autonomy, software algorithms are constantly learning and improving as they heavily rely on machine learning, especially in the management field, (Orlikowski & Scott, 2015; Strohmeier, 2020), with the aim to provide employees with resources that can help enhance their work flexibility and allow them to create more value at work (Meijerink & Bondarouk, 2023). "*While conventional companies rely on power hierarchies to increase workers' productivity, algorithmic management is frequently presented in a manner that conceals traditional power structures*" (Toyoda et al.,2020, p.1405). Despite the prevalent use of algorithmic management systems and practices, these systems do not monitor or control all employees' activities (Gal et al., 2020; Wood et al., 2019). This suggests that autonomy might still be attainable when using algorithmic management (Kinowska & Sienkiewicz 2022). In this sense, Meijerink & Bondarouk (2023) argue that managing human resource with the support of algorithms is more complex than reinforcing negative outcomes for workers only. Instead, algorithmic management also has the potential to provide value and promote autonomy for employees.

In that sense, many scholars have argued that algorithmic management enables decentralized decision-making, and hence greater job autonomy, in a large part because of the wider distribution of information, the hierarchical structure and the high flexible environment of companies that implement algorithmic management (Parker & Grote, 2022). Moreover, new technology enabled business models allow greater self-direction for teams, which increases autonomy in work in addition to promoting flexible work arrangements (virtual/remote and other forms of flexible work). Ultimately, technology-enabled work practices are believed to prevent employers from stripping away autonomy from workers subject to algorithmic management (Kellogg et al., 2020; Shapiro, 2018; Veen et al., 2020). This further implies that utilizing software algorithms can both constrain and enable workers' autonomy. Hence, the structural features of algorithms serve as both facilitators and inhibitors for workers' autonomy, mainly due to the reliance of algorithmic management on data that fails to fully capture the experiences and reality of employees (Newlands, 2021).

In sum, algorithmic management can have a dual effect on workers, algorithms simultaneously can foster autonomy and restrain it, as there is strong evidence suggesting that job autonomy diminishes with the increasing dependence on algorithms (Leicht-Deobald et al., 2019; Meijerink & Bondarouk 2023). As a monitoring tool, algorithmic management assist managers in their tasks including controlling employees' performance, which is contrary to arguments supporting that algorithmic management fosters workers' autonomy (Carlson et al, 2017; Duggan et Al, 2020). Accordingly, we propose the following hypothesis:

Hypothesis 3: Algorithmic management is negatively related to job autonomy.

Based on the arguments discussed above, we propose that autonomy may play a mediating role in the relationship between algorithmic management, performance, and well-being. The importance to investigate this link resides in the fact that relatively little empirical research has focused on the mediating role of autonomy, when examining the relationship between algorithmic management and work outcomes, which is more formally expressed by the hypothesis below; Figure 2 depicts our conceptual model.

Hypothesis 4: Autonomy mediates the relationship between algorithmic management and performance and well-being.

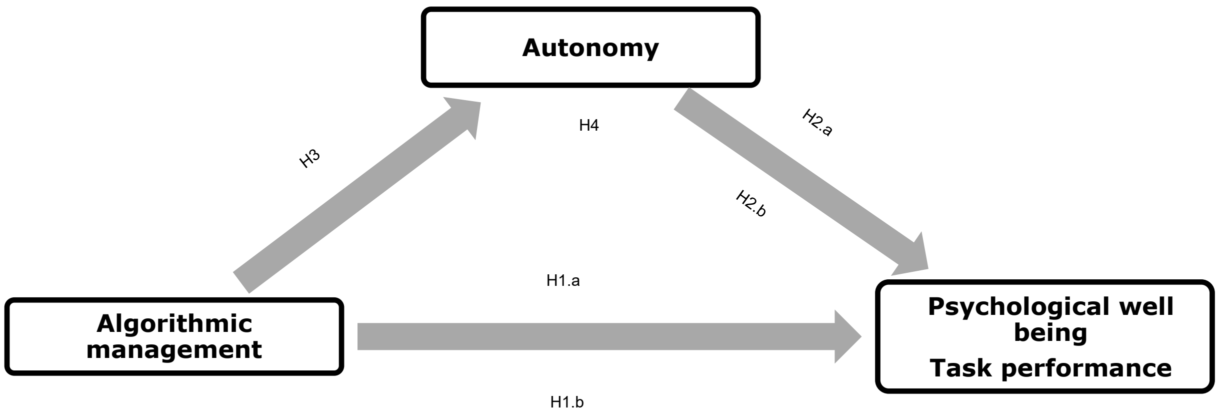

Figure 2. Conceptual framework of the study

3. Methods

3.1 Study design

In order to test our hypotheses, we conducted a survey by administering an online questionnaire. The rationale behind this choice is based on the efficacy and ease of disseminating a survey in data collection and sharing it through various channels, as well as facilitating access to potential respondents. To that end, an online questionnaire was developed using Qualtrics.
One advantage of relying on an online questionnaire lies in its ability to efficiently engage with large numbers of individuals within limited time constraints and collect large amounts of data from respondents. Other benefits include cost-effectiveness and easiness to administer, thanks to software available for creating questionnaires. Online surveys also provide high flexibility since participants can pause and continue responding at their convenience (Ball, 2019; Regmi et al., 2016), as they might choose to complete a questionnaire in several intervals. In addition to facilitating the process of data collection, digital questionnaires reduce issues experienced while transferring datasets for analysis, making it less prone to errors. However, a few limitations can be linked to this method due to the need for more capacity to ask follow-up questions based on responses received. Despite respondents' data remaining anonymous, survey bias can occur due to participants potentially answering questions more positively than their actual feelings towards a topic, which can undermine the objectivity of their responses (Ball, 2019).

3.2. Sample and data collection

For our sampling method, participants were chosen based on their professional background and relevance to the study's topic, to ensure a degree of representativeness in the sample. As such, we could access a large and a diverse population through our network on LinkedIn without being limited to specific regions or companies, which is one of the advantages of online questionnaires. Accordingly, we set some inclusion criteria, such as being at least 18 years old, and made sure to target workers with different levels of expertise and experience in various fields, representing different companies, to get a better overview of the practice of algorithmic management and increase the overall validity of our results and the representativeness of our sample.

To participate in this survey, respondents were asked to answer a series of questions about how they experience algorithmic management in their workplace and how they experience their functioning. A link to the questionnaire was posted on LinkedIn and shared through an anonymous link. When following the link, information about the aim of the study and the questionnaire were presented to the participants. Participants' decisions to partake in the study were made personally and voluntarily; they were not requested to represent or promote their companies. Participation was also completely anonymous, as it was not possible nor intended to identify individual participants' personal details (names, addresses…).

The survey contains five sections; Part I requests demographic details about respondents. Part II contains six questions on employees' exposure to algorithmic management. Part III asks about respondents' job performance, whereas Part IV contains psychological well-being questions. Finally, Part V assesses job autonomy among employees. Expect from Part I, all parts utilized 7-point Likert scales. On average, the questionnaire takes 15 to 20 minutes to complete. Participants who did not complete the questionnaire were excluded from the analysis.

The data analyzed in this study was gathered through an online survey, which was distributed between March and June of 2023. Out of 155 responses, 30 were dropped due to respondents not finishing the questionnaire. Thanks to the forced response option included in every question, no missing values within the survey were possible, which made up for a high response rate (80%). A total of 125 complete responses were attained, resulting in a fairly large sample of respondents. The sample characteristics are displayed in Table 2. Our sample consisted of 125 individuals, with an age range of 20 to 47 years. The mean age was found to be 29.74 years. The most common age group in the sample was 27, with 14 respondents, representing 11.2% of the total sample. The second most common age groups were 25 and 29, each with 14 respondents as well, accounting for 10.4% and 11.2% of the sample, respectively. Accordingly, the variable "age" has been recoded into three age groups. The first group (19 to 28 years old) accounted for 50.4% of the total sample. The group 29 to 38 years old included 50 respondents, making up 40.0% of the total sample. While the last age category (39 to 48 years old) included 11 respondents, accounting for 8.8% of the total sample.

Out of the 125 respondents, 43 identified as male, representing 34.4% of the sample. On the other hand, 53 respondents identified as female, accounting for 42.4% of the sample. Two respondents identified as "other," making up 1.6% of the sample. Additionally, 27 respondents preferred not to disclose their gender, representing 21.6% of the sample. These findings suggest a relatively balanced representation of gender in the sample, with a slightly higher proportion of female respondents. The sample included respondents from various countries, providing a diverse range of perspectives. The country of residence with the highest number of respondents recorded was Belgium, with 50 respondents, accounting for 40% of the sample. France was the second most common country, with 15 respondents, representing 12% of the sample. Morocco followed closely behind, with 19 respondents, making up 15.2% of the sample. Other countries included the "UK, "Germany" and "India", "Ukraine" and "UAE", amongst others.

The most prevalent educational attainment among the respondents was a "master's degree", with 58 individuals, accounting for 46.4% of the sample. Followed closely behind by the category of "professional or academic college/university degree", with 52 respondents, representing 41.6% of the sample. A smaller proportion of respondents reported having obtained a "doctoral degree", with 8 individuals, making up 6.4% of the sample. Additionally, 7 respondents reported having completed only primary or secondary school, constituting 5.6% of the sample. These findings suggest a relatively high level of educational attainment among the respondents, with a majority holding at least a master's degree or higher. The most common role reported among the respondents was "Professional staff (e.g., expert role)," with 43 individuals, accounting for 34.4% of the sample. The next most prevalent roles were "Team Leader/Line manager" with 23 respondents (18.4%), "Manager" with 16 respondents (12.8%), and "Operational personnel" with 21 respondents (16.8%). Additionally, 18 respondents identified themselves as "Administrative or support personnel," making up 14.4% of the sample. A smaller proportion of respondents held the role of "Senior Manager" with 4 individuals (3.2%).

Regarding employees' years of experience in their current jobs, a significant proportion of the sample was reported to have between 3 and 5 years of experience in their current job. The most common years of experience reported among the respondents was 5 years, with 27 individuals, accounting for 21.6% of the sample. Following closely behind were the categories of 4 years of experience with 22 respondents (17.6%) and 3 years of experience with 21 respondents (16.8%). The overall years of experience recorded was ranging from 1 to 17 years. The most common department reported among the respondents was "Sales/Marketing," with 30 individuals, accounting for 24% of the sample. The next most prevalent departments were "Production" with 21 respondents (16.8%), "Administration/Professional Services" with 20 respondents (16%), and "Others (please specify)" with 18 respondents (14.4%). Additionally, 12 respondents were distributed among the following departments: "Accounting/Finance," "Human Resource Management," and "Logistics," all of which were representing 9.6% of the sample.

Table 2. Characteristics of the respondents

	Minimum	Maximum	Mean	Std. Deviation
Age (years)	20	47	29.74	5.389
Job experience (years)	1	17	4.19	2.561

	Frequency	%
Age group		
19 to 28 years old	63	50.8
29 to 38 years old	50	40.3
39 to 48 years old	12	8.9
Total	125	100.0
Gender		
Male	43	34.4
Female	53	42.4
Other	2	1.6
Prefer not to say	27	21.6
Total	125	100.0
Education level		
Primary or secondary school	7	5.6
Professional or academic college/university degree	52	41.6
Master degree	58	46.4
Doctoral degree	8	6.4
Total	125	100.0
Job position		
Senior Manager	4	3.2
Manager	16	12.8
Team Leader/Line manager	23	18.4
Professional staff (eg. expert role)	43	34.4
Operational personnel	21	16.8
Administrative or support personnel	18	14.4
Total	125	100.0
Department		
Accounting / Finance	12	9.6
Production	21	16.8
Sales / Marketing	30	24.0
Human Resource Management	12	9.6
Logistics	12	9.6
Administration / Professional Services	20	16.0
Others (please specify)	18	14.4
Total	125	100.0

Notes: N= 125

3.3. Measurements

3.3.1. Algorithmic management

There is no well-established approach in the work design literature for measuring algorithmic management, and no validated method exists that can be used to measure workers' perceptions of algorithmic management (Jabagi et al., 2021), especially for workers in 'traditional' work contexts. Scholars have investigated, mainly through qualitative methods, the implications of algorithmic management on gig workers (Vignola et al., 2023). To address this gap, this study proposes a measure of algorithmic management based on workers' perception of specific criteria, drawing upon previous studies (Lee, 2018; Holubová et al., 2022). Our measure consists of 6 items, covering workers' exposure to algorithmic tools such as monitoring, feedback, schedule, support, and surveillance. Employees assess each of these items on a 7-point Likert scale ranging from 'To a Very Small Extent' to 'To a Very Large Extent.' Our survey questions to measure their exposure to algorithmic management included questions like: "To what extent do you feel that your work tasks are determined by algorithms or automated systems?", "To what extent do you interact with algorithms and technology-enabled surveillance tools in your daily work?", "To what extent have you noticed an increase in the use of computerized tools or software for employee monitoring and evaluation in your workplace?". The Cronbach's alpha coefficient obtained for this scale was .859.

3.3.2. In-role performance

In-role performance was measured based on Williams and Anderson's (1991) scale, who developed the original in-role performance scale based on the definition of in-role performance as the job outcomes that result from the requirements of the job descriptions. Thus, our questions were adapted from the in-role performance scale, which uses seven items to measure employees' in-role performance. We chose to exclude three reverse-scored scale items from our survey, for more reliability and clarity and to avoid respondents' confusion. Accordingly, respondents were asked about the extent to which they agree with the following items; "I adequately complete assigned duties"; "I fulfill responsibilities specified in the job description"; "I perform tasks that are expected of me"; "I meet formal performance requirements of the job". The respondents were asked to rank these statements on a 7-point Likert scale, from 1 'Strongly disagree' to 7 'Strongly agree'. The Cronbach's alpha for the in-role performance scale was .861

3.3.3. Psychological well-being

Our scale for psychological well-being at work was based on the psychological well-being scale developed by Ryff (1989), which was adapted to the work context. The scale has been confirmed and adapted by various studies in different contexts, and throughout different samples (Diaz et al., 2006; van Dierendonck et al., 2008). The scale proposes six major categories to measure psychological well-being, namely, self-acceptance, positive relationships, autonomy, environmental mastery, purpose in life, and personal growth. Each dimension corresponds to one item, amounting in total to six items. For example, "In general, I feel confident and positive about my job"; "I trust my opinions, even if they are contrary to those of others"; "I have been able to build a work environment and a work-life balance that is much to my liking"... Similar to in-role performance, these items were rated on a 7-point Likert scale, from 1 'Strongly disagree' to 7 'Strongly agree'. The reliability of the psychological well-being scale was recorded at .871.

3.3.4. Job autonomy

Job autonomy was measured using the Job Diagnostic Survey (JDS; Hackman & Oldham, 1975). Respondents were asked to use a scale ranging from 1 (very inaccurate) to 7 (very accurate) to assess the accuracy of statements, such as: "The job gives me a considerable opportunity for independence and freedom in how I do the work"; "The job gives me a chance to use my personal initiative and judgment in carrying out the work". The latter is a revised item based on Idaszak and Drasgow's (1987) revision of the JDS. Instead of the reverse-scored item "The job denies me any chance to use my personal initiative or judgment in carrying out the work", the item was positively worded, as several studies suggested that reverse-scored items were a major source of inconsistencies within the job diagnostic survey (Harvey et al., 1985; Fried & Ferris 1987). Cronbach's alpha for this scale was .824.

3.3.5. Control Variables

Control variables retained in our study included age and educational background, as they were demonstrated to influence well-being (Cram et al., 2022). We also identified as control variables occupation, hierarchy levels, years of experience, and gender. According to the literature, these control variables are prominent in determining employees' productivity, job satisfaction, and overall organizational performance (Casucci et al., 2020). For example, years of experience can impact employees' productivity and job satisfaction, as individuals with more experience may have greater knowledge and skills to perform their job effectively, leading to higher productivity and job satisfaction. Other variables such as occupation and hierarchy levels can impact an employee's level of responsibility, workload, autonomy, and job demands (Cheung, 2022; Nuryanti et al., 2019). As for gender, including it as a control variable helps to account for any potential gender bias in our results, since gender has been found to impact employees' performance and well-being in prior research (Geldenhuys & Henn, 2017).

Controlling for these variables can help to isolate the effects of algorithmic management on employee outcomes and also helps determine whether algorithmic management has a unique impact on performance and well-being beyond these factors, in addition to ensuring the demographic diversity and the representativeness of our sample. These variables are transformed into dummy variables. Our choice for the reference category was motivated by the highest number of responses for each variable. For gender, respondents were given 4 options "Male", "Female", "Other", "Prefer not to say" (Female was used as a reference category). Educational level has 6 items, as indicated in Table 2 (Primary or secondary school, Professional or academic college/university degree, Master degree, Doctoral degree). Master's degree was used as the reference category. As for role and department, we have proposed respectively 7 and 9 items to measure these variables (see Table 2). "Professional staff" and "Sales and Marketing" were set as the reference category respectively, to control for the control variables: role and department. Age and job experience were considered continuous variables and were both measured in years.

3.4 Data analysis

First, we performed a descriptive analysis of the demographic data and computed scale reliabilities (Cronbach Alpha to examine the reliability of all the constructs and items used in the survey). Nunnally and Bernstein (1994) demonstrated that a Cronbach's alpha value higher than 0.70 is deemed viable and is considered as a standard value when measuring scales' reliability. We calculated the Cronbach's alpha values for all of our scales, which were all estimated at around 0.80, indicating a high level of reliability of the scales used in our study. The overall high Cronbach's alpha coefficients suggest that all scales demonstrated good internal consistency. In other words, the items within the scales are highly correlated with each other and measure the same underlying constructs effectively.

We also run a correlation analysis to examine the relationship between all of our study variables. Then, we ran multiple regression analyses to test the proposed hypotheses to determine the relationships between algorithmic management, psychological well-being, and in-role performance and the mediating effect of job autonomy on this relationship. In testing the mediation relationship, we adopted the four-step method designed by Baron and Kenny (1986), while controlling for the control variables in different models. Firstly, in Model 1 and 2, we checked if the independent variable (algorithmic management) was associated with the dependent variables (performance and well-being respectively). Next, we checked if the independent variable (algorithmic management) was related to the mediator variable, autonomy (Model 3). In the third step of the regression analysis, we checked for the potential effect of the mediator variable (autonomy) and the dependent variables (performance and well-being). Finally, while adding the independent variable (algorithmic management) to the model, we checked if the independent variable together with the mediator (autonomy) were related to dependent variables (performance and well-being). The last two steps were performed simultaneously in Model 4 and 5.

Finally, we undertook a Sobel test (Sobel 1982) to determine the mediating effect's significance further. We have opted for the interactive calculator tool for mediation tests developed by Preacher & Leonardelli (2001) to test the significance of the indirect effect of algorithmic management on both task performance and psychological well-being, via the mediator job autonomy.

4. Results

4.1 Descriptive Results

All data collected from the online survey was measured using IBM SPSS Statistics 28. Multiple correlations among major variables were calculated (see Table 3), to give an indication of the associations between algorithmic management as an independent variable, job autonomy as a mediator, and the outcome variables psychological well-being and task performance. Age exhibited a significant positive correlation with job experience ($r = .589$, $p < .01$), which means that job experience increases with age. Except for age, gender did not show significant correlations with any of the variables. Job experience on the other hand showed a negative correlation with role performance ($r = -.206$, $p < .05$), job autonomy ($r = -.294$, $p < .01$), and psychological well-being ($r = -.305$, $p < .01$), suggesting an inverse relationship between high levels of employees' experience on one hand, and role performance, job autonomy and psychological well-being on the other. Educational background showed a positive correlation with job autonomy ($r = .301$, $p < .01$) and psychological well-being ($r = .256$, $p < .01$), suggesting that individuals with a higher education experience more job autonomy and more well-being at work.

As expected, a significant positive correlation was observed between algorithmic management and the study variables of our mediation model, for role performance ($r = .222$, $p < .05$), job autonomy ($r = .527$, $p < .01$) and psychological well-being ($r = .574$, $p < .01$), indicating that individuals who reported higher levels of algorithmic management also experienced higher levels of psychological well-being, job performance, and job autonomy in their work. Job autonomy displayed a significant positive correlation with psychological well-being ($r = .750$, $p < .01$). As for role performance, there was no significant correlation between the variable and job autonomy ($r = .143$, $p = .129$).

Overall, table 3 provides valuable insights into the relationships between algorithmic management, role performance, job autonomy, and psychological well-being. Algorithmic management is positively correlated with psychological well-being and job autonomy. The latter is also positively correlated with psychological well-being.

Table 3. Means, standard deviations and correlations of study variables.

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10
1.Age	29.74	5.389	1									
2.Gender			.239**	1								
3.Educational background			-.168	-.030	1							
4. Role			-.293**	-.025	-.410**	1						
5. Job experience	4.19	2.56	.589**	.229*	-.320**	.073	1					
6. Department			-.080	.180	-.211*	.282**	.117	1				
7.Algorithmic Management	4.46	1.06	-.013	-.049	.175	-.145	-.042	-.177	1			
8. Role performance	5.53	.96	-.086	-.144	.062	-.156	-.206*	-.041	.222*	1		
9. Job autonomy	4.33	1.38	-.391**	-.038	.301**	-.142	-.294**	-.139	.527**	.143	1	
10. Psychological well being	4.96	1.07	-.309**	-.046	.256**	-.208*	-.305**	-.203*	.574**	.432**	.750**	1

Notes: N=125

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

4.2 Hypotheses testing

Table 4 reports the results of the regression models. Model 1 predicting job performance with the control variables showed a coefficient of determination (adjusted R-square) of .235, indicating that approximately 23.5% of the variance in role performance can be explained by the predictors included in the model, which is relatively weak. The standardized coefficient (Beta) for algorithmic management of .261 at a level of confidence ($p=0.11$) showed no association between algorithm management and role performance, which contradicts hypothesis 1b (H1.b) stating that algorithmic management is positively related to employees' task performance.

Model 2 showed the results of the regression analysis when the variable psychological well-being was included, while controlling for the control variables. The model accounted for 43% of the variance in psychological well-being (adjusted $R^2 = .430$). The regression coefficient for algorithmic management was .505 ($p < 0.001$), suggesting that the relationship between algorithmic management and psychological well-being is statistically significant. Therefore, the regression model predicting psychological well-being with the control variables and algorithmic management was statistically significant. Algorithmic management is positively associated with employees' psychological well-being, which contradicts hypothesis 1a (H1.a), as we expected a negative association.

In order to test hypothesis 3 which predicts a negative association between job autonomy and algorithmic management, job autonomy was entered into Model 3, while controlling for control variables. The regression model was statistically significant, accounting for 41.3% of the variance in job autonomy (adjusted $R^2 = .413$). Contrary to Hypothesis 3, algorithmic management was positively associated with job autonomy ($\beta = .494$, $p < 0.001$). The association between algorithmic management and job autonomy was statistically significant, warranting its inclusion in the model.

Model 4 and Model 5, respectively predicted the relationship between job performance and algorithmic management on one hand, and psychological well-being and algorithmic management on the other, with job autonomy added in both models, while controlling for the control variables. According to the regression analyses (Model 4), the results show that the model accounted for a small amount of variance in role performance (adjusted $R^2= .068$). The change statistics suggest that adding job autonomy as a mediator, did not significantly improve the prediction of role performance. The standardized coefficient (Beta) for job autonomy was -.028 ($p = .69$), which implies that job autonomy is not related to role performance. Consequently, hypothesis 2b (H2.b) predicting that job autonomy is positively related to employees' job performance is not supported, as no association was found between the two variables.

On the other hand, Model 5 revealed a strong positive association between job autonomy and psychological well-being. Job autonomy significantly predicts psychological well-being, explaining a substantial proportion of its variance (61.8%). The Adjusted R Square value of 0.618 suggests that the model's explanatory power remains high even after adjusting for the number of predictors. Controlling for other variables, the standardized coefficient (Beta) for job autonomy is .580 ($p < 0.01$), which corroborates hypothesis 2a (H2.a), as we established a positive relation between job autonomy and psychological well-being in our hypothesis.

Table 4. Regression analysis of study variables

Variable	Model 1 job performance		Model 2 psychological well being		Model 3 job autonomy		Model 4 job performance		Model 5 psychological well being	
	Std. Error	Beta	Std. Error	Beta	Std. Error	Beta	Std. Error	Beta	Std. Error	Beta
(Constant)	.795		.697		.928		.911		.647	
Algorithmic management	.092	.261	.080	.505***	.107	.494***	.110	.269	.078	.218***
Gender (ref. Female)										
Male	.207	-.122	.181	-.124	.244	-.012	.214	-.127	.152	-.135
Other	.697	-.102	.611	.032	.808	-.013	.708	-.099	.502	.037
Prefer not to say	.265	-.235	.233	-.063	.309	.078	.272	-.232	.193	-.122
Education (ref. Master's degree)										
Primary or secondary school	.473	.098	.414	.105	.550	-.126	.486	.105	.345	.183
Professional or academic college/university degree	.200	.190	.175	.040	.236	-.051	.207	.209	.147	.074
Doctoral degree	.409	.108	.359	.083	.475	-.021	.416	.113	.295	.100
Role (ref. Professional staff)										
Senior Manager	.708	-.049	.620	.107	.821	.115	.725	-.049	.514	.037
Manager	.326	.169	.285	.210*	.379	.180	.339	.172	.240	.098
Team Leader/Line manager	.273	.012	.240	.154	.318	-.015	.279	.006	.198	.155
Operational personnel	.274	-.116	.240	-.035	.326	-.002	.286	-.128	.203	-.052
Administrative/support personnel	.287	-.057	.251	-.016	.334	-.049	.293	-.062	.208	.002
Department (ref. Sales&Marketing)										
Accounting/ Finance	.339	.173	.298	.023	.394	.009	.346	.170	.245	.011
Production	.273	.031	.239	-.013	.317	.017	.278	.024	.197	-.026
Human Resource Management	.332	.069	.291	-.006	.385	-.069	.339	.063	.240	.029

Logistics	.332	.072	.291	.032	.398	.046	.350	.057	.248	-.013
Administration/Professional Services	.302	.123	.265	-.042	.360	.036	.316	.089	.224	-.063
Others	.351	.146	.308	-.137	.413	-.042	.362	.130	.257	-.128
Age	.025	.048	.022	-.354**	.029	-.434*	.027	.029	.019	-.103
Experience (...in years)	.047	-.230	.041	-.060	.054	.029	.048	-.230	.034	-.074
Job autonomy							.089	-.028	.063	.580**
R^2	.235		.526			.514		.237		.687
Adjusted R^2	.081		.430			.413		.068		.618
F	1.524		5.484			5.083		1.406		9.944
P value	<.001		<.001			<.001		<.001		<.001

Notes: N=125

***. Regression is significant at the 0.001 level (2-tailed).

**. Regression is significant at the 0.01 level (2-tailed).

*. Regression is significant at the 0.05 level (2-tailed)

4.3 Mediation model

Based on the findings above, it does not appear that job autonomy mediates the relationship between algorithmic management and employees' role performance. The non-significant coefficient and the overall lack of statistical significance between job autonomy and role performance suggest that job autonomy does not play a mediating role in this relationship. Initially, algorithmic management had no association with role performance (Path C1= .261; p-value=0.11). In line with these findings, the effect of algorithmic management on role performance via the mediator job autonomy was not significant (Path C'1= -.269; p-value=0.28). Thus, our findings suggest that job autonomy does not mediate the relationship between algorithm management and role performance.

Turning to the relationship between algorithmic management and psychological well-being with the mediation effect of job autonomy, model 5 shows a strong relationship between job autonomy and psychological well-being. Algorithmic management has a significant positive association (Path C2= .505; p-value < 0.001) with employees' well-being. On the other hand, the impact of algorithmic management on psychological well-being through job autonomy is also significant (Path C'2=.218; (p < 0.001). We can conclude at his level, that job autonomy mediates the relationship between algorithmic management and employees' psychological well-being.

In summary, the results indicate that algorithmic management is associated to both job autonomy and psychological well-being. Furthermore, job autonomy, may mediate the relationship between algorithm management and psychological well-being, suggesting that job autonomy plays a role in translating the effects of algorithm management into improved psychological well-being. However, no association was found between algorithmic management and job performance. There is no significant indirect effect of algorithmic management on role performance, through job autonomy. Based on the above, hypothesis 4 stating that autonomy mediates the relationship between algorithmic management and performance and well-being is not supported.

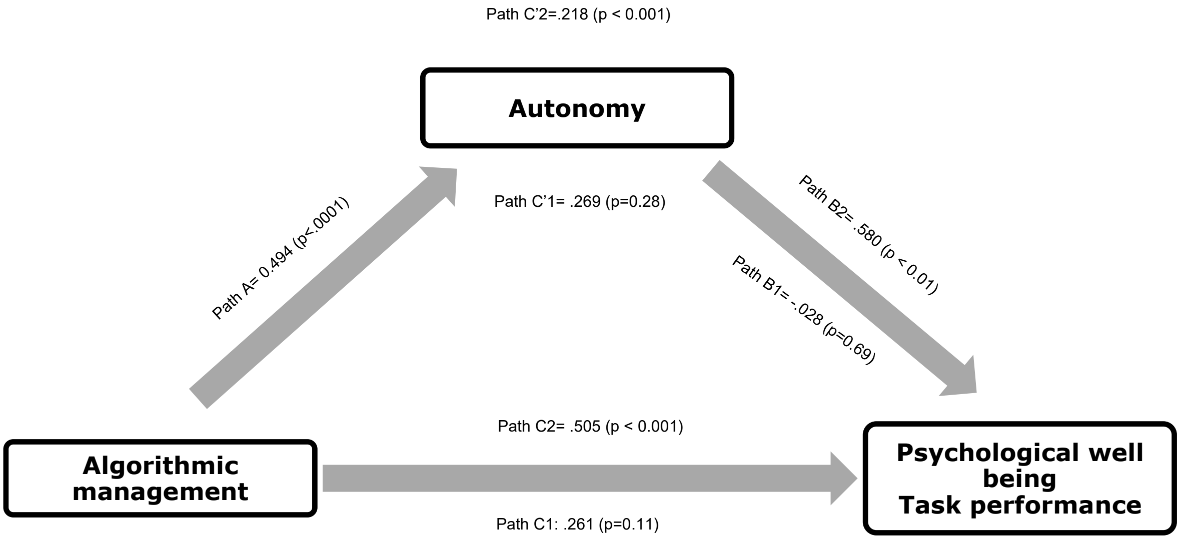

Figure 3. Mediation model

To assess the strength and direction of the mediation effect of our model, a Sobel test was undertaken to further test the significance of the indirect effect of algorithmic management by calculating the regression coefficients and the corresponding standard errors for path a and path b for both dependent variables. The following represents the Sobel test equation:

z-value = $a*b/\text{SQRT}(b^2*s_a^2 + a^2*s_b^2)$

s_a and $s_b > 0$[1].

The test statistic value for psychological well-being is (z= 4.13; p < .001) which confirms the significance of the indirect effect of algorithmic management on psychological well-being via job autonomy. For job performance, the Sobel test indicates a z-value of -0.314 (p=0.37), supporting our earlier interpretation that job autonomy does not mediate the relationship between algorithmic management and task performance. The Sobel test shows no evidence to support the presence of a significant indirect effect.

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[1] Path *a*: corresponds to the unstandardized coefficient of the regression analysis involving the independent variable (algorithmic management) predicting the mediator (job autonomy).

Path b: is the unstandardized coefficient provided from the regression analysis involving the independent variable together with the mediator predicting the dependent variable.

s_a and s_b are respectively the standard error of Path a and Path b.

5. Discussion

Our primary objective in this study was to examine the extent to which algorithmic management can impact employees task performance and well-being, through the mediating effect of job autonomy. To achieve this goal, we conducted an online survey and collected responses from 125 employees within different working contexts, belonging to different backgrounds and countries. By establishing the impact of algorithmic management in traditional working contexts, our work adds on to the existing literature on algorithmic management, from workers' perspective, and sheds light on how employees perceive their autonomy, well-being and job performance when they're exposed to algorithms in different aspects of their work life. We found that algorithmic management was related to psychological well-being but not to job performance. Specifically, our results showed that the mediating effect of job autonomy is significant when determining the relationship between algorithmic management and psychological well-being, which confirms some of our hypotheses. In line with these findings, job autonomy is set to mediate the relationship between algorithmic management and employees' psychological well-being within our sample.

Prior research on algorithmic management has hypothesized the impact of algorithmic management on workers' well-being and performance both in positive and negative ways, which attests of the challenging nature of implementing algorithms in management practices. Studies have shown that algorithmic management has the potential to improve efficiency and optimize resource and task allocation (Kittur et al., 2013), which increases productivity and job satisfaction, hence increasing employees' performance. Conversely, previous research exploring the negative aspects of algorithmic monitoring showed that software and algorithms used to monitor employees and track their productivity, lead to negative and counterproductive attitudes and behaviors in workers (Gagné et al, 2022). Despite its benefits in terms of efficiency, consistency, or decision-making processes, our study revealed no association between algorithmic management and performance (H1.b).

Unlike performance, most research thus far suggested negative effects on employees' well-being. On this basis, hypothesis 1.a was formulated, the negative impact established between the two variables was not validated by our study, suggesting that algorithmic management is positively related to employee psychological well-being. As such, our findings are similar to those of Kinowska & Sienkiewicz (2022), where algorithmic management practices do not necessarily influence employees' working conditions negatively, including their wellbeing and their workplace relations.

Drawing on the job characteristics model (Hackman & Oldham, 1974) and the job demand control model of Karasek (1979), we hypothesized that the work characteristic job autonomy can positively impact both employees' well-being and performance (H2.a and H2.b respectively), especially since this job resource has the most impact on organizations, since it allows them to support their employees and generate high performance levels. Our results highlighted that only autonomy had a positive impact on well-being but not on performance, attesting of the validity of only hypothesis 2.a.

The mediation model introduced in this study was empirically analyzed, to investigate the impact of algorithmic management on both psychological well-being and performance. The mediating impact of job autonomy was also assessed. As such, our study supports the argument that algorithmic management significantly impacts job autonomy, which also significantly influences psychological well-being. Despite the literature being quite mitigated on algorithmic management effect on autonomy, as it can both foster autonomy (Meijerink & Bondarouk, 2023) and restrain it (Leicht-Deobald et al., 2019). Our study revealed that algorithmic management has the potential to promote autonomy for employees, and could provide employees with more flexibility and independence in their work, contrary to our hypothesis stating that job autonomy diminishes with the increasing dependence on algorithms (H3). Based on our literature review and our earlier hypotheses, we've established that autonomy plays a mediating role in the relationship between algorithmic management, performance and well-being (H4). According to our results, autonomy only mediates the relationship between algorithmic management and psychological well-being, which does not support hypothesis 4.

Our results highlighted that the adoption of automated and autonomous practices in organizational management is positively associated with employees' well-being. Parker and Grote (2022) stressed the importance of workers' well-being when dealing with algorithmic management practices. Our research supports this statement, since algorithmic management can enable employees to adapt work to their needs and preferences, and enhance their well-being (e.g., having the power to make decisions on how to do work, choosing their own schedule...). However, algorithmic management which is considered as an automated decision-making vehicle, might be related to a lack of autonomy, where employees feel under constant scrutiny, surveillance and control of their movements (Möhlmann & Zalmanson, 2017), which often threatens employees' well-being. As for information asymmetry, which is considered a point of concern that might undermine workers' autonomy when algorithmic management systems are implemented in the workplace (Lee et al. 2015), studies revealed that the asymmetric relationship between workers' autonomy and algorithmic management is less predominant in 'traditional' working contexts (Wood, 2021), compared to the gig economy and platform businesses, where algorithms tend to reduce human involvement and limit interactions between managers and employees. The inherent difference between the two working contexts results in a distinct exposure to algorithmic management between gig workers and their counterparts in 'traditional' companies. The negative relationship established in our hypothesis (H1.a), which was not confirmed in our study, was based on the literature on algorithmic management in the gig economy, as we noted a lack of research on this subject in 'traditional' or conventional companies.

Another argument mentioned in the literature, is the ethical issues related to algorithmic monitoring which decreases algorithmic fairness (Lee, 2018; Li et al., 2023). If algorithms are not transparent or are biased, or if workers cannot control what data is collected and used, prerequisites for workers' autonomy cannot be achieved (Unruh et al., 2022). According to Charlwood & Guenole (2022), this argument is not valid since algorithms learn from their mistakes depending on previous data inputs, which allows for continuous learning curves throughout the course of time. In this case, automated decisions based on algorithms are more objective and bias free (Gal et al. 2020), and do not restrict workers' autonomy, unlike humans who are subject to errors and biases (Benlian et al., 2022; Davenport & Kirby, 2015). In other words, algorithmic management does not drift apart from fair and ethical management, which is highly viewed by employees and contributes to higher occupational and psychological well-being (Kellogg et al.,2020; Sparr & Sonnentag, 2008).

Besides, algorithmic management can also be used in ways that can promote feelings of autonomy. Numerous studies have shown that autonomy can be enhanced when employees are allowed input into the design of the monitoring system, and have some control over it (Spitzmüller & Stanton, 2006; Stanton & Julian, 2002). Algorithmic monitoring systems have been deemed less stressful when they are used in conjunction with increased job autonomy (Charlwood & Guenole, 2022). According to Toyoda et al., (2020, p.1406) when "*algorithmic management was framed as a support tool and used autonomy-supportive language, and work was provided a meaningful rationale, task engagement significantly increased*". Conversely, when algorithmic management was presented as a monitoring tool, it increased the 'working-for-data' phenomenon (Gal et al., 2020; Schafheitle et al., 2020), where workers only focus their efforts on the aspects of work that are being monitored and quantified, at the expense of other tasks that might be more valued or meaningful to them (Tomczak et al., 2018).

On the other hand, the use of algorithmic management did not have a positive or negative impact on employee performance based on our findings, as no association was found between algorithmic management and job performance. The absence of association between algorithmic management and employee performance may be attributed to several plausible factors rooted in the complexity of organizational dynamics. Apart from the particularity of the working context in which algorithmic management is implemented, the effectiveness of algorithmic management may also depend on the nature of tasks within organizations. As research shows, the type of algorithm-enabled activity and complexity have different implications for worker outcomes (Langer & Landers, 2021), depending on the context in which algorithmic management is implemented. With this in mind, the restraining or enabling features of algorithmic management differ across working contexts ('traditional' companies vs gig economy platforms), states and professions (full-time vs part-time employees). As previous studies found that algorithmic management can optimize processes and improve tasks performance, especially tasks involving routine and repetitive work (Brynjolfsson & McAfee, 2014), the reduction of meaningful tasks occasioned by algorithms might lead to employees feeling less challenged, productive and engaged in their streamlined routine tasks, resulting in less performance and job satisfaction. As for non-routine tasks, algorithms prove to be less impactful in creative or non-routine tasks (Meijerink & Bondarouk 2023), which require more innovation and human judgment. The different effects in terms of performance between routine and non-routine tasks might result in an overall null effect when aggregated across diverse job functions, which might explain the non-existing association between algorithmic management and task performance found in our study.

5.1 Theoretical and managerial implications

This study has several theoretical implications. Our most significant contribution is the development of a conceptual framework for algorithmic management for a better interpretation of the practice within the management field. Our study extends the research on algorithmic management beyond the gig work and digital platforms' context which was largely addressed by the literature, and explores the use of algorithmic management within 'traditional' companies. Additionally, we address algorithmic management in traditional working contexts from the perspective of workers, whereas previous studies have mainly focused on managers and employers' incentives (Li et al., 2023). Our study explores algorithmic management with employees' perception of well-being and performance and inspires future research to pay more attention to workers' perception of algorithmic management. The combination of two work outcomes provides a large perspective for understanding the diverse impacts of algorithmic management and sheds light on its duality in restraining and promoting different work outcomes (Meijerink & Bondarouk, 2023). In that sense, we also contribute to the job autonomy literature in relation to algorithmic management practices. Finally, our findings add to our understanding of the determinants of well-being and performance in algorithmic management work settings and provide valuable insights for future research on algorithmic management and its impacts on various work outcomes.

As for managerial implications, our study highlights the importance of including employees' incentives and understanding their exposure to algorithmic management practices, knowing that employees' motives generally lead to better work outcomes (Gagné et al, 2022). As algorithmic management continues to face many challenges, it's important for companies to share with employees' details about how their algorithms work, including for automated decisions, performance monitoring and feedback, and empower their workers by involving them directly in their companies' algorithmic management practices and policies. In this same line, the human element should be at the center of any decision regarding algorithmic management, especially since algorithmic management practices might alter workplace relations and impact directly workers (Möhlmann & Zalmanson, 2017). Human resources remain important in the sense where there is still a need of human interventions even in algorithmic management systems, as humans interact and will continue to work alongside algorithms. In that sense, managers should regularly review the work of algorithmic management systems and adjust outcomes that may harm employees' well-being or hinder their performance. Therefore, they should also identify challenges and hindrance stressors embedded in algorithmic management and consider their effects on employees' growth, development and well-being. To maintain and promote algorithmic management practices, organizations should try their best to mitigate the negative effects of algorithmic management, which requires introducing more challenging elements into their algorithmic management systems for employees' growth and development and eliminate hindrances affecting work engagement, motivation and job satisfaction at work as much as possible. Managers can also conduct regular checkups with their employees and conduct surveys on their employees' perceptions and attitudes towards algorithmic management to have a better understanding of their needs, and expectations from algorithmic management (Kinowska, & Sienkiewicz, 2022), with the perspective of turning algorithmic management's adverse effects into opportunities.

5.2 Conclusion, limitations and future research

Our study focuses on algorithmic management and is considered one amongst the few in the management field to discuss this topic from the perspective of workers in traditional working contexts. Drawing on the existing literature, we conceptualized three key concepts that might be related to algorithmic management practices, in order to have a better understanding of how these variables interact with our independent variable. We collected responses from our sample characterized by workers operating in various fields and in different countries. Based on the job characteristics model (Hackman & Oldham, 1974) and the job demand-control model of Karasek (1979), we conceptualized an empirical model to explore how algorithmic management characteristics affected employees' well-being and performance, and assessed the mediating effect of job autonomy. The relationship between algorithmic management and these variables, namely job autonomy, well-being and performance of employees on one hand and algorithmic management on the other, was empirically analyzed.

Our results showed that algorithmic management is positively associated to both psychological well-being and job autonomy. Meanwhile, job autonomy is positively related to the well-being of employees. Furthermore, job autonomy mediates the relationship between algorithmic management and workers' well-being, but no statistical evidence was found to support the mediating effect of job autonomy between algorithmic management and employees' task performance. Our analysis sheds light on issues related to the implementation of algorithmic management systems as well as the perception of the practice. Overall, this study contributes to the research on algorithmic management in traditional work settings, and provides deeper insights into its impacts on workers' well-being and performance, by revealing one mediating mechanism. In addition to contributing to the existing literature, our findings offer useful support for managers and companies when working with their newly implemented algorithmic management systems or trying to improve their already existing ones.

Our study has several limitations. Our model was based on state of the art of the actual knowledge and mainly on the previous work related to algorithmic management in the gig economy context. Future research can focus more on workers' attitudes towards algorithmic management in traditional working contexts and in various industries, especially since the practice is constantly growing, with new companies and platforms using algorithms and adopting the practice on a daily basis (Möhlmann & Zalmanson; 2017). Further work outcomes and related variables could also be included in our model. For instance, future studies may investigate other moderators and mediators related to algorithmic management that might impact employees' psychological well-being. It is also important to address other algorithmic management functions and additional components of the practice that might have an effect on the work design and might be important in the future (Parent-Rocheleau & Parker, 2022). In this regard, future studies could incorporate other job characteristics from the job characteristics model (Hackman & Oldham, 1974) into their research frameworks to provide a comprehensive understanding of the impact of algorithmic management on employees and on different work outcomes. In the absence of a clear association between algorithmic management with task performance, future studies might also explore other mechanisms that might be related to algorithmic management, such as workers' motivation, organizational support, task engagement, and feedback and training, and job satisfaction.

Another limitation of our study is that we performed a multiple linear regression analysis to analyze the relationship between algorithmic management and our study constructs. While task performance and algorithmic management were positively correlated, our regression analysis results showed that algorithmic management was not associated to task performance. In other words, the correlation between these two variables did not translate into statistical significance in our multiple regression analysis. This might be because the relationship between our independent variable (algorithmic management) and dependent variable (task performance) is non-linear. Accordingly, we see a need in checking for the linearity of the relationship between these two variables in our research model, and exploring the non-linear relationship by conducting other types of regression analyses.

Age is also an important factor to consider in our study. With an age range of 20 to 47 years, and a mean age of 29.74 years, millennials represent most of our respondents, which limits the representativeness of our sample. Other studies should explore employees' perception of algorithmic management across various age groups and categories to gain a better comprehension and a broader understanding of the practice, since millennials interact more with new technologies and can be more welcoming towards algorithms compared to older generations. By ensuring that all employees' age groups are represented, future studies can also explore how the perception of algorithmic management can vary significantly across different age groups.

Future research could also focus on drawing a comparative analysis between algorithmic management practices in traditional working contexts and in digital businesses, as well as examine the difference between algorithmic and non-algorithmic management and explore how activities managed by algorithms and decisions made by human managers interact with each other in the same working environment. This could also involve investigating different types of algorithms, and additional contextual factors. Another line of inquiry is to examine how employees influence the implementation of algorithmic managements practices. This is especially relevant since human resource activities in highly digitalized workplaces continue to be implemented by human managers, and employees are likely to continue to operate alongside algorithms (Newlands, 2021; Shapiro, 2018).

We focused on how employees perceive their performance, autonomy and well-being and their experience of algorithmic management. In some cases, it might be the case that respondents in our sample have exaggerated or embellished their performance, assessments of autonomy and well-being, since we relied on self-report survey design to collect data from employees. To avoid self-report bias, we recommend future research on algorithmic management to include all stakeholders' perspectives, and design survey tools that consider both employees and employers perspectives, in order to get a complete picture. Additionally, there is no well-established approach in the work design literature for measuring algorithmic management, which calls for developing reliable survey tools to measure how employees perceive algorithmic management and to which degree they're exposed to the algorithmic management practices (Kinowska, & Sienkiewicz, 2022).

Provided that algorithms are embedded with rules and resources, we can expect them to reflect the institutional context in which they are applied. While some countries and organizations are stricter on implementing rules regarding the collection of their employees' personal data (e.g. GDPR rules), others might leave more room for corporations to share data on their employees. Which brings us to our next point, that algorithmic management might be experienced differently from one work context to the other and from one employer to the other. Hence, labeling algorithmic management broadly as good or bad is oversimplified, as it may be experienced by employees and organizations positively or negatively (Li et al., 2023), depending on the context in which it is implemented. Since algorithms have interpretive flexibility, we agree with Meijerink & Bondarouk (2023) on the fact that the autonomy and value coming from algorithmic management might differ across workers.

While interest in digital workplaces, automated systems and algorithms use within organizations is continuously growing, both positive and negative effects on employees must be considered. Algorithms rely on data mining techniques and predictive analysis to analyze current employees' performance and predict future performances (Cheng & Hackett, 2021). They also enable human resource managers to scan a large number of resumes in a limited time frame, predict job satisfaction and employee turnover, schedule employee shifts, and monitor worker performance (Li et al., 2023). As a result, many organizations implement algorithmic management to scale up their processes and operations, including those related to human resource management, while expecting in return some positive financial incentives due to the advantages offered by algorithms notably in terms efficiency, time saving and cost-effectiveness. Which leads us to the following questions: Does algorithmic management benefit workers and employers equally? Does it lead to a high return on investment for organizations that chose implement and invest in such systems?

References

Adelmann, P. K. (1987). Occupational complexity, control, and personal income: Their relation to psychological well-being in men and women. Journal of Applied Psychology, 72(4), 529.

Akdere, M., & Egan, T. (2020). Transformational leadership and human resource development: Linking employee learning, job satisfaction, and organizational performance. Human Resource Development Quarterly, 31(4), 393-421.

Alfes, K., Shantz, A., & Truss, C. (2012). The link between perceived HRM practices, performance and well-being: The moderating effect of trust in the employer. Human Resource Management Journal, 22(4), 409-427.

Ali, S. A. M., Said, N. A., Abd Kader, S. F., Ab Latif, D. S., & Munap, R. (2014). Hackman and Oldham's job characteristics model to job satisfaction. Procedia-Social and Behavioral Sciences, 129, 46-52.

Araujo, T., Helberger, N., Kruikemeier, S., & De Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. AI & society, 35, 611-623.

Baiocco, S., Fernández-Macías, E., Rani, U., & Pesole, A. (2022). The algorithmic management of work and its implications in different contexts (No. 2022/02). JRC Working Papers Series on Labour, Education, and Technology.

Bakker, A. B., & Demerouti, E. (2017). Job demands–resources theory: Taking stock and looking forward. Journal of occupational health psychology, 22(3), 273.

Ball, H. L. (2019). Conducting online surveys. Journal of human lactation, 35(3), 413-417.

Ball, K. (2021). Electronic monitoring and surveillance in the workplace. European Commission Joint Research Centre.

Barlage, M., van den Born, A., & van Witteloostuijn, A. (2019). The needs of freelancers and the characteristics of ‘gigs’: Creating beneficial relations between freelancers and their hiring organizations. Emerald Open Research, 1, 8.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. Journal of personality and social psychology, 51(6), 1173.

Bass, B. M., & Riggio, R. E. (2006). Transformational leadership.

Benlian, A., Wiener, M., Cram, W.A., et al. Algorithmic Management. Bus Inf Syst Eng (2022). https://doi.org/10.1007/s12599-022-00764-w

Benzell, S. G., Kotlikoff, L. J., LaGarda, G., & Sachs, J. D. (2015). Robots are us: Some economics of human replacement (No. w20941). National Bureau of Economic Research.

Berg, J. M., Wrzesniewski, A., & Dutton, J. E. (2010). Perceiving and responding to challenges in job crafting at different ranks: When proactivity requires adaptivity. Journal of Organizational Behavior, 31, 158 –186.

Berg, J., Furrer, M., Harmon, E., Rani, U., & Silberman, M. S. (2018). Digital labour platforms and the future of work. Towards decent work in the online world. Rapport de l'OIT.

Bernstein, E. S., & Li, S. (2017). Seeing where you stand: From performance feedback to performance transparency. In Academy of Management Proceedings (Vol. 2017, No. 1, p. 14752). Briarcliff Manor, NY 10510: Academy of Management.

Bessen, J. (2015). Toil and technology: Innovative technology is displacing workers to new jobs rather than replacing them entirely. Finance & Development, 52(001), 16.

Boonzaier, B., Ficker, B., & Rust, B. (2001). A review of research on the job characteristics model and the attendant job diagnostic survey. South African journal of business management, 32(1), 11-34.

Borman, W. C., & Motowidlo, S. J. (1993). Expanding the criterion domain to include elements of contextual performance. In N. Schmitt & W. C. Borman (Eds.), Personnel selection in organizations (pp. 71-98). San Francisco: Jossey-Bass.

Borman, W. C., & Motowidlo, S. J. (1997). Task performance and contextual performance: The meaning for personnel selection research. Human performance, 10(2), 99-109.

Borman, W. C., & Motowidlo, S. J. (2014). Task performance and contextual performance: The meaning for personnel selection research. In Organizational Citizenship Behavior and Contextual Performance (pp. 99-109). Psychology Press.

Bowling, N. A., Eschleman, K. J., & Wang, Q. (2010). A meta-analytic examination of the relationship between job satisfaction and subjective well-being. Journal of Occupational and Organizational Psychology, 83(4), 915-934.

Briône, P. (2020). My boss the algorithm: an ethical look at algorithms in the workplace. Involvement & Participation Association, March, 13.

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. Journal of Management & Organization, 24(2), 239-257.

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company.

Campbell, J. P., & Wiernik, B. M. (2015). The modeling and assessment of work performance. Annu. Rev. Organ. Psychol. Organ. Behav., 2(1), 47-74.

Carlson, J. R., Carlson, D. S., Zivnuska, S., Harris, R. B., & Harris, K. J. (2017). Applying the job demands resources model to understand technology as a predictor of turnover intentions. Computers in Human Behavior, 77, 317-325.

Carpini, J. A., Parker, S. K., & Griffin, M. A. (2017). A look back and a leap forward: A review and synthesis of the individual work performance literature. Academy of Management Annals, 11(2), 825-885.

Cascio, W., & Boudreau, J. (2010). Investing in people: Financial impact of human resource initiatives. Ft Press.

Casucci, T., Locke, A. B., Henson, A., & Qeadan, F. (2020). A workplace well-being game intervention for health sciences librarians to address burnout. Journal of the Medical Library Association: JMLA, 108(4), 605.

Charlwood, A., & Guenole, N. (2022). Can HR adapt to the paradoxes of artificial intelligence?. Human Resource Management Journal, 32(4), 729-742.

Cheng, M. M., & Hackett, R. D. (2021). A critical review of algorithms in HRM: Definition, theory, and practice. Human Resource Management Review, 31(1), 100698.

Cooper, C. L., & Barling, J. (2008). The Sage handbook of organizational behavior. The SAGE Handbook of Organizational Behavior, 1-776.

Cram, W. A., & Wiener, M. (2020). Technology-mediated control: Case examples and research directions for the future of organizational control. Communications of the Association for Information Systems, 46(1), 4.

Cram, W. A., Wiener, M., Tarafdar, M., & Benlian, A. (2022). Examining the impact of algorithmic control on Uber drivers' technostress. Journal of Management Information Systems, 39(2), 426-453. https://doi.org/10.1080/07421222.2022.2063556

Davenport, T. H., & Kirby, J. (2015). Beyond automation. Harvard Business Review, 93(6), 58-65.

Delfanti, A., & Frey, B. (2021). Humanly extended automation or the future of work seen through Amazon patents. Science, Technology, & Human Values, 46(3), 655-682.

Diaz, D., Rodriguez-Carvajal, R., Blanco, A., Moreno-Jimenez, B., Gallardo, I., Valle, C., & van Dierendonck, D. (2006). Spanish adaptation of the psychological well-being scales (PWBS). Psicothema, 18(3), 572-577.

Diener, E. (2009). Well-being for public policy. Oxford University Press.

Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2020). Algorithmic management and app-work in the gig economy: A research agenda for employment relations and HRM. Human Resource Management Journal, 30(1), 114-132.

Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2022). Boundaryless careers and algorithmic constraints in the gig economy. The International Journal of Human Resource Management, 33(22), 4468-4498.

Evans, L., & Kitchin, R. (2018). A smart place to work? Big data systems, labour, control and modern retail stores. New Technology, Work and Employment, 33(1), 44-57.

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. Information and Organization, 28(1), 62-70.

Felstead, A., & Henseke, G. (2017). Assessing the growth of remote working and its consequences for effort, well-being and work-life balance. New Technology, Work and Employment, 32(3), 195-212.

Felstead, A., Gallie, D., Green, F., & Henseke, G. (2019). The determinants of skills use and work pressure: A longitudinal analysis. Economic and Industrial Democracy, 40(3), 730-754.

Fourcade, M., & Healy, K. (2017). Categories all the way down. Historical Social Research/Historische Sozialforschung, 286-296.

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation?. Technological forecasting and social change, 114, 254-280.

Fried, Y., & Ferris, G. R. (1987). The validity of the job characteristics model: A review and meta-analysis. Personnel Psychology, 40(2), 287-322.

Gagné, M., Parent-Rocheleau, X., Bujold, A., Gaudet, M. C., & Lirio, P. (2022). How algorithmic management influences worker motivation: A self-determination theory perspective. Canadian Psychology/Psychologie canadienne, 63(2), 247.

Gal, U., Jensen, T. B., & Stein, M. K. (2020). Breaking the vicious cycle of algorithmic management: A virtue ethics approach to people analytics. Information and Organization, 30(2), 100301.

Gameiro, M., Chambel, M. J., & Carvalho, V. S. (2020). A person-centered approach to the job demands–control model: A multifunctioning test of addictive and buffer hypotheses to explain burnout. International Journal of Environmental Research and Public Health, 17(23), 8871.

Ganster, D. C., & Murphy, L. (2000). Workplace interventions to prevent stress. Industrial and organizational psychology: Linking theory with practice. Massachusetts: Blackwell.

Garey, M. R. (1997). Computers and intractability: A guide to the theory of np-completeness, freeman. Fundamental.

Geldenhuys, M., & Henn, C. M. (2017). The relationship between demographic variables and well-being of women in South African workplaces. SA Journal of Human Resource Management, 15(1), 1-15.

Gent, C. (2018). The politics of algorithmic management class: composition and everyday struggle in distribution work (Doctoral dissertation, University of Warwick).

Godin, I., Kittel, F., Coppieters, Y., & Siegrist, J. (2005). A prospective study of cumulative job stress in relation to mental health. BMC public health, 5(1), 1-10.

Green, F. (2004). Why has work effort become more intense? Industrial Relations: A Journal of Economy and Society, 43(4), 709-741.

Griffin, M. A., Neal, A., & Parker, S. K. (2007). A new model of work role performance: Positive behavior in uncertain and interdependent contexts. Academy of management journal, 50(2), 327-347.

Gürerk, Ö., Bönsch, A., Kittsteiner, T., & Staffeldt, A. (2019). Virtual humans as co-workers: A novel methodology to study peer effects. Journal of behavioral and experimental economics, 78, 17-29.

Hackman, J. R., & Lawler, E. E. (1971). Employee reactions to job characteristics. Journal of applied psychology, 55(3), 259.

Hackman, J. R., & Oldham, G. R. (1974). Job diagnostic survey. Journal of Applied Psychology.

Hackman, J. R., & Oldham, G. R. (1974). The Job Diagnostic Survey: An instrument for the diagnosis of jobs and the evaluation of job redesign projects.

Hackman, J. R., & Oldham, G. R. (1976). Motivation through the design of work: Test of a theory. Organizational behavior and human performance, 16(2), 250-279.

Harter, J. K., Schmidt, F. L., & Keyes, C. L. (2003). Well-being in the workplace and its relationship to business outcomes: A review of the Gallup studies.

Harvey, R. J., Billings, R. S., & Nilan, K. J. (1985). Confirmatory factor analysis of the Job Diagnostic Survey: Good news and bad news. Journal of applied psychology, 70(3), 461.

Holman, D., Johnson, S., & O'Connor, E. (2018). Stress management interventions: Improving subjective psychological well-being in the workplace. Handbook of well-being. Salt Lake City, UT: DEF Publishers, 2.

Humphrey, S. E., Nahrgang, J. D., & Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: a meta-analytic summary and theoretical extension of the work design literature. Journal of applied psychology, 92(5), 1332.

Huppert, F. A. (2009). Psychological well‐being: Evidence regarding its causes and consequences. Applied psychology: health and well‐being, 1(2), 137-164.

Park, H., Ahn, D., Hosanagar, K., & Lee, J. (2021, May). Human-AI interaction in human resource management: Understanding why employees resist algorithmic evaluation at workplaces and how to mitigate burdens. In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (pp. 1-15). https://doi.org/10.1145/3411764.3445304

Iacovides, A., Fountoulakis, K. N., Kaprinis, S., & Kaprinis, G. (2003). The relationship between job stress, burnout and clinical depression. Journal of affective disorders, 75(3), 209-221.

Idaszak, J. R., & Drasgow, F. (1987). A revision of the Job Diagnostic Survey: Elimination of a measurement artifact. Journal of applied psychology, 72(1), 69.

Jabagi, N., Croteau, A. M., & Audebrand, L. (2020, January). Perceived Organizational Support in the Face of Algorithmic Management: A Conceptual Model. In Proceedings of the 53rd Hawaii International Conference on System Sciences.

Jabagi, N., Croteau, A. M., Audebrand, L., & Marsan, J. (2021). Unlocking perceived algorithmic autonomy-support: Scale development and validation.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business horizons, 61(4), 577-586.

Jarrahi, M. H., & Sutherland, W. (2019). Algorithmic management and algorithmic competencies: Understanding and appropriating algorithms in gig work. In Information in Contemporary Society: 14th International Conference, iConference 2019, Washington, DC, USA, March 31–April 3, 2019, Proceedings 14 (pp. 578-589). Springer International Publishing.

Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2021). Algorithmic management in a work context. Big Data & Society, 8(2). https://doi.org/10.1177/20539517211020332

Johnson, J., Hall, L. H., Berzins, K., Baker, J., Melling, K., & Thompson, C. (2018). Mental healthcare staff well-being and burnout: A narrative review of trends, causes, implications, and recommendations for future interventions. International journal of mental health nursing, 27(1), 20-32.

Judge, T. A., Bono, J. E., & Locke, E. A. (2000). Personality and job satisfaction: the mediating role of job characteristics. Journal of applied psychology, 85(2), 237.

Kain, J., & Jex, S. (2010). Karasek's (1979) job demands-control model: A summary of current issues and recommendations for future research. In New developments in theoretical and conceptual approaches to job stress (pp. 237-268). Emerald Group Publishing Limited. https://doi.org/10.1108/S1479-3555(2010)0000008009

Karasek, R. A. (1979). Job demands, job decision latitude, and mental strain: Implications for job redesign. Administrative Science Quarterly, 24, 285-307.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. Academy of Management Annals, 14(1), 366-410. https://doi.org/10.5465/annals.2018.0174

Kinowska, H., & Sienkiewicz, Ł. J. (2023). Influence of algorithmic management practices on workplace well-being–evidence from European organisations. Information Technology & People, 36(8), 21-42.

Kittur, A., Nickerson, J. V., Bernstein, M., Gerber, E., Shaw, A., Zimmerman, J., ... & Horton, J. (2013, February). The future of crowd work. In Proceedings of the 2013 conference on Computer supported cooperative work (pp. 1301-1318).

Langer, M., & Landers, R. N. (2021). The future of artificial intelligence at work: A review on effects of decision automation and augmentation on workers targeted by algorithms and third-party observers. Computers in Human Behavior, 123, 106878.

Leclercq-Vandelannoitte, A. (2017). An ethical perspective on emerging forms of ubiquitous IT-based control. Journal of Business Ethics, 142(1), 139-154.

Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. Big Data & Society, 5(1), 2053951718756684.

Lee, M. K., Kusbit, D., Metsky, E., & Dabbish, L. (2015, April). Working with machines: The impact of algorithmic and data-driven management on human workers. In Proceedings of the 33rd annual ACM conference on human factors in computing systems (pp. 1603-1612).

Leicht-Deobald, U., Busch, T., Schank, C., Weibel, A., Schafheitle, S., Wildhaber, I., & Kasper, G. (2019). The challenges of algorithm-based HR decision-making for personal integrity. Journal of Business Ethics, 160(2), 377–392. https://doi.org/10.1007/s10551-019-04204-w

Li, W., Lu, Y., Hu, P., & Gupta, S. (2023). Work engagement of online car-hailing drivers: the effects of platforms' algorithmic management. Information Technology & People.

Lippert, I., Kirchner, K., & Wiener, M. (2023). Context Matters: The Use of Algorithmic Management Mechanisms in Platform, Hybrid, and Traditional Work Contexts.

López-Cabarcos, M. Á., Vázquez-Rodríguez, P., & QuinoA-Pineiro, L. M. (2022). An approach to employees' job performance through work environmental variables and leadership behaviours. Journal of Business Research, 140, 361-369.

Martela, F., & Riekki, T. J. (2018). Autonomy, competence, relatedness, and beneficence: A multicultural comparison of the four pathways to meaningful work. Frontiers in psychology, 9, 1157.

Martin, D., O'Neill, J., Gupta, N., Hanrahan, B.V.: Turking in a Global Labour Market. Comput. Support. Coop. Work 25, 39-77 (2016).

Mateescu, A., & Nguyen, A. (2019). Explainer. Algorithmic management in the workplace, Data & Society, 6, 1-15.

Meijerink, J., & Bondarouk, T. (2023). The duality of algorithmic management: Toward a research agenda on HRM algorithms, autonomy and value creation. Human resource management review, 33(1), 100876.

Melchior, M., Caspi, A., Milne, B. J., Danese, A., Poulton, R., & Moffitt, T. E. (2007). Work stress precipitates depression and anxiety in young, working women and men. Psychological medicine, 37(8), 1119-1129.

Mendonça, P., Kougiannou, N. K., & Clark, I. (2023). Informalization in gig food delivery in the UK: The case of hyper-flexible and precarious work. Industrial Relations: A Journal of Economy and Society, 62(1), 60-77.

Mijakoski, D., Karadzinska-Bislimovska, J., Basarovska, V., Minov, J., Stoleski, S., Angeleska, N., & Atanasovska, A. (2015). Work demands-burnout and job engagement-job satisfaction relationships: teamwork as a mediator and moderator. Open access Macedonian journal of medical sciences, 3(1), 176.

Miller, K. I., & Monge, P. R. (1986). Participation, satisfaction, and productivity: A meta-analytic review. Academy of management Journal, 29(4), 727-753.

Misselbrook, D. (2014). W is for wellbeing and the WHO definition of health. British Journal of General Practice, 64(628), 582-582.

Möhlmann, M., Zalmanson, L., Henfridsson, O., & Gregory, R. W. (2021). ALGORITHMIC MANAGEMENT OF WORK ON ONLINE LABOR PLATFORMS: WHEN MATCHING MEETS CONTROL. MIS quarterly, 45(4). https://doi.org/10.25300/misq/2021/15333

Möhlmann, M., & Zalmanson, L. (2017, December). Hands on the wheel: Navigating algorithmic management and Uber drivers'. In Autonomy', in proceedings of the international conference on information systems (ICIS), Seoul South Korea (pp. 10-13).

Mokyr, J., Vickers, C., & Ziebarth, N. L. (2015). The history of technological anxiety and the future of economic growth: Is this time different?. Journal of economic perspectives, 29(3), 31-50.

Moore, S., Hayes, L. (2018). The Electronic Monitoring of Care Work—The Redefinition of Paid Working Time. In: Moore, P., Upchurch, M., Whittaker, X. (eds) Humans and Machines at Work. Dynamics of Virtual Work. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-319-58232-0_5

Moorhead, G., & Griffen, R. W. (2008). Managing organizational behaviour. 10. Jersey City, NJ: South-Western Cengage Learning.

Morgan, J., Neckermann, S., & Sisak, D. (2020). Peer evaluation and team performance: An experiment on complex problem solving. mimeo.

Morgeson, F. P., & Humphrey, S. E. (2008). Job and team design: Toward a more integrative conceptualization of work design. In J. Martocchio (Ed.), Research in personnel and human resources management, vol. 27 (pp. 39-91). Emerald Group Publishing.

Murray, W. C., & Rostis, A. (2007). Who's running the machine? A theoretical exploration of work stress and burnout of technologically tethered workers. Journal of individual employment rights, 12(3), 249-263.

Newlands, G. (2021). Algorithmic surveillance in the gig economy: The organization of work through Lefebvrian conceived space. Organization Studies, 42(5), 719-737.

Nielsen, K., Nielsen, M. B., Ogbonnaya, C., Känsälä, M., Saari, E., & Isaksson, K. (2017). Workplace resources to improve both employee well-being and performance: A systematic review and meta-analysis. Work & Stress, 31(2), 101-120.

Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric Theory New York. NY: McGraw-Hill.

Nurisman, H., & Sampurna, D. S. (2020, April). Factors Affecting Work-Life Balance in Technology Era. In 6th Annual International Conference on Management Research (AICMaR 2019) (pp. 84-88). Atlantis Press.

Oldham, G. R., & Cummings, A. (1996). Employee creativity: Personal and contextual factors at work. Academy of management journal, 39(3), 607-634.

Oosthuizen, R. M. (2022). The fourth industrial revolution–Smart technology, artificial intelligence, robotics and algorithms: industrial psychologists in future workplaces. Frontiers in artificial intelligence, 5, 913168.

Organ, D. W. (1988). A restatement of the satisfaction-performance hypothesis. Journal of management, 14(4), 547-557.

Orlikowski, W. J., & Scott, S. V. (2015). The algorithm and the crowd. MIS quarterly, 39(1), 201-216.

Parent-Rocheleau, X., & Parker, S. K. (2022). Algorithms as work designers: How algorithmic management influences the design of jobs. Human Resource Management Review, 32(3), 100838.

Parker, S. K., & Grote, G. (2022). Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. Applied Psychology, 71(4), 1171-1204.

Parker, S. K., & Ohly, S. (2008). Designing motivating jobs: An expanded framework for linking work characteristics and motivation.

Parker, S. K., Williams, H. M., & Turner, N. (2006). Modeling the antecedents of proactive behavior at work. Journal of applied psychology, 91(3), 636.

Parker, S. K., Wall, T. D., & Cordery, J. L. (2001). Future work design research and practice: Towards an elaborated model of work design. Journal of occupational and organizational psychology, 74(4), 413-440.

Pol, E., & Reveley, J. (2017). Robot induced technological unemployment: Towards a youth-focused coping strategy. Psychosociological Issues in Human Resource Management, 5(2), 169-186.

Preacher, K. J., & Leonardelli, G. J. (2001). Calculation for the Sobel test: An interactive calculation tool for mediation tests.

Pregenzer, M., Remus, U., & Wiener, M. (2021, June). Algorithms in the Driver's Seat: Explaining Workers' Reactions to Algorithmic Control. In ECIS.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. Academy of management review, 46(1), 192-210.

Regmi, P. R., Waithaka, E., Paudyal, A., Simkhada, P., & Van Teijlingen, E. (2016). Guide to the design and application of online questionnaire surveys. Nepal journal of epidemiology, 6(4), 640.

Roberts, K. H., & Glick, W. (1981). The job characteristics approach to task design: A critical review. Journal of applied psychology, 66(2), 193.

Roos, W., & Van Eeden, R. (2008). The relationship between employee motivation, job satisfaction and corporate culture. SA journal of industrial psychology, 34(1), 54-63.

Ropponen, A., Hakanen, J. J., Hasu, M., & Seppänen, L. (2019). Workers' health, wellbeing, and safety in the digitalizing platform economy. Digital work and the platform economy: Understanding tasks, skills and capabilities in the new era, 9780429467929-4.

Rosenblat, A., & Stark, L. (2016). Algorithmic labor and information asymmetries: A case study of Uber's drivers. International journal of communication, 10, 27.

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. Journal of personality and social psychology, 57(6), 1069.

Saavedra, R., & Kwun, S. K. (2000). Affective states in job characteristics theory. Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior, 21(2), 131-146.

Schafheitle, S., Weibel, A., Ebert, I., Kasper, G., Schank, C., & Leicht-Deobald, U. (2020). No stone left unturned? Toward a framework for the impact of datafication technologies on organizational control. Academy of Management Discoveries, 6(3), 455-487.

Sewell, G., & Taskin, L. (2015). Out of sight, out of mind in a new world of work? Autonomy, control, and spatiotemporal scaling in telework. Organization studies, 36(11), 1507-1529.

Shapiro, A. (2018). Between autonomy and control: Strategies of arbitrage in the "on-demand" economy. New Media & Society, 20(8), 2954-2971.

Shultz, K. S., Wang, M., Crimmins, E. M., & Fisher, G. G. (2010). Age differences in the demand—control model of work stress: An examination of data from 15 European countries. Journal of Applied Gerontology, 29(1), 21-47.

Snell, S. A., & Bohlander, G. W. (2013). Principles of Human Resource Management: International Edition. South Western: Cengage Learning.

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. Sociological methodology, 13, 290-312.

Sparr, J. L., & Sonnentag, S. (2008). Fairness perceptions of supervisor feedback, LMX, and employee well-being at work. European journal of work and organizational psychology, 17(2), 198-225.

Spector, P. E., Dwyer, D. J., & Jex, S. M. (1988). Relation of job stressors to affective, health, and performance outcomes: a comparison of multiple data sources. Journal of Applied Psychology, 73(1), 11.

Spector, P. E., & Jex, S. M. (1991). Relations of job characteristics from multiple data sources with employee affect, absence, turnover intentions, and health. Journal of applied psychology, 76(1), 46.

Spitzmüller, C., & Stanton, J. M. (2006). Examining employee compliance with organizational surveillance and monitoring. Journal of occupational and organizational psychology, 79(2), 245-272.

Stanton, J. M., & Julian, A. L. (2002). The impact of electronic monitoring on quality and quantity of performance. Computers in human behavior, 18(1), 85-101.

Steyn, R., & Vawda, N. (2014). Job characteristics: their relationship to job satisfaction, stress and depression. Journal of Psychology in Africa, 24(3), 281-284.

Strohmeier, S. (2020). Digital human resource management: A conceptual clarification. German Journal of Human Resource Management, 34(3), 345-365.

Sullivan, C. (2012). Remote working and work-life balance. In Work and quality of life: Ethical practices in organizations (pp. 275-290). Dordrecht: Springer Netherlands.

Theorell, T., Karasek, R. A., & Eneroth, P. (1990). Job strain variations in relation to plasma testosterone fluctuations in working men-a longitudinal study. *Journal of internal medicine*, *227*(1), 31-36.

Tomprou, M., & Lee, M. K. (2022). Employment relationships in algorithmic management: A psychological contract perspective. Computers in Human Behavior, 126, 106997.

Torraco, R. J. (2005). Work design theory: A review and critique with implications for human resource development. Human resource development quarterly, 16(1), 85-109.

Toyoda, Y., Lucas, G., & Gratch, J. (2020, May). The effects of autonomy and task meaning in algorithmic management of crowdwork. In Proceedings of the 19th International Conference on Autonomous Agents and MultiAgent Systems (pp. 1404-1412).

Umair, A., Conboy, K., & Whelan, E. (2019). Understanding the influence of technostress on workers' job satisfaction in gig-economy: an exploratory investigation.

Unruh, C. F., Haid, C., Johannes, F., & Büthe, T. (2022, July). Human autonomy in algorithmic management. In Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society (pp. 753-762).

Van der Doef, M., & Maes, S. (1999). The job demand-control (-support) model and psychological well-being: A review of 20 years of empirical research. Work & stress, 13(2), 87-114.

Van Dierendonck, D., Díaz, D., Rodríguez-Carvajal, R., Blanco, A., & Moreno-Jiménez, B. (2008). Ryff's six-factor model of psychological well-being, a Spanish exploration. Social Indicators Research, 87, 473-479.

Vandenberghe, C., Panaccio, A., Bentein, K., Mignonac, K., & Roussel, P. (2011). Assessing longitudinal change of and dynamic relationships among role stressors, job attitudes, turnover intention, and well-being in neophyte newcomers. Journal of Organizational Behavior, 32(4), 652-671.

Veen, A., Barratt, T., & Goods, C. (2020). Platform-capital's 'app-etite' for control: A labour process analysis of food-delivery work in Australia. Work, Employment and Society, 34(3), 388-406.

Vignola, E. F., Baron, S., Abreu Plasencia, E., Hussein, M., & Cohen, N. (2023). Workers' Health under Algorithmic Management: Emerging Findings and Urgent Research Questions. International Journal of Environmental Research and Public Health, 20(2), 1239.

Wall, T. D., Jackson, P. R., & Davids, K. (1992). Operator work design and robotics system performance: A serendipitous field study. Journal of applied Psychology, 77(3), 353.

Waytz, A., & Norton, M. I. (2014). Botsourcing and outsourcing: Robot, British, Chinese, and German workers are for thinking—not feeling—jobs. Emotion, 14(2), 434.

Wells, D. L., Moorman, R. H., & Werner, J. M. (2007). The impact of the perceived purpose of electronic performance monitoring on an array of attitudinal variables. Human Resource Development Quarterly, 18(1), 121-138.

West, D. M. (2018). The future of work: Robots, AI, and automation. Brookings Institution Press.

Wiener, M., Cram, W. A., & Benlian, A. (2023). Algorithmic control and gig workers: a legitimacy perspective of Uber drivers. European Journal of Information Systems, 32(3), 485-507. https://doi.org/10.1080/0960085x.2021.1977729

Williams, L. J., & Anderson, S. E. (1991). Job satisfaction and organizational commitment as predictors of organizational citizenship and in-role behaviors. Journal of management, 17(3), 601-617.

Williams, S., & Cooper, C. L. (1998). Measuring occupational stress: development of the pressure management indicator. Journal of occupational health psychology, 3(4), 306.

Wilson, M. G., Dejoy, D. M., Vandenberg, R. J., Richardson, H. A., & Mcgrath, A. L. (2004). Work characteristics and employee health and well-being: Test of a model of healthy work organization. Journal of occupational and organizational psychology, 77(4), 565-588.

Wood, A. J., Graham, M., Lehdonvirta, V., & Hjorth, I. (2019). Good gig, bad gig: autonomy and algorithmic control in the global gig economy. Work, employment and society, 33(1), 56-75. https://doi.org/10.1177/0950017018785616

Wood, A. J. (2021). Algorithmic management consequences for work organisation and working conditions (No. 2021/07). JRC Working Papers Series on Labour, Education and Technology.

Wright, T. A., & Cropanzano, R. (2004). The role of psychological well-being in job performance: a fresh look at an age-old quest. Organizational dynamics, 33(4), 338-351.

Wu, J., & Shang, S. (2020). Managing uncertainty in AI-enabled decision making and achieving sustainability. Sustainability, 12(21), 8758.

Zuboff, S. (2019, January). Surveillance capitalism and the challenge of collective action. In New labor forum (Vol. 28, No. 1, pp. 10-29). Sage CA: Los Angeles, CA: SAGE Publications.

Appendix

Model of questionnaire:

Professional background:

How old are you ?

….. (in years)

What is your gender ?

-Male

-Female

-Other

-I don’t want to share this information

In what country do you currently live in ?

(Write your own county)

What is the highest educational degree you have obtained?

- Primary or secondary school

- Professional or academic college/university degree

- Master degree

- Doctoral degree

Which of the following best describes your role?

-CEO / President / Owner

-Senior Manager

-Manager

-Team Leader/Line manager

-Professional staff (eg. expert role)

-Operational personnel

-Support personnel

How many years of experience do you have in your current job ?

… (in years)

Which of the following best describes your department?

-Accounting / Finance

-Production

-Sales / Marketing

-Human Resource Management

-Logistics

-Administration / Professional Services

-Other (please specify): ___________________________

Algorithmic management:
These questions measure your exposure to algorithmic management in your workplace. Kindly answer using the following scale:
1-To a Very Small Extent, 2-To a Small Extent, 3-To a Moderate Extent, 4-To a Large Extent, 5-To a Very Large Extent.

To what extent do you feel that your work tasks are determined by algorithms or automated systems?
To what extent do you interact with algorithms and technology-enabled surveillance tools in your daily work?
To what extent have you noticed an increase in the use of computerized tools or software for employee monitoring and evaluation in your workplace?
To what extent do you receive feedback or guidance from algorithms or artificial intelligence technologies on how to perform your work tasks?
To what extent do algorithms determine the work schedule of employees in your company?
To what extent do you feel that algorithms or automated systems support your work performance?

Autonomy: (scale adapted from Hackman & Oldham (1974))
Listed below are a number of statements that could be used to describe job autonomy. You are to indicate whether each statement is an accurate or an inaccurate description of your job, according to the following scale:

1-Very inaccurate; 2-Mostly inaccurate; 3-Slightly inaccurate; 4-Uncertain; 5-Slightly accurate; 6-Mostly accurate; 7-Very accurate.

The job gives me a considerable opportunity for independence and freedom in how I do the work.
The job gives me a chance to use my personal initiative and judgment in carrying out the work.

How much autonomy is there in your job? That is, to what extent does your job permit you to decide on your own how to go about doing the work?

1. Very little: The job gives me almost no personal “say” about how and when the work is done.
……
4. Moderate autonomy: Many things are standardized and not under my control, but I can make some decisions about the work.
…
7. Very much: The job gives me almost complete responsibility for deciding how and when the work is done.

In-role performance: (adapted from Williams & Anderson (1991))

The following questions are about your role performance at work. Indicate to what extent you agree with each statement on a scale from 1 'Strongly disagree' to 7 'Strongly agree'.
1-Strongly disagree, 2-Disagree, 3-Somewhat disagree, 4-Neither agree or disagree, 5-Somewhat agree, 6-Agree, 7-Strongly agree.

I adequately complete assigned duties.
I fulfill responsibilities specified in job description.
I perform tasks that are expected of me.
I meet the formal performance requirements of the job.

Psychological well-being: (adapted from Ryff, (1989))

The following questions assess your psychological well-being at work. Indicate to what extent you agree with each statement on a scale from 1 'Strongly disagree' to 7 'Strongly agree'.
1-Strongly disagree, 2-Disagree, 3-Somewhat disagree, 4-Neither agree or disagree, 5-Somewhat agree, 6-Agree, 7-Strongly agree.

In general, I feel confident and positive about my job.
I know that I can trust my colleagues, and they know they trust me.
I trust my opinions, even if they are contrary to those of others.
I have been able to build a work environment and a work-life balance that is much to my liking.
I feel good when I think of what I have achieved so far and about my future career.
I have the sense that I have developed a lot of skills over time.