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A QUALITATIVE STUDY ON ALGORITHMIC MANAGEMENT IN THE CONSULTING INDUSTRY

Key Words: Algorithmic Management, Algorithmic Functions, Sociotechnical Moderators, Digital Mindset, J D-R

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Abstract

Due to the rise of big data and networking capabilities, information systems can now automate management practices and perform complex managerial tasks such as goal setting, monitoring, job termination, deciding compensation, and managing performance together categorized as algorithmic management. The emergence of algorithmic management functions is postulated to affect several work design characteristics and this study explores a subset containing autonomy, task variety, task significance, feedback from job, job complexity, workload, social support, and emotional demands. The novelty in our research is twofold, firstly, we explore AM within the under researched industry of consulting, secondly, we hypothesize that having a set of skills termed digital mindset influences support for AM amongst employees. Building on previous research, we incorporate socio-technical moderators, namely, system transparency, system fairness, and human influence to address the most important parameters for optimal work design as identified in the Parent-Parker and Rochleau's conceptual model. The qualitative study comprises 14 interviews across India, Sweden, and the United States. Empirical evidence finds that a digital mindset increases the propensity to support algorithmic management and human influence is deemed paramount amongst the three moderators. Additionally, the five functions are categorized into three scopes based on fit for automation. Algorithmic goal setting and monitoring are placed into high scope, followed by algorithmic monitoring and job termination in moderate and algorithmic compensation in the low scope category.

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Definitions

Table 1: Definitions

Concept	Definition
Socio-Technical Systems	A perspective that organizations are made up of people producing products or services using some technology, that affects the operation of the technology as well as the actions of the people operating it.
Socio Technical Moderators	Parameters affecting algorithmic management that help to create well-designed jobs
The Digital Mindset	A set of attitudes and behaviors that enable people and organizations to see how data, algorithms, and AI open up new possibilities for success in a business.
Algorithmic Functions	A set of six managerial functions executed by algorithms.
Monitoring	It includes algorithms used in systems aiming to collect and report any data on employees during their work.
Goal-Setting	It incorporates algorithms assigning tasks or rides, organizing employees' work, or setting performance or productivity targets.
Performance Management	It is the process of algorithms carrying out and/or displaying employees' performance ratings or providing automated performance feedback.
Scheduling	It refers to algorithms carrying out employee's schedules or sending nudges for suggested working times.
Compensation	It is the automated calculation of pay based on algorithmically managed conditions and metrics.

Job termination	Activities like algorithmic termination decision making and/or announcement are part of this category.
The 30-percent Rule	The minimum threshold of acquiring knowledge and skills in a domain to achieve mastery.
Computation	Knowledge related to coding and programming languages.
Collaboration	Knowledge related to use of applications for working with others virtually.
Change	A set of attitudes and beliefs of an individual that motivates them to upskill themselves in a digital world.

Table of Contents

Executive Summary

This study explores the topic of algorithmic management in the consulting industry. Five human resource management (HRM) functions, namely monitoring, goal setting (task allocation), performance management, compensation, and job termination are researched. Previous research has highlighted the challenges of garnering support for algorithmic management (AM) from employees. Our study provides a fresh perspective, revealing that individuals with a digital mindset are more receptive to AM adoption. To successfully implement AM, firms should prioritize digital skill development, like coding and collaboration skills among employees and employ effective change management strategies. HR departments can enhance their hiring evaluations by considering the digital mindset.

Moreover, evidence suggests a positive correlation between team size and the potential for automation. However, firms must carefully determine the optimal level of automation, as complete automation often lacks support. Therefore, systems should allow for human intervention, leveraging automation highlighting the long-term learning and development value add for employees rather than mere surveillance or profit maximization. Additionally, maintaining in-person communication channels remains essential, while certain processes like compensation resist dynamic automation due to standardization.

For consulting firms considering AM implementation,. algorithmic monitoring may encounter resistance from employees but could be embraced if geared towards workload regulation and stress reduction with consent. Utilizing algorithms as supportive tools for synthesizing performance data alongside human-generated feedback may enhance acceptance. Exclusive algorithmic management of performance or job termination lacks support, highlighting the importance of human oversight and control. Algorithmic goal setting could be welcomed for its potential to facilitate task discovery and enhance efficiency, but caution is warranted to ensure human input and consultant autonomy are preserved.

Ultimately, successful AM integration hinges on maintaining human influence over these systems, fostering trust between employees and algorithms.

1. Introduction

1.1. Background

The rise of big data and networking capabilities, information systems can now automate management practices and perform complex tasks that were previously the responsibility of middle or upper management (Mohlmann & Zalmanson, 2017). Organizations in both private and public sectors are increasingly relying on algorithms to automate various decision-making processes (Ammitzbøll et al., 2020; Wang et al., 2021), and such mass scale usage of algorithms is disrupting most, if not all sectors of the economy. Management, like the combustion engine, is a mature technology that must now be reinvented for a new age (Gary Hamel; Moon Shots for Management 2009). This has sparked the development of Scientific Management 2.0 (McDonald, 2011) and consequently paved the way for Algorithmic management (AM). Algorithmic management refers to a system of control where algorithms are given the responsibility for making and executing decisions affecting labor, thereby limiting human involvement and oversight of the labor process (Duggan, Sherman, Carbery, & McDonnell, 2020, p. 6). This paper aims to build upon the framework of the conceptual model for AM that integrates algorithmic functions, socio-technical systems (STS) moderators, and the J D-R model by hypothesizing the precursory role of a new variable termed as *digital mindset* to study effects of AM on J D-R model (Parent-Rocheleau & Parker, 2021; Neeley & Leonardi, 2022).

Existing research derived largely from the gig-economy has found negative effects of AM use on employees for all six functions (ibid). All functions lead to decrease in autonomy of workers, the effect on other key job resources and demands is variable (Jabagi, Croteau, Audebrand, & Marsan, 2019). Mainly two AM functions are attributed with significant consequences for job demands i.e. scheduling and performance management. A preliminary AM literature review revealed a research gap of studying AM in the consulting industry and heavy reliance on the gig-economy and platform work (Keith et al., 2019; Kirven, 2018; Lehdonvirta, 2018). Hence, we augmented our research purpose to first test the conceptual model in more traditional work settings like the consulting industry, and second to explore any influence of the aforementioned variable.

1.2. Knowledge Gap

First, the emerging literature on the topic is spread across different streams of research and conceptual approaches, and has mainly examined one algorithmic function at the time, lacking theoretical integration. Two examples of such studies which lack theoretical integration are "Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management" (Lee et al., 2015) and "Perceived Organizational Support in the Face of Algorithmic Management: A Conceptual Model" (Jabagi et al., 2019) are examples of typical AM studies lacking theoretical integration.

Second, empirical research has focused on the context of gig work, such that AM in traditional work contexts has been overlooked. In the context of gigwork where several task functions rely on individual customer demand and satisfaction with little autonomy over task allocation processes (Gerber & Krzywdzinski, 2019; Gregory, 2020; Griesbach et al., 2019) making it contextually different from traditional work settings, in this case consulting industry.

The lack of theoretical integration combined with the lack of research in the service industry are the foundational research gaps in the field of AM. Additionally, the AM conceptual model lacks empirical validation due to its limited integration into AM research (Parent-Rocheleau et al., 2023). Given the development of most AM literature outside the professional service industry our research will bridge that knowledge gap.

1.3. Research Purpose and Research Question

The purpose of this research project is twofold and will be fulfilled as part of a qualitative study.

Firstly, we aim to bridge the knowledge gap identified previously by testing the conceptual model for algorithmic management in the consulting industry as prior research conducted about the subject in gig economies approaches algorithmic management functions differently (see Section 1.2).

Secondly, we propose a new dimension for the AM conceptual model. We plan to investigate the influence of the variable *digital mindset* on employee support for algorithmic management (Neeley & Leonardi, 2022).

RQ: *How does the conceptual model for algorithmic management fare in a consulting work setting?*

1.4. Focus and Delimitations

The primary objective of the research project is to uncover opinions about effects of AM in the consulting sector to facilitate the shift in research towards white collar professionals.

This study excludes researching the "scheduling" function due to differences between the gig-economy and consulting industry, the latter having work design characteristics that mitigate the scope of algorithmic nudges, for example, consulting firms' dependence on clients is not the same as workers on ridesharing or food-delivery platforms. Additionally, we exclude role clarity as a task characteristic, problem-solving as a knowledge characteristic and physical demands as identified in the conceptual model (Figure 1) due to difficulty in procuring sensitive information as well as difference in job demands between gig-work and traditional work.

This qualitative study is carried across participants from India, Sweden and the United States and acknowledges the differences in work-cultures and other social norms (Galinha et al., 2016). The compelling discovery of empirical evidence to support the addition of the *digital mindset* variable, requires statistically significant results across a large sample population, however, in this study we are limited to exploratory interviews to investigate any relevant trends that can be useful for future quantitative research projects.

A bias affecting our study could be non-response error, where non-respondents in the intended sample differ from those who are willing to participate in the research. Given we are only interviewing participants who are willing, we may be omitting a large proportion who are not and whose responses may differ significantly from those we interview primarily due to differences in level of interest.

2. Literature Review

2.1. Emergence of Algorithmic Management

Algorithmic management (AM) is a diverse set of technological tools and techniques that structure the conditions of work and remotely manage workforces (Mateescu et al., 2019). An algorithm functions independently, utilizing statistical models or decision rules to make decisions without direct human intervention. (Duggan, et al., 2020). Algorithms are used in many data-based systems used in HRM and management (Cheng & Hackett, 2019; Duggan et al., 2020; Leicht-Deobald et al., 2019).

The term algorithmic management was coined in a qualitative study of Uber and Lyft drivers, which was the first study looking at social, psychological and organizational factors that shaped adoption of new technological practices at a workplace (Lee et al., 2015). Since its inception, empirical research has focused AM research in gig, on-demand, and platform economies (Shapiro, 2017; Rosenblat, 2018; Lehdonvirta, 2018 etc.). While research hasn't diversified in terms of industry choice, it has expanded considerably from the perspective of management theory. The research by Curchod et al., (2019) explored power asymmetries in platform economies highlighting inefficiencies in the absence of human interaction. In another paper, Dietvorst et al., (2018) focused on studying decision making through AM and found acceptance of AM if people are given autonomy to modify algorithms. The little research conducted in more traditional work settings, it has largely focused on use of IT systems for surveillance in industries like telecommunications, fashion retail, finance (Leclercq-Vandelannoitte, 2015; Son, H., 2015; Moore & Hayes, 2017; Van Oort, 2018).

2.2. Use of Algorithms in Human Resource Management

Within algorithmic management systems, algorithms form and automatically execute a range of managerial decisions (Mohlmann & Zalmanson, 2017). Parent-Rocheleau and Parker (2021) synthesize six key managerial functions and HRM activities namely, *monitoring, goal setting, performance management, scheduling, compensation* and *job termination.* In particular, HRM scholars have examined the role of algorithms in performance management and compensation scheduling. (Duggan, et al., 2020; Schneider & Harknett, 2019; Strohmeier & Piazza, 2015; Tambe et al., 2019), meanwhile, monitoring, goal-setting, and job termination have been explored within the management field (Kellogg et al., 2019; Robert et al., 2020); Schafheitle et al., 2020).

While AM systems provide benefits in data collection and analysis, they also raise significant ethical and psychological concerns relating to employee autonomy, job complexity, and surveillance. (Evans & Kitchin, 2018; Kellogg et al., 2020). Algorithmic goal setting has raised concerns and linked with reduction of autonomy. In gig work individuals value autonomy, particularly in task selection, algorithms use KPIs to evaluate workers and allocate tasks according to satisfaction rates leading to reduction in autonomy (Gerber & Krzywdzinski, 2019; Gregory, 2020; Griesbach et al., 2019). While it provides efficiency and precision in task allocation, it also presents challenges concerning worker autonomy, job complexity, physical demands, and job security. Performance management enhances the quantity and accuracy of useful feed provided to employees, potentially increasing role clarity. Nevertheless, workers frequently view algorithmic feedback as unfair, opaque, or irrelevant (Gerber & Krzywdzinski, 2019; Greenwood, Adjerid, & Angst, 2019). AM enhances performance management, however, it presents challenges related to fairness, autonomy, job security, emotional demands, and workload when utilized to calculate workers' pay through customer reviews (Griesbach et al., 2019; Rani & Furrer, 2021). Workers have expressed concerns about the reliance on algorithms for compensation, citing a decrease in autonomy, perceived significance of tasks, and increased workloads in the pursuit of efficiency and productivity (Newman et al., 2020). Lastly, the capability of algorithms to facilitate job termination has found managerial support, but heightens job insecurity perceptions (Van Doorn, 2017; Van Oort, 2019) and strong lack of support against increasing datafication (Rani & Furrer, 2021; Williams & Beck, 2018).

Despite the negative consequences associated with AM use, strategically integrating algorithms into HRM activities offers significant potential for improving organizational effectiveness, optimizing workforce management, and fostering sustainable business success in the digital age through the ethical design of AM systems (Cheng & Hackett, 2019).

2.3. The Business Ethics of Algorithmic Management

Data has been referred to as “the new oil” (Tarnoff 2017; Thorp 2012). Organizations must leverage algorithms effectively.(Gillespie 2014). Scholars (Martin and Freeman, 2003) and critical algorithm studies (Ananny, 2016; Kitchin, 2017; Willson, 2017) have extensively investigated the challenges of ethical AM implementation. Privacy, accountability, transparency, power asymmetry are examples of issues problematized in previous research. (Martin and Nissenbaum 2016; Diakopoulos 2016; Neyland 2015; Ananny and Crawford 2018; Martin 2018; Stohl et al. 2016; Beer 2016; Neyland and Möllers 2017; Boyd and Crawford 2012).

Evidently, numerous challenges and constraints emerge regarding the utilization of algorithms in HRM practices. Fortunately, research focusing on overcoming such constraints is simultaneously getting popular in the field. Tambe et al. (2019) identified constraints which explored the importance of *fairness* for completion of HR tasks using algorithms. Kim et al. (2019) focused on improving acceptance of AM by increasing accountability through *transparency.* According to Shin and Park (2019) transparency and fairness play a crucial role in gaining trust of employees subject to AM. Finally, Dietvorst et al., (2018) provides strong empirical evidence for

AM support when a degree of human modification and control is permitted even if the algorithms are imperfect. The possibility to have a human watchdog to take control when something goes wrong makes an important difference towards AM as observed in the (Backhaus, 2019. The emerging human-in-the-loop literature about algorithmic decision-making underscores the importance of *human influence* within AM (Aoki, 2021; Grønsund & Aanestad, 2020).

3. Theoretical Framework

3.1. Theory Usage

This study utilizes primarily the conceptual model for algorithmic management as conceived by Parent-Rocheleau and Parker (2022). Firstly, the conceptual model (Figure 1) has identified six HRM functions, i.e. monitoring, goal setting, performance management, scheduling, compensation, and job termination. Secondly, it includes three STS moderators, i.e. system transparency, system fairness, and human influence.

The AM functions are equated to key job resources and key job demands (Demerouti et al., 2001) . To assess job resources we focus on characteristics such as autonomy, feedback, task significance, task variety, job complexity, and social support (Morgeson and Humphrey, 2006). To assess emotional demands, we focus on workload, emotional demands and job insecurity (ibid).

For the purpose of our research, we later update the conceptual model (see Figure 7) to indicate the exploratory component of the study to assess the influence of an additional variable – *the digital mindset* of individuals (Neely and Leonardi, 2019).

3.2. The Relationship between AM Functions and J D-R

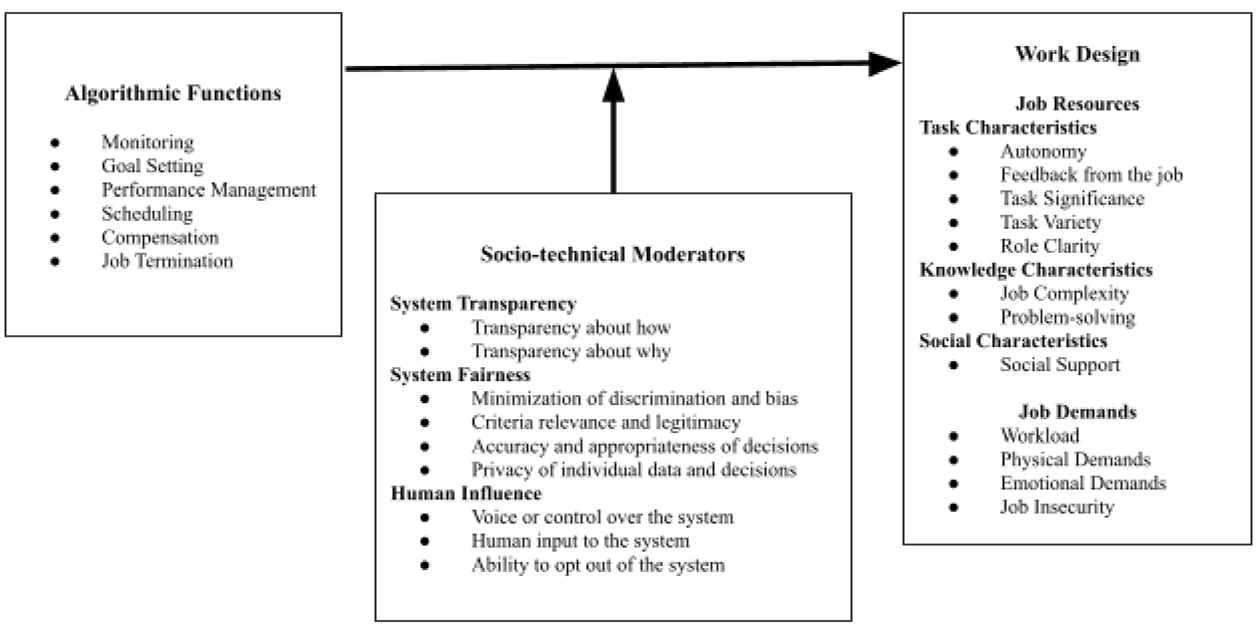

Figure 1: Conceptual Model for Algorithmic Management (Parent-Parker, Rochleau. 2021)

Algorithmic Monitoring

The data collected by monitoring devices is frequently utilized to store and analyze performance, emotions, health, and other activities (Evans & Kitchin, 2018; Schafheitle et al., 2020). Generally, the J D-R characteristics of task variety, autonomy, and task significance are significantly diminished (Tomczak, Lanzo, & Aguinis, 2018).

Algorithmic Goal-Setting

The algorithmic goal setting function includes two aspects: task assignment and performance target setting. In gig-economy settings Brione (2017, p. 12) reports using a task planning algorithm with better sequencing of work, avoiding bottlenecks and meeting all deadlines, but observes a reduction of workers' autonomy in the choice of tasks and method, as well as a simplification of tasks. Having no control over the tasks or targets you are assigned to has the potential to result in an increase of work demands, namely in terms of physical demands and workload (Reyes, 2018)

Algorithmic Performance Management

The function refers to the evaluation of productivity and other task metrics to ascertain approval or satisfaction rates. On one hand, AM enhances the quantity of feedback received from the job and aligns it more accurately with the employees' actual performance (Rosenblat & Stark, 2016, pp. 73–74). Conversely, research on gig work indicates that workers often respond negatively to algorithmic feedback, perceiving it as unfair, opaque, lacking transparency, or based on irrelevant metrics. (Gregory, 2020; Rosenblat, 2018). "The metrification of work in traditional work settings has also been found to lead to perceived reductionism" (Newman et al., 2020), and also reduced work meaningfulness, or lowered the task significance (Moore et al., 2017; Moore & Robinson, 2016).

Algorithmic Compensation

The function includes using algorithms to set workers pay and bonuses. It contributes to reduce the autonomy of the workers in constraining them to work longer hours and decrease the control they have on the rewards they gain from work (Veen & Dagevos, 2019; Griesbach et al., 2019; Moore & Hayes, 2017, 2018; Rani & Furrer, 2021). Performance-based compensation lowers the perception of autonomy and is more likely to generate a controlled and extrinsic type of motivation (Gagné & Forest, 2008).

Algorithmic Job Termination

The ability of algorithms to decide and execute job termination through performance and other metrics constitutes the function, it is seen to increase job insecurity perceptions. Authors find strong evidence for negative social support (Van Doorn, 2017; Van Oort, 2019) due to extremely unilateral decision making parameters being used for algorithmic job termination (Rani & Furrer, 2021; Williams & Beck, 2018).

3.2.1. The Three Socio-Technical Moderators

The sociotechnical moderators include, *system transparency, system fairness* and *human influence.* Manipulating the effect of these elements are postulated to have positive effects on motivation, well-being and performance.

1. System Transparency: It refers to the degree to which explanation is provided with regards to why and how an algorithmic system is used (Brown, Davidovic, & Hasan, 2021; Pieters, 2011)

2. System Fairness: The absence (or minimization) of bias and discrimination (Choudhury, Starr, & Agarwal, 2020).

3. Human Influence: It refers to the ability of workers to exert control, opt out of the system if wanted, and to provide an input or to contribute to the system (Aoki, 2021; Grønsund & Aanestad, 2020).

3.3. What is The Digital Mindset?

The digital mindset refers to a collection of attitudes and behaviors that empower individuals and organizations to leverage opportunities presented by data, algorithms, and AI. (Neeley & Leonardi, 2022). Developing a digital mindset involves engaging with the following three key processes: (1) Collaboration, (2) Computation, and (3) Change. An individual qualifies to possess a digital mindset when they adhere to *the 30 percent rule.* This implies that individuals or organizations can be considered to possess such a mindset if they acquaint themselves with approximately one-third of the knowledge related to digital collaboration, computational or coding techniques, and change management strategies, thereby recognizing the importance of adaptation and continual learning to avoid obsolescence. The rule is based on the premise that to demonstrate mastery of the English language, a nonnative speaker must acquire roughly 12,000 vocabulary words. But to be able to communicate and interact effectively with other people in the workplace, all they need is about 3,500 to 4,000 words — about 30 percent of what it takes to achieve mastery (Neeley & Leonardi, 2022).

3.4. Theory Discussion

Firstly, defining the scope of theory usage and focusing on the AM function, STS moderators and J D-R characteristics simultaneously allows us to dive deeper into the employee perspective to address the research gap relating to lack of empirical research in the industry and provides for theoretical integration of multiple AM functions as opposed to pre deterministically analyzing a single one (see section 1.2). Secondly, cross-fertilizing *digital mindset* as a variable to the conceptual model we adapt the concept to categorically evaluate the support for AM between two population groups.

Secondly, we rely on the meta analytic summary of the key effects of AM on J D-R, such as AM being associated with a reduction of workers' autonomy (Jabagi et al., 2019; Mohlmann & Zalmanson, 2017), and the creation of power asymmetry in information availability (Calo & Rosenblat, 2017; Rosenblat & Stark, 2016; Shapiro, 2017) to allow for comparison between the two, gig-work and consulting industry. Additionally, AM has also been shown to result in in negative emotions, unfairness perceptions, low trust (Lee, 2018; Zarsky, 2016), low job satisfaction (Brawley & Pury, 2016; Griesbach et al, 2019), and reduced engagement in work (Bucher, Fieseler, & Lutz, 2019). It is a given that the theoretical model establishes pre deterministic negative conclusions on majority algorithmic functions, however the addition of digital mindset challenges these assumptions to find support for AM.

Hence, we hypothesize that AM acceptance stems from an individual's mindset towards said technology, and concur that STS moderators control the strength of AM influence. Simply put, having a digital mindset positively influences the likelihood of an individual supporting AM use in their workplace.

4. Methodology

This section delves into the research philosophy and methodological decisions that underpin the study.

4.1. Research Philosophy

The research project adheres to the positivist paradigm. The authors adopt an objectivist ontological stance. This means they believe in a single, external reality that can be objectively measured and observed. Their goal is twofold: to establish order within the sample population and to study this reality as something independent of social actors (Saunders et al., 2019). Epistemologically, the study prioritizes verifiable facts to assess participants' digital skills for computation and collaboration. While anecdotal evidence and opinions are included, the focus is on universally observable aspects within organizations to ensure generalizability of findings. Finally, the authors strive for a value-free and independent axiological position, aiming for neutrality during data collection and analysis. However, it's important to acknowledge a potential bias due to shared social norms of the Swedish workforce, influenced by the researchers' location and the majority of participants.

4.2. Research Design

The study employs a qualitative approach, specifically utilizing grounded theory. This method allows researchers to analyze interview data and develop new theories about the emerging concept of algorithmic management (Saunders et al., 2019). Grounded theory offers flexibility to incorporate unforeseen factors and dimensions that may arise during data collection, aligning well with the abductive approach to theory development.

The study adopts a cross-sectional design due to time constraints for data collection (Saunders et al., 2019). This means data is collected during a short period of time. While the research question doesn't necessitate a longitudinal study, i.e. tracking changes over time, future research could explore temporal aspects, especially considering the evolving landscape of AI tools.

4.3. Data Collection

4.3.1. Delimitations and Scope

The authors exclude the *scheduling* function from the conceptual model for this research project as the main aim of a scheduling process is to determine, for a specific timeframe, the best match between labor requirements and supply which holds true for on-demand and platform economies but not for the professional service industry due to formalized staffing protocols (Parent-Rocheleau & Parker, 2021). Additional J D-R characteristics are also ruled out due to the information being unattainable by means of interviews and the inability to verify standardized protocols of organizations which are confidential. Task characteristics such as *role clarity*, and knowledge characteristics such as *problem solving* are excluded from job resources for the aforementioned reason. Job demands such as *physical demands* and *job insecurity* are excluded as these are not significant barriers for full-time employees in the professional service industry from the perspective of understanding AM support of employees.

4.3.2. Sample

The selection of interviewees was strategically designed to obtain a rich and varied dataset in terms of professional expertise and familiarity with digital tools for computation and collaboration. Therefore, the sample group was meticulously constructed to encompass consulting employees from three geographically distinct regions: the United States, Sweden, and India. All participants held positions within the consulting industry, ensuring a common professional background. However, to capture a diverse range of perspectives a non-probability sampling method has been chosen, individuals were recruited from various organizational levels within their respective consulting firms. This approach allowed the study to incorporate insights from both managerial decision-makers and employees on the ground level.

4.3.3. Interview Process

The interviews followed a semi-structured approach, and questions on the themes explored in the study were decided in advance to ensure consistency throughout all interviews while allowing for follow-up queries (Saunders et al, 2019). This choice of semi-structured interviews were made to facilitate free expression from interviewees and better enable a holistic understanding of algorithmic management and the role of the digital mindset. The interviews were conducted in English as all participants and authors were fluent in the language. Interviews were held, recorded and transcribed using Microsoft Teams, with consent and rights of participants expressed and collected prior to them. The initial two interviews and questions asked within them differ from the rest as after conducting them, the authors deemed it appropriate to slightly modify the interview guide to better align with the aim of the study and conceptual model.

4.4. Data Analysis

Initially, a transcript was generated by Microsoft Teams. The transcripts were reviewed, tested and edited using the recordings to ensure correctness. The interviews were then independently coded, after which they were discussed and edited by authors to mitigate bias. The manner in which the interviews were coded were in line with the study's research objective and philosophy, as advised by Saunders et al. (2019). 13 codes were initially identified, after which they were re-coded and grouped into seven categories expressed in the empirics section.

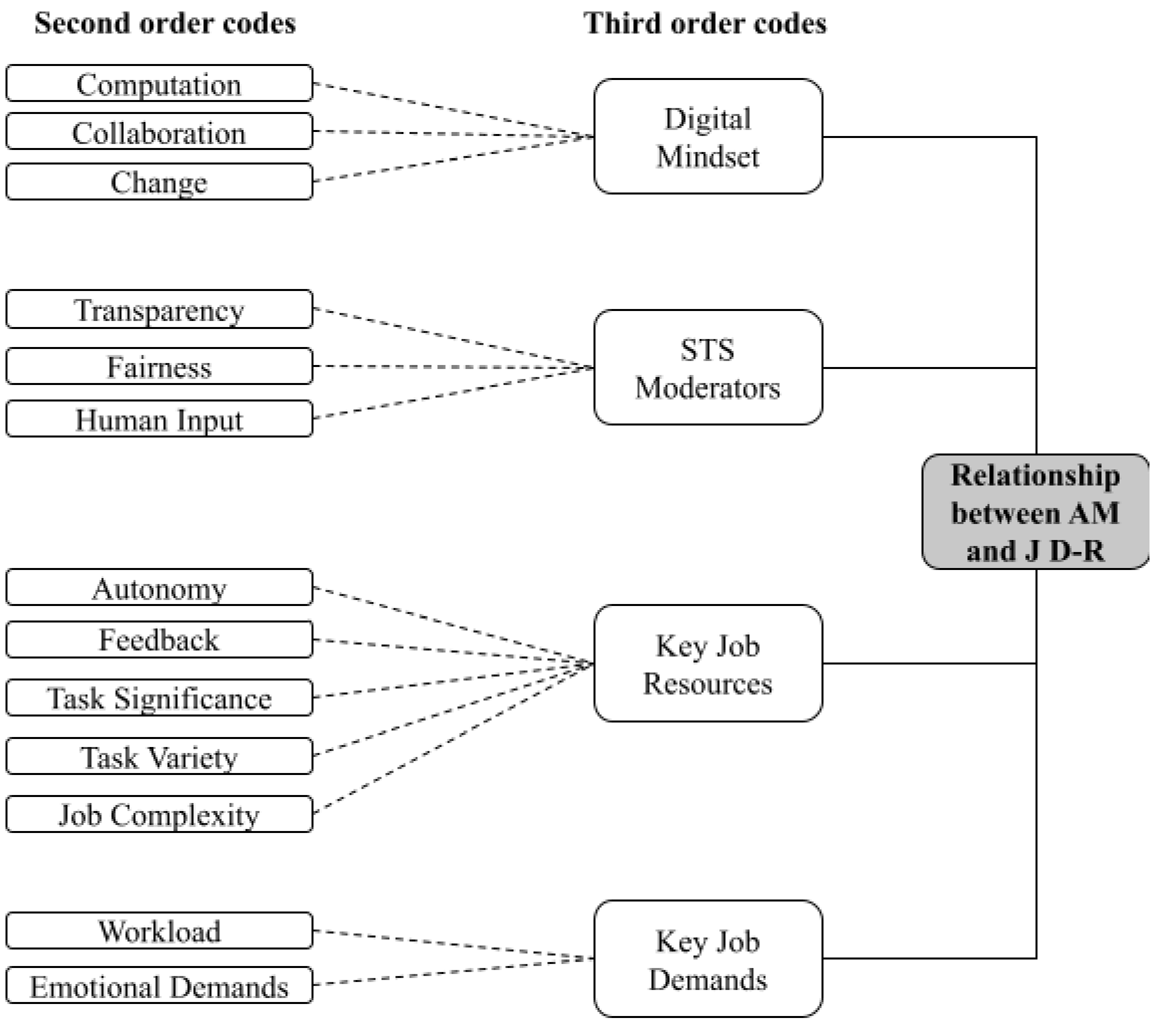

Figure 2: Second and Third Order Codes for Empirics

4.5. Ethical and Other Considerations

The ethical concerns of this study were addressed by adopting a deontological ethical position, implying that a defined set of rules defines what is ethical (Saunders et al., 2019). The rules defining the ethicality of this study are derived from SSE Student Handbook, national law and General Data Protection Regulation (GDPR).

In order to address concerns regarding data management, confidentiality and anonymity of participants, several steps were taken. Before undergoing the interview, participants signed a consent form. Interviewees were informed about their rights under GDPR and their ability to withdraw their participation at any time, as well as assured about their anonymity.

The impact of an interviewee's personality, For instance, individuals' dispositional tendencies to experience positive or negative affect can influence their perception of AM use and such qualitative characteristics are not observed as part of the study (Rhoades and Eisenberger, 2002). Additionally, cultural differences between US, EU, and Indian participants on workplace norms differ on multiple accounts, for instance, US employees are more informal, confrontational, and detached whereas EU employees are more reserved, non confrontational and formal (Galinha et al., 2016; EuroDev, 2023).

5. Empirics

5.1. Establishing the Digital Mindset

The respondents categorized as having a digital mindset met or exceeded the *30 percent rule* of having mastered digital collaboration skills, computational skills and awareness for learning new skills.

All respondents met and exceeded the *30 percent rule* of digital collaboration.

> *"I think those two are the primary channels for communication (Office, Outlook) and then of course we have the site's office interactions and then a weekly office meeting. We have, of course, a Yammer channel as well, which is for a little bit different kind of communication."* **- 5A**

For nomenclature purposes, the respondents who exhibited a digital mindset, marked 'Y', will be referred to as "Group B" or and the respondents who did not exhibit a digital mindset, marked 'N', will be referred to as "Group A".

Respondents 8B and 12B met and exceeded the *30 percent rule* of computational skills.

> *"So the work I've done I would say is 60% coding, 30% PowerPoint, 10% handling Outlook so to say."* **- 8B**

> *"So I've used JavaScript as well. I've coded for my previous internships and projects I've worked on Nodejs, Express JS and I also have familiarity with HTML, CSS, C++, Python."* **-12B**

In contrast, respondents 2A and 7A did not meet the *30 percent rule* of computational skills.

> *"I mean, that's (coding languages) not my expertise."* **- 2A**

> *"No, I don't use any (coding languages). It's a different world for me."* **- 7A**

Respondents 9B and 5A met and exceeded the *30 percent rule* of awareness for learning new skills.

> *"I became much more well versed with AWS and its services as well. And then reporting in terms of Power Bi, Tableau, Tableau, definitely. And scripting in bash."* **- 9B**

“I've learned quite a lot. I've gone to a folkhogskolan school and studied design for a year. So, idea generation, development products, validation and just physical and craftsmanship when it comes to cabinet making and textile drawing, et cetera. It was a very broad general design course, so I learned quite a lot of that and also practiced Spanish in my spare time. I know how to speak French.” **- 5A**

In contrast, respondents 3A did not meet the *30 percent rule* of change management skills.

“Ohh no. (skills learned after university)”

Below is a table listing all respondents and whether they demonstrated a digital mindset.

Table 1: Digital Mindset Versus Non-Digital Mindset Split of Participants

Respondent	Computational Skills	Collaboration Skills	Change Techniques	Digital mindset (Y/N)
1A		✔		N
2A		✔		N
3A		✔		N
4A		✔	✔	N
5A		✔	✔	N
6A		✔	✔	N
7A		✔	✔	N
8B	✔	✔	✔	Y
9B	✔	✔	✔	Y
10B	✔	✔	✔	Y
11B	✔	✔	✔	Y
12B	✔	✔	✔	Y
13B	✔	✔	✔	Y
14B	✔	✔	✔	Y

5.2. Evaluating the STS Moderators

Figures 3, 4, and 5 show the frequency participants ranked human influence, system transparency and system fairness in rank 1 (most important), rank 2, and rank 3 (least important) split by Group A and Group B.

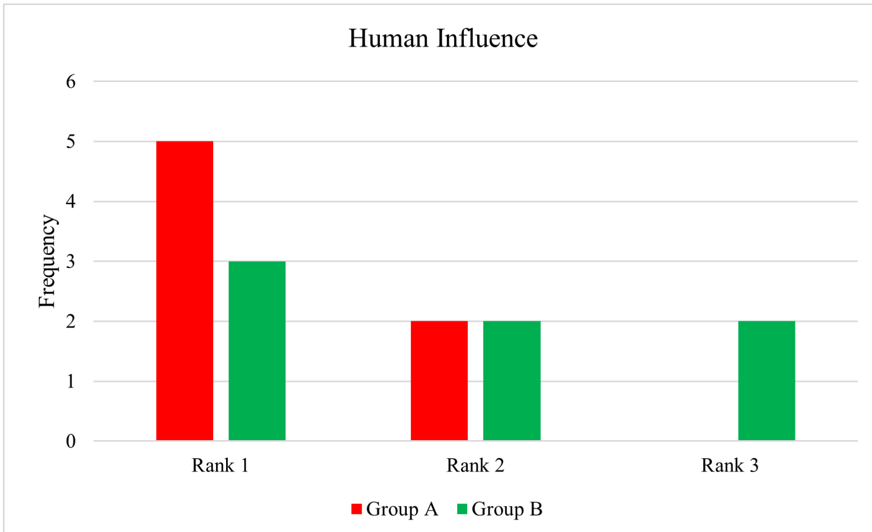

Figure 3: Human Influence Rankings

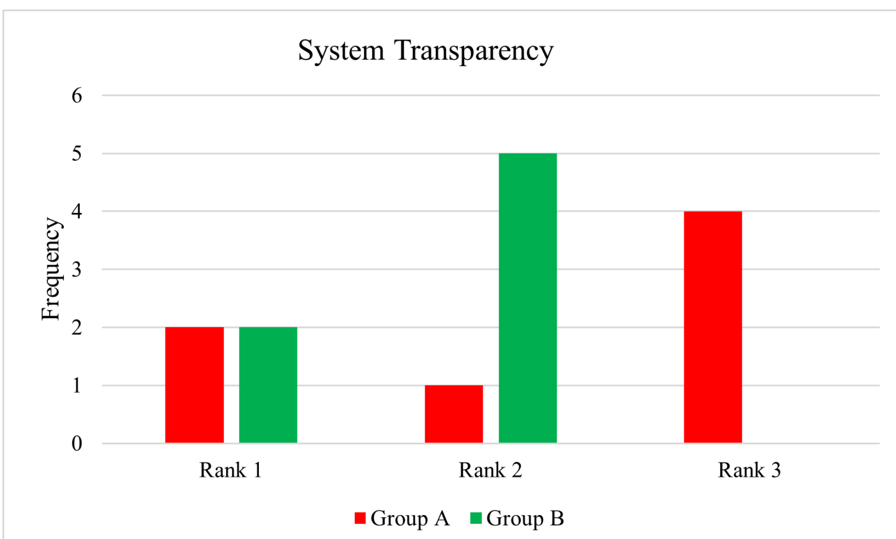

Figure 4: System Transparency Rankings

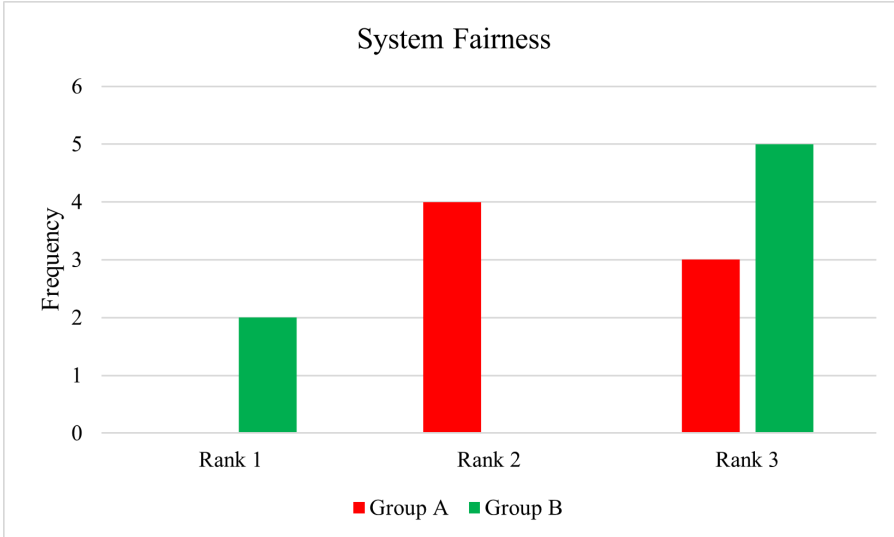

Figure 5: System Fairness Rankings

Figure 6 shows the frequency of combinations of orders that the three STS moderators were placed in by respondents. For example, "HTF" means that the respondent placed human influence as most important, transparency second and fairness last.

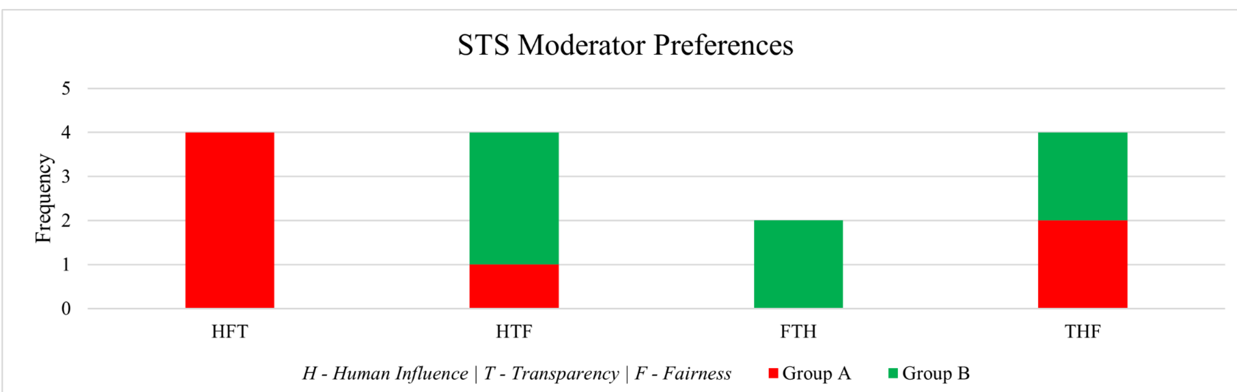

Figure 6: Frequency of STS Moderator Preferences

Respondent 5A preference of STS moderators, observed as the most common ranking order within Group A.

> *"I think human influence is the key factor here. If we're going to have a competent workforce, that is the primary priority. And then fairness is the second one because of accuracy and not violating fundamental human rights. And then of course, transparency.*

So first the human influence then that humans are being treated fairly and then that they know that they're being treated fairly."

Respondent 13B preference for STS moderators, observed as the most common ranking order within Group B.

> *"First, I would put in human influence. So there needs to be some kind of human interference or some way to control whatever it is being put on. Second is transparency, for obvious reasons like data should be transparent and be known properly by everyone who is involved here, so that is important and the last one is fairness. So the model can be fine-tuned like if we work on it, we see improvements and we keep building on it. So it's like an everlasting project which will go on for years. That's why I would give it the least priority."*

5.3. Relationship between Monitoring and J D-R

In group A, 5 participants were opposed to monitoring while 2 were supportive. For group B, 3 participants were opposed to monitoring while 4 were supportive. Overall, participants leaned against monitoring.

Respondents 6A and 11B agree on the value monitoring could add from a managerial point of view.

Group A respondents expressed their opinion that monitoring could lead to negative social support amongst colleagues, while Group B respondents did not.

5.3.1. Group A Perspective

Respondents 4A, 5A and 6A thought that an algorithm used for monitoring would face disapproval amongst colleagues.

> *"But I think having that sort of productivity scrutiny might be like very if it's very data-driven, might - there might be some pushback because it feels like surveillance."* **-4A**

> *"I think it's a very neat way to hide the profit maximization agenda first to say that it's an employee benefit to throw stress levels into the mix, but I mean surveillance and being monitored is never appreciated."* **-5A**

"I think some people would think that being monitored and observed is a no no." **- 6A**

Respondent 4A saw potential in a system that monitors the emotional toll of work due to the heavy workload expected of employees in the consulting industry.

"I mean, we're consultants, it's quite long hours and stressful work. So every week we do actually have a survey for each individual to fill in, which is like how much did you work, how do you feel about this? Is this sustainable or not? So definitely there should be an interest there."

Respondent 6A believes that due to the nature of a managerial position, there would be support for monitoring.

"Personally, I think monitoring is valuable, especially from a management point of view. You need to see what's being produced and at what time, and so like more from the sense what do we need to complete and what's left to do? Like what's the status?"

5.3.2. Group B Perspective

Respondent 8B believes that the usage of monitoring could not be realistically used to measure and reduce stress of employees.

"Perhaps what you're hinting at is that managers would use this, and then maybe give work to people who are less stressed, but I don't think that is how it would work realistically."

Respondent 9B has the opinion that algorithmic monitoring could be useful to check quality of work.

"Sometimes it doesn't require days of work, it's more about how much expertise you have simply because you're struggling to do something and taking more time is not the value add if the product that you are delivering is not is not impressive or does not meet standards, then yes, there should be some level of checks."

Respondent 10B is of the opinion that monitoring would increase his stress at work.

"I would think that that would add on my stress level if I'm being monitored like that."

Respondent 12B acknowledges the value of monitoring from a managerial point of view, and that it could reduce stress if it is used to distribute work efficiently.

> *"If I am working for them, they need work out of me and monitor my level of productivity or stress, balancing different things in life, all of that comes into play when you're working. That is something that they will have to gauge to decide how much work is to be given to me and so that we can set deadlines and all accordingly."*

Respondent 13B mentions that monitoring would lead to a sense of being micromanaged.

> *"I would say it is very difficult for me because I am someone who will feel this big feeling of being micromanaged as someone who is a bit senior now.."*

5.4. Relationship between Goal Setting and J D-R

For group A, 4 participants were opposed to algorithmic goal setting while 3 were supportive.
For group B, 1 participant was opposed to algorithmic goal setting while 6 were supportive.
Overall, participants were in support of algorithmic goal setting.

Both DM and non-DM participants emphasize the importance of an algorithm taking task variety into account in order to effectively set goals.

Only DM participants expressed their opinion that there is higher social support for a person facilitating goal setting as opposed to an algorithm due to factors such as culture, convenience and preference.

5.4.1. Group A Perspective

Respondent 2A believes that an algorithm being used in setting goals for employees would not be feasible due to the high variety of tasks in his role.

> *"Yeah, I would say no since the variety of tasks is so broad. If in a setting where it was more streamlined, I would probably say yes."*

Respondents 4A and 6A bring up their opinion that there is more social support for goal setting to be done by a person due to factors such as convenience, corporate culture, and preference.

"So I think it is feasible but not preferable, so I don't see a good rationale for why you would like to automate that process. Like it's a luxury to be interacting with your line manager and when you have these conversations, you can touch on things that you haven't inserted in the interest database or that person might be knowledgeable of projects that you didn't even know existed at the firm, so I think that the bilateral physical interaction is actually preferable both because you have a wider array of options potentially, but also because it's more enjoyable and less alienating to be having a interaction about your future with someone rather than having an algorithm decide it for you." **- 4A**

"But at least something we value at [firm] is that you sort of build your own careers, so the direction you want to go, you can raise your voice and say I want to go here and that will be considered. So that's why the informal part becomes really important to us to be able to say "I want to work with these types of clients or these types of engagements" and that will probably not be picked up by algorithms." **- 6A**

Respondent 6A sees the value of algorithm usage in goal setting from a managerial point of view - as the task of assigning tasks to a team is complex and the current system of using an excel file could be improved.

"I think that you could benefit from it - If you take in the fact that it's also a forecast, because when you plan, you also need to consider that the projects will take a long time and people sit with multiple projects at the same time. So the manager of the project needs to forecast how many hours per week it will take for that person to do the job and if that's accurate then you can probably automate it quite a bit but it takes someone to do the estimation and that estimation needs to be correct to also not mess up for other engagements that needs to be planned. So, I can surely see there to be benefits, but it requires that the data is correct. If you put it that way."

"I've come to the position now that I'm staffing projects and it's a mess working with that Excel file so if it could be automated somehow I definitely see the benefits from it."

Respondent 7A values her autonomy, and so would not appreciate an algorithm to have absolute decisive authority over task assignment, but recognizes the benefit in using it as a suggestive tool.

"Maybe the algorithm could also help match me to things which would be good for my development or things that I wouldn't think about myself necessarily."

“I wouldn't want it to have absolute power and just assign me without my inputs essentially.”

5.4.2. Group B Perspective

Respondents 9B and 10B believe that algorithms used for goal setting have an application to identify more urgent tasks and develop current and new interests.

> *“These things can be automated in some areas, but you have to be able to apply the context of priority and you know how much work something will require and things like that. And then based on that, you have to do it.”* **- 9B**

> *“Yeah, a level of human contact is necessary, but I think that it could be automated. Like if I recall in instance we had two or three different tasks at hand and they required different skills. One of them required a skill that I knew and one of them required a skill that I did not know. And I had to. I would have had to spend my time learning that. So if there was a system in place which, you know, categorized the skills according to the tasks, and then I could just, you know, decide, I could just feed in that if I want to learn a new skill, assign me this task or if I want to work with the comfortable skill right now, assign me this to it could definitely be automated that way as well.”* **- 10B**

Respondent 10B mentions that the ease of receiving feedback from the job is higher when the process of assigning tasks is done by humans, but respondent 12B sees the possibility of fully automating this process if feedback loops and differences in job complexity were taken into account by the algorithm.

> *“I mean it's easier to get feedback and answers straight away if any questions are up or something.”* **- 10B**

> *“For example if a file or folder is edited and the owner of the folder will just decide and will automatically ask for review so that others can review it, and if that is also something that can be automated, it is possible I think.”* **-12B**

5.5. Relationship between Performance Management and J D-R

For group A, 3 participants were opposed to algorithmic performance management while 4 were supportive. For group B, 2 participants opposed algorithmic performance management while 5 were supportive. Overall, more participants were in support of algorithmic performance management.

5.5.1. Group A Perspective

Respondents 3A and 7A mention that their jobs are very nuanced, so implementing an algorithm to manage performance may be difficult.

> *"Yeah, but I think it would be hard to do for us like we have our utilization KPI, but that's still pretty subjective like there's still a lot of nuances and context behind that."* **- 3A**

> *"Unfortunately, I think a lot of the performance metrics that are valued, at least in my profession now, are hard to evaluate just automatically because it's a lot about how the client perceives me? How do my colleagues perceive me? And maybe some things you could monitor, like how quickly do you finish a PowerPoint? But then you would have to also measure well what is the quality and the impact you know, not just speed."* **-7A**

Respondent 2A highlights the approval for human interaction versus algorithmic interaction with regards to performance management.

> *"I think it could come from a person, but it could be backed up with some algorithmic info, but it should come from the person. I mean, that's the one responsible for you. We are not living in a robotic world, right?"*

Respondent 4A believes that there is an application for algorithms in performance management as the current system of relaying feedback may be prone to human errors such as recency biases - so there could be higher quality of feedback from the job from an algorithm paired with human input.

> *"Yes, I think there's definitely an application for algorithms to take that over because right now you have a mentor talk about this and then it can easily become that you talk about the most recent projects and not the overall picture. But directly after a project, I don't see much use of algorithms giving feedback. And we don't really have KPIs in that way. I think it should try to identify areas to improve."*

Respondent 7A comments that an algorithm carrying out performance management checks may increase her stress at work.

"I guess I wouldn't love to have something that's on my computer. That's always checking how quickly I am doing my excel? Uh, how quickly am I doing this? I think I'll find it quite stressful, to be honest, so it will probably impact my performance negatively."

5.5.2. Group B Perspective

Respondents 8B, 9B and 11B mention that they do not see a clear path for algorithms managing performance because their tasks are complex and include qualitative factors that are not as easily picked up by an algorithm.

"I guess you could in terms of productivity surely, but, it really depends on how well the task is done too, it's not just the numbers of how many tasks you're performing, but also the actual thing. So I also think the quality of the work depends on it." **-8B**

"It's quite a nuanced job. I wouldn't say there's any one KPI or a few KPIs which you can use, I would say. I would prefer the human one, like how other people review you or think of your work, is perhaps the best way." **-9B**

"So when that's subjective, algorithms tend to get really complex and inaccurate. So on that I would really not trust an algorithmic approach for getting my feedback through that." **-11B**

Respondent 13B thought that he would benefit from increased feedback from an algorithm carrying out performance management checks.

"I think I would benefit because currently I'm not sure what exactly I'm lacking behind. So it would be useful especially because we need to learn a lot of things kind of on the go. And general feedback can only go so far in helping someone improve."

5.6. Relationship between Compensation and J D-R

Respondents commented on the rigidity of the compensation structure at their firms, and the variety of tasks and roles across the organization - both factors which would render it difficult for an algorithm to decide compensation.

"There's automatic financial inclusions every year and then obviously performance based bonuses. It's a combination of that with your base salary for a month or something

of that sort. It's a complicated formula. In that sense, the numbers are decided beforehand and can't be changed on an individual level." **- 9B**

"Yeah. So the compensation for us at least is fixed. There's no scope for negotiation and there are no bonuses or extra cuts apart from leads. And there's time before I have any kind of appraisal review." **-12B**

"I guess also if you work in sales or business development, it would be very straightforward I guess to be able to determine bonuses." **-7A**

"Different parts of the organization work differently – so my department will have very busy periods. We sit with [role], which is quite a popular topic right now, so we have clients asking us all the time for work and we do take on more than we can. So our overtime will be a lot higher. And then there are other departments with the same sort of salary track who basically don't have any clients and they do internal work every day or go home. And then we are on the same salaries So at some points you absolutely wish that the salary tracks were more individual, but from an organizational point of view I see why that would be difficult." **- 6A**

5.7. Relationship between Job Termination and J D-R

Respondents thought that the news of one's job being terminated should never be relayed via an algorithm and that the reasons or feedback behind the decision should be expressed by a person, but there could be some use of algorithms as a tool for reducing human bias in termination decisions.

*"So you use that to kind of support you in the as we talked about the evaluation and kind of to ensure to remove bias for example, I mean that could be you know and you know in Sweden there is obviously still some gender bias, but there's also bias towards you know foreigners. So I mean in an ideal world you could use an algorithm to kind of check the humans work to make sure that you know well.Now you're firing all the women. What's going on here? Or you're firing all the foreigners. Something is up."***-7A**

"I believe there's an application for algorithms to aggregate the feedback part and the reasons for HR, for instance, but there still definitely needs to be some sort of human interaction in all of it too, to maintain the relationship." **- 4A**

*"Might be preferable in person because like the reason for underperforming is something that should be known. So definitely that I think is pretty important."***- 14B**

"I think the decision should be made by a human that also takes other things into account, which might be problematic due to their assumptions and other things. Algorithmic information can point to what this person has done, but when it comes to, for example, the quality of hours they put in I think we need the human side. Or, maybe this person is actually making the team perform better since he or she is really good at spreading the mood." **- 2A**

6. Analysis

The following section aims to fulfill the twofold purpose of this research project as outlined in section 1.2 using the empirics above and theory outlined in chapter 3. First, we analyze if the *digital mindset* variable affects the support for AM in the professional service industry to test our novelty. Second, we categorize the five out of six analyzed AM functions into three tiers based on insights from the industry.

6.1. The Role of Digital Mindset and Moderators

In section 5.1, seven participants (1A-7A) meet the 30 percent rule (Neely and Leonardi, 2022) who depict the DM population, the remaining seven participants comprise the population of Non- DM (8B-14B) individuals. Subsequently, the insights gained from section 5.2 through section 5.6, offers the answer to the first objective of the study, i.e. if having a *digital mindset* increases support towards Algorithmic Management.

For four out of five algorithmic functions: *goal setting, performance management, monitoring, and job termination* the empirics signal more support for AM use by Group B compared to Group A participants (see section 5.2-5.6). For algorithmic *compensation,* Group A prefers AM slightly more than Group B, however, both groups later confirm the identical limitations associated with algorithmic compensation which are unique to the consulting industry. Hence, possessing a digital mindset is likely to enhance the inclination towards its adoption.

The differentiated scope of using algorithmic management systems in this industry, compared to previously researched gig economies, are crucial to understand the role of other elements of theory in addition to the role of the *digital mindset.*

Since all participants are assigned into one of two groups, A and B (Table 1), the differences in rankings for sociotechnical moderators if AM were used to determine most relevant STS moderators for both (see section 5.2). Firstly, *human influence* is the most important feature in an AM system for both groups. It signals the preference of having humans actively participate in the decision making loop (Aoki 2021). Secondly, *system fairness* and *system transparency* have interchangeable preferences, with the majority of Group A preferring fairness over transparency and vice-versa. This doesn't conclusively prove that fairness or transparency come second to human influence for one group as evident from the mixed support (see Figure(s) 3,4, and 5).

6.2. Functions with High Scope of AM Use

Based on the empirical findings, two functions, *goal setting* and *performance management* are ideal candidates for use of algorithmic management systems. The selection criteria for high scope of AM use comprises general impressions from Groups A and B, perceived effects on relevant J D-R characteristics as well as anecdotal evidence from the industry for legitimate use cases within the organization.

For algorithmic goal setting, the relevant J D-R characteristics: job *complexity, task variety, task significance, social support, autonomy,* and *feedback from job* outline the focal points for optimal work design for the function. In addition to J D-R characteristics, the number of employees within a team or organization directly correlates with support for AM. Group B respondents highlight that high *task variety* is preferable for automation as it will allow people to work with and learn new things depending on their expertise and interests. The majority from Group A cite lack of *social support*, despite acknowledging the ease of automation, as the informal communication and physical interactions with senior managers is highly valuable for enhancing *task variety* allowing individuals to discover new interests which can be identified by their peers (4A). Also noteworthy is the context of priority, i.e. *task significance* for assignment of tasks and a level of human interaction is still needed, prioritizing the STS moderator (12B, 14B). Respondents raised concerns about algorithmic goal setting hampering the level of *feedback from the job* which is essential in determining new tasks for them (10B, 13B). Respondent 6 highlights how staffing people on projects could be made efficient compared to existing methods, and acknowledges that high accuracy and reliable data points are required to assign the tasks to the right person. The high *job complexity* stems from considering time, people and fit for consulting projects (6A). Respondent 7A brings up that new learning opportunities come at the cost of their *autonomy* if a system is unilateral and doesn't allow any human interaction to give inputs. Consequently, *system fairness* and *human influence* are the two STS moderators that most improve support for algorithmic goal setting. The empirical evidence coupled with moderate support from Group A and majority support from Group B, algorithmic goal setting can have successful implementation in larger firms or teams when designed in accordance with above-mentioned moderators.

For algorithmic performance management, the relevant J D-R characteristics: *social support, job complexity, feedback from job and emotional demands* form the basis for optimal work design. Despite the categorization into the high scope category, fully automated performance management is viewed as undesirable by all respondents while they strongly support a combined approach of human and algorithmic performance evaluation. Being judged on metrics of speed and task completion as part of automated performance management is linked with increasing *emotional demands* and negative impact on overall performance (7A). The overwhelming majority describes algorithmic use for evaluation as beneficial, however, the communication should be personal (2A, 5A). Respondent 2A highlights how a fully automated performance management system receives low *social support* owing to the difficulty of use and lack of interest in receiving impersonal feedback (2A). Respondents 3A and 8B allude to difficulty in establishing KPIs for complex job environments where output can be subjective or non-quantifiable for algorithms and therefore hard to evaluate highlighting the high *job* *complexity* within the industry (3A, 8B). On the other hand, evaluating productivity metrics like task completion are easier to execute (9B, 12B). The quality of *feedback from the job* can be improved with statistics for learning and development especially over longer time frames, where algorithms can identify improvement areas through pattern recognition, as opposed to broad level feedback (4A, 13B). The empirical evidence from both groups strongly advocates that *human influence,* the STS moderator, is indispensable to designing function. Despite citing weak support initially, the acceptance for high potential of employee benefit places algorithmic performance management in the high scope category.

6.3. Functions with Moderate Scope of AM Use

The functions *algorithmic monitoring* and *algorithmic job termination* are categorized into moderate scope of AM use. This implies that the functions can be automated, however, are less desirable due to marginally less benefit from automation and contemporaneous support from respondents.

For algorithmic monitoring, the relevant J D-R characteristics: *social support, task significance, job complexity, workload, emotional demands,* and *autonomy* outline the vital components for work design. One key benefit is, monitoring productivity and stress can enhance *workload* management and even aid in implementing other functions such as *goal setting* (12B). Moreover, it has potential to enhance *task significance* by identifying priority segments and secondary ones (6A). However, monitoring consultants on qualitative competencies, for example the effectiveness and efficiency of utilizing one's expertise at the job signals the high degree of *job complexity* resulting in negative consequences for work design (9B). The majority acknowledge that monitoring stress is definitely possible and beneficial for regulating *workload* or *emotional demands* of consultants (5A), however, in all likelihood surveillance (monitoring) is designed to benefit the management more than the employee resulting in overall low social support amongst workers (6A). Participants also acknowledge that as seniority increases, monitoring in such an industry would hamper *autonomy* and perhaps create a feeling of being micromanaged (13B). In conclusion, the empirics signal few benefits of algorithmic monitoring from an employee perspective, hence a prudential evaluation of use cases and general impressions positions it within the moderate scope.

For algorithmic job termination, the relevant J D-R characteristics: *job complexity, social support,* and *feedback from job* encompass the key features for work design. Looking at initial impressions, the majority respondents from both groups moderately support automation of job termination. Akin to performance management, the participants believe that the evaluation can be automated, however the decision must be communicated in person. Respondents claim that accounting for subjective factors like quality of working hours and effect on team morale signal high *job complexity* posing difficulty for automation (2A). An argument is made that algorithmic job termination can help reduce biases leading to stricter penalties for some groups compared to others by eliminating discrimination based on gender, nationality or personal biases which in turn increases *social support* for automation (7A). The majority believe that having a human in the loop would help improve *feedback from the job* in such a scenario allowing for the possibility of clarifications and maintaining future relationships (14B, 4A). The empirical evidence stresses the STS moderator, *human influence* of the utmost importance which draws similarities to performance management placed in the high scope. The difference lies in the comparatively lesser benefits from a worker's perspective attributed to algorithmic job termination over performance management placing it in this category.

6.4. Functions with Low Scope of AM Use

The function *algorithmic compensation* is categorized as the sole candidate for the low scope of AM use category. The empirics revealed a myriad of underlying reasons, however, the most frequent was the negligent scope of automation possibilities relating to calculating compensation in the professional service industry compared to gig economies.

For algorithmic compensation, the sole instance of J D-R characteristics from empirics was that of *task variety* and *workload*. For larger firms comprising several departments, an individual approach for determining compensation is ruled out as a norm. An algorithmic approach would allow for more individual salary tracks to reward employees on individual or team level contributions instead of standardized pay for employees belonging to a department or seniority level. This would account for differences in overtime as opposed to under utilization of resources within the same team allowing for *workload* management (6A). Another benefit observed was the added fairness to remuneration if a company wishes to have a completely fair compensation system. Lastly, in the case of businesses or departments with less *task variety*, such as sales, automation for bonus calculations would be simple and achievable (7A). Despite support for algorithmic compensation being on the positive side in both groups, it is observed that salaries within majority roles are fixed and future bonuses, increments, or negotiations are accounted for within the respective salary tracks (9B, 12B). While this standard may be absent in gig economies and few other industries, in this case, it eliminates the scope of automation for implementing algorithmic compensation. As a result, the function must be categorized as low scope of AM use due to the lack of use cases within the industry in spite of moderate support.

7. Discussion

7.1. Answer to Research Question

This study has investigated the perceptions of algorithmic management and its functions through 14 qualitative interviews of consulting professionals to test the conceptual model on algorithmic management in a consulting work setting and to investigate the effect of the variable *digital mindset* following an abductive approach (Neeley & Leonardi, 2022).

RQ: *How does the conceptual model on support for algorithmic management fare in a consulting work setting, and what influence does the variable digital mindset have on it?*

In essence, varying levels of support are observed across different algorithmic functions, particularly, human influence was identified as the paramount STS moderator to shape the influence of algorithmic management on work design characteristics. The variable digital mindset increases the support for algorithmic monitoring, performance management and goal setting, while having no significant effect on support for algorithmic compensation and job termination. Given these conclusions, an updated version of the conceptual model (Figure 7), incorporating the nuances of *digital mindset*, has been synthesized.

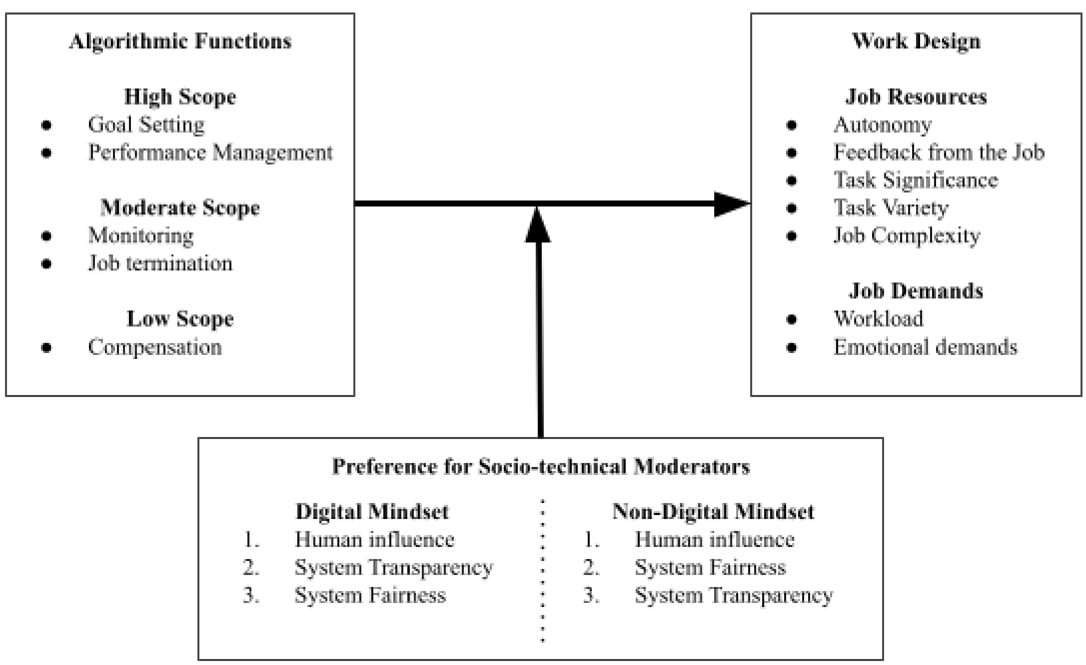

Figure 7: *Updated Model for Algorithmic Management in the Consulting Industry (Edited by Afzal and Pandian, 2024)*

7.2. Literature Contributions

First, as established in section 1.2, the study addresses two primary limitations by exploring AM in a context outside of gig–work and evaluating multiple algorithmic functions for a holistic view. Prior AM research from gig-work has had a heavy dependence on metrics related to surveillance and customer ratings which are not useful for studying AM in traditional work settings, particularly, consulting (Parent-Parker and Rochleau, 2022). Our empirical findings uncover that the focal point for algorithmic management KPIs in consulting would be:

(1) Human Agency
(2) Learning and Development
(3) Employee Well-being

Second, contradictory to results from previous research, the perception of consultants on goal setting reports an increase in task variety, leading to new opportunities in a consulting setting, whereas it was observed earlier that it simplifies tasks (Brione (2017, p. 12)). Consultants do not find that workload would increase from algorithmic goal setting, unlike the finding that it would in another study conducted in a gig-economy setting (Reyes, 2018). That being said, the finding that algorithms managing performance in a unilateral manner leads to the perceptions of feedback provided as a result of irrelevant metrics (Gregory, 2020; Rosenblat, 2018) is consistent in both a gig-economy and consulting setting.

Third, categorization of AM functions into the three scopes (see Section 6), builds further on the research focused on determining perceived organizational support for AM in gig work (Jabagi et al., 2019), and integrates work design theory as proposed by AM scholars like Rochleau and Parker.

7.3. Practical Implications

This study has explored a new perspective to gauge support for AM, and found evidence that people possessing a digital mindset (Neely and Leonardi, 2020) have a higher propensity towards AM implementation. Firms and managers looking to automate HRM functions will benefit by upskilling the digital skills of their employees and should also consider change management techniques that can be useful to keep employees motivated to do the same. HR departments can also devise evaluation mechanisms for new hires, taking into account the digital mindset. Furthermore, there was evidence indicating that the larger the team size, the greater the potential and support for automation.

Firms must take into account the optimal extent of automation. Our study uncovers evidence suggesting that complete automation is rarely supported, hence all systems should be designed allowing for human intervention. Automation is perceived as more beneficial for analyzing long term trends to facilitate learning and development rather than simply being a tool for surveillance and profit maximization. Additionally, physical communication is deemed essential, and certain processes, such as compensation, are too standardized to be dynamically automated.

Third, Algorithmic monitoring of performance data may have some support from management, but could be overwhelmingly resisted by other employees. However, regulating workload to foster a less stressful workplace would be welcomed by all as long as it is done with the consent of those being monitored. Exclusive use of algorithms to manage performance lacks any support from consultants, however its use as a supporting tool for synthesizing performance statistics to be coupled with personal feedback and delivered via humans to employees may be well received. A similar theme of non-exclusivity is found for the usage of algorithms in job termination. Algorithmic goal setting would be well received by consultants as they perceive that it would facilitate the discovery of new learning and knowledge opportunities. Potentially, it may help increase utilization rates. That being said, firms must be prudent in ensuring that an algorithm is not carrying out unilateral decisions without human input as this decreases the autonomy of consultants.

7.4. Limitations

Firstly, this study primarily sits within the positivist paradigm. It qualitatively explores the topic, hence its ability to illuminate how individuals perceive algorithmic management at work is somewhat restricted due to the authors' bias.

Second, as highlighted in section 4.3.1, the authors' predeterministic assumptions to study *digital mindset* (Neely and Leonardi, 2020) and exclusion of work design characteristics due to difficulties in acquiring or using confidential details, limits the scope of exploring algorithmic management.

Third, given the broad scope of the consulting industry and firm related characteristics pose external validity limitations despite all interviews belonging to different firms due to the sample size. For example, characteristics such as the size of the interviewee's teams was shown to partially explain their views on AM.

7.5. Suggestions for Future Research

Based on evidence from this study, we recommend future research exploring the nuances of digital mindset and potentially other new variables or STS moderators that are unique to the consulting industry. Other than that, research can focus on evaluating moderators individually to better capture their influence on shaping work design, or investigate the role of organizational structure and norms on support for AM. Furthermore, other new perspectives focusing on parameters that impede AM implementation or adoption can provide foundational knowledge for academia and industry stakeholders to design AM systems or tools suited for white collar workers.

8. Conclusion

The study reveals varying levels of support for different algorithmic functions, with human influence identified as the primary STS moderator shaping algorithmic management's impact on work design characteristics. The digital mindset variable enhances support for algorithmic management. Performance management and goal setting are ideal candidates for automation followed by algorithmic while algorithmic monitoring and job termination whereas algorithmic compensation is deemed unfit for AM in the consulting industry. Consequently, an updated AM model has been synthesized to incorporate these nuances and guide future research.

9. Appendices

Appendix 1: Interview Guide

Background

1. Briefly describe your role at the company. What do you do?
2. Who do you report to?

Establishing Digital Mindset

Computation Skills

3. What are the commonly used programmes, softwares, or coding languages that are used at your workplace?

Collaboration Skills

4. If you are working on projects with others, what do you use for collaborating together with others?

Change Techniques

5. Have you learnt any new skills after completing your last university degree, such as learning a new language, art, sport, coding language? (Change Techniques)

Algorithmic Management Functions

Respondents were given hypothetical scenarios where their organization uses algorithms to perform certain tasks that might be currently performed by people.

Goal Setting

6. Imagine that you are part of a few consulting projects and work is going on as routine. Soon you are to be assigned new projects or tasks soon. Who is responsible for assigning you your next project(s) or tasks?
7. Are you able to influence the decision maker to give you projects that you like? If yes, how and to what extent?
8. Do you think you or your boss would prefer using algorithms which know your preferences and interests to assign you projects as they come?

Monitoring

9. If you know that your employer wants to monitor you to check for things like: being productive, stress-levels, task completion etc. Do you think such metrics should be observed by employers?

Performance Management

10. Could you tell us about any experiences from performance evaluations you've had at your workplace? Were you given useful feedback and were there any metrics used to evaluate your work?
11. Do you think using algorithms that track your performance through certain KPIs that you are aware about would be beneficial to you as an employee when receiving feedback about your performance?

Compensation

12. Would you like to share any previous experiences you've had negotiating your salary?
13. Do you think algorithms can be utilized to suggest routine raises or bonuses for employees?

Job Termination

14. Imagine a scenario where an employee has consistently underperformed or not aligned with the needs of an organization. Do you think the evaluation of their performance and subsequent decision to terminate them can be done by using algorithms?

STS Moderators

15. Now we will define three concepts relating to the way algorithms are designed. Please rank the following in order of most important to least important.
    - System transparency: transparency about how and why
    - System fairness: no discrimination, appropriateness and accuracy, privacy, legitimacy
    - Human Influence: ability to override with human input.
16. Would you rank these differently depending on what the algorithm's function is? E.g. compensation, task allocation, etc.

Additional Questions

17. Do you have any further thoughts on algorithms and/or the way they could be used in your workplace?

Appendix 2: Example of Coded Interview

Codes:
Digital Mindset
Human Influence
System Fairness
System Transparency
Autonomy
Feedback
Task significance
Task variety
Job complexity
Emotional demands
Other relevant information

I've learned quite a lot. I went to a folkhogskola school in Sweden and studied design for a year. So, idea generation, development products, validation and just physical and craftsmanship when it comes to cabinet making, textile drawing etc. and practicing Spanish in my spare time. I know how to speak French. I read a lot but. I haven't learned a new coding language. [.....]I mean, surveillance is never appreciated and being monitored.[.....]These things can be automated in some areas, but you have to be able to apply the context of priority and you know how much work something will require and things like that. And then based on that, you have to do it[....] You can touch on things that you haven't inserted in the interest database or that person might be knowledgeable of projects that you didn't even know existed at the firm, so I think that the bilateral physical interaction is actually preferable both because you have a wider array of options potentially, but also because it's more enjoyable and less alienating to be having a interaction about your future with someone rather than having an algorithm decided for you.[......]I would say that our system is, I mean it's so standardized[....]I think human influence is the key factor here. [.....]I think the completeness and accuracy of the data is very important.[.....]Second is transparency, for obvious reasons like data should be transparent and be known properly by everyone who is involved here, so that is important[.....]Yeah, but I think it would be hard to do for us like we have our utilization KPI, but that's still pretty subjective like there's still a lot of nuances and context behind that.[....]I guess I wouldn't love to have something that's on my computer. That's always checking how quickly I am doing my excel? Uh, how quickly am I doing this? I think I'll find it quite stressful, to be honest, so it will probably impact my performance negatively.

Appendix 3: Information About Interviews

Interview Number	Participant	Position	Duration	Setting
1	A	Consultant	28 mins	Microsoft Teams
2	A	Consulting Executive Trainee	32 mins	Microsoft Teams
3	A	Strategy Manager	29 mins	Microsoft Teams
4	A	Consultant	34 mins	Microsoft Teams
5	A	Associate Consultant	31 mins	Microsoft Teams
6	A	Management Consultant	36 mins	Microsoft Teams
7	A	Management Consultant	24 mins	Microsoft Teams
8	B	Data Scientist	24 mins	Microsoft Teams
9	B	Data Engineer	30 mins	Microsoft Teams
10	B	Data Engineer	26 mins	Microsoft Teams
11	B	Partner Manager	28 mins	Microsoft Teams
12	B	Software developer	35 mins	Microsoft Teams
13	B	Software developer	23 mins	Microsoft Teams
14	B	Machine Learning Engineer	28 mins	Microsoft Teams

Appendix 4: Initial Email To Potential Interview Participants

Hey!

How's it going?

I'm a BSc in Business & Economics student in my final year at SSE, and I'm writing my thesis on the way algorithmic management may change the consulting industry.

Would you be free for a short, 30-minute interview sometime in the coming weeks? :)

Best regards,

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