Algorithmic Management in White Collar Professions

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The Influence of Algorithmic Management Practices on Job Motivation Among Graduates and Soon-to-Be Graduates Entering White-Collar Professions

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Title: The Influence of Algorithmic Management Practices on Job Motivation Among Graduates and Soon-to-Be Graduates Entering White-Collar Professions

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Abstract

As algorithmic management (AM) becomes increasingly integrated into modern workplaces, understanding its impact on job motivation is essential, particularly for graduates and soon-to-be graduates entering white-collar professions. This study investigates how AM practices influence key motivational factors—autonomy, competence, and relatedness—drawing upon the Self-Determination Theory (SDT) framework.

Using a controlled experimental design, we surveyed recent and soon-to-be graduates to assess their motivation levels under conditions managed by either AM systems or human supervisors. The sample consisted of 150 participants, all of whom were presented with a realistic job scenario tailored to reflect typical white-collar tasks. Data were analysed using ANOVA and regression models to explore the relationships between AM, job motivation, and job appeal.

The results indicate that AM negatively impacts job motivation, with significant differences observed between AM and human management conditions. Specifically, AM was associated with lower levels of perceived autonomy, competence, and relatedness, which, in turn, reduced overall job motivation and job appeal. These findings suggest that while AM can enhance efficiency, it may also undermine the psychological drivers critical to employee engagement.

The study's implications emphasize the need for a balanced approach to AM implementation, one that safeguards employee well-being while maintaining operational efficiency. Future research should explore additional mediators and employ longitudinal studies to provide deeper insights into how AM influences motivation and job outcomes over time.

Keywords: Algorithmic Management, White Collar, Graduates, Employee Motivation

Título: A Influência das Práticas de Gestão Algorítmica na Motivação para o Trabalho entre Graduados e Futuros Graduados que Ingressam em Profissões de Colarinho Branco

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Resumo

Com a crescente integração da gestão algorítmica (GA) nos ambientes de trabalho, é crucial entender seu impacto na motivação, especialmente entre recém-licenciados e futuros profissionais de colarinho branco. Este estudo examina como as práticas de GA afetam fatores-chave de motivação — autonomia, competência e relacionamento — com base na Teoria da Autodeterminação (TDA).

Utilizando um desenho experimental controlado, pesquisamos 150 recém-licenciados e estudantes prestes a se formar para medir seus níveis de motivação sob gestão algorítmica ou supervisão humana. Os participantes foram expostos a cenários de trabalho realistas de tarefas típicas de colarinho branco. Os dados foram analisados por meio de ANOVA e regressão para explorar as relações entre GA, motivação e atração pelo trabalho.

Os resultados revelam que a GA impacta negativamente a motivação, com diferenças significativas em comparação à gestão humana. A GA foi associada a percepções mais baixas de autonomia, competência e relacionamento, diminuindo a motivação e a atração pelo trabalho. Esses achados sugerem que, apesar de aumentar a eficiência, a GA pode prejudicar fatores psicológicos essenciais ao engajamento dos trabalhadores.

O estudo destaca a importância de equilibrar a implementação da GA, preservando o bem-estar dos trabalhadores sem comprometer a eficiência. Futuras pesquisas devem investigar outros mediadores e adotar estudos longitudinais para entender melhor os impactos da GA ao longo do tempo.

Palavras-chave: Gestão algorítmica, colarinho branco, licenciados, motivação dos trabalhadores

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1. Introduction

"Technology is a useful servant but a dangerous master."
— Christian Lous Lange

1.1 Presentation of the Topic

Christian Lous Lange's observation about technology from over 100 years ago, which he included in his acceptance speech after receiving the Nobel Peace Prize in 1921, still holds truth until the present day and probably long into the future as well. It serves as a notable reminder of the careful balance required when leveraging technological advancements in many different disciplines but especially within the workplace and its perception by humans (Lange, 1921). As we evolve even further into the era of digital transformation, the deployment of algorithmic management systems (AMS) in organizational settings introduces both unprecedented opportunities and notable challenges (Kellogg et al., 2019). These systems, driven by the latest advancements in data analytics and artificial intelligence, promise to enhance operational efficiency but also present significant concerns regarding their influence on human roles and employee satisfaction (Mateescu & Nguyen, 2019).

Algorithmic management (AM) is a relatively new field that involves the use of algorithms to manage task assignments, evaluate performance, and handle organizational planning, effectively automating decisions traditionally made by human managers (Lee et al., 2018). For instance, companies like Uber and Amazon employ advanced algorithms to manage their workforce, optimize task distribution, and monitor performance in real time. While this approach offers efficiency, it also prompts questions about its influence on employee motivation, particularly regarding autonomy, competence, and relatedness—key components of Self-Determination Theory (SDT; Manganelli et al., 2018).

1.2 Importance of the Topic

The rise of AM is driven by substantial advancements in big data, machine learning, and pervasive computing—a concept where computing is embedded seamlessly into everyday objects, allowing them to communicate information (Weiser, 1991). With the advent of technologies like OpenAI's ChatGPT, approximately one-third of global companies have already integrated AI into their operations, and this trend is expected to grow (McKinsey &

Company, 2023). This widespread adoption highlights the need to understand how such technologies affect essential aspects of job motivation and job appeal.

Research suggests that while AM can create stressful work environments and negatively impact job satisfaction (Duggan et al., 2020), it can also enhance perceptions of fairness and boost intrinsic motivation (Lee et al., 2015). For example, a study by Kellogg et al. (2020) explored the effects of AM on gig economy platforms like Uber and Lyft. The researchers found that although these systems offer flexibility in work schedules, the high level of control they exert—through task allocation and performance monitoring—often leads to a reduced sense of autonomy among workers. This study highlights the complexity of AM's impact, balancing operational benefits with potential drawbacks in employee autonomy and satisfaction.

By exploring the multifaceted effects of AM on employee motivation and well-being, these studies underscore the critical need to understand and manage these technologies' impact on the modern workforce.

1.3 Problem Statement and Research Objective

While there is a growing body of research on the technical effectiveness of algorithmic systems, there is a notable lack of comprehensive studies focusing on their impact on job motivation (Cameron, 2024). Existing research often prioritizes operational efficiency metrics over more subjective measures of emotional well-being and workplace motivation (Parent-Rocheleau & Parker, 2021). This thesis intends to contribute to bridging this gap by examining how the integration of AM affects these critical human factors in the broader white-collar workforce, contributing to providing a more balanced view of technological advancements, that goes beyond the focus on efficiency, and acknowledges the psychological consequences of this disruption of traditional workplace dynamics. This research aims to critically examine the impact of AM on job motivation among both (soon to be) graduates entering white-collar professions and employees currently working in these roles, exploring several key dimensions:

- The direct effects of AM on employee motivation.
- The interplay between perceived autonomy, competence, relatedness, and job motivation and appeal in environments managed by algorithms.

1.4 Managerial and Academic Relevance

The insights from this study are poised to influence both managerial practices and academic theory. For organizational leaders, the findings can provide guidance on refining AM implementations to align more closely with employee needs, potentially enhancing motivation and retention. Academically, this research fills a critical void by offering empirical data on the psychological impact of AM, enriching theoretical discussions related to advanced technologies in workplace management. This study could serve as a foundational reference for future investigations into the long-term effects of these practices on organizational culture and employee well-being.

1.5 Structure

After this Introduction, which sets the stage for the research by highlighting the significance of the study and outlining the main research questions, a comprehensive Literature Review follows and further explores AM and its impact on work practices and job motivation in context of SDT. This section synthesizes existing research, identifies gaps, and sets the theoretical framework for the study.

The Methodology section explains the quantitative research approach adopted in this study, detailing the development and deployment of an online survey used to gather data from (soon to be) graduates and white-collar professionals. This section also covers the sampling methods, data collection procedures, and analytical techniques employed.

The results of the survey are presented and analysed in the Results section, which is followed by the Discussion. This part interprets the findings in light of the hypotheses posed and the broader context provided by the literature review. It discusses the implications of the findings for current practices and theoretical understanding.

The thesis concludes with the Limitations of this study and provides an Outlook for future research, suggesting areas that could further enhance our understanding of AM’s impact on the modern workplace.

2. Literature Review

The purpose of this literature review is to explore and synthesize existing research on AM and its influence on job motivation within the workplace. As AMSs become increasingly prevalent across various industries, understanding their impact on the workforce is crucial. This literature review aims to map the terrain of current academic and industry insights, focusing on how such systems alter work practices, affect employee motivation, and reshape employee perceptions of their job.

By examining scholarly articles, papers and industry reports, this review seeks to identify the benefits and challenges of AM as reported in contemporary research. It helps to understand how algorithmic systems are implemented and perceived in the workplace.

The insights gathered from this review will directly inform the research methodology, guiding the development of survey questions that are sensitive to the documented effects and concerns associated with AM. Additionally, by highlighting gaps in the existing literature, this review sets the stage for the current study to contribute new knowledge and perspectives to the ongoing discourse on technology's role in modern organizational environments.

2.1 Introduction to Algorithmic Management

AM is an innovative and increasingly prevalent approach in modern workplaces characterized by the use of sophisticated algorithms to make decisions traditionally made by human managers (Lee et al., 2018). This management style currently focuses, among others, on three critical tasks: Team assignment and management, task assignment, and performance monitoring, each of which utilizes technology to streamline operations and increase productivity (Kellogg et al., 2020).

Team Management: AMSs are characterized by dynamic management of staff allocation based on predictive analytics and real-time performance data. These systems evaluate historical and current workflow data to optimize staff deployment and ensure that staff are available when and where they are needed most (Author, 2015). For example, at times when demand is expected to be high, algorithms can adjust staffing levels to match workloads, maintaining operational efficiency without unnecessary staff overhead. This capability not only helps to balance operational demands with labour costs, but also supports optimal team productivity in fluctuating business environments (Weil, 2014).

Task Allocation: In the area of task allocation, AM systems intelligently distribute tasks to available workers by analysing the nature of tasks and the skills of available workers. This involves assigning tasks to employees based on their skills, current workload and past performance to ensure that each task is handled by the most appropriate person (Parker, 2017). Such strategic task allocation increases the overall speed and quality of task completion, potentially improving employee job satisfaction by matching tasks to appropriate skill levels and helps achieve faster and more accurate results (Lee, 2018).

Performance Monitoring and Feedback: AM integrates performance monitoring and feedback by utilizing continuous data collection to assess metrics such as task completion rates and quality of output (O'Neil, 2016). This real-time insight helps managers identify outstanding performance, address areas for improvement and refine strategies to increase productivity. Automated feedback systems provide timely, specific feedback, promote immediate self-correction and professional growth, and improve organizational adaptability (Kellogg et al., 2020).

2.1.1 Application across various Sectors

The previously outlined roles are being applied in different industries and are changing traditional management functions. The gig economy, one of the most impacted sectors, is defined by a labour market where short-term contracts and freelance work dominate, rather than permanent employment (Woodcock & Graham, 2020). In this sector, companies such as Uber and Lyft use algorithmic systems to manage their networks of independent contractors. These platforms automate the assignment of tasks based on real-time data such as location and demand, dynamically adjust pricing, and use performance metrics to manage and incentivize drivers (Rosenblat, 2018). The flexibility and efficiency that these systems bring have revolutionized urban transportation, although they also pose significant challenges in terms of worker autonomy and job security (Sundararajan, 2016).

In logistics, companies such as Amazon are using AMSs to optimize supply chains and distribution networks (De Stefano, 2020). These algorithms manage everything from inventory and delivery routing to task assignment in warehouses, increasing operational efficiency, but often at the cost of high physical strain on workers (Cachon & Terwiesch, 2017).

Customer service also benefits from AM, systems assign service tickets and calls based on algorithmic analysis of employee workload and performance, which increases efficiency but potentially also increases employee stress (Kellogg et al., 2020; Donnelly, 2019).

2.1.2 Algorithmic Management in the Work Environment

AM in the workplace is primarily a tool for enhancing efficiency, and its integration has a notable effect on operational productivity. Numerous studies have documented improvements across various areas. For instance, the automation of both routine and complex tasks has driven significant efficiency gains. In manufacturing, algorithms that optimize machine usage and maintenance schedules have successfully reduced downtime and boosted production (Kumar & Reinartz, 2020). Similarly, in the retail sector, inventory management algorithms have minimized stock levels while ensuring product availability, significantly cutting costs associated with overstocking and understocking (Peterson & Kumar, 2021).

Additionally, AM has been associated with productivity improvements. By better aligning tasks with employees' skills and performance, these systems can enhance job satisfaction and motivation. However, the effects on productivity can vary depending on the context. An over-reliance on algorithmic monitoring, for example, can lead to increased stress and reduced job satisfaction if employees feel excessively controlled by the system (Jensen & Morris, 2022).

2.1.3 AM and Motivation in the Work Environment

Despite the profound impact on efficiency, the prevailing view of AM in business circles has often focused only on these operational aspects and not on the potential to increase employee motivation (Kellogg et al. 2020). Typically, the focus has been on how these systems can reduce costs, increase speed and eliminate human error, with less attention paid to how they might also impact employee drive and engagement. However, the view that AM is merely a tool to increase efficiency is increasingly being challenged. There is a growing realization that AM, when used thoughtfully, has the potential to significantly increase employee motivation (Barrick et al. 2014).

Studies have begun to explore how features of AM, such as immediate feedback from performance monitoring systems and a fairer allocation of tasks, could contribute positively to employee motivation. A study by Zhang (2018) shows that immediate feedback can help employees feel more engaged and connected to their work outcomes, which promotes feelings of accomplishment and satisfaction. This study showed that employees who received real-time feedback on their performance were able to adjust their efforts immediately, resulting in better performance and a greater sense of competence. Similarly, a study conducted by Gkorezis, and collaborators (2011) found that performance feedback systems increase employee motivation by providing clear and timely information about their work, helping them to set and achieve personal and professional goals.

In addition, equitable task allocation facilitated by AM can reduce perceived bias and favouritism, improving fairness in the workplace. This was demonstrated in a study by Lee, and collaborators (2015), which highlighted that algorithmic task assignment led to a perception of fairness and impartiality among employees, which in turn increased their intrinsic motivation and job satisfaction.

2.1.4 Challenges and Ethical Considerations

The benefits of AM customisation are many: it can eliminate human error and bias in certain types of decisions, provide real-time feedback and adjustments, and streamline operations to unprecedented levels of efficiency (Noponen et al., 2023). Therefore, the adoption of AMSs is likely to increase in white-collar occupations and beyond, driven by technological advances and the pursuit of greater operational efficiency (Kellogg et al., 2020).

However, the transition to AM also brings with it some challenges and ethical considerations. A primary concern is privacy, as these systems require continuous monitoring and data collection, which can lead to a potential invasion of personal employee data (Lee, 2018). Furthermore, the emphasis on quantitative metrics and monitoring can significantly affect employees' perception of autonomy, making them feel like cogs in a machine rather than valued members of an organisation (Rahman, 2021).

Furthermore, the impersonal nature of algorithmic feedback and task management can reduce workplace connectedness and camaraderie among team members. Without the nuanced understanding that typically comes from human management, there is a risk of employees feeling disconnected, undervalued or misunderstood (Shestakofsky, 2017). This aspect is particularly worrying as work motivation and satisfaction are closely linked to employees' sense of connection and relevance in their work environment (Duggan, 2020).

The ongoing debate about the pros and cons of AM emphasises the need for balanced approaches that harness the benefits of technology while considering the ethical implications and human factors (Mateescu & Nguyen, 2019). The future of AM will likely depend on the development of systems that not only optimise efficiency but also promote fairness, transparency and respect for worker autonomy and connectedness (Jarrahi et al., 2021).

2.1.5 Perceptions of AM and its Impact on Motivation

The perception of AI-driven management systems by managers and employees has a significant impact on the effectiveness of these systems, especially on employee motivation. Research shows that when AI management systems are perceived as tools to improve fairness and efficiency, employees are more likely to respond positively, leading to higher levels of motivation and job satisfaction (Kellogg, Valentine, & Christin, 2020). However, negative perceptions - e.g., when AI is seen as overly controlling or invasive - can lead to resistance, lower motivation and even burnout (Jarrahi, 2018; Bankins et al., 2022). The expectation that AI systems should provide fair, unbiased and supportive management is crucial. If these expectations are not met, for example, if AI does not provide personalised feedback or assigns tasks incorrectly, this can lead to disappointment, reduced trust and have a negative impact on employee engagement and motivation (Glikson & Woolley, 2020). Furthermore, the perception of AI in decision-making is often coloured by broader societal narratives and media portrayals that can either strengthen or weaken trust in these systems (Fast & Horvitz, 2017). Therefore, the success of AMS depends largely on how they are perceived and integrated into the workplace, with clear communication and education playing a central role in managing expectations and fostering a supportive work environment (Bankins et al., 2022).

Given the profound changes that AM can bring to workplace dynamics, it is crucial to explore the psychological underpinnings that influence employee motivation in these environments. Understanding how AI-driven management systems impact motivation is important not only for theoretical development, but also for practical application in the development of more human-centred technologies. This requires a closer examination of the psychological factors that influence motivation, particularly in the context of AM, where the balance between efficiency and employee wellbeing needs to be carefully managed. The following section therefore introduces SDT, a comprehensive framework that explains how key psychological needs - autonomy, competence and relatedness - can influence motivation in AI-driven environments.

2.2 Introduction to Employee Motivation using Self-Determination Theory

As AM redefines the landscape of modern workplaces through the automation of key management tasks, it is important to examine the impact of these technologies on employee psychology and motivation. This investigation leads to SDT, a robust framework for understanding motivation in the workplace first developed in the 1970s by psychologists

Edward L. Deci and Richard M. Ryan and formally introduced in their 1985 publication (Deci & Ryan, 1985). It explains employee motivation on the basis of 3 main dimensions:

Autonomy: At the centre of SDT is autonomy, i.e. the individual's control over their actions and decisions. It is crucial for fostering intrinsic motivation, which leads to greater job satisfaction, higher productivity and improved psychological well-being (Deci & Ryan, 2000; Gagné & Deci, 2005).

Competence: This includes the feeling of being effective and having the opportunity to utilise one's own abilities. An environment that supports the mastery of skills leads to higher engagement and motivation (Ryan & Deci, 2000; Vallerand, 1997).

Relatedness: This dimension refers to the feeling of being connected to others and having a sense of belonging (Baumeister & Leary, 1995). In the workplace, this means supportive relationships with colleagues and superiors, which are associated with greater organisational commitment and lower turnover. Social interactions and a supportive culture are critical, as isolation can significantly impact motivation (Niemiec & Ryan, 2009).

SDT provides a powerful lens through which to view employee motivation. It emphasises that meeting these three basic psychological needs leads to higher levels of self-motivation and mental health. The theory assumes that the more these needs are satisfied in an integrated way, the greater the individual's well-being and engagement at work (Deci & Ryan, 1985; Ryan & Deci, 2017).

2.2.1 Application of SDT in Work Environments

Research on SDT in the workplace shows that meeting the psychological needs for autonomy, competence and relatedness leads to significant improvements in employee engagement, productivity and satisfaction. For example, when employees have a choice in how they complete their tasks (autonomy), when they have the opportunity to develop their skills (competence), and when they have a supportive team environment (relatedness), this is associated with less workplace stress and higher job satisfaction (Deci, Olafsen, & Ryan, 2017). In addition, organizations that incorporate these principles into their management practices often report improved innovation and adaptability, which are essential for competitiveness in dynamic markets (Gagné & Deci, 2005).

2.3 AM and SDT in the Work Environment

SDT suggests that employee autonomy can be facilitated through more personalized task management, improving competence through real-time feedback and fostering connectedness through collaborative digital tools. However, this integration is not without its challenges. For example, automating decision making could compromise perceived autonomy, potentially clashing with the SDT tenet that autonomy fosters motivation (Deci & Ryan, 2000). AM capabilities can also be enhanced to address the basic human needs described by SDT, potentially resulting in a workforce that is not only more efficient, but also more motivated and satisfied. However, this alignment requires careful implementation and a deep understanding of both concepts (Kellogg et al. 2020). In the following, the specific effects of AM on the different dimensions of SDT are examined in more detail.

2.3.1 Impact of Algorithmic Management on Autonomy

Autonomy, a key component of SDT, refers to the control and choice that individuals have over their actions and decisions in the workplace. Technology, including AMSs, can either increase or decrease perceived autonomy. While it can equip employees with tools and information for informed decision making (Zuboff, 1988), automating decision making can reduce discretion, leaving employees feeling as if they are performing predetermined tasks without meaningful input (Ryan & Deci, 2000). This ambiguity is evident in several studies examining the complex relationship between technology and perceived autonomy, which are reviewed next.

2.3.1.1 Review of Studies assessing Autonomy in technologically driven Work Environments

The impact of technology on perceived autonomy in the workplace has been examined in several studies that have explored different aspects of this complex relationship. Morgeson and Humphrey (2006) found that technology can increase the importance and complexity of tasks, potentially increasing perceived autonomy. However, they also found that it can impose rigid structures and standardize processes, which can reduce autonomy. This duality is echoed in the work of Oudshoorn and Pinch (2003), who emphasized that technological systems often reflect management priorities that are not necessarily aligned with promoting employee autonomy. These studies provide a broad overview, but more specific contexts offer deeper insights.

In a more specific context, Kellogg and collaborators (2020) focused on AM within gig economy platforms such as Uber and Lyft. They discovered that while these systems offer flexibility in choosing work hours, they also exert significant control over the details of the work, such as route assignments and customer interactions. This control creates a superficial perception of autonomy. While Morgeson and Humphrey (2006) provide a broader overview of the impact of technology on work design, Kellogg et al. (2020) provide a detailed examination of algorithmic control in gig work. Despite the differences in focus, both studies highlight the potential of technology to limit true autonomy by imposing rigid structures. This finding is crucial as it demonstrates the importance of striking a balance between operational efficiency and preserving employee autonomy.

2.3.1.2 Implications for Practice

Together, these studies highlight the dual nature of AM's impact on worker autonomy. Both perspectives are critical to understanding the subtle effects of AM. For practitioners, this means balancing the operational efficiencies gained through AM with strategies that mitigate the reduction in true autonomy.

For graduates entering white-collar professions, understanding these dynamics is critical to navigating and negotiating their roles in increasingly automated work environments. The results of the mentioned studies suggest that perceived autonomy is significantly lower under AM compared to environments led by human supervisors. This leads to the first hypothesis:

H1: *Graduates in white-collar jobs will report lower perceived autonomy in algorithm-managed task allocations compared to those managed by human supervisors.*

2.3.2 Impact of Algorithmic Management on Competence

Building on the integration of SDT and AM, it is important to examine how AM specifically affects the dimension of competence. Competence, a fundamental aspect of SDT, refers to the need to feel effective and capable in one's activities. Understanding how feedback mechanisms in algorithmic systems affect perceived competence is crucial for assessing the overall motivational outcomes of AM.

2.3.2.1 Feedback Mechanisms

AMS often incorporate advanced feedback mechanisms that provide employees with real-time performance data, offering clear and immediate insights into their work. This enables employees to make timely adjustments and improve their skills. For example, performance dashboards and automated reports can highlight areas of strength and identify skills that require further development, fostering a continuous learning environment. However, the nature and delivery of feedback through these systems can significantly influence how it is perceived.

While data-driven feedback offers objective performance benchmarks, it can also be viewed as impersonal and lacking the nuanced understanding typically provided by human supervisors. Studies suggest that although algorithmic feedback enhances competence by delivering clear metrics, it may fall short of offering the individualized support that employees receive from a human supervisor (Guzzo, Jette, & Katzell, 1985). This highlights the complexity of feedback in AMSs, revealing both its advantages and limitations when compared to traditional feedback mechanisms.

Human feedback, by contrast, is often characterized by personal interaction and emotional intelligence. Supervisors can tailor their feedback to the individual, taking into account their unique circumstances, strengths, and weaknesses, which helps employees feel understood and supported in their development efforts (Kluger & DeNisi, 1996).

Nevertheless, the immediacy and frequency of algorithmic feedback can still be beneficial for performance improvement, as constant updates allow employees to adjust their efforts and enhance their skills more efficiently (Brand et al., 2020).

2.3.2.2 On the Effectiveness of Automated Feedback

Empirical research offers mixed results regarding the effectiveness of automated feedback in promoting skill development and improving performance. On the positive side, a study by Anseel, Lievens, and Schollaert (2009) found that automated feedback systems can significantly boost performance by delivering clear, actionable insights. The immediacy of the feedback allows employees to quickly identify and correct mistakes, leading to faster skill acquisition and enhanced performance. Additionally, automated feedback can eliminate the biases often present in human feedback, fostering a more meritocratic environment where competence is accurately acknowledged and rewarded (Zou et al., 2024). However, for this approach to be effective, the feedback must be precise and contextually relevant to avoid being perceived as generic or impersonal.

On the other hand, research also highlights some challenges and limitations. Nash and Winstone (2017) pointed out that the impersonal nature of automated feedback can sometimes lead to disengagement among employees. When feedback lacks context and fails to acknowledge individual efforts, employees may feel undervalued, resulting in lower perceived competence. Automated systems may miss the motivational benefits of personal recognition and encouragement that human supervisors provide (Greller & Herold, 1975), further diminishing their effectiveness in promoting long-term employee development.

The integration of AM with SDT underscores the complex impact of automated feedback mechanisms on perceived competence. While AMS can provide immediate, objective feedback that fosters skill development, the lack of personal interaction and contextual understanding can undermine employees' sense of competence, showing particular relevance for graduates entering white-collar professions, where nuanced feedback and professional development are critical for career growth. This leads to the second hypothesis:

H2: *Graduates in white-collar jobs will report lower perceived competence in feedback environments managed by algorithms compared to human supervisors.*

2.3.3 Impact of Algorithmic Management on Relatedness

Lastly, to completely understand the integration of SDT with AM, it is necessary to explore how AM specifically impacts the dimension of relatedness. Relatedness refers to the need to feel connected to others, to belong, and to maintain close relationships (Deci & Ryan, 2000). Understanding how technology-mediated communication influences workplace relationships is crucial in assessing the overall motivational outcomes of AM.

2.3.3.1 Effects of Reduced Human Interaction on Team Dynamics and Sense of Belonging

Reduced human interaction in environments managed by algorithms can have a negative impact on team dynamics and employees' sense of belonging (Tang et al., 2023). In traditional settings, human managers play an essential role in creating a sense of community and building relationships through personal, direct interactions (Edwards, 2011). These interactions are critical for fostering team cohesion, trust, and collaboration.

Face-to-face communication is especially important for building trust and rapport within teams, as it allows for the exchange of non-verbal cues such as body language and facial expressions, which are key to understanding and empathy (Hinds & Mortensen, 2005). When these interactions are reduced in algorithmically managed environments, the quality of relationships can suffer, potentially weakening team cohesion and lowering morale (Gajendran & Joshi, 2012). This issue is evident in gig economy platforms like Uber and Lyft, where drivers often report feelings of isolation due to minimal interaction with peers or supervisors (Rosenblat & Stark, 2016). Such isolation can significantly affect their sense of belonging and motivation, highlighting the need to maintain personal connections, even within highly automated systems.

While technology can facilitate communication, it can also create barriers to forming meaningful relationships. Walther (1996) found that although computer-mediated communication is effective for exchanging information, it is less effective for fostering relational communication. Employees may feel disconnected from their peers and supervisors, leading to a diminished sense of belonging. This trend, first observed nearly 30 years ago, is still evident in modern work environments (Pratt & Cakula, 2020). The absence of personal connections can leave employees feeling undervalued and isolated, which in turn can negatively affect their motivation and engagement.

2.3.3.2 Team Coordination and Relationship Building in Algorithm-Controlled Environments

A relevant case study illustrating the effects of AM is that of gig economy platforms such as Uber and Lyft, where the use of AM is widespread. Research by Rosenblat and Stark (2016) found that drivers on these platforms often experience feelings of isolation and a lack of connection with colleagues. This is largely due to the nature of AM for task assignment and communication, which relies heavily on automated processes for coordination. As a result, drivers seldom interact with one another or with human supervisors, which diminishes their sense of belonging and community.

Similar issues have been observed in virtual teams, as highlighted by Gilson et al. (2015). Their study found that while virtual teams can be effective, they often face challenges related to trust, cohesion, and relationship building. The absence of face-to-face interactions can lead to misunderstandings and a lack of personal connection, both of which are essential for fostering strong team dynamics and a sense of connectedness.

In environments where AM governs team coordination and communication, the effects on interpersonal relationships can be significant. Employees may come to feel that their interactions are purely transactional and lack the personal touch that human managers typically provide. This can lead to feelings of alienation and a decline in team spirit, both of which are critical for creating a collaborative and supportive work environment (O'Leary, Wilson, & Metiu, 2014).

The integration of AM with SDT further underscores the complex impact of technology-mediated communication on relationship-building skills. While AM can enhance efficiency and streamline communication, the reduction in face-to-face interactions and reliance on automated processes can weaken employees' sense of belonging and connectedness. This issue is particularly relevant for graduates entering white-collar professions, where establishing professional relationships and maintaining team cohesion is essential (Gersick et al., 2000). This observation forms the basis for the third hypothesis.

H3: *Algorithmic Management will be associated with lower perceived relatedness among team members due to reduced interpersonal interactions compared to human coordination*.

2.3.4 Impact of Algorithmic Management on Job Motivation

In the previous sections, the influence of AM on three basic psychological needs - autonomy, competence and relatedness - was analysed in terms of SDT. Research shows that AMSs often reduce perceived autonomy by enforcing rigid task structures (Deci, Olafsen, & Ryan, 2017), reduce perceptions of competence through impersonal feedback mechanisms (Brougham & Haar, 2018), and weaken relatedness by limiting opportunities for meaningful interpersonal interactions (Glikson & Woolley, 2020).

These psychological needs are closely linked to overall work motivation, according to SDT. When employees experience reduced autonomy, reduced competence and a lack of relatedness, their intrinsic motivation is likely to decrease (Ryan & Deci, 2000). Each of these factors is critical to fostering a motivated, engaged and satisfied workforce, and their disruption through AM can lead to a significant decline in work motivation.

Given that the effects on autonomy, competence and relatedness collectively influence work motivation, it is important to examine how AM directly impacts this broader outcome. Whilst the impact on individual psychological needs has already been discussed, this section hypothesises that:

H4: *The mode of task delivery impacts job motivation, such that task delivery by AM leads to lower job motivation than human-performed task delivery.*

2.3.5 Impact of Algorithmic Management on Job Appeal via Job Motivation

The impact of AM also goes beyond work motivation and influences how attractive a workplace is to both current employees and potential new employees. The attractiveness of a workplace is a critical factor in the success of an organisation and affects employee recruitment, retention and overall satisfaction. The relationship between work motivation and job attractiveness is well known. Numerous studies have shown that motivated employees are more likely to rate their workplace favourably (Gagné & Deci, 2005).

2.3.5.1 The Mediating Role of Job Motivation for Job Appeal

Work motivation is an important mediator between the methods of task fulfilment and the attractiveness of the job. If AMS have a negative impact on motivation by reducing autonomy, competence and relatedness, this can have a direct and negative impact on job attractiveness. Vandenberghe et al (2004) point out that employees who feel demotivated are likely to find their work less attractive, resulting in lower job satisfaction and an increased intention to turnover.

A study by Bapuji, Patel and Ertug (2020) supports this view by finding that jobs managed by algorithms are perceived as less attractive, especially when employees feel that their motivation is affected by the inflexible and impersonal nature of AM. This decline in job attractiveness poses significant challenges for companies, especially when it comes to retaining top talent and maintaining a competitive edge in the labour market.

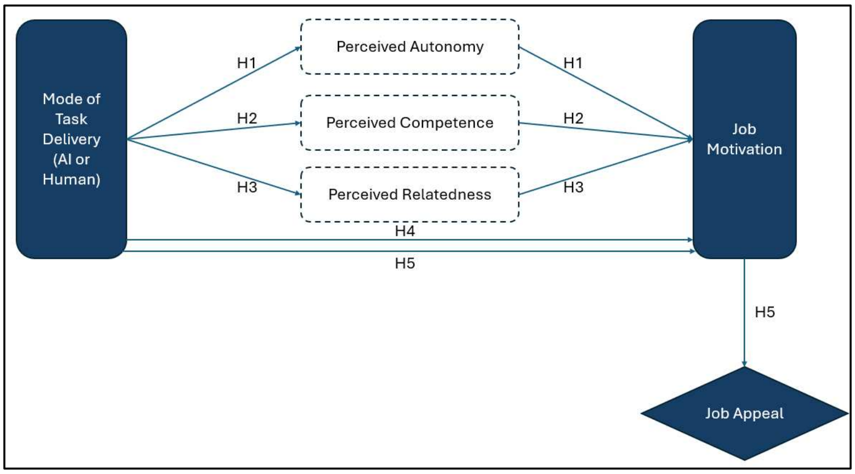
In addition, the perception of AM by employees and job applicants plays a crucial role in determining the attractiveness of jobs. Employees who perceive that AMS will negatively impact their job satisfaction are likely to rate such positions less favourably, even if they have not yet experienced the management style first-hand (Brougham & Haar, 2018). This highlights the need for organisations to carefully manage expectations and perceptions when implementing AMS and ensure that employees feel supported and valued despite the shift to AM. Based on these findings, it is hypothesised that:

H5: *AM as a mode of task delivery in the workplace leads to lower job motivation, which then leads to lower job appeal.*

2.3.6 Conceptual Framework

The combination of these five hypotheses leads to the development of a comprehensive conceptual framework for this thesis. This framework illustrates how the different dimensions of AM impact on the key psychological needs - autonomy, competence and relatedness - as outlined in SDT, and subsequently influence work motivation and job appeal. The integration of these hypotheses provides a structured approach to understanding the complex relationships between mode of task delivery, employee motivation and overall job appeal in algorithmically driven environments. The conceptual framework is illustrated as follows:

Figure 1: Conceptual Framework



3. Methodology

Based on the theoretical foundations and the research questions identified in the literature review, this chapter describes the methodological approach used to investigate the impact of AM on work motivation and job attractiveness. The following sections describe the research design, data collection procedures and analysis techniques used to investigate the study's hypotheses.

3.1 Research Design

Building on previous studies that have investigated how technology influences the perceptions of management and employees (e.g. Jarrahi et al., 2021), a quantitative approach was chosen. The online survey tool Qualtrics was used to conduct the experiment. Online surveys are particularly suitable for this type of research as they allow for quick and efficient data collection from a broad and diverse audience while minimising the logistical challenges associated with in-person experiments, such as scheduling and location constraints (Wright, 2005).

A controlled experimental design was used to investigate the impact of AM on employee motivation. This approach was chosen because it allows the establishment of clear cause-effect relationships by manipulating a key factor - whether a management system is operated by humans or algorithms - and observing its influence on employee motivation (Campbell & Stanley, 1963). The aim was to create a scenario that closely resembles the real work environment, but in a controlled setting in which the effects of AM can be studied in isolation and without being influenced by external variables. The strength of this scenario-based approach lies in the ability to control the narrative and ensure that participants' responses reflect their reactions to the specific leadership style described, rather than their previous experiences or expectations (Aguinis & Bradley, 2014).

The independent variable in this study is the type of management system. One group of participants experienced a scenario managed by a human supervisor, while the other group experienced the same scenario with an algorithmic system. Randomising the participants to these different conditions ensured that any differences in the results were due to the type of management system and not to other factors such as previous experience or personal characteristics of the participants. Randomisation is crucial in experiments of this type as it helps to distribute potential biases equally between the two groups, thereby strengthening the internal validity of the study (Shadish, Cook, & Campbell, 2002).

3.2 Procedure

The experiment began with a consent form explaining the general purpose of the study, the procedure for participation and the expected duration. The description was kept general so as not to influence the participants' responses (Creswell & Creswell, 2017).

Participants were then randomly assigned to one of two groups. The first group was presented with a scenario in which the tasks were led by a human supervisor. In this scenario, the supervisor was described as making task assignments based on their knowledge of the employee's skills, past performance and current workload. The second group experienced a scenario in which tasks were managed by an algorithm. This algorithm was presented as using similar criteria - skills, performance and workload - to assign tasks.

In both scenarios, participants were asked to imagine that they were applying for a white-collar job in the organisation described. This approach helped to make the scenario more personal and relatable and encouraged participants to engage with the material at a deeper level (Dillman, Smyth, & Christian, 2014). After reading the scenario, participants completed a series of questions designed to measure key outcomes such as their perceived autonomy, competence, relatedness, overall work motivation, and job attractiveness. These measures were adapted from established psychological scales, including the Job Diagnostic Survey (Hackman & Oldham, 1975) and the Basic Psychological Need Satisfaction at Work Scale (Deci et al., 2001).

At the end of the survey, participants provided demographic information including age, gender, nationality, education level and current employment status. This information was crucial for understanding the broader context of the results and ensured that the results could be interpreted accurately (Groves et al., 2009). In addition, participants were asked about their prior knowledge of AMS and whether they felt they had paid good attention throughout the survey. These questions were used for quality control to ensure the integrity of the data and to identify potential confounding factors (Podsakoff, MacKenzie, & Podsakoff, 2012).

The survey concluded with a debriefing section that further explained the actual purpose of the study and thanked the participants for their time and contribution.

3.3 Sample

Participants in this study were recruited through a combination of online platforms, social media and personal networks. This recruitment strategy facilitated the recruitment of a diverse group of participants, which is important for the generalisability of the results (Bryman, 2016). Participants were predominantly from Europe, particularly Germany, Austria and Portugal, ensuring a sample representative of the population of interest.

The data collection took place over a period of four weeks and comprised a total of 148 responses. After checking the data for completeness, attention and manipulation, 139 responses were selected for analysis. This sample was then randomly assigned to either the human or algorithm-administered condition, with 70 participants in the HM group and 69 participants in the AM group.

Whilst the demographic profile of participants was narrowed down to the specific focus group, it still included a range of ages, educational backgrounds and work experience. The age of participants ranged from 22 to 31, with an average age of 24. The sample comprised 45% male and 52% female participants, with only a few participants declining to state their age.

3.4 Variable Description

Several key variables were measured to understand how the type of management system (human or algorithmic) affects motivation, perception and job attractiveness. These variables were carefully selected based on their relevance to the research questions and their proven use in similar studies.

3.4.1 Independent Variable

Mode of Task Delivery (human vs. AM): This variable represents the type of management system participants were exposed to in the experimental scenario. In one condition, the tasks were managed by a human supervisor, while in the other condition an algorithmic system was responsible for task allocation. The aim was to investigate how these different approaches influence employees' motivation and perceptions (Jarrahi et al., 2021).

3.4.2 Dependent Variables

Job appeal: Refers to how attractive the job offer was to the participants after they had experienced the scenario. This was determined by asking participants whether they would accept a job offer from the company, request further information or seek an interview. This variable provides insight into how the nature of management influences not only immediate motivation but also the broader attractiveness of a job to potential employees (Deci et al., 2001).

3.4.3 Mediator Variables

Perceived Autonomy, Competence, and Relatedness: These mediator variables were included to explore the underlying processes through which the mode of task delivery affects job motivation and job appeal. These were measured using items adapted from the Basic Psychological Need Satisfaction at Work Scale (Deci et al., 2001). Participants rated their agreement with statements that reflected their sense of, competence, and relatedness on a 5-point Likert scale.

Job motivation: As further mediator variable was measured using items adapted from the Job Diagnostic Survey (Hackman & Oldham, 1975). Participants indicated on a 5-point Likert scale the extent to which they agreed with the statements about their motivation to perform the job described in the scenario.

3.4.4 Control Variables:

Demographics and Familiarity with AM Systems: To ensure that the observed effects were truly due to the experimental manipulation and no other factors, several control variables were measured. These included participants' age, gender, nationality, educational background, and current employment status (Groves et al., 2009). Additionally, participants' prior familiarity with AMSs was assessed to control for any pre-existing knowledge or biases that might influence their responses (Podsakoff, MacKenzie, & Podsakoff, 2012).

4. Results

Building upon the methodological framework outlined in the previous chapter, the following section presents the findings of this study. The results are organized to first address the data preparation process, followed by the detailed analysis of the key hypotheses.

4.1 Data Cleaning and Sample Description

The original survey was distributed to 148 participants, 140 of whom completed the survey in full. To ensure the integrity of the analysis, data cleaning was performed to remove incomplete or inconsistent responses, resulting in a final sample size of 139 participants. This rigorous data cleaning process is essential to maintaining the validity of the research findings and ensures that the final dataset is both reliable and accurate (Hair et al., 2014; Groves et al., 2009).

The demographic composition of the sample was carefully matched to the study's focus on graduates to ensure the relevance and applicability of the findings to this target group. The majority of participants were recent graduates or individuals currently in higher education, reflecting the study's focus on white-collar candidates. The narrow demographic profile was intentional as the study aims to specifically understand the perspectives and experiences of graduates entering the workforce (Creswell & Creswell, 2017).

The gender balance in the sample was almost even, with a slight majority of female participants (72 or 52%) compared to male participants (62 or 45%). A small proportion of the sample identified as non-binary (4 participants), with one participant preferring not to declare their gender.

In terms of education level, the sample was predominantly made up of people with a bachelor’s degree (66%), followed by people with a master's degree (30%). This educational profile is consistent with the study's focus on entry-level workers and makes the sample particularly relevant for examining the transition from education to employment (Groves et al., 2009).

The professional status of the participants underlines their consistency with the study's target demographic. The majority of participants were students (53%), likely recent graduates or those about to graduate. A further significant proportion (40%) were employed in white-collar occupations, highlighting the study's focus on individuals either embarking on or considering a professional career in white collar professions. For further details see Appendix 2.

The age distribution was relatively narrow, with most participants aged between 22 and 31. The most common age was 25, which accounted for 24% of the sample. This distribution is reasonable considering the focus on young professionals and recent graduates.

Participants were predominantly from Europe, with Germany strongly represented at 68%. Other European countries, such as Austria and Portugal, were also represented, although in smaller numbers. Income levels varied, but the majority of participants reported having incomes commensurate with student occupations and early career stage, with 44% earning less than €10,000 per annum. Higher income groups were less well represented, which was to be expected given that the sample was focused on graduates. Detailed demographic data, including nationality and income distribution, can be found in Appendix 2.

4.2 Scale Reliability

To assess the internal consistency of the scales used in this study, Cronbach's alpha was calculated for each of the key constructs (see Table 1): perceived autonomy, competence, relatedness, motivation, and job appeal, as this is a widely recognized measure of reliability that provides information about how well a set of items captures a single underlying construct (Nunnally & Bernstein, 1994).

Table 1: Cronbach's alphas

Scale	Human Management (α)	Algorithmic Management (α)
Autonomy	0.8711240	0.8958772
Competence	0.8830387	0.9158526
Relatedness	0.8882551	0.9422054
Motivation	0.8978341	0.9362090
Job Appeal	0.8755906	0.9212472

As can be seen from the table, the Cronbach's alpha values for both the Human Management (HM) and AM groups were between 0.87 and 0.94, indicating a high level of internal consistency across all constructs (Nunnally & Bernstein, 1994). These results confirm that the scales used in this study are reliable and suitable for further analysis and support the consistency of the constructs measured (DeVellis, 2017).

4.3 Manipulation Check

To ensure that the participants perceived the experimental conditions correctly, a manipulation check was carried out. Participants were asked to indicate whether the task management in their scenario was carried out by a human supervisor or an algorithmic system.

Of 140 participants who completed the survey, 139 correctly identified the management style to which they were exposed, while only one participant did not. A chi-square test confirmed that this distribution was significantly different from chance ($\chi^2 = 136.03$, $p < .001$), indicating that the manipulation was highly effective. This high success rate was to be expected as the group assignment (human or AI) was explicitly displayed to participants during the survey, providing clarity and minimizing confusion about which condition they were in.

As the only misidentification was an outlier, this participant was excluded from further analysis. Exclusion of outliers in cases such as this is a common practice to maintain the integrity of the data and ensure that the results accurately reflect the intended experimental conditions (Field, 2013; Osborne & Overbay, 2004). After exclusion, a final sample size of 139 participants remained, which was used for all subsequent analyses.

4.4 Hypotheses Testing

Having laid the groundwork for data preparation and initial analyses, this section moves into the critical phase of hypothesis testing. Based on the previously established conceptual framework, the following analysis evaluates the proposed relationships between AM and key psychological outcomes.

4.4.1 Hypothesis 1 to 3: The effect of AM on the SDT dimensions

Hypotheses H1 to H3 examine the influence of AM on three important psychological needs: Autonomy, Competence and Relatedness. These hypotheses state that (soon to be) college graduates in white-collar occupations will report lower perceived autonomy, competence, and relatedness in algorithm-driven environments compared to those driven by human supervisors.

Initial analytical approach

The original plan for testing these hypotheses was to apply a parallel mediation model. This model would allow to simultaneously assess the effects of leadership style on perceived autonomy, competence and relatedness (mediators) and then on work motivation. A parallel mediator model is typically used when multiple mediators are expected to act independently and influence the outcome variable in different ways (Hayes, 2013).

However, during the analysis, the parallel mediator model (Model 1) encountered significant problems with data fit. As can be seen in Table 3.

Table 2: Mediator Model fit

	Fit Measure	Value
chisq	Chi-Square	386.356
df	Degrees of Freedom	6.000
pvalue	p-value	0.000
cfi	CFI	0.672
rmsea	RMSEA	0.678
srmr	SRMR	0.193

Specifically, the high correlations among the three mediators suggested multicollinearity problems (see Table 3), which can inflate standard errors and make it difficult to obtain reliable estimates of the mediator effects.

Table 3: Correlation Table

	Variable	Perceived Autonomy	Perceived Competence	Perceived Relatedness
Perceived_Autonomy	Perceived_Autonomy	1.000	0.926	0.925
Perceived_Competence	Perceived_Competence	0.926	1.000	0.929
Perceived_Relatedness	Perceived_Relatedness	0.925	0.929	1.000

Multicollinearity is a common issue when the mediators are conceptually similar or when they are expected to influence each other (Tabachnick & Fidell, 2019).

Adjusted Model: Combining Mediators

Given these challenges, the model was adapted by combining the three mediators (Perceived Autonomy, Competence and Relatedness) into a single composite variable, which is referred to as “Perceived Experience” in Model 2. This approach is supported by the literature, which suggests that mediators that are highly correlated can be combined into a single index to reduce multicollinearity and still provide meaningful insights (Kline, 2015; VanderWeele & Vansteelandt, 2014). Combining these variables helped to improve model fit and reduce issues related to multicollinearity, allowing for a clearer interpretation of the results.

Results and Interpretation

Model 1 (Original Parallel Mediator Model):

Table 4: Results Model 1

Outcome	Predictor	Estimate	Standardized Estimate	p-value
Perceived_Autonomy	Mode_of_Task_Delivery	-1.630	-0.770	<.001
Perceived_Competence	Mode_of_Task_Delivery	-1.567	-0.723	<.001
Perceived_Relatedness	Mode_of_Task_Delivery	-1.716	-0.774	<.001

Perceived Autonomy: AM had a significant negative effect on perceived autonomy (β = -1.630, $p < .001$).

Perceived Competence: AM significantly reduced perceived competence (β = -1.567, $p < .001$).

Perceived Relatedness: AM was also associated with a significant reduction in perceived relatedness (β = -1.716, $p < .001$).

These results indicate that the hypotheses H1, H2, and H3 could be accepted based on this model, as the independent variable (Mode of Task Delivery) significantly influenced each mediator.

Model 2 (Combined Mediator Model):

Table 5: Results Model 2

Outcome	Effect	Predictor	Estimate	Standardized Estimate	p-value
Perceived_Experience	~	Mode_of_Task_Delivery	-1.586	-0.784	<.001
Job_Motivation	~	Perceived_Experience	1.581	1.021	<.001

Perceived Experience: AM had a significant negative effect on the combined "Perceived Experience" variable (β = -1.586, $p < .001$) as it was to be expected after the negative effects on all of its components.

Job Motivation: The combined variable “Perceived Experience” had a significant positive effect on job motivation (β = 1.581, $p < .001$) such that higher perceived experience leads to higher job motivation.

Conclusion

The results of both models lead to the conclusion that hypotheses H1, H2 and H3 are supported. The switch to the combined mediator model was justified due to the high correlations between the mediators and the need for a more stable and interpretable model. While Model 1 provided significant results, the combined Model 2 offered a more robust approach due to less multicollinearity, leading to more reliable estimates (Hayes, 2013; Kline, 2015). The support for H1–3 is further supported by the significant difference in both groups also supported by Welch's t-test results (see Appendix 3).

4.4.2 Hypothesis 4: The effect of AM on job motivation

Hypothesis H4 states that the mode of task delivery - whether by AM or human management - has a significant influence on work motivation. In particular, it states that the handover of tasks by AM leads to lower work motivation than the handover of tasks by a human supervisor.

To test this hypothesis, an analysis of variance (ANOVA) was conducted. ANOVA is a suitable statistical method for comparing mean values between two groups to determine whether there are statistically significant differences (Keppel & Wickens, 2004). In this context, ANOVA was used to compare the mean scores of job motivation between the participants who were guided by AM and those who were guided by a human supervisor.

Table 6: Results ANOVA

Source	Degrees of Freedom	Sum of Squares	Mean Square	F Value	p-value
Mode_of_Task_Delivery	1	164.13	164.13	127.73	<.001

The ANOVA results revealed a highly significant effect of the mode of task delivery on job motivation $F(1, 136) = 127.73$, $p < .001$. This result strongly supports the hypothesis that the mode of task delivery has a significant impact on job motivation, such that task delivery by AM leads to lower job motivation compared to task delivery by human management.

4.4.3 Hypothesis 5: The effect of AM on job appeal

Hypothesis H5 states that the mode of task delivery influences work motivation, which in turn influences the attractiveness of the job. Specifically, the hypothesis states that AM as a type of task delivery leads to lower work motivation and thus to a lower attractiveness of the job.

To test the hypothesis a mediation analysis was conducted. This analysis examined the indirect effect of task delivery mode on job appeal through job motivation, alongside the direct effects of task delivery mode and job motivation on job appeal. Mediation analysis is an appropriate method for this type of hypothesis as it allows for the exploration of the mechanism through which an independent variable (AM as a mode of task delivery) affects a dependent variable (job appeal) via a mediator (job motivation) (Baron & Kenny, 1986).

Table 7: Results Mediation Model

Path	Predictor	Estimate	P-value
Job_Appeal	Mode_of_Task_Delivery	-0.570	0.005
Job_Motivation	Mode_of_Task_Delivery	-2.181	<.001
Job_Appeal	Job_Motivation	0.665	<.001
Job_Motivation	Job_Motivation	1.266	<.001
indirect_effect	a*b	-1.450	<.001
total_effect	c+(a*b)	-2.020	<.001

Job Motivation: The analysis revealed that AM as a mode of task delivery is a strong and significant predictor of job motivation ($\beta = -2.181, p < 0.001$). The negative coefficient suggests that AM significantly decreases job motivation.

Job Appeal: Job motivation significantly predicted job appeal ($\beta = .665, p < .001$), with higher job motivation associated with higher job appeal. Additionally, the indirect effect of task delivery mode on job appeal through job motivation was significant (indirect effect = -1.450, $p < .001$), indicating that AM decreases job appeal by reducing job motivation.

Total Effect: The total effect of AM on job appeal (combining both direct and indirect effects) was significant (total effect = -2.020, $p < 0.001$), confirming that AM reduces job appeal overall.

These results support the hypothesis, showing that AM as a mode of task delivery negatively impacts job appeal, primarily through its detrimental effect on job motivation.

5. Discussion

The main objective of this study was to investigate how AM affects key aspects of employee motivation of graduates or prospective graduates in white-collar occupations. Five hypotheses were tested, focussing on the relationship between AM and perceived autonomy, competence, relatedness, work motivation and work attractiveness.

H1-H3: The original analysis plan included a parallel mediator model to test the impact of AM on perceived autonomy, competence and relatedness, with work motivation as the dependent variable. However, the model had significant problems due to the high correlations between the mediators, resulting in poor model fit. This problem is not uncommon in psychological research, as related constructs can exhibit multicollinearity, complicating their independent effects (Tabachnick & Fidell, 2013). To address this issue, the mediators were combined into a single composite variable representing an aggregate of perceived psychological need satisfaction. This revised model showed a significant negative effect of AM on the combined mediator, which in turn significantly reduced work motivation. This suggests that AM has a negative impact on the psychological needs that are essential for promoting motivation at work.

H4: The ANOVA results provided robust evidence that AM significantly decreases work motivation compared to human management. The F-value was highly significant, indicating a strong effect size. This result is in line with previous research highlighting the potential drawbacks of reducing human interaction in management, which can lead to feelings of alienation and lower motivation (Brynjolfsson & McAfee, 2014).

H5: The mediation model for H5 revealed that work motivation mediates the relationship between AM and job attractiveness. The model suggests that while AM directly reduces job attractiveness, a significant part of this effect is mediated by its impact on work motivation. This finding is consistent with the broader organisational behaviour literature, in which work motivation is often a key determinant of job attractiveness and employee retention (Judge & Kammeyer-Mueller, 2012).

5.1 Theoretical Implications

This study makes an important contribution to the fields of organisational behaviour and management science, in particular by examining the impact of AM on work motivation and job attractiveness among graduates entering white-collar occupations. In particular, the study builds on the SDT framework (Deci & Ryan, 2000), which emphasises that autonomy, competence and relatedness are critical factors for intrinsic motivation. The challenges faced by the parallel mediator model in this study highlight the inherent interconnectedness of these psychological needs and reaffirm that they do not function independently but are interdependent, as suggested by Deci and Ryan (2000). By consolidating these factors into a single construct, this study contributes to our understanding of how motivation functions in algorithm-driven environments.

Importantly, this study offers new insights into the impact of AM on job attractiveness, a topic that has not been adequately explored in the literature. While much of the previous research has focused on the gig economy (Kellogg, Valentine, & Christin, 2020), this study shifts the focus to white-collar occupations and college graduates - a population that is able to experience AM systems in their early career stages. By targeting this group, the study adds to the growing literature by examining how AM affects not only motivation but also the overall attractiveness of a workplace, a key factor in recruitment and retention.

Whilst AM is often used for improving operational efficiency, this study highlights the significant cost it can have on employee wellbeing. Morgeson and Humphrey (2006) suggest that the reduction in perceived autonomy is a critical issue, and this research confirms these findings. The reduced sense of control and connectedness observed in this study extends the discussion beyond the gig economy into more traditional employee contexts and provides a broader perspective on how AM can affect workplace dynamics in different sectors.

Furthermore, the study's focus on job attractiveness as a result of AM adds an important dimension to the ongoing debate about automation and human motivation. Brynjolfsson and McAfee's (2014) concerns about the potential for automation to reduce job satisfaction are supported here, particularly through the lens of how AM affects employee engagement and desire to remain in a position. This contribution is critical as organisations increasingly rely on AM systems and it is therefore crucial to understand the wider organisational implications, including talent retention.

To summarise, this study not only underpins existing theories in the fields of motivation and management science, but also extends them by providing new empirical evidence on the impact of AM on employee motivation and job attractiveness in white-collar occupations. These findings are crucial for both academics and practitioners seeking to balance the efficiency gains of AM with the need to maintain a motivated and engaged workforce.

5.2 Managerial Implications

The practical implications of this research are essential for managers and organizations contemplating the introduction or expansion of AMSs. While AM offers clear benefits such as efficiency, cost reduction, and consistency, this study brings to light the potential drawbacks related to employee motivation and job attractiveness.

Improving job attractiveness is particularly important, as the study suggests that the efficiency gains brought by AM could be offset by a decrease in motivation if employees perceive these systems as limiting their autonomy, competence, and sense of connectedness. Organizations must recognize that a purely algorithmic approach may diminish employee engagement and should consider hybrid models that blend AM with elements of human control. For instance, allowing employees to influence algorithmic decisions or incorporating more personalized feedback can help sustain, or even enhance, motivation in the workplace (Ryan & Deci, 2017).

Likewise, fostering job appeal in an AM context becomes crucial. Managers should focus on designing AM systems that are transparent and inclusive, ensuring employees understand how decisions are made and that their contributions are valued. By promoting a sense of ownership and engagement, organizations can enhance the attractiveness of positions managed by AM, making them more appealing to both current staff and prospective hires (Gagné & Deci, 2005).

Retention of talent also emerges as a key concern, as the findings suggest that AM could have a negative impact on retaining employees if not handled with care. Given that job attractiveness plays a significant role in retention, organizations need to be mindful of the risks associated with AM. To counteract these risks, companies should consider strategies such as regular check-ins with HR, offering professional development opportunities, and ensuring clear communication regarding the role and scope of AM. Thoughtfully tailoring these systems to the needs of employees will likely lead to better outcomes for both employers and their workforce.

6. Limitations

Despite the valuable insights provided by this study, several limitations must be acknowledged. One key limitation is the composition of the sample. The study focuses on university graduates entering white-collar professions, which restricts the generalizability of the findings. While this demographic aligns well with the objectives of the research, the results may not fully apply to other groups, such as blue-collar workers or individuals from different cultural contexts. To enhance the applicability of these findings, future research should consider expanding the scope to include a more diverse range of participants, ensuring broader validation and extension of the results (Smith & Nichols, 2015).

Another limitation arises from the study's experimental design. Although the controlled nature of the experiment allows for effective isolation of the effects of AM, it falls short in reflecting the full complexity of AM systems as implemented in real-world settings. The actual deployment of AM can vary greatly depending on industry, organizational culture, and specific use cases. Future studies might benefit from using longitudinal designs to examine how AM influences motivation and job attractiveness over time, offering a deeper understanding of how employees adapt to or resist these systems. Such an approach could provide more nuanced and dynamic insights into the ongoing interaction between employees and AM.

The scenarios described in the study were intentionally brief to maintain participant engagement, but this brevity may have introduced a degree of bias. Participants might have filled in gaps with their own perceptions and preconceptions about artificial intelligence, potentially skewing the results. This is particularly relevant given the rapid advancements and widespread awareness of AI technologies like ChatGPT. Participants, especially those with higher levels of education, may have held strong opinions about AI, viewing it either as a threat to job security or as a tool for enhanced efficiency. Future research should aim to present more detailed scenarios to better control for these preconceived notions, ensuring a clearer understanding of how AM truly impacts motivation.

Finally, the issue of multicollinearity among the mediators—autonomy, competence, and connectedness—presented a significant challenge during the analysis. The decision to combine these into a single construct was necessary to address the problem, but it limited the specificity and granularity of the findings. Future research could explore alternative approaches to addressing multicollinearity, such as structural equation modelling or employing larger, more diverse samples. These methods might offer better opportunities to disentangle the complex relationships between these key motivational factors (Tabachnick & Fidell, 2013).

7. Future Research

Building on the limitations identified, future research could expand on this study by exploring various areas to deepen our understanding of the impact of AM on work motivation and job appeal. One potential direction is to examine additional mediators that might influence the relationship between AM and work outcomes, such as job satisfaction, organizational commitment, or perceived fairness. These variables could provide further insights into the mechanisms by which AM affects employee attitudes and behaviours. Including such mediators would help clarify the pathways through which AM impacts different dimensions of employee well-being, offering a more comprehensive view of its effects.

Another valuable avenue for future research involves moving beyond controlled experimental designs to consider longitudinal and real-world studies. Such research could track how employees' perceptions and behaviours change over time as they are continuously exposed to AMSs. This approach would offer richer insights into the long-term effects of AM on work motivation and job attractiveness, helping to capture the evolving nature of employee experiences in dynamic work environments.

As AMSs become more sophisticated, there is also a growing need to explore how these systems can be personalized to align better with individual employee preferences and ethical standards. Future research should investigate how transparent, fair, and adaptable AMSs can be designed to meet the diverse needs of different employee groups. This would include a focus on ethical considerations, ensuring that AM systems operate in a manner that respects fairness and inclusivity in the workplace (O'Neil, 2016).

While this study provides valuable insights into the current impact of AM on work motivation, it is important to recognize that these findings represent only a snapshot of the current landscape. With the rapid advancements in generative AI and its increasing integration into the workplace, the dynamics explored in this research may evolve significantly in the near future. Future studies should continue to monitor these developments, as the influence of AM on employee motivation could shift in unexpected ways, potentially altering the balance between efficiency and employee well-being. Ongoing research is crucial for understanding and adapting to these rapid changes in workplace dynamics.

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V. Appendix

Appendix 1: Survey Questionnaire

Dear participant,

thank you for participating in my study!
This research study is being conducted as part of my master thesis at Católica Lisbon. This survey is

expected to take **5 minutes to complete**, and your participation is voluntary and anonymous. The data collected will be kept strictly confidential and will only be used within this study.

Do you consent to take place in this survey

- ○ Yes
- ○ No

End of Block: Introduction

Start of Block: Definitions

I am investigating in the **white-collar job market,** first a quick **definition** for a common understanding:

A **white-collar job** typically refers to a position that involves administrative or managerial work. These jobs are usually performed in an office environment and do not involve manual labour. Examples include roles in finance, marketing, legal services, and administration. White-collar workers are often associated with higher education and professional skills.

End of Block: Definitions

Start of Block: Seeking

Are you currently in, or seeking a job in a white collar profession?

- ○ Yes
- ○ No

End of Block: Seeking

Start of Block: Scenario AM

Before we start with the scenario description here one **last definition** for a common understanding since I am investigating the impact of **algorithmic management in the white-collar job market:**

Algorithmic management is an innovative and increasingly prevalent approach in modern workplaces characterized by the use of sophisticated algorithms to make decisions traditionally made by human managers. This management style primarily focuses on three critical tasks: team allocation and management, task allocation, and performance monitoring, each leveraging technology to streamline operations and enhance productivity

Page Break

Now follows a scenario description. Imagine you are on the job market and read an offer. Here is a detail from it, please take your time to read it carefully and answer the questions that follow to your best understanding:

You will be part of a team working on a critical project. In this company, an **Algorithmic Management System is used** for task and team allocations. This system considers each team member's skills, past performance, and current workload to distribute tasks and form sub-teams efficiently.
Feedback on your performance is provided continuously by the Algorithmic Management System, based on real-time data. This feedback is specific and actionable, helping you improve and stay aligned with project goals.

End of Block: Scenario AM

Start of Block: Scenario Human

Now follows a **scenario description**. Imagine you are on the job market and read an offer. Here is a detail from it, please take your time to **read it carefully** and answer the questions that follow to your best undestanding:

You will be part of a team working on a critical project. In this company, **a typical manager** is responsible for task and team allocations. The manager considers each team member's skills, past performance, and current workload to distribute tasks and form sub-teams efficiently.
Feedback on your performance is provided regularly by the Human Manager, based on their observations. This feedback is specific and actionable, helping you improve and stay aligned with project goals.

End of Block: Scenario Human

Start of Block: Main Questions AM

Please indicate how much you agree with the following statements, on a scale from 1 (strongly disagree) to 5 (strongly agree).
Keep in mind that the job role described is managed by an Algorithmic Management System

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I would feel like I can be myself at my job	○	○	○	○	○
I would feel free to express my ideas and opinions in this job	○	○	○	○	○
At this work, I would often feel like I have to follow other people's commands	○	○	○	○	○
If I could choose, I would do things at work differently	○	○	○	○	○
The tasks I would have to do at work are in line with what I really want to do	○	○	○	○	○
I would feel free to do my job the way I think it could best be done	○	○	○	○	○
In this job, I would feel forced to do things I do not want to do	○	○	○	○	○

Please indicate how much you agree with the following statements, on a scale from 1 (strongly disagree) to 5 (strongly agree).
Keep in mind that the job role described is managed by an Algorithmic Management System

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I would feel competent in this job	○	○	○	○	○
I would doubt whether I am able to execute this job properly	○	○	○	○	○
I would have the feeling that I can even accomplish the most difficult tasks at this work	○	○	○	○	○
I would really master my tasks at this job	○	○	○	○	○
I wouldn't really feel competent in this job	○	○	○	○	○
I would be good at the things I do in this job	○	○	○	○	○

Page Break

Please indicate how much you agree with the following statements, on a scale from 1 (strongly disagree) to 5 (strongly agree).
Keep in mind that the job role described is managed by an Algorithmic Management System

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
At this work, I would feel part of a group	○	○	○	○	○
At this work, there would be people who really understand me	○	○	○	○	○
At this work, no one would care about me	○	○	○	○	○
There is nobody I could share my thoughts with if I would want to do so	○	○	○	○	○
I wouldn't really feel connected with other people at my job	○	○	○	○	○
I wouldn't really mix with other people at my job	○	○	○	○	○
At this work, I could talk with people about things that really matter to me	○	○	○	○	○
I would often feel alone when I am with my colleagues	○	○	○	○	○
At this work, people would involve me in social activities	○	○	○	○	○
Some people I would work with would be close friends of mine	○	○	○	○	○

Page Break

Please indicate how much you agree with the following statements on a scale from 1 (none at all) to 7 (completly).
Keep in mind that the job role described is managed by an Algorithmic Management System

	None at all	Very little	A little	moderatly	strongly	very strongly	completly
I would put a lot of effort into this job, because I would have fun doing this job.	◯	◯	◯	◯	◯	◯	◯
I would put a lot of effort into this job, because what I would do in my work would be exciting	◯	◯	◯	◯	◯	◯	◯
I would put a lot of effort into this job, because the work I would do is interesting.	◯	◯	◯	◯	◯	◯	◯
I do little because I don’t think this work would be worth putting efforts into.	◯	◯	◯	◯	◯	◯	◯
I would not put a lot of effort into this job, because I really feel that I'm wasting my time at this job	◯	◯	◯	◯	◯	◯	◯
I don’t know why I would be doing this job, it’s pointless work	◯	◯	◯	◯	◯	◯	◯

Page Break

Please indicate how much you agree with the following statements on a scale from 1 (strongly disagree) to 7 (Strongly agree).
Keep in mind that the job role described is managed by an Algorithmic Management System

	strongly disagree	Disagree	somewhat disagree	neighter agree or disagree	somewhat agree	agree	strongly agree
I would accept a job offer from this company	◯	◯	◯	◯	◯	◯	◯
I would request more information about this company	◯	◯	◯	◯	◯	◯	◯
If this company visited campus I would want to speak with a representative	◯	◯	◯	◯	◯	◯	◯
I would attempt to gain an interview with this company	◯	◯	◯	◯	◯	◯	◯
I would actively pursue obtaining a position with this company	◯	◯	◯	◯	◯	◯	◯
If this company was at a job fair I would seek out their booth	◯	◯	◯	◯	◯	◯	◯

End of Block: Main Questions AM

Start of Block: Manipulation1

Please select the Management style described in your scenario

◯ Algorithmic Management

◯ Human Supervisor

To make sure you read this question carefully, please select “Agree”

- Strongly disagree
- Disagree
- Agree
- Strongly agree

End of Block: Attention

Start of Block: Demo AM

How familiar were you with the concept of Algorithmic Management before this survey

- Not familiar at all (1)
- Slightly familiar (2)
- Moderately familiar (3)
- Very familiar (4)
- Extremely familiar (5)

Page Break

What’s your gender?

- Male
- Female
- Non-binary / third gender
- Prefer not to say

*

What is your age?

____

Please specify your nationality

- ○ German
- ○ Portuguese
- ○ Austrian
- ○ Other European Country
- ○ Other Country ________________________________

What is the highest level of education you have completed or the highest degree you have obtained?

- ○ Less than high school
- ○ High school graduate
- ○ Bachelor Degree
- ○ Master Degree
- ○ Doctorate
- ○ Professional degree
- ○ Prefer not to say

What is your yearly income after taxes?

- ◯ Less than €10,000
- ◯ €10,000 - €19,999
- ◯ €20,000 - €29,999
- ◯ €30,000 - €39,999
- ◯ €40,000 - €49,999
- ◯ €50,000 - €74,999
- ◯ €75,000 - €99,999
- ◯ €100,000 - €150,000
- ◯ More than €150,000
- ◯ Prefer not to say

What is your current employment status?

- ◯ Employed full time (in a white collar profession)
- ◯ Employed full time (in another profession)
- ◯ Freelancer
- ◯ Retired
- ◯ Student
- ◯ Disabled
- ◯ Other ____

End of Block: Demo AM

Start of Block: Thank you message

Please press the "Next" button to finish

Thank you for participating in this survey! Your responses have been transmitted. The goal of this study was to measure how Algorithmic Management Systems influence employee motivation in white collar environments. Therefore, participants were randomly assigned to an AI supervised scenario and a human supervised one and then asked questions about their motivation. If you have any questions or comments, do not hesitate to send me an email via s-ykirn@ucp.pt. Thank you very much again and have a great day!

Appendix 2: Sample Demographics

Gender Distribution

Gender	Count	Percentage
Male	62	44.6
Female	72	51.8
Non-binary/Third Gender	4	2.9
Prefer not to say	1	0.7

Country Distribution

Country	Count	Percentage
Germany	94	67.6
Portugal	19	13.7
Austria	20	14.4
Other European Country	4	2.9
Other Country	2	1.4

Education Level Distribution

Education Level	Count	Percentage
Less than Highschool	0	0.0
Highschool	4	2.9
Bachelor	91	65.5
Masters	42	30.2
PhD	0	0.0
Professional Degree	1	0.7
Prefer not to say	1	0.7

Employment Status

Employment Status	Number of Participants	Percentile Abundance (%)
FT - White Collar	56	40.29
FT - Other	7	5.04
Freelancer	0	0.00
Retired	0	0.00
Student	74	53.24
Disabled	0	0.00
Prefer not to say	1	0.72

Income Distribution

Income	Count	Percentage
< 10.000€	61	43.9
10.000€ - 19.999€	9	6.5
20.000€ - 29.999€	9	6.5
30.000€ - 39.999€	9	6.5
40.000€ - 49.999€	13	9.4
50.000€ - 74.999€	23	16.5
75.000€ - 99.999€	7	5.0
100.000€ - 149.999€	1	0.7
> 150.000€	0	0.0
Prefer not to say	7	5.0

Age Distribution

Age	Count	Percentage
22	1	0.7
23	6	4.3
24	17	12.2
25	31	22.3
26	28	20.1
27	27	19.4
28	13	9.4
29	12	8.6
30	2	1.4
31	2	1.4

Appendix 3: Welch's Test Results

T-Test Results for Each Scale

Scale	t-value	p-value	Mean (Human Management)	Mean (Algorithmic Management)
Autonomy	-14.22679	0	3.921325	2.285714
Competence	-12.34417	0	3.942029	2.366667
Relatedness	-14.40092	0	4.001449	2.285714
Motivation	-11.34430	0	5.348039	3.166667
Job Appeal	-10.43059	0	5.458333	3.438095