The Impact of Perceived Algorithmic Goal Setting on Job Satisfaction, Stimulating Job Characteristics and the Role of Organizational Culture.

Master Thesis

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1: Introduction

The advancement of technology has historically led to prioritizing the effective integration of technology over the preservation of the quality of jobs of the employees working together with new technologies (Wolfgramm et al., 2021). The most prominent and recent example of disruptive technological change impacting the workplace are the advances made in Artificial Intelligence (AI). The growth in use of AI has given way to the rapid adaptation of Algorithmic Management (AM) in modern workplaces. However, integrating these technologies into the workplace is changing the nature of workplaces and the work itself. This has presented organizations with challenges, since both organizational structures and individual roles are affected by these changes, making it difficult for organizations and their employees to adapt (Baiocco et al., 2022). Therefore, the impact of changes brought on by AM to employee well-being and the quality of job design has become a concern for many stakeholders in organizations (Baiocco et al., 2022).

Research on this topic is relevant for organizations, managers and employees for several reasons. Having already seen prominent use in gig economy platforms, AM is now expanding into traditional work contexts as well (Baiocco et al., 2022; Parent-Rocheleau & Parker, 2022). In a survey done in several European countries, 76% of respondents say that at least one form of AM is used in their workplace (Jensen et al., 2024). However, managing this change is not easy for managers who must integrate AM into already existing processes and systems due to the high cost of expertise and technology (Bhargava et al., 2020; Lanni, 2021). The long-term legal and regulatory risks of AM remain unclear but could be significant for firms that adopt these systems unsustainably (Bhargava et al., 2020). While the specific legal and regulatory risks of AM are not the focus of this study, these are important consequences for managers to keep in mind while managing the implementation of AM.

Since the use of AM has high costs and potentially negative long-term consequences for workers, managers and organizations, these effects can be managed by organizational stakeholders to preserve or even improve employee outcomes (Parent-Rocheleau & Parker, 2022). To achieve this, the relationship between workers and managers will have to be reconfigured and negotiated throughout the implementation of AM in organizations (Jarrahi et al., 2021). Understanding the potential effects of implementing AM systems can help organizations in designing responsible and sustainable AM systems that satisfy both organizations and their employees (Mettler, 2023).

In the past, changes to work by technological advances often negatively impact employee outcomes, such as job satisfaction (Bellou, 2010; Wolfgramm et al., 2021). However, in contrast to previous technological changes, AM is fundamentally changing employees' perceptions of work and social relationships at work (Jago et al., 2024). This transformation of work means AM could either enhance or hamper the achievement of high-quality job design, and thus impact both organizational outcomes and employee outcomes (Parker & Grote, 2020). Effects of AM can be influenced and managed by decisions of organizational stakeholders, highlighting the need to research how AM can be designed and implemented in a way that benefits employees (Parent-Rocheleau & Parker, 2022).

Job design is a valuable perspective for understanding the effects of new technology being introduced to the workplace, such as AM (Parker & Grote, 2020). In organizations AM is not just a 'technology', but also a type of managerial actor that reshapes job design characteristics (Parker & Grote, 2020). An element of job design that could be affected by AM is the stimulating job characteristics. Stimulating job characteristics are characterized as work requiring a high degree of mental complexity and variety (Parker & Knight, 2024). For workers, research on this topic to better inform decisions about AM's effects on job design is particularly relevant because of the positive relationship between job design and job satisfaction (Parker & Grote, 2020; Parker & Knight, 2024).

However, research on the effects of AM lacks studies conducted with employees who are affected by current AM systems (Jarrahi et al., 2021). Most research on AM and its impact in organizations involves previous generations of AI, meaning that these studies do not fully reflect some technological characteristics of emerging AI systems and their applications in AM (Jarrahi et al., 2021). For example, a unique characteristic of these emerging systems is that they teach themselves, which sets them apart from previous AI generations. This indicates the need for more research on perceptions of the effects of current AM systems from the employee perspective (Gagné et al., 2022; Jarrahi et al., 2021).

Furthermore, understanding the potential effects of AM is also difficult because studies on AM so far are lacking in nuance (Parent-Rocheleau & Parker, 2022; Parent-Rocheleau et al., 2024). Many studies treat AM as a single entity instead of considering its separate functions, missing out on crucial depth in the understanding its effects. For instance, the perceived effects of AM on job design are highly variable across AM's different functions, indicating the importance of considering these functions separately (Parent-Rocheleau & Parker, 2022).

In practical terms, an example of this is algorithmic goal setting (AGS), which is the assignment of tasks and performance goal setting for employees. This function differs from algorithmic compensation, which is used to set workers' pay (Parent-Rocheleau & Parker, 2022). Many studies overlook the diversity in AM functions and fail to recognize the increasingly complex nature of algorithmic systems in the workplace. This increases the need to research AM's functions with a toolkit appropriate for examining and analyzing the complexity of this construct (Parent-Rocheleau & Parker, 2022; Parent-Rocheleau et al., 2024).

Additionally, besides individual factors (such as skills or attitudes), many different higher-level contextual factors (such as organizational culture or the occupation's skill level) exist that influence the way AM is designed and implemented (Parker & Grote, 2020). As literature on the perceived effects of AM is nascent, there are few empirical studies that measure the influence of moderating contextual factors (Gagné et al., 2022). Studies have found these contextual factors could influence perceptions around AM usage, making perceptions vary from one context to another (Gagné et al., 2022). This indicates the need for further research on the role contextual factors play in forming perceptions on the implementation of AM (Jarrahi et al., 2021; Keegan & Meijerink, 2025; Parent-Rocheleau & Parker, 2022; Parker & Grote, 2020).

For instance, while not having been researched previously, organizational culture is an example of a contextual factor that could play a role in moderating the effects of AM (Parent-Rocheleau & Parker, 2022). Organizational culture is the distinct identity that every organization has, existing out of values, beliefs, assumptions, expectations, philosophies, attitudes and norms (Bellou, 2010). While organizational culture is hard to exactly pinpoint, it can roughly be categorized in four different categories: adaptability-, consistency-, mission- or involvement-oriented (Denison & Mishra, 1995). Further research on possible moderators such as organizational culture will help realize strategies for stakeholders in designing and implementing AM systems sustainably (Parent-Rocheleau & Parker, 2022).

To summarize, this study makes several important contributions to existing literature. First, research on AM is relevant because it fundamentally alters how employees perceive work and workplace relationships, which either enhances or hampers high-quality job design (Jago et al., 2024; Parker & Grote, 2020). AM acts as a managerial actor that reshapes stimulating job characteristics, which are closely linked to job satisfaction (Parker & Knight, 2024). Second,

use of AM is rapidly expanding beyond the gig economy into traditional organizations, with 76% of European workers reporting exposure to AM systems (Jensen et al., 2024). However, implementation remains challenging due to high costs, expertise demands, and unclear legal risks (Bhargava et al., 2020). Given these risks, responsible design and implementation of AM is essential to preserve or improve job design and employee outcomes (Parent-Rocheleau & Parker, 2022).

Third, current research on this topic is limited by a lack of employee-focused studies and outdated views of AI, missing the complexity and opacity of newer AM systems (Gagné et al., 2022; Jarrahi et al., 2021). Additionally, many studies oversimplify AM by treating it as a single function rather than examining its diverse functions (Parent-Rocheleau & Parker, 2022). Finally, contextual factors like organizational culture, which shapes how AM is designed and perceived, are underexplored in empirical research, despite their possible moderating role (Jarrahi et al., 2021; Keegan & Meijerink, 2025; Parent-Rocheleau & Parker, 2022; Parker & Grote, 2020). Further research into these moderators is needed to support sustainable AM integration in organizations.

This study aims to address the lack of insight into how employee perceptions of a specific AM function – algorithmic goal setting (AGS) – affect job design and employee outcomes, and what moderating role organizational culture plays. AGS involves the assignment of tasks and performance target setting for employees. Validated and reliable theoretical models can be used to better understand the perceived effects of AGS on job design and employee outcomes and what contextual factors could moderate these relationships. Given the research gaps stated above, the following research question has been chosen for this study: "*does perceived Algorithmic Goal Setting influence job satisfaction directly and indirectly through stimulating job characteristics and is this indirect effect moderated by different types of organizational culture? (Involvement, Adaptability, Mission, Consistency)"*

The increase in knowledge and insight gained from this study should help inform decisions around designing AM to preserve employee outcomes. Doing so with awareness of job design risks and organizational context can prevent unintended harm and enhance long-term sustainability for integrating AM into organizational processes (Parent-Rocheleau & Parker, 2022).

In this study, the second chapter will provide the theoretical background by reviewing existing literature on this topic and develop hypotheses and the conceptual model that is the

foundation of this study. Chapter 3 will dive into the methodology of this study, by laying out the research design and motivation for the epistemological choices and the data collection and measurement procedures will be developed. Chapter 4 contains the data-analysis of the conducted quantitative research and a description of the results found by this research. In chapter 5, results will be interpreted considering the research question and theory. The implications and limitations of this study will be discussed, as well as opportunities for future research to conclude this study.

2: Theoretical Framework

In this chapter, a theoretical framework will be developed where the existing literature on job satisfaction, perceived AGS, stimulating job characteristics and organizational culture will be further explored.

2.1: Algorithmic Goal Setting

In the past decades, employers have been increasingly using digital systems and technologies to support decision-making and improve work processes to ultimately increase productivity (Brancati & Curtarelli, 2021). This process is called 'digitalization' and has been found to positively affect employee outcomes and job characteristics (Bolli & Pusterla, 2022). On the other hand, with digitalization, cognitive tasks are being increasingly replaced, leading to worse job design (Parent-Rocheleau & Parker, 2022; Parker & Grote, 2020). However, effects of digitalization can vary depending on various factors, such as how this technology is implemented and used (Parker & Grote, 2020).

Algorithmic management (AM) is the latest example of this dual nature within digitalization, offering both benefits and drawbacks to organizations that implement it. AM refers to the use of algorithmic systems to manage employees and can take on many different forms. This is enabled by collecting large amounts of data on productivity and employee behavior (Aloisi & Gramano, 2019).

AM has been a difficult phenomenon to research for two reasons. Because of the complicated neural networks that enable recent AM systems to teach themselves, their inferences are intrinsically opaque (Jarrahi et al., 2021). This opacity of AM systems, along with variations in individual perceptions of AM exposure make it hard to measure the outcomes of the implementation of AM systems objectively (Jarrahi et al., 2021; Parent-Rocheleau et al., 2024). Therefore, measuring employee perceptions on the effects of AM is crucial for

determining how best to design and implement these systems (Jarrahi et al., 2021; Parent-Rocheleau et al., 2024).

Measuring these perceptions has proven to be difficult so far, because the perceived effects of AM on job design are highly variable across AM's different functions, highlighting the importance of considering these functions separately (Parent-Rocheleau & Parker, 2022). The Algorithmic Management Questionnaire (AMQ), however, has provided a validated way to assess employees' exposure and perceptions of specific functions of AM (Parent-Rocheleau et al., 2024). This allows for separate examination of certain forms of AM, and for this study to be able to examine the perceived effects of AGS separate from other AM functions.

The form of AM most relevant for this study is Algorithmic Goal Setting (AGS), which refers to algorithms assigning tasks, organizing employees' work or setting performance or productivity targets (Parent-Rocheleau & Parker, 2022). This function of AM has developed the most in digital labor platforms, also known as 'gig work' (Baiocco et al., 2022). However, AGS is also rapidly being adopted in certain traditional industries like telecommunication, electronics, public transport and parcel delivery (Parent-Rocheleau & Parker, 2022). Growth of AGS use in these traditional work sectors could collapse existing work hierarchies by shrinking low- and middle level management, changing power dynamics by further consolidating power at the top of company hierarchies (Baiocco et al., 2022).

This change in organizational structure leaves employees with less power and causes managers to prioritize efficiency over employee outcomes through AGS systems. This is exemplified in reports of manufacturing plants using task planning algorithms to improve work sequencing, avoid bottlenecks and meet production deadlines. However, this also led to a negative change to job design by decreasing stimulating job characteristics. Employees were less stimulated at work through the simplification of tasks and fewer problem-solving opportunities (Parent-Rocheleau & Parker, 2022).

To summarize, digitalization has generally been found to have mixed consequences for the workplace and the most recent innovation within digitalization is Algorithmic Management (AM). AM uses data-driven algorithmic systems to oversee and direct employee work. Although AM is broad and complex, the development of the Algorithmic Management Questionnaire (AMQ) makes it possible to isolate and assess the impact of specific AM functions on employees' experiences. This study focuses specifically on Algorithmic Goal Setting (AGS), a form of AM where algorithms assign tasks or set performance targets. While

AGS originated in gig work, it is now increasingly used in traditional industries, potentially reshaping workplace hierarchies and thereby affect employee outcomes and the quality of job design.

2.2: Job satisfaction

Job satisfaction has been widely examined both as an outcome of work-related factors and as a predictor of important workplace behaviors, such as job performance, productivity and turnover (Ay et al., 2024; Bowling & Hammond, 2008). This makes job satisfaction an important topic of research for both organizations and their workforces (Ay et al., 2024). Job satisfaction can be defined as a positive or negative evaluative judgment one makes about one's job or job situation (Weiss, 2002). Several antecedents for job satisfaction have been identified in the extensive body of research done on this topic, such as job design, work stressors and organizational culture (Bowling & Hammond, 2008; Lund, 2003).

Given that both organizational structures and individual roles are affected by the integration of AGS in the workplace, AGS could affect job satisfaction directly, as well as indirectly through these antecedents (Baiocco et al., 2022; Humphrey et al., 2007). So far, no research has been done on the perceived effects of AGS on job satisfaction directly in traditional work contexts. This absence of empirical research in traditional contexts limits the understanding of how AGS works outside of the gig economy (Baiocco et al., 2022; Parent-Rocheleau & Parker, 2022).

However, findings from other studies investigating similar related technologies and processes could inform expectations of possible effects. For instance, digitalization is negatively associated with job satisfaction because of increases in time pressure and a worsening work-life balance (Bolli & Pusterla, 2022). Furthermore, AM in general has been shown to lower job ssatisfaction by increasing physical demands and reducing employee autonomy (Baiocco et al., 2022; Jensen et al., 2024). While these findings suggest that AGS may negatively affect job satisfaction, other studies suggest that AM may also improve job satisfaction by eliminating boring and repetitive tasks and by creating a better match between work and skills through AI-based recruiting (BusinessEurope, 2023; Lee, 2018).

These contrasting findings highlight the importance of empirically researching how AGS directly affects job satisfaction. Much of the reasoning for implementing AGS lies in improving efficiency based on data-driven decision-making. However, this goal may clash with human elements of work that improve job satisfaction, such as job design (Humphrey,

Nahrgang & Morgeson, 2007; Parent-Rocheleau & Parker, 2022). Constructs such as job satisfaction are difficult to objectively measure using algorithms, unlike the productivity data that feed AGS systems (Jarrahi et al., 2021). Therefore, previous studies have called for further investigation into the perceived effects of specific AM functions on employee outcomes, such as job satisfaction (Parent-Rocheleau & Parker, 2022; Parent-Rocheleau et al., 2024).

Since most of the existing literature suggests the potential for a negative link between AGS and job satisfaction, the following hypothesis can be derived:

H1: *''AGS has negative perceived effects on job satisfaction."*

2.3: Stimulating job characteristics

Job design is 'the content and organization of one's work tasks, activities, relationships and responsibilities' (Parker & Knight, 2024), p. 266) and is important for a range of individual, group and organizational outcomes (Humphrey & Morgeson, 2006). Researchers have increasingly applied job design theory to understand how digitalization affects employee outcomes, such as job satisfaction. Job design is an important lens for understanding how people can work collaboratively with AI in a digitalized work environment (Parker & Grote, 2020). In work design theory, job satisfaction is very commonly measured, and studies have found positive relationship between work design and job satisfaction: when people experience a high quality of job design, they feel satisfied when doing their job (Bowling & Hammond, 2008; Humphrey & Morgeson, 2006, Parker & Knight, 2024).

For instance, when job characteristics such as task or skill variety are increased, job satisfaction improves as a result (Bowling & Hammond, 2008; Humphrey & Morgeson, 2006; Parker & Grote, 2020). However, job characteristics are affected by the technological context of jobs (Parker & Knight, 2024; Shepard, 1977). For instance, digitalization can lead to poor job design quality by a reduction of job design elements such as variety and skill use (Brawley & Pury, 2016). Therefore job design is an important tool to inform stakeholders how jobs should be designed for employees to work collaboratively alongside AI and automation in a way that is not detrimental to workers (Parker & Knight, 2024).

Parker & Knight (2024) have developed the SMART model to help view the emergence of algorithmic management through a more comprehensive lens. This model builds further on the principles of job design. Job design refers to *'the content and organization of one's work*

tasks, activities, relationships and responsibilities' (Parker, 2014). However, the SMART model is more integrative than previous models, providing a structured and multidimensional way to empirically measure perceptions of employee job characteristics. Additionally, this model is more suitable for studying how job quality can be preserved and even improved in the context of increasing digitalization (Parker & Knight, 2024). This study is the first to apply the SMART model in examining the perceived effects of AM.

The SMART model includes five dimensions of job design: Stimulation, Mastery, Agency, Relational and Tolerable job characteristics. Each dimension reflects a psychological or social need that contributes to meaningful, satisfying and sustainable work in modern, digitalized work environments. Stimulating job characteristics are characterized by work having a high degree of variety and mental complexity and is usually reduced when an individual repeats similar, low-level tasks. This dimension contains four work characteristics: task variety (the range of different tasks a job requires); skill variety (the variety of skills to be used in the job); problem-solving requirements (degree to which a job requires new ideas and solutions) and information processing requirements (extent to which the job is required to process data and information) (Parker & Knight, 2024).

This study focuses specifically on stimulating job characteristics for several reasons. Firstly, prior research consistently links stimulation to job satisfaction, the central outcome in this study (Humphrey & Morgeson, 2006; Parker & Knight, 2024). Furthermore, employees are very likely to be affected by AGS possibly changing stimulating job characteristics such as the mental complexity or variety of work (Gagné et al. 2022; Parent-Rocheleau & Parker, 2022; Parker & Grote, 2020). While other dimensions of the SMART model are also linked to job satisfaction and can be affected by AGS, elements of stimulating job characteristics (skill variety, task variety, problem solving requirements, information processing requirements) are consistently found to be affected by AGS in previous studies (Gagné et al. 2022; Parent-Rocheleau & Parker, 2022; Parker & Grote, 2020). Therefore, the expectation is that stimulating job characteristics are theoretically and empirically the most relevant dimension for examining AGS's perceived effects on job satisfaction.

The adaptation of AGS in workplaces has the potential to influence these characteristics, though existing research presents mostly negative findings. Some studies found that AGS decreases job complexity by simplifying tasks and reducing opportunities for variety (Parent-Rocheleau & Parker, 2022; Parent-Rocheleau et al., 2024). To enable AGS, tasks need to be

broken down into small, standardized units which eliminate complexity and problem-solving opportunities, thereby negatively affecting dimensions such as task variety and problem-solving requirements (Parent-Rocheleau & Parker, 2022; Parent-Rocheleau et al., 2024). AGS can also reassign or interrupt tasks dynamically, leading to workers not being able to fully engage with cognitively demanding tasks and negatively affecting stimulating job characteristics (Baiocco et al., 2022). However, other studies report more positive findings: by automating repetitive or unskilled tasks, AGS can allow workers to focus more on skilled and meaningful work, potentially improving skill variety and problem-solving requirements (Gagné et al., 2022; Parker & Grote, 2020).

Given that most findings on the potential effects of AGS present negative patterns, a negative effect is expected to be more likely. Therefore, the following hypothesis can be derived:

H2: ‘’*Perceived AGS has a negative effect on stimulating job characteristics.”*

As stated above, stimulating job characteristics have been found to be important predictors of job satisfaction. Higher levels of stimulating job characteristics (skill variety, task variety, problem-solving opportunities & information processing opportunities) lead to higher levels of job satisfaction (Bowling & Hammond, 2008; Humphrey & Morgeson, 2006; Parker & Grote, 2020; Shepard, 1977). Therefore, the following hypothesis can be formulated for this study:

H3: ‘’*Stimulating job characteristics positively affect job satisfaction.”*

Perceived AGS is expected to affect job satisfaction indirectly by altering how stimulating employees perceive their work to be. Specifically, AGS can reduce levels of stimulating job characteristics, which are important predictors of job satisfaction in job design theory (Bowling & Hammond, 2008; Humphrey & Morgeson, 2006; Parker & Grote, 2020; Shepard, 1977). Thus, it is not AGS itself that directly determines job satisfaction, but its impact on the level of stimulating job characteristics that mediate this relationship. This leads to the final hypothesis of this section:

H4: ‘’*Stimulating job characteristics mediate the relationship between perceived AGS and job satisfaction.”*

2.4: Organizational culture

Organizational culture is an important concept in understanding how employees interpret and respond to structural changes within their work environments. It refers to the shared values, beliefs, assumptions, expectations, attitudes philosophies and norms that characterize an organization (Bellou, 2010; Hofstede, 1998). Yet, the perceptions of a culture within an organization can differ according to their unique understanding and explanation of their working condition, based on their own characteristics, preferences and personality (Bellou, 2010). This has been an important topic for researchers, since organizational culture is a predictor of employee job satisfaction and overall performance (Denison & Mishra, 1995).

Organizational culture plays an important role when implementing new technology in the workplace. Because job satisfaction involves a judgment of job characteristics based on what an employee finds meaningful, the way job characteristics are experienced is inherently influenced by the cultural environment the job is part of (Belias & Koustelious, 2014). Furthermore, the effect of job design on job satisfaction differs across organizational cultures (Erez, 2010). This leads to technological change, job satisfaction, job design and organizational culture being extremely intertwined (Orlikowski, 2007, Parker & Grote, 2020).

In the case of AM, organizational context has already been found to be an important factor that influences the way AM is designed and implemented into jobs (Jarrahi et al., 2021; Keegan & Meijerink, 2025; Parent-Rocheleau & Parker, 2022; Parker & Grote, 2020). The reason for this is that while algorithms have a central bearing on how work is managed, their outcomes in changing management and relationships between workers and workers are socially constructed and enacted. Therefore, the effects of AM have sociocultural differences across industries and organizational contexts (Jarrahi et al., 2021).

As AM is socially constructed and embedded within cultural power structures, its effects are unlikely to be uniform across different types of organizational cultures (Jarrahi et al., 2021). For example, AM may appear different in organizations where employees are involved in decision-making processes than organizations with rigid, top-down decision-making (Jarrahi et al., 2021). However, despite the rapid adoption of AM systems in traditional workplaces, not much research has been done on the interaction between these systems and organizational culture (Baiocco et al., 2022). Furthermore, most studies are focused on the gig economy, where organizational culture plays little to no role. This limits the transferability of these

findings to traditional work environments that contain more structure and culture than platforms in the gig economy (Jarrahi et al., 2021).

Organizational culture can be categorized into 4 different cultural archetypes (Denison & Mishra, 1995): Involvement, Consistency, Adaptability and Mission. Each type could have distinct implications for how employees experience technological interventions such as AGS. First, the involvement organizational culture type emphasizes employee empowerment, participation and team orientation. High involvement cultures aim to create a sense of ownership and leadership, leading to greater motivation, skill development and alignment with organizational goals (Denison & Mishra, 1995). In these environments, perceived loss of skill or task variety could be mitigated by the participatory nature of this culture type (Parent-Rocheleau & Parker, 2022). Employees may be able to adapt and maintain their stimulating job characteristics through being able to exert influence, even when algorithms define their tasks (Parent-Rocheleau & Parker, 2022). This leads to the following hypothesis:

H5: *''The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be weakened in organizations with a strong Involvement culture."*

Second, consistency culture focuses on the internal systems, values and norms that promote coordination and integration with an organization. These organizations have shared beliefs and strong norms that emphasize control and predictability (Denison & Mishra, 1995). In these environments, AGS could limit employees' ability to decide when and what tasks to complete, thereby potentially reducing task variety and problem-solving opportunities (Jarrahi et al., 2021; Parker & Grote, 2020). Therefore, this culture type's rigidity could increase the loss of stimulating job characteristics. This leads to the following hypothesis:

H6: *''The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be strengthened in organizations with a strong Consistency culture."*

Third, adaptability culture types prioritize learning and adaptability to changes in the external environment. Organizations with this type of culture prioritize being adaptable to trends in the market and encourage employees to innovate and take risks when completing tasks (Denison & Mishra, 1995). This can lead to adaptable organizations introducing AGS systems to increase productivity through the automation of simple and repetitive tasks, leaving more complex tasks for employees (Parker & Grote, 2020). The capacity of workers to adapt their ways of working and embrace new technologies such as AGS is essential for the implementation of these systems (Parker & Grote, 2020). Therefore, using AGS as a tool

for productivity could help reduce the potential negative perceived effects it might have on stimulating job characteristics, leading to the following hypothesis:

H7: *''The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be weakened in organizations with a strong Adaptability culture."*

Fourth, mission cultures are centered around a defined long-term direction, vision and purpose. This culture type provides meaning for employees through its mission and aligns the organization's strategy with its overarching goals (Denison & Mishra, 1995). The manner how AGS is implemented affects stimulating job characteristics so if AGS is implemented in a manner that aligns with the organization's mission, employees could be more accepting of the changes in job design AGS systems bring (Parker & Grote, 2020). This sense of alignment can weaken the potential negative perceived effect of AGS on stimulating job characteristics, leading to the following hypothesis:

H8: *''The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be weakened in organizations with a strong Mission culture."*

2.5: Conceptual model

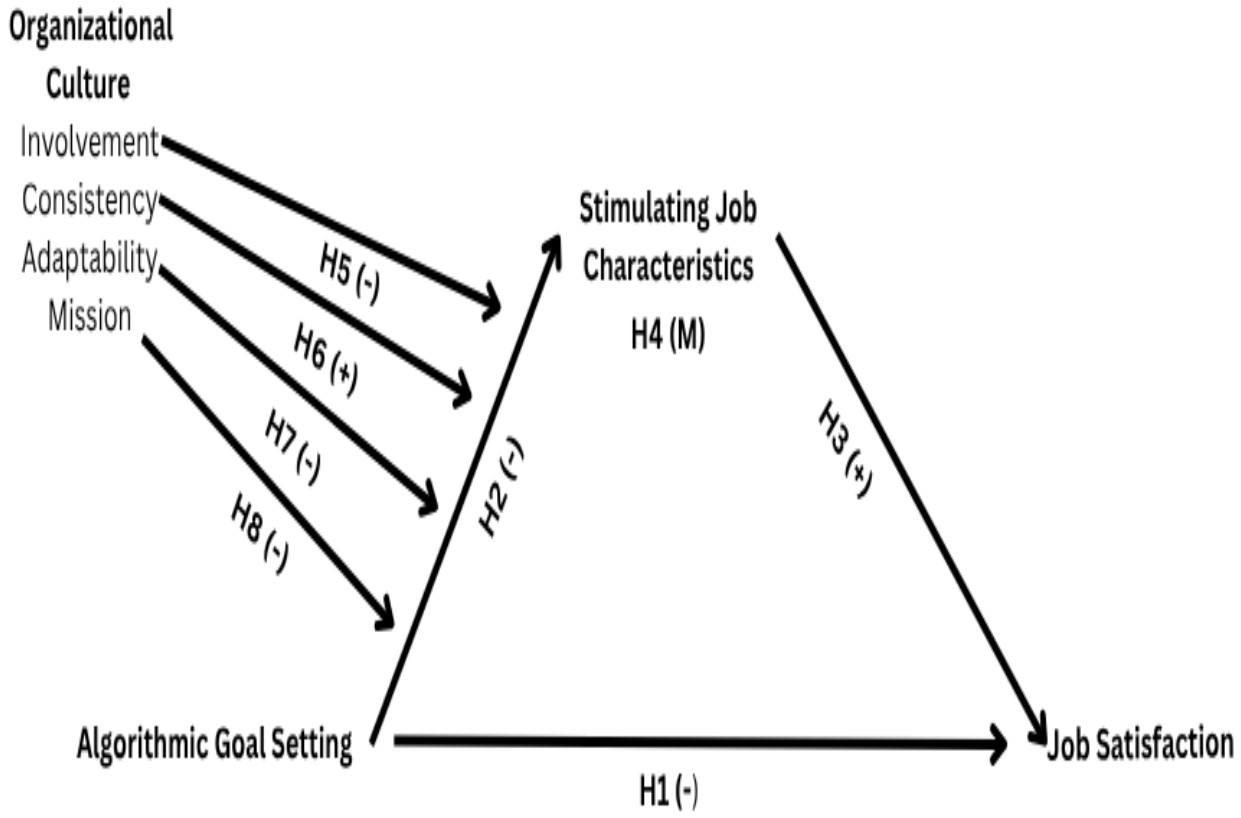
To conclude, this chapter has delved into the existing literature surrounding AGS, job satisfaction, organizational culture and stimulating job characteristics. 8 hypotheses were derived to answer the research question of this study, which is: "*does perceived Algorithmic Goal Setting influence job satisfaction directly and indirectly through stimulating job characteristics and is this indirect effect moderated by different types of organizational culture? (Involvement, Adaptability, Mission, Consistency)"*
In table 1, all the hypotheses that have been tested are summarized. In figure 1, a visual representation is made on how AGS influences job satisfaction directly and indirectly through stimulating job characteristics, and how this effect is moderated by different types of organizational culture.

Table 1: List of Hypotheses:

Hypothesis	Statement
H1	AGS has negative perceived effects on job satisfaction.
H2	Perceived AGS has a negative effect on stimulating job characteristics.

H3	Stimulating job characteristics positively affect job satisfaction.
H4	Stimulating job characteristics mediate the relationship between perceived AGS and job satisfaction.
H5	The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be weakened in organizations with a strong Involvement culture.
H6	The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be strengthened in organizations with a strong Consistency culture.
H7	The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be weakened in organizations with a strong Adaptability culture.
H8	The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be weakened in organizations with a strong Mission culture.

Figure 1: Conceptual Model



3: Methodology

This chapter outlines the methodology used in this study. First, arguments for this study's research design are described. Second, the data collection method and ethical considerations are explained. Third, the variables and how these were measured are explained. Fourth, the plan for analyzing the data is explained and the limitations of this study are discussed last.

3.1: Research Design

The aim of this research paper is to examine this research question: "*does perceived Algorithmic Goal Setting influence job satisfaction directly and indirectly through stimulating job characteristics and is this indirect effect moderated by different types of organizational culture? (Involvement, Adaptability, Mission, Consistency)"*. To test the hypotheses in the conceptual model (figure 1), a quantitative, cross-sectional approach to research design has been chosen, which aligns with a positivist epistemological standpoint. The cross-sectional approach is best suited for this study due to limited time and resources, even though this approach limits the ability to draw causal inferences. Furthermore, this approach is best suited for the simultaneous assessment of multiple variables in a single moment in time (Wang & Cheng, 2020). The quantitative approach, using research methods such as surveys, is used best for analyzing and measuring relationships between multiple variables, such as AGS, stimulating job characteristics, organizational culture and job satisfaction, supposedly existing in social reality.

To focus on researching the effects of AGS, conducting a survey was found to be most suited for this study and its epistemological position (Vennix, 2019). Using a survey allows for the measurement of individual perceptions of AGS exposure, which is of paramount importance for informing decisions around the design and implementation of AM (Parent-Rocheleau et al., 2024).

The survey targets people who are currently employed. Also, the goal is to establish a relationship directly between AGS and job satisfaction and indirectly through dimensions of stimulating job characteristics while also investigating the moderating role of organizational culture plays in the indirect relationship between AGS, stimulating job characteristics and job satisfaction. This use of survey-based measurement allows us to identify general correlations and trends within these relationships.

3.2: Data Collection Method

For this survey to have enough statistical power for moderated mediation and multiple regression analyses, sample size was aimed to be above 100 (Hair et al., 2019). The target population for this study included all individuals who are currently employed, regardless of sector, industry or type of job. While the primary focus of this study was to examine the perceived effects of AGS, the survey was designed to include both respondents who are exposed to AGS and respondents who are not. This approach includes respondents who may experience high levels of AGS to respondents who may experience little to no AGS exposure. This gave insight into whether differences in job satisfaction and stimulating job characteristics levels could be attributed to perceived AGS exposure, and if different organizational culture types influenced this effect. To examine perceived exposure, respondents self-reported whether their job currently involves algorithms assigning them goals or tasks.

The survey was distributed in the Netherlands using the researcher's social media networks, such as WhatsApp, LinkedIn, Instagram and Facebook, where many qualified respondents were found to participate in this study. However, this sampling strategy could lead to the survey population being skewed toward certain demographic populations and limiting generalizability. To prevent a skewed sample, the survey was also distributed at the researcher's place of work, creating a diverse population spread across all ages and educational backgrounds. This measure preserved a more diverse sample and increased the generalizability of this study.

Additionally, the survey has been conducted using Qualtrics, a secure web-based tool that facilitates conducting surveys. The benefits of using this research tool are its user-friendliness and the option to export data into SPSS, the software which was used to analyze the data, conduct multiple regression analyses and extract findings from this data (Radboud University, 2025). The cross-sectional approach of this study has the advantage of rarely causing ethical issues, because of subjects being neither deliberately exposed nor treated (Wang & Cheng, 2020). However, certain ethical considerations have been taken into account. While conducting the survey, anonymity and compliance with the General Data Protection Regulation (GDPR) has been ensured. Participants have been informed of the study's purpose and data use before starting the survey and filled in a consent form about their data being

stored according to GDPR guidelines. Respondents also had the option to withdraw from the survey at any stage.

3.3: Participants

The final sample consisted of 102 participants. The age of respondents ranged from 18 to 62 years old, with most respondents being concentrated on the younger age brackets (M=31.62, SD= 11.9). The most frequently reported age was 23 years (12.6%), followed by 24 and 25 years (each 10.7%). Overall, 67.0% of the sample was within the 20–30-year age range, suggesting a young adult population was predominantly responding to the survey. Older age groups were less represented, with only a few participants aged above 40. In terms of gender, slightly more than half of the participants identified as male (53.4%), while 44.7% identified as female. Two respondents (1.9%) preferred not to disclose their gender. This relatively balanced distribution provides an appropriate amount of gender diversity, although male participants were slightly overrepresented.

Educational background showed that the sample was relatively highly educated. Most participants (66.0%) reported having completed higher education, with equal proportions having completed either an HBO (university of applied sciences) bachelor's or master's degree (33.0%) or a WO (university) bachelor's or master's degree (33.0%). Additionally, 26.2% of participants had completed MBO (vocational school), and a smaller group (7.8%) reported high school as their highest completed education level. These results suggest that the study has attracted respondents with above-average education.

3.4: Variables and Measures

To examine the relationship between AGS, job satisfaction, stimulating job characteristics and organizational culture, several key independent and dependent variables will be operationalized. For each construct, the study uses validated and reliable measures and respondents will answer most questions on a 7-point Likert scale (1=strongly disagree, 7= strongly agree). Using the 7-point scale instead of the 5-point scale gives the respondents greater ability to share their experiences and give a more reliable view of nuanced employee perceptions. The 7-point scale has also been found to be more reliable than the 5-point scale, with regards to internal consistency (Russo et al., 2021). Since the researcher's social and professional network is mostly in the Netherlands, respondents were expected to be mostly Dutch. Therefore, all of the scales were translated from English to Dutch using the DeepL translation software and checked by the researcher to maintain validity.

Independent variable: AGS exposure.

The extent to which a respondent perceives exposure to AGS will be measured on a 7-point Likert scale using the AGS-subscale found in the AMQ, which measures AGS through five items. The AMQ was developed by Parent-Rocheleau et al. (2024) and an example of one question measuring AGS by the AMQ is *'My daily tasks are assigned by an automated system.'*

Unlike previous research that treated AM as a binary (yes/no) variable, this scale helps us to measure the intensity and frequency of perceived AGS exposure. Using this subscale allows for a more nuanced method of measuring perceived exposure to AGS, making it suited for identifying these effects on job design and employee outcomes (Parent-Rocheleau et al., 2024).

Dependent variable: job satisfaction

Job satisfaction is measured using the Job Satisfaction Sub scale of the MOAQ (MOAQ-JSS) (Bowling & Hammond, 2008). Scores on the MOAQ-JSS are computed using the average of three items. One example of a question in the MOAQ-JSS is: *"All in all I am satisfied with my job."*

Responses are averaged to form a composite score, with higher values indicating greater job satisfaction. The MOAQ-JSS has shown strong internal consistency, with Cronbach's alpha values typically being >.80 and has been validated across many organizational and technological settings (Bowling & Hammond, 2008). This makes the MOAQ-JSS suitable for this study's focus on how job satisfaction is affected directly by perceived AGS and indirectly by stimulating job characteristics.

However, it is important to acknowledge that job satisfaction is not only shaped by job characteristics or technological systems like AGS, but also by demographic factors such as age and gender. The gender-job satisfaction paradox is an example of this manifesting itself and refers to women often reporting higher job satisfaction than men, despite often holding worse positions with regards to salary, authority and career opportunities (Souza-Poza & Souza-Poza, 2003). This can be explained by contextual factors such as organizational culture influencing differing expectations and values, which affects how individuals perceive the same job conditions. While this paradox is not the focus of this study and gender differences

will not be examined explicitly, it is important to acknowledge the existence of it and the possible role it plays in this study.

Mediating variable: stimulating job characteristics.

Stimulating job characteristics are measured using the Stimulation dimension subscale of the SMART model of job design, developed by Parker & Knight (2024). This subscale measures if respondents' jobs require mental complexity, variety and problem-solving. Stimulating job characteristics are made up of four components: skill variety, task variety, problem-solving requirements, and information processing requirements. These components, in this case skill variety, are measured using questions such as '*the job requires me to use a number of complex or high-level skills'.*

Items will be measured using a 7-point Likert scale (strongly agree-strongly disagree). This subscale was chosen for its connection to employees' demand for varied and complex work, which has been hypothesized to be affected by AGS. The SMART model has been shown to be empirically valid in digitalized work environments, making it appropriate for this study (Parker & Knight, 2024).

Moderating variable: organizational culture

The Denison Organizational Culture Scale (DOCS) by Denison & Mishra (1995) is used to measure organizational culture in this study. This scale measures culture across four dimensions: involvement, consistency, adaptability and mission organizational culture types. Each cultural dimension is measured using items on a 7-point Likert scale. These dimensions capture differences in organizational culture that could influence how AGS is implemented and perceived. For example, cultures with high levels of adaptability could weaken potential negative effects of AGS by its ability to adapt to change. On the other hand, consistency cultures may face difficulty in adapting due to their rigid structures.

The DOCS has seen widespread use in academic and organizational research and has been extensively validated (Denison et al., 2014). During this study, including all four culture types has allowed for moderated mediation analyses to test how each type affects the relationship between AGS, stimulating job characteristics and job satisfaction.

3.5: Data Analysis

After data collection, the raw data was evaluated and prepared for analysis. The first step in this process was checking for missing data and inspecting for data entry errors and further inconsistencies. Respondents with missing data entries were removed from data analysis, to preserve the validity of the data set. The presence of missing data can bias the results of multivariate analyses and reduce their generalizability (Hair et al., 2019). Then, univariate and multivariate methods were used to identify and remove outliers. The next step was to examine variable distribution, by checking for skewness and kurtosis and visually examining relationships between variables. Then, the statistical assumptions were tested to obtain valid statistical inferences from multivariate techniques. Since this survey does not contain nonmetric variables, no dummy variables had to be created. When all these steps were completed, the data was entered into SPSS and evaluated.

The data analysis was carried out as follows: first, the reliability of the scales was examined using Cronbach's Alpha. Second, the descriptive statistics for each variable (algorithmic goal setting, stimulating job characteristics, job satisfaction and each organizational culture type) were summarized in a table to examine the central tendencies and distribution patterns. Third, Pearson's correlation was calculated to identify relationships between these variables. Fourth, a simple mediation model analysis was conducted to research the direct relationships between the variables. These relationships were examined as part of the testing of hypotheses in this study using regression analyses. This step was supported by PROCESS macros (version 4.1) by Hayes (2022) in SPSS. To examine the first four hypotheses, PROCESS Model 4 was used to examine the direct effect of perceived AGS on job satisfaction and the mediation of stimulating job characteristics between perceived AGS exposure and job satisfaction.

To examine the last four hypotheses, four separate moderated mediation analyses were conducted using PROCESS Model 7. This model was used in four separate analyses of the moderating effect of each organizational culture type (involvement, consistency, adaptability and mission). These models examined whether the indirect effect of perceived AGS on job satisfaction through stimulating job characteristics was influenced by different types of organizational culture. The moderated mediation calculation was divided into these two equations:

$$SJC = \beta_0 + \beta_1(AGS) + \beta_2(OC\ type) + \beta_3(AGS \times OC\ type) + \varepsilon_1$$

$$Job\ Satisfaction = \beta_0 + \beta_4(SJC) + \beta_5(AGS) + \varepsilon_2$$

These models allow for the simultaneous testing of moderation (OC type influencing AGS > SJC path) and mediation (AGS>SJC>Job satisfaction).

Bootstrapping procedures were also used to increase robustness of the estimates. 5.000 samples were used for mediation analyses and 10.000 samples were used for the moderated mediation models. To determine statistical significance, bias-corrected 95% confidence intervals were used with intervals that excluded zero for the indication of significant effects. Results were interpreted using unstandardized coefficients, p-values, confidence intervals and R^2 values. All the regression assumptions were evaluated, including linearity, normality, homoscedasticity, multicollinearity and independence of residuals to ensure validity.

4: Analyses

In this section, the data will be analyzed and its results with regards to answering the research question will be described. As stated in the methodology, simple mediation analysis and moderated mediation analyses are used to test hypotheses and answer the research question. These analyses require that several assumptions must be met, specifically when multiple regression analyses are conducted.

4.1: Reliability, Descriptives and Correlations

First, reliability analyses were conducted using Cronbach's alpha to determine the internal consistency of this study's model. Each subscale's Cronbach's alpha was added to table 2. All subscales demonstrated acceptable to high values of Cronbach's alpha, indicating high internal consistency. Only the subscale of Consistency organizational culture type gave a low alpha, meaning that interpretation of effects involving this subscale should be done with caution.

To explore the distribution and central tendencies of the study variables, descriptive statistics were calculated for the perceived level of algorithmic goal setting, stimulating job characteristics, job satisfaction, and organizational culture. These variables were measured and displayed in the same table (table 2) in terms of their mean, standard deviation, minimum and maximum values, skewness and correlations. In table 2, Pearson's Correlation values are displayed in bold to avoid confusion with the descriptive statistics. The variables with one apostrophe indicate that the correlation is statistically significant at the $p < .05$ level. Variables with two apostrophes indicate a correlation statistically significant at the $p < .01$ level. No apostrophes means that the correlation is not statistically significant.

Table 2: Descriptives and Correlations Table

Variable	CA	Min	Max	M	SD	1	2	3	4	5	6	7
1. AGS (Algorithmic Goal Setting)	.870	1.0	6.3	2.37	1.37	—						
2. SJC (Stimulating Job Characteristics)	.937	2.0	7.0	5.41	1.00	–.33**	—					
3. Job Satisfaction	.856	2.0	7.0	5.32	1.10	–.14	.42**	—				
4. Involvement Culture	.835	1.0	7.0	4.89	1.36	–.12	.45**	.43**	—			
5. Consistency Culture	.588	2.0	7.0	4.38	1.25	.01	.10	.32**	.41**	—		
6. Adaptability Culture	.743	1.0	7.0	3.89	1.45	.05	.25*	.38**	.44**	.37**	—	
7. Mission Culture	.777	1.0	7.0	4.83	1.29	.11	.13	.39**	.36**	.40**	.53**	—

Note. *CA* = Cronbach's Alpha; *M* = Mean; *SD* = Standard Deviation.
$p < .05$, **p** < .01 (2-tailed).

The mean score of AGS was relatively low (M = 2.36, SD = 1.36), suggesting that most participants reported low exposure to AGS in their current roles. However, the wide range and relatively high SD indicate that some participants did experience moderate-to-high levels of AGS. The mean score of the stimulating job characteristics variable was high (M = 5.43, SD = 1.00), indicating that participants generally viewed their work as stimulating. The average level of job satisfaction was also high (M = 5.28, SD = 1.18). The involvement (M= 4.89, SD = 1.36) and mission (4.83, SD = 1.29) organizational culture types were perceived strongest, indicating strong perceptions of purpose and involvement in the organizations respondents belong to. Adaptability (M=3.89, SD = 1.45) cultures had the lowest mean and highest variability. This suggests that there were greater differences in perceptions of how responsive and innovative organizations are. All variables demonstrated skewness and kurtosis values within acceptable thresholds (±2).

Furthermore, Pearson correlation coefficients were used to assess relationships among the variables. The results show that perceived AGS was significantly negatively correlated with stimulating job characteristics ($r = –.33$, $p < .001$), indicating that higher levels of perceived

AGS were associated with less stimulating work environments. Stimulating job characteristics were also significantly associated with higher levels of job satisfaction (r = .42, p = .001). Job satisfaction was positively associated with the involvement (r = .43, p < .001), consistency (r = .32, p = .001), adaptability (r = .38, p < .001), and mission (r = .39, p < .001) organizational culture types, indicating significant positive correlations with all four organizational culture dimensions. Stimulating job characteristics also showed a significant positive relationship with several aspects of organizational culture. The strongest relationship was with involvement (r = .45, p < .001). There was also a moderate positive correlation with adaptability (r = .25, p = .011). All four organizational culture dimensions were significantly intercorrelated, with correlation coefficients ranging from r = .36 to r = .53 (all p < .001).

4.2: Assumptions

For checking assumptions, a composite measure was used for organizational culture since the assumptions check the structure of the dataset and all subscales are moderately correlated. For the sake of time this was deemed the best option, instead of checking assumptions for all subscales separately. However, in the regression analysis, the effects of separate subscales will be evaluated. In the first assumptions check, two very large residuals were found. After further investigation of these outliers, it was concluded that these cases were likely not the result of data entry mistakes. While independence, multicollinearity and linearity appeared acceptable, normality and homoscedasticity were possibly influenced by these influential outliers. Instead of removing these cases outright, a second analysis was run to see if assumptions improve if the cases were removed. These two analyses were compared to determine if removal of these cases would benefit the check of assumptions. After close comparison, the removal of these cases improved assumptions and were subsequently excluded from further analyses. Specifically, visual plots were used to identify and remove these outliers to ensure that the statistical assumptions of the model were met, thereby improving the generalizability and validity of the findings (Hair et al., 2019). The second analysis will now be analyzed with regards to meeting the assumptions of regression analysis, following the example set by Clement & Bradley-Garcia (2022).

Linearity was evaluated using partial regression plots and the scatterplot of standardized residuals versus standardized predicted values. The scatterplot showed a fairly random spread of points, without discernible patterns. This indicates that the assumption of linearity was

reasonably met, and that the relationships between the predictors and the dependent variable are appropriately modeled using a linear function.

The independence of residuals was assessed using the Durbin-Watson statistic, which was reported as 1.652. This value falls within the acceptable range of 1.5 to 2.5, suggesting no evidence of autocorrelation in the residuals. Hence, the assumption of independent errors is satisfied. To test homoscedasticity, a scatterplot of standardized residuals against standardized predicted values was examined. The points appeared to be randomly dispersed across the range of predicted values, without a funnel or curved pattern, which supports the conclusion that the residuals show homoscedasticity. Therefore, the assumption of equal variance across all levels of the predictors is considered met.

The assumption of normality was assessed through both statistical output and visual inspection of the Q-Q plot. These residuals show that most data points align closely with the diagonal line, which represents a normal distribution despite a few points at the lower and upper tails deviating from the line. Apart from this mild violation of normality in the tails, the overall distribution of residuals appears acceptable for regression analyses. The visual charts found in the Appendix support the interpretation of residual normality. This is also supported by the histogram and statistical properties of the residuals, which showed a mean of zero and standard deviation close to one.

Multicollinearity was assessed through Variance Inflation Factor (VIF) and t-values. All VIFs were below 1.3, which is below the maximum value of 10, and t-values were above the critical value of 0.1, ranging from 0.792 to 0.886. These results indicate that the predictors do not share excessive variance and that multicollinearity is not a concern in this model. One case was found with a standardized residual of -3.354, exceeding the conventional ±3.0 threshold. Although this is an extreme value, Cook’s distance was only 0.180, which is below the maximum accepted value of 1. Upon closer examination, it was also concluded that this case was not a product of data entry mistakes. Therefore, while this case may be an outlier, it does not have a significant impact on the regression model and was retained in the analysis with caution.

4.4: Simple Mediation Analysis

To examine whether the relationship between perceived AGS and job satisfaction is mediated by stimulating job characteristics, a simple mediation analysis was conducted using PROCESS Model 4 (Hayes, 2022). This model answers the first 4 hypotheses of this study (also found in table 1), and its results are presented in table 3. In this model, AGS served as the independent variable (X), job satisfaction as the dependent variable (Y), and stimulating job characteristics as the mediator (M). Bootstrapping with 5,000 resamples was used to generate bias-corrected confidence intervals for the indirect effect. Table 3 summarizes the statistical outcomes for hypotheses H1 to H4, including coefficients (b), standard errors (SE), t-values, p-values, confidence intervals, and R^2 where applicable.

The first step in the mediation model tested H1 (*"AGS has negative perceived effects on job satisfaction"*). This effect was not statistically significant when stimulating job characteristics were included in the model ($b = –0.0044$, $t = –0.0563$, $p = .955$). This suggests that any relationship between AGS and job satisfaction is explained entirely through its effect on stimulating job characteristics.

Next, the model tested H2 (*"Perceived AGS has a negative effect on stimulating job characteristics"*). The results indicated a significant negative relationship ($b = –0.2385$, $t = –3.462$, $p < .001$). This suggests that higher levels of perceived AGS are associated with lower perceptions of stimulating job characteristics. The model explained 10.7% of the variance in stimulating job characteristics ($R^2 = .107$).

The third step tested H3 (*"Stimulating job characteristics positively affect job satisfaction"*). A statistically significant and positive association was found ($b = 0.4586$, $t = 4.289$, $p < .001$). This suggests that more stimulating job characteristics are associated with higher job satisfaction. The full model explained 17% of the variance in job satisfaction ($R^2 = .174$).

H4 (*"Stimulating job characteristics mediate the relationship between perceived AGS and job satisfaction"*) was also statistically supported. The indirect effect of AGS on job satisfaction through stimulating job characteristics was significant ($b = –0.1094$); the confidence interval excluded zero, confirming this result.

Table 3: Findings Hypotheses 1-4

Hypothesis	b	SE	t	p	95% CI	R^2
H1	-0.0044	0.0779	-0.0563	0.955	[-0.1590, 0.1503]	0.174
H2	-0.2385	0.0689	-3.462	0.0008	[-0.3751, -0.1018]	0.107
H3	0.4586	0.1069	4.289	<.001	[0.2465, 0.6708]	0.174
H4 (Indirect)	-0.1094	0.043			[-0.1976, -0.0295]	

The results confirm a full mediation model: perceived AGS does not directly influence job satisfaction but does so indirectly by reducing perceptions of stimulating job characteristics.

4.5: Moderated Mediation Analyses

Next, four separate moderated mediation analyses were conducted to examine H5, H6, H7 and H8 using PROCESS Model 7 (Hayes, 2022). These hypotheses can also be found in table 1. Findings of these hypotheses have also been visually represented in figure 2. Bootstrapping with 10,000 samples was used to attain 95% confidence intervals (CIs) for conditional indirect effects and the index of moderated mediation. In each model, AGS functioned as the independent variable (X), stimulating job characteristics as the mediator (M), job satisfaction as the dependent variable (Y), and the respective culture subscale as the moderator (W).

For H5 (*'The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be weakened in organizations with a strong Involvement culture.'*), the moderating effect of involvement culture was tested. The interaction between AGS and involvement on stimulating job characteristics was not statistically significant (b = 0.051, p = .384), indicating no evidence that involvement moderated this relationship. Despite the lack of significant moderation, the conditional indirect effects of AGS on job satisfaction via stimulating job characteristics remained statistically significant at low (effect = –0.1193) and average levels (effect = –0.0876) of involvement. At high levels of involvement, the indirect effect was slightly significant (effect = –0.0558). These results

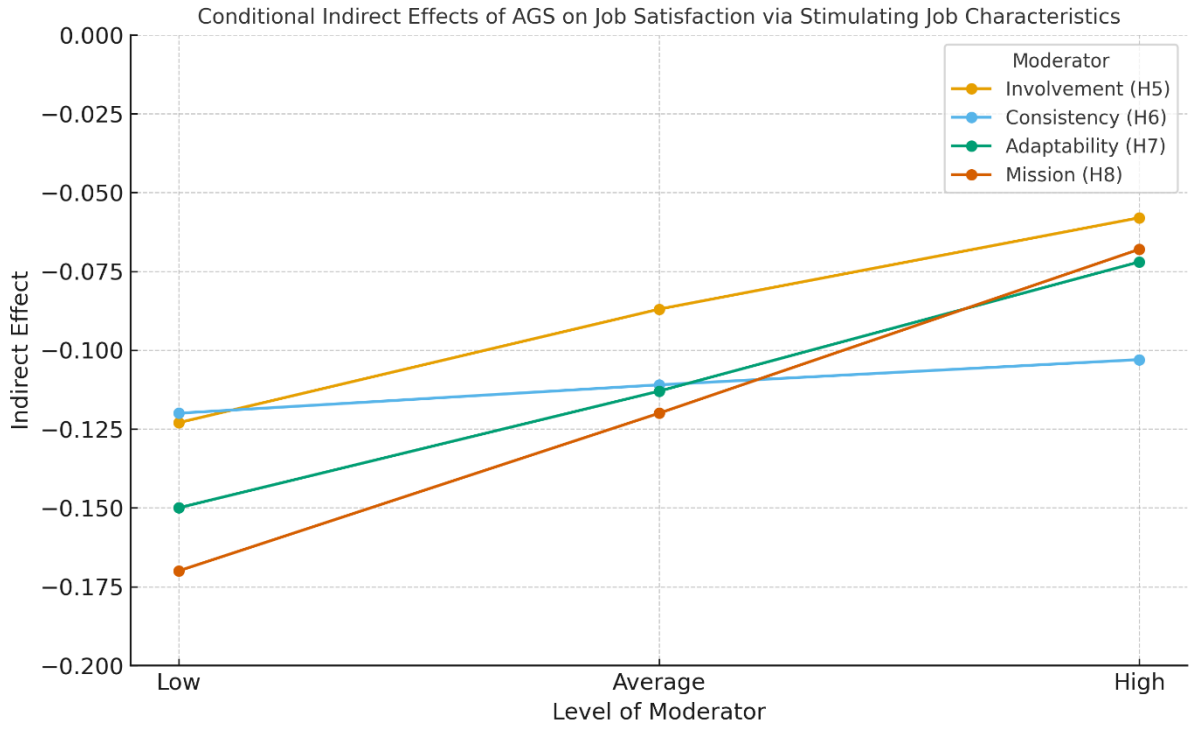
indicate that while involvement did not significantly moderate the mediation effect, the strength of the indirect effect decreased as involvement increased. Therefore, H5 was not supported.

H6 (*'The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be strengthened in organizations with a strong Consistency culture.*') assessed whether consistency culture moderated the indirect relationship. The interaction between AGS and consistency was not significant (b = 0.0124, p = .858), and the index of moderated mediation was similarly non-significant (index = 0.0057). However, the indirect effect remained significant across all levels of consistency: low (effect = –0.1163), average (effect = –0.1092), and high (effect = –0.1020). These findings reveal a consistent negative indirect effect of AGS on job satisfaction via stimulating job characteristics, but without any significant moderation by consistency culture. As a result, H6 was not supported.

H7 (*'The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be weakened in organizations with a strong Adaptability culture.')* focused on the potential moderating role of adaptability culture. The interaction effect between AGS and adaptability was not statistically significant (b = 0.0563, p = .369), and the index of moderated mediation did not reach significance (index = 0.0258). However, the conditional indirect effects were again significant at low (effect = –0.1496) and average (effect = –0.1121) levels of adaptability, while at high levels the effect approached marginal significance (effect = –0.0746). These results indicate that the indirect effect was weakened at higher levels of adaptability, although the moderation was not statistically significant. Therefore, H7 was not supported.

Finally, H8 (*'The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics can be weakened in organizations with a strong Mission culture.*') tested the moderating effect of mission culture. The interaction between AGS and mission was not significant (b = 0.0831, p = .271), and the index of moderated mediation was also not statistically significant (index = 0.0381). Nevertheless, the conditional indirect effects remained significant at low (effect = –0.1680) and average (effect = –0.1189) levels of mission culture. At high levels, the indirect effect approached but did not reach significance (effect = –0.0698). Although the indirect effect tended to weaken as mission culture increased, the moderation effect was not statistically supported. H8 was therefore not supported.

Figure 2: Findings Hypotheses 5-8



In conclusion, none of the tested dimensions of organizational culture significantly moderated the indirect relationship between AGS and job satisfaction through stimulating job characteristics. Although the interaction terms and indices of moderated mediation were not statistically significant, the conditional indirect effects were significant across most levels of the culture subscales. In each case, the indirect effect was strongest at low levels of cultural alignment and weakened at higher levels, which suggests a pattern in which strong organizational culture may buffer the negative effects of AGS. However, this pattern did not reach the statistical significance needed in any of the models tested.

Figure 3: Effects of Hypotheses 1-8

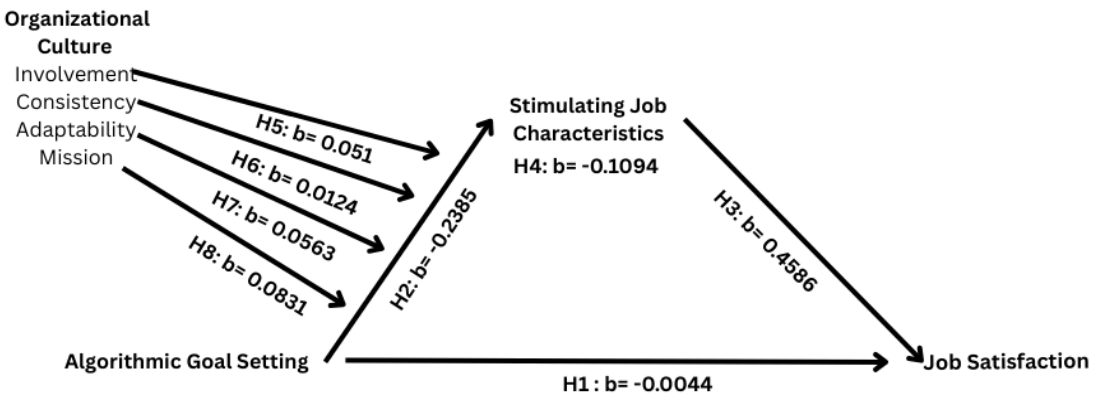


Table 4: Results of analyses leading to the conclusion concerning the hypotheses:

Hypotheses	Supported?
H1: AGS has negative perceived effects on job satisfaction.	Not supported (no direct effect found)
H2: Perceived AGS has a negative effect on stimulating job characteristics.	Supported
H3: Stimulating job characteristics positively affect job satisfaction.	Supported
H4: Stimulating job characteristics mediate the relationship between perceived AGS and job satisfaction.	Supported (full mediation)
H5: The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be weakened in organizations with a strong Involvement culture.	Not supported
H6: The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be strengthened in organizations with a strong Consistency culture.	Not supported
H7: The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be weakened in organizations with a strong Adaptability culture.	Not supported
H8: The perceived negative indirect effect of AGS on job satisfaction through stimulating job characteristics will be weakened in organizations with a strong Mission culture.	Not supported

5: Discussion and Conclusion

5.1: Summary and Interpretation of Findings

The aim of this study was to investigate "*does perceived Algorithmic Goal Setting influence job satisfaction directly and indirectly through stimulating job characteristics and is this indirect effect moderated by different types of organizational culture? (Involvement, Adaptability, Mission, Consistency)"*. Findings of the hypotheses will first be shortly summarized and their effects have also been visually represented in figure 3. Results of the analyses leading to the conclusion of the hypotheses have also been summarized in table 4. This chapter will answer the research question and discuss the findings and their implications.

The simple mediation analysis (H1–H4) revealed that perceived AGS does not directly affect job satisfaction, but instead has a significant negative indirect effect through reduced perceptions of stimulating job characteristics. AGS was associated with lower levels of stimulating job characteristics (H2), which in turn were positively related to job satisfaction (H3). The mediation was statistically significant (H4), supporting a full mediation model.

In the moderated mediation analyses (H5–H8), none of the four organizational culture types (Involvement, Consistency, Adaptability, or Mission) significantly moderated the indirect effect of AGS on job satisfaction. While the indirect effect remained significant across most levels of each cultural dimension, and tended to weaken at higher levels of cultural strength, these moderation patterns did not reach statistical significance. Therefore, H5 through H8 were not supported.

5.1.1: Interpreting the Simple Mediation Analysis

The findings of the simple mediation analysis provide significant support for the indirect relationship between AGS and job satisfaction. Higher levels of perceived AGS were associated with significantly lower perceptions of stimulating job characteristics, which predicted lower job satisfaction. Furthermore, contrary to the hypothesis (1), AGS had no significant direct effect on job satisfaction once stimulating job characteristics were included in the model. This indicates that the impact of AGS on employee satisfaction is not direct but rather operates through changes in how stimulating employees find their work. This result was in line with prior studies and theoretical frameworks such as the SMART-model (Parker & Knight, 2024) which describes the importance of job design in determining employee outcomes like job satisfaction (Bowling & Hammond, 2008; Humphrey & Morgeson, 2006; Parker & Grote, 2020).

AGS systems, by allocating tasks and setting goals without human intervention may unintentionally reduce stimulating job characteristics such as task and skill variety, problem solving needs and information processing capabilities, thereby reducing job satisfaction (Parker & Knight, 2024). Additionally, AGS negatively affecting stimulating job characteristics confirms the findings of several prior studies on this subject (Gagné et al. 2022; Parent-Rocheleau & Parker, 2022; Parker & Grote, 2020). This implies that the emergence of AGS negatively impacts job satisfaction through its negative effect on stimulating job characteristics. Therefore, it is crucial for organizations to maintain high quality job design while implementing AGS systems into their processes.

5.1.2: Interpreting the Moderated Mediation Analyses

The moderated mediation models introduced four subscales of organizational culture as potential moderators in the relationship between AGS and job satisfaction. Across all models, while the indirect effect remained statistically significant at low and average levels of organizational culture, none of the organizational culture types significantly moderate the

indirect effect, despite the theoretical reasoning for moderation. This may be because of several reasons. First, the Consistency subscale of the Denison Organizational Culture Subscale (DOCS) was found to have a low Cronbach's alpha, indicating limited reliability. This could indicate that the nonsignificant moderation effect might be due to measurement error.

However, research has suggested older scales for researching organizational culture (such as the DOCS) could be obsolete in contemporary, digitalized workplaces. AM has been found to change work dynamics by transforming both organizational structures, individual job design and work relationships (Baiocco et al., 2022). Therefore, by changing these elements of the workplace, strong AM systems can override organizational cultures (Jarrahi et al., 2021). This leads to older scales possibly not being fit for studies in a digitalized workplace. Furthermore, the lack of significant moderation could be because of the self-reporting way culture was measured or that the sample lacked sufficient variance in culture. As a result, the four hypotheses (H5-H8) testing the effects of organizational culture in this study were not supported.

5.2: Theoretical Contributions

This study makes several contributions to existing literature, especially to the emerging literature on AM and the SMART model of job design by Parker & Knight (2024). First, it extends the growing body of research on AM by specifically examining how AGS influences employee attitudes and job design. This is important, because there is no pre-determined effect of technology on these constructs and AM is increasingly being rolled out in traditional work contexts (Jensen, 2024; Parker & Grote, 2020). Through studies such as these, organizations can be better informed as to how to implement AM systems sustainably to benefit organizations and their employees in the short and long-term (Jarrahi et al., 2021; Keegan & Meijerink, 2025).

Furthermore, AI capabilities are constantly evolving, making studies focusing on earlier generations of AI obsolete. However, the complexity and opacity of recent AM systems make it difficult to objectively measure their effects (Jarrahi et al., 2021). Therefore, by researching employee perspectives on the effects of current AM systems, this study has contributed to the literature on the ever-evolving capabilities of AM (Jarrahi et al., 2021).

Additionally, many studies to date have focused on broader algorithmic control or monitoring; this study isolates a particular feature of AM and empirically tests its relationship

to job satisfaction. In doing so, this study is among the first to study algorithmic goal setting empirically by measuring perceptions from the employee perspective. This is in line with prior research that has called for functions of AM to be researched separately and from the employee perspective (Jarrahi et al., 2021; Parent-Rocheleau & Parker, 2022; Parent-Rocheleau et al., 2024). This is important, because empirical research into the employee perspective is vital in understanding how AM is experienced and offers considerable value in determining how to ensure a fair and sustainable roll-out of AM (Jarrahi et al., 2021).

This study also contributes to the existing literature on the effects of AM by confirming that AGS does not impact job satisfaction directly, but rather indirectly through job design characteristics. This further affirms the view that the use of AM has consequences for workers but these can be influenced and managed by decisions of stakeholders in organizations, in this case by maintaining a high level of job design (Parent-Rocheleau & Parker, 2022). This is an important contribution, because organizations will know job design is essential for maintaining job satisfaction while implementing AGS systems into their processes. Because of this, implementation of AGS can be conducted sustainably and with less risk for organizations and employee outcomes, by paying attention to human and social aspects and maintaining a high level of job design quality.

Finally, it can be argued that this study adds to the discussion of certain subscales being obsolete in the modern, digitalized workplace (Jarrahi et al., 2021). Since the DOCS (Denison & Mishra, 1995) was conceptualized in a time when computers and the internet played a small role in workplaces, it is plausible that the massive influence digitalization has on the modern workplace renders this subscale obsolete. Besides the theoretical basis for this claim, the relatively low Cronbach's alpha values seem to suggest that the DOCS should be avoided in similar studies when researching the role of organizational culture.

5.3: Practical Implications

The results have important implications for organizations that may or are in the process of utilizing AGS systems. While AGS systems may increase efficiency and goal alignment, implementing these systems can have unpredictable effects on job design and job satisfaction depending on higher level factors (such as organizational culture), individual factors (such as skills) and how these elements interact with one another. Many of these factors reflect choices about job design during technological change (Parker & Grote, 2020). Potentially important moderating factors to do with the way AGS is designed and implemented can either

strengthen its positive effects or weaken its negative effects (Parent-Rocheleau & Parker, 2022). So, when new technologies such as AGS are introduced, there are different potential options for job design that should be, while often these are not, actively considered by managers implementing technologies. Therefore, managers should have more proactive perspectives when implementing AGS in which job design issues are considered alongside individual and higher factors (Jarrahi et al., 2021; Parker & Grote, 2020).

In practice, when implementing AGS systems, managers should have the option to adjust these systems based on employee feedback. Incorporating employee feedback has been shown to improve the implementation of AM systems (Parent-Rocheleau & Parker, 2022; Parker & Grote, 2020). These adjustments should be communicated regularly to employees. Organizations should also monitor continuously how AGS systems affect perceptions employees have of their work. If stimulating job characteristics such as task variety or problem-solving opportunity are reduced, jobs should be redesigned, or tasks should be rotated to make work more stimulating for these employees (Parker & Grote, 2020). Preserving these stimulating job characteristics helps ensure that employees remain satisfied.

To conclude, these points have been informed by the findings of this study and could help organizations preserve or even improve job design when implementing AI systems in a human-centered way.

5.4: Limitations & Implications for Future Research

Several limitations are present within this study. First, the study is cross-sectional, which limits the ability to draw causal inferences. Because all data was self-reported at a single moment in time, there is also a risk of common method bias in this study. Common method bias happens when a measurement approach (such as the use of a single survey in this study) causes variables to appear more strongly than they are. This can lead to inflated correlations between variables, which can result in decreased internal validity by leading to misleading conclusions (Hair et al., 2019).

While PROCESS models help the theoretical modeling of mediation and moderation, the directions of relationships cannot be established definitively. Therefore, any impact or effect AGS might have in this study should be interpreted as an association. (Hair et al., 2019). To improve the ability to draw causal inferences and reduce negative consequences from common method bias, different methodological choices could be used to further explain the effects of perceived AM functions. Longitudinal research designs could better investigate

how perceptions evolve over time, while qualitative methods could find deeper insights into how employees perceive and navigate AGS systems in different cultural settings.

Furthermore, future research should further explore the role of organizational culture in influencing the effects of AM. Although the current study did not find significant moderation effects, existing research on AM has found contextual factors such as organizational culture can play an important role in moderating its effects (Keegan & Meijerink, 2025; Parent-Rocheleau & Parker, 2022; Parent-Rocheleau et al., 2024; Parker & Grote, 2020). However, AM has been found to change work dynamics by transforming both organizational structures, individual job design and work relationships (Baiocco et al., 2022). Therefore, by changing these elements of the workplace, strong AM systems can change organizational cultures (Jarrahi et al., 2021).

This could mean that older scales for measuring organizational culture, such as Denison's Organizational Culture Scale (1995) are no longer suitable for studying culture in modern workplaces (Denison & Mishra, 1995; Jarrahi et al, 2021). Older scales such as the DOCS were conceptualized in a much less digitalized time, which could mean a different scale that takes digitalization into account is better suited for studies on the effects of AM. Therefore, future research should avoid using the DOCS for research in digitalized contexts and use or develop a scale that is better suited to research in these contexts.

Besides organizational culture, various other higher-level factors could play a role in influencing the effects of AM on employees. For instance, national culture, local leadership and organizational design have been identified as factors that could influence the way job design is affected by technology (Keegan & Meijerink; Parker & Grote, 2020). Furthermore, labor market variables and differences between individual employees could also be important moderators to consider (Parent-Rocheleau & Parker, 2022). Intervention studies are also better suited to study the tangible influence of moderators on the effects of AM, because the way people work with technology is closely observed. In this research, the effects of job and organizational design choices will be shown and yield important information on this subject (Parker & Grote, 2020).

5.6: Conclusion

To conclude, this study has sought to answer: "*does perceived Algorithmic Goal Setting influence job satisfaction directly and indirectly through stimulating job characteristics and*

is this indirect effect moderated by different types of organizational culture? (Involvement, Adaptability, Mission, Consistency)".

To answer the research question, the findings indicate that, unlike expectations, perceived AGS does not directly influence job satisfaction. However, AGS does affect job satisfaction indirectly through stimulating job characteristics. Different types of organizational culture have not been found to moderate this indirect effect.

Answering this research question highlights the importance of designing AGS systems not only for technical performance but also with attention to human experience. Even though this study did not find significant differences between culture types, organizations should still use an approach that prioritizes job stimulation and considers cultural context to preserve job satisfaction when implementing AGS systems. Additionally, this study offers novel insights into the suitability of the SMART model of job design in algorithmic work contexts. This study contributes to a more nuanced understanding of how AM systems interact with job design and organizational context, which is an area of research that will become increasingly important in the future of work.

Several reflections have emerged from the process of conducting research for and writing this thesis. First, the choice for a cross-sectional survey was made with regards to time constraints, although this came at the cost of not being able to draw causal inferences definitively. The strength of this study was the use of validated scales in an emerging and constantly evolving area of study; a weakness, however, was the author's position as a student likely influencing the survey sample. This population was skewed to a young, highly educated demographic and this probably influenced findings significantly. As a researcher, this gave valuable insight into the importance of sampling strategy with regards to generalizability.

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7: Appendix

7.1: Questionnaire

Stimulerende baaneigenschappen (Stimulating job characteristics, Parker & Knight, 2024)

In de volgende vragen wordt bevraagd in hoeverre uw baan als stimulerend ervaren wordt door u. Denk aan dat u bijvoorbeeld uitgedaagd wordt doordat u verschillende complexe vaardigheden gebruikt in het uitvoeren van uw werkzaamheden.

- De baan vereist een verscheidenheid aan vaardigheden.
- De baan vereist dat ik een verscheidenheid aan verschillende vaardigheden gebruik om het werk te voltooien.
- De baan vereist dat ik een aantal complexe of geavanceerde vaardigheden gebruik.
- De baan vereist het gebruik van meerdere vaardigheden.

- De baan omvat een grote mate van taakvariatie.
- De baan omvat het uitvoeren van een aantal verschillende taken.
- De baan vereist de uitvoering van een breed scala aan taken.
- De baan omvat het uitvoeren van verschillende soorten taken.
- De baan vereist dat ik veel informatie moet monitoren.

- De baan vereist dat ik een grote hoeveelheid denkwerk verricht.
- De baan vereist dat ik meerdere dingen tegelijk moet bijhouden.
- De baan vereist dat ik veel informatie moet analyseren.

- De baan omvat het oplossen van problemen waarvoor geen duidelijke juiste oplossing bestaat.
- De baan vereist dat ik creatief ben.
- De baan houdt vaak in dat ik te maken krijg met problemen die ik nog niet eerder heb meegemaakt.
- De baan vereist unieke ideeën of oplossingen voor problemen.

Algoritmische doelstellingen en werktoebedeling (AGS, AMQ by Parent-Rocheleau et al., 2024)

In de volgende vragen wordt gevraagd of een automatisch systeem u werkzaamheden toebedeeld en doelen stelt aan u (denk aan snelheid, sales targets, etc.). Voorbeelden hiervan zijn de volgende bestemming van een pakketbezorger of het volgende inkomende belletje van een callcenter medewerker.

- Mijn dagelijkse taken worden door een geautomatiseerd systeem aan mij toebedeeld.
- Een geautomatiseerd system bepaalt welke taken ik ga uitvoeren.
- In mijn werk bepaalt een geautomatiseerd system wat er moet gebeuren
- Een geautomatiseerd system bepaalt de doelen die ik moet halen in mijn werk (productiequota, tijdsdoelen, salesdoelen etc.).

- De doelen die ik moet halen worden door een geautomatiseerd systeem voor mij bepaald.

Werktevredenheid (Job satisfaction, MOAQ-JSS by Bowling & Hammond, 2008):

- Over het algemeen ben ik tevreden met mijn baan.
- Over het algemeen vind ik mijn baan niet leuk.
- Over het algemeen vind ik het leuk om in mijn huidige baan werkzaam te zijn.

Organisatiecultuur (Organizational culture, DOCS by Denison & Mishra, 1995)

- De meeste mensen in mijn bedrijf hebben inbreng in de beslissingen die hen aangaan. (Involvement)
- Samenwerking tussen mensen in verschillende functies wordt actief aangemoedigd. (Involvement)
- Er is veel overeenstemming op de werkvloer over de manier waarop we dingen doen in mijn bedrijf. (Consistency)
- De manier van zakendoen van mijn bedrijf is zeer consistent en voorspelbaar. (Consistency)
- Opmerkingen en aanbevelingen van klanten leiden vaak tot verandering in mijn organisatie. (Adaptability)
- Mijn organisatie reageert zeer snel en verandert gemakkelijk. (Adaptability)
- Mijn bedrijf heeft een doel en een richting op lange termijn. (Mission)
- Er is een gedeelde visie over hoe deze organisatie er in de toekomst uit zal zien. (Mission)

7.2: SPSS Outputs

Demographics

Wat is uw leeftijd? (in jaren)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	1	1,0	1,0	1,0
	19	1	1,0	1,0	1,9
	20	3	2,9	2,9	4,9
	21	3	2,9	2,9	7,8
	22	4	3,9	3,9	11,7
	23	13	12,6	12,6	24,3
	24	11	10,7	10,7	35,0
	25	11	10,7	10,7	45,6
	26	4	3,9	3,9	49,5
	27	4	3,9	3,9	53,4
	28	4	3,9	3,9	57,3
	29	3	2,9	2,9	60,2
	30	7	6,8	6,8	67,0
	31	1	1,0	1,0	68,0
	32	2	1,9	1,9	69,9
	33	2	1,9	1,9	71,8
	37	1	1,0	1,0	72,8
	38	2	1,9	1,9	74,8
	39	2	1,9	1,9	76,7
	40	1	1,0	1,0	77,7
	41	1	1,0	1,0	78,6
	43	1	1,0	1,0	79,6

	44	2	1,9	1,9	81,6
	45	1	1,0	1,0	82,5
	46	2	1,9	1,9	84,5
	48	1	1,0	1,0	85,4
	49	1	1,0	1,0	86,4
	50	1	1,0	1,0	87,4
	51	1	1,0	1,0	88,3
	52	1	1,0	1,0	89,3
	53	2	1,9	1,9	91,3
	54	2	1,9	1,9	93,2
	55	2	1,9	1,9	95,1
	56	1	1,0	1,0	96,1
	57	1	1,0	1,0	97,1
	58	1	1,0	1,0	98,1
	60	1	1,0	1,0	99,0
	62	1	1,0	1,0	100,0
	Total	103	100,0	100,0	

Ik ben een

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Man	55	53,4	53,4	53,4
	Vrouw	46	44,7	44,7	98,1
	Ik zeg dat liever niet	2	1,9	1,9	100,0
	Total	103	100,0	100,0	

Wat is uw hoogst afgeronde opleiding?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Middelbare school	8	7,8	7,8	7,8
	MBO	27	26,2	26,2	34,0
	HBO bachelor of master	34	33,0	33,0	67,0
	WO bachelor of master	34	33,0	33,0	100,0
	Total	103	100,0	100,0	

Reliability analysis

Overall model Reliability Statistics

Cronbach's Alpha	N of Items
,679	7

AGS Reliability Statistics

Cronbach's Alpha	N of Items
,870	4

SJC Reliability Statistics

Cronbach's Alpha	N of Items
,937	16

Job satisfaction Reliability Statistics

Cronbach's Alpha	N of Items
,856	3

InvolvementReliability Statistics

Cronbach's Alpha	N of Items
,835	2

Consistency Reliability Statistics

Cronbach's Alpha	N of Items
,588	2

Adaptability Reliability Statistics

Cronbach's Alpha	N of Items
,743	2

Mission Reliability Statistics

Cronbach's Alpha	N of Items
,777	2

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosi
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic
AGS_mean	103	1,00	6,25	2,3592	1,36423	,888	,238	-,275
SJC_mean	103	2,00	7,00	5,4266	1,00475	-1,029	,238	1,358

JS_Mean	103	1,00	7,00	5,2783	1,17721	-1,246	,238	1,661
OC_Mean	103	2,13	6,25	4,5085	1,00554	-,177	,238	-,644
Valid N (listwise)	103							

Correlations

		AGS_mean	JS_Mean	SJC_mean	Involvement_Mean	Consistency_Mean
AGS_mean	Pearson Correlation	1	-,141	-,327**	-,119	,007
	Sig. (2-tailed)		,157	<,001	,233	,941
	N	102	102	102	102	102
JS_Mean	Pearson Correlation	-,141	1	,417**	,426**	,316**
	Sig. (2-tailed)	,157		<,001	<,001	,001
	N	102	102	102	102	102
SJC_mean	Pearson Correlation	-,327**	,417**	1	,448**	,096
	Sig. (2-tailed)	<,001	<,001		<,001	,339
	N	102	102	102	102	102
Involvement_Mean	Pearson Correlation	-,119	,426**	,448**	1	,408**
	Sig. (2-tailed)	,233	<,001	<,001		<,001
	N	102	102	102	102	102
Consistency_Mean	Pearson Correlation	,007	,316**	,096	,408**	1
	Sig. (2-tailed)	,941	,001	,339	<,001	
	N	102	102	102	102	102
Adaptability_Mean	Pearson Correlation	,045	,375**	,250*	,443**	,368**
	Sig. (2-tailed)	,650	<,001	,011	<,001	<,001
	N	102	102	102	102	102
Mission_Mean	Pearson Correlation	,114	,391**	,129	,358**	,395**
	Sig. (2-tailed)	,255	<,001	,196	<,001	<,001

N	102	102	102	102	102

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

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

Assumptions

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	OC_Mean, AGS_mean, SJC_mean[b]	.	Enter

a. Dependent Variable: JS_Mean

b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,575[a]	,331	,310	,91606	1,652

a. Predictors: (Constant), OC_Mean, AGS_mean, SJC_mean

b. Dependent Variable: JS_Mean

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	40,633	3	13,544	16,140	<,001[b]
	Residual	82,239	98	,839		
	Total	122,871	101			

a. Dependent Variable: JS_Mean

b. Predictors: (Constant), OC_Mean, AGS_mean, SJC_mean

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95,0% Confi
		B	Std. Error	Beta	t	Sig.	Lower Bound
1	(Constant)	1,772	,646		2,743	,007	,490
	AGS_mean	-,049	,071	-,061	-,689	,493	-,190
	SJC_mean	,293	,103	,265	2,850	,005	,089
	OC_Mean	,462	,096	,421	4,797	<,001	,271

a. Dependent Variable: JS_Mean

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	AGS_mean	SJC_mean	O
1	1	3,739	1,000	,00	,01	,00	,0
	2	,220	4,126	,00	,76	,02	,0
	3	,029	11,384	,07	,01	,19	,9
	4	,013	17,146	,92	,22	,79	,0

a. Dependent Variable: JS_Mean

Casewise Diagnostics[a]

Case Number	Std. Residual	JS_Mean	Predicted Value	Residual
23	-3,354	2,00	5,0727	-3,07267

a. Dependent Variable: JS_Mean

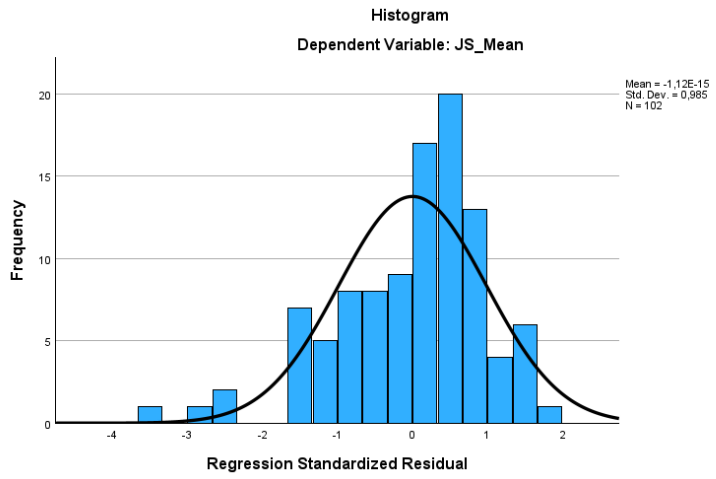
Residuals Statistics[a]

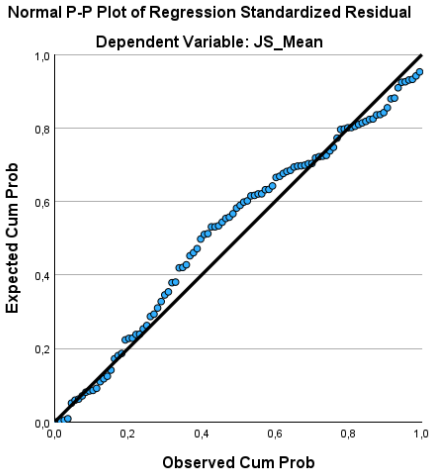
	Minimum	Maximum	Mean	Std. Deviation	N

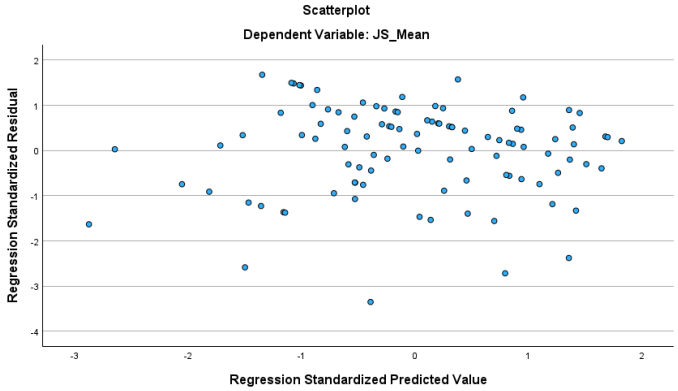
Predicted Value	3,4981	6,4769	5,3203	,63427	102
Std. Predicted Value	-2,873	1,824	,000	1,000	102
Standard Error of Predicted Value	,097	,370	,173	,054	102
Adjusted Predicted Value	3,6393	6,4675	5,3262	,62452	102
Residual	-3,07267	1,53318	,00000	,90236	102
Std. Residual	-3,354	1,674	,000	,985	102
Stud. Residual	-3,454	1,698	-,003	1,008	102
Deleted Residual	-3,25828	1,57727	-,00589	,94572	102
Stud. Deleted Residual	-3,667	1,714	-,008	1,024	102
Mahal. Distance	,139	15,496	2,971	2,694	102
Cook's Distance	,000	,180	,012	,029	102
Centered Leverage Value	,001	,153	,029	,027	102

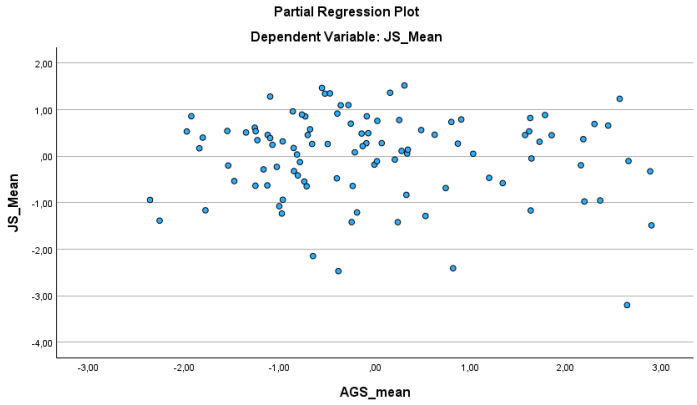
a. Dependent Variable: JS_Mean

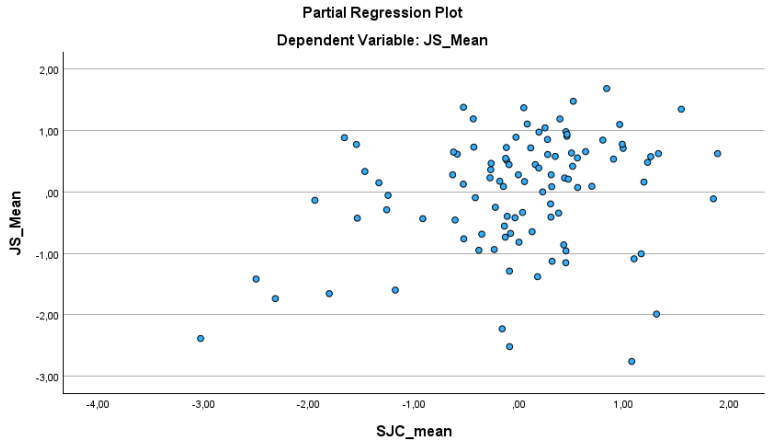
Visual Charts

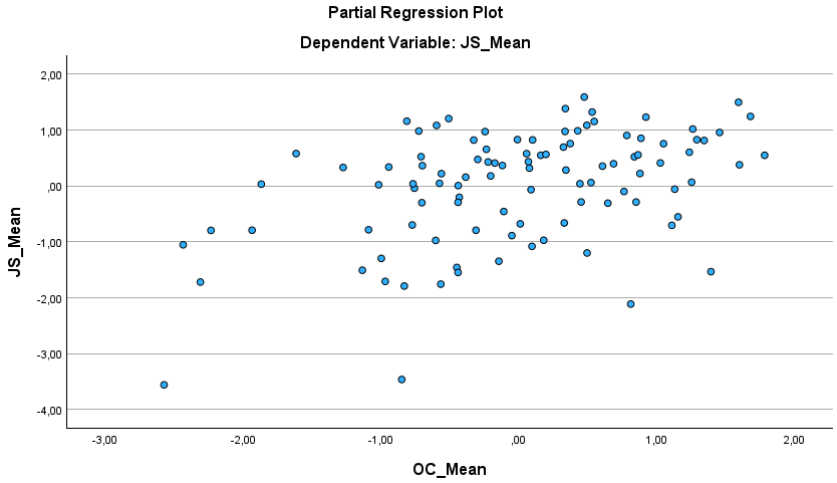


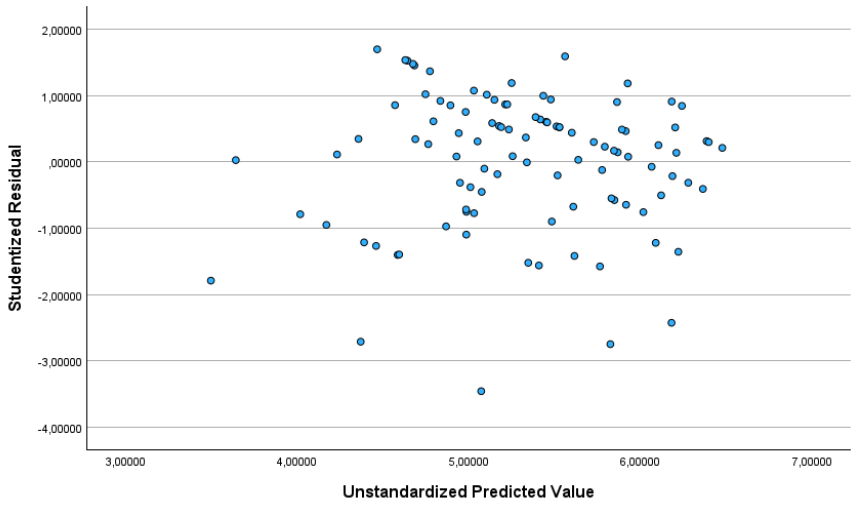

Normal P-P Plot of Regression Standardized Residual
Dependent Variable: JS_Mean
Expected Cum Prob
Observed Cum Prob
0,0
0,2
0,4
0,6
0,8
1,0

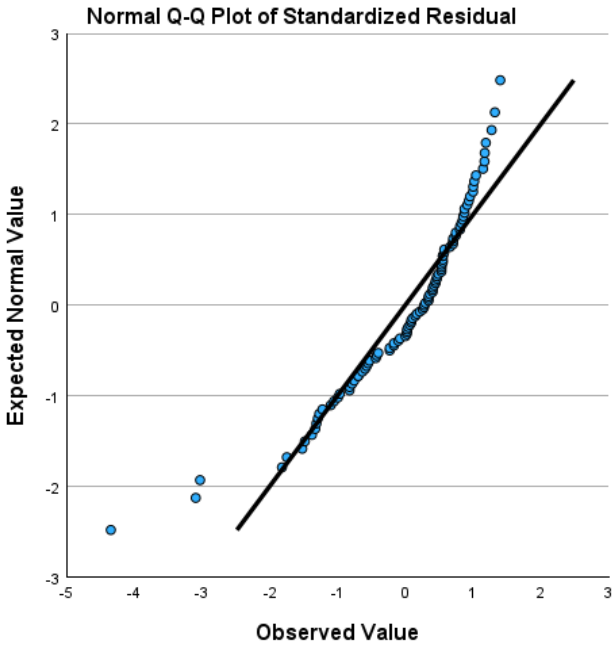

Scatterplot
Dependent Variable: JS_Mean
Regression Standardized Residual
Regression Standardized Predicted Value


Partial Regression Plot
Dependent Variable: JS_Mean
JS_Mean
AGS_mean


Partial Regression Plot
Dependent Variable: JS_Mean
JS_Mean
SJC_mean


Partial Regression Plot
Dependent Variable: JS_Mean
JS_Mean
OC_Mean
2,00
1,00
,00
-1,00
-2,00
-3,00
-4,00
-3,00
-2,00
-1,00
,00
1,00
2,00


Studentized Residual
Unstandardized Predicted Value
2,00000
1,00000
,00000
-1,00000
-2,00000
-3,00000
-4,00000
3,00000
4,00000
5,00000
6,00000
7,00000


Normal Q-Q Plot of Standardized Residual
Expected Normal Value
Observed Value
3
2
1
0
-1
-2
-3
-5
-4
-3
-2
-1
0
1
2
3

Simple Mediation Model:

Model : 4

Y : JS_Mean

X : AGS_mean

M : SJC_mean

Sample

Size: 102

****

OUTCOME VARIABLE:

SJC_mean

Model Summary

R	R-sq	MSE	F	df1	df2	p
,3271	,1070	,8972	11,9842	1,0000	100,0000	,0008

Model

	coeff	se	t	p	LLCI	ULCI
constant	5,9757	,1881	31,7631	,0000	5,6025	6,3490
AGS_mean	-,2385	,0689	-3,4618	,0008	-,3751	-,1018

****

OUTCOME VARIABLE:

JS_Mean

Model Summary

R	R-sq	MSE	F	df1	df2	p

,4165 ,1735 1,0258 10,3913 2,0000 99,0000 ,0001

Model

	coeff	se	t	p	LLCI	ULCI
constant	2,8489	,6699	4,2529	,0000	1,5198	4,1781
AGS_mean	-,0044	,0779	-,0563	,9552	-,1590	,1503
SJC_mean	,4586	,1069	4,2892	,0000	,2465	,6708

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y ******************

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
-,0044	,0779	-,0563	,9552	-,1590	,1503

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
SJC_mean	-,1094	,0430	-,1976	-,0295

************************ ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:

95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

------ END MATRIX -----

Moderated Mediation Analyses

Involvement Moderated Mediation Analysis

Model : 7

Y : JS_Mean

X : AGS_mean

M : SJC_mean

W : Involvem

Sample

Size: 102

OUTCOME VARIABLE:

SJC_mean

Model Summary

R	R-sq	MSE	F(HC4)	df1	df2	p
,5374	,2888	,7292	9,2075	3,0000	98,0000	,0000

Model

	coeff	se(HC4)	t	p	LLCI	ULCI
constant	5,4223	,0927	58,5119	,0000	5,2384	5,6062
AGS_mean	-,1909	,0731	-2,6121	,0104	-,3359	-,0459
Involvem	,3058	,0987	3,0978	,0025	,1099	,5016
Int_1	,0509	,0583	,8737	,3844	-,0647	,1666

Product terms key:

Int_1 : AGS_mean x Involvem

Test(s) of highest order unconditional interaction(s):

```
      R2-chng     F(HC4)        df1         df2          p
X*W      ,0120      ,7633     1,0000    98,0000      ,3844
----------
   Focal predict: AGS_mean (X)
         Mod var: Involvem (W)
DATA LIST FREE/
  AGS_mean   Involvem   SJC_mean   .
BEGIN DATA.
   -1,3676    -1,3605     5,3622
    ,0000    -1,3605     5,0063
    1,3683    -1,3605     4,6503
   -1,3676     ,0000     5,6834
    ,0000     ,0000     5,4223
    1,3683     ,0000     5,1611
   -1,3676     1,3605     6,0047
    ,0000     1,3605     5,8383
    1,3683     1,3605     5,6719
END DATA.
GRAPH/SCATTERPLOT=
 AGS_mean WITH     SJC_mean BY       Involvem .

************************************************************************
OUTCOME VARIABLE:
 JS_Mean

Model Summary
        R       R-sq        MSE     F(HC4)        df1         df2          p
     ,4165      ,1735     1,0258     7,4243     2,0000    99,0000      ,0010
```

Model

	coeff	se(HC4)	t	p	LLCI	ULCI
constant	2,8386	,7934	3,5776	,0005	1,2642	4,4129
AGS_mean	-,0044	,0935	-,0469	,9627	-,1900	,1812
SJC_mean	,4586	,1441	3,1821	,0020	,1726	,7446

********** DIRECT AND INDIRECT EFFECTS OF X ON Y **********

Direct effect of X on Y

Effect	se(HC4)	t	p	LLCI	ULCI
-,0044	,0935	-,0469	,9627	-,1900	,1812

Conditional indirect effects of X on Y:

INDIRECT EFFECT:

AGS_mean -> SJC_mean -> JS_Mean

Involvem	Effect	BootSE	BootLLCI	BootULCI
-1,3605	-,1193	,0467	-,2010	-,0182
,0000	-,0876	,0355	-,1600	-,0212
1,3605	-,0558	,0427	-,1543	,0108

Index of moderated mediation:

	Index	BootSE	BootLLCI	BootULCI
Involvem	,0234	,0200	-,0263	,0541

Pairwise contrasts between conditional indirect effects (Effect1 minus Effect2)

Effect1	Effect2	Contrast	BootSE	BootLLCI	BootULCI
-,0876	-,1193	,0318	,0273	-,0357	,0735
-,0558	-,1193	,0636	,0545	-,0715	,1471
-,0558	-,0876	,0318	,0273	-,0357	,0735

********** ANALYSIS NOTES AND ERRORS **********

Level of confidence for all confidence intervals in output:

95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

10000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: A heteroscedasticity consistent standard error and covariance matrix estimator was used.

NOTE: The following variables were mean centered prior to analysis:

Involvem AGS_mean

Consistency Moderated Mediation Analysis

Model : 7

Y : JS_Mean

X : AGS_mean

M : SJC_mean

W : Consiste

Sample

Size: 102

****

OUTCOME VARIABLE:

SJC_mean

Model Summary

R	R-sq	MSE	F(HC4)	df1	df2	p
,3421	,1170	,9052	3,1155	3,0000	98,0000	,0297

Model

	coeff	se(HC4)	t	p	LLCI	ULCI
constant	5,4110	,0964	56,1103	,0000	5,2196	5,6024
AGS_mean	-,2380	,0850	-2,8013	,0061	-,4066	-,0694
Consiste	,0808	,0807	1,0018	,3189	-,0793	,2409
Int_1	,0124	,0691	,1795	,8579	-,1248	,1496

Product terms key:

Int_1 : AGS_mean x Consiste

Test(s) of highest order unconditional interaction(s):

	R2-chng	F(HC4)	df1	df2	p
X*W	,0004	,0322	1,0000	98,0000	,8579

Focal predict: AGS_mean (X)

Mod var: Consiste (W)

DATA LIST FREE/

AGS_mean Consiste SJC_mean .

BEGIN DATA.

-1,3676 -1,2511 5,6566

,0000 -1,2511 5,3099

1,3683 -1,2511 4,9630

-1,3676 ,0000 5,7365

,0000 ,0000 5,4110

1,3683 ,0000 5,0853

-1,3676 1,2511 5,8164

,0000 1,2511 5,5121

1,3683 1,2511 5,2077

END DATA.

GRAPH/SCATTERPLOT=

AGS_mean WITH SJC_mean BY Consiste .

****

OUTCOME VARIABLE:

JS_Mean

Model Summary

R	R-sq	MSE	F(HC4)	df1	df2	p
,4165	,1735	1,0258	7,4243	2,0000	99,0000	,0010

Model

	coeff	se(HC4)	t	p	LLCI	ULCI
constant	2,8386	,7934	3,5776	,0005	1,2642	4,4129
AGS_mean	-,0044	,0935	-,0469	,9627	-,1900	,1812
SJC_mean	,4586	,1441	3,1821	,0020	,1726	,7446

********** DIRECT AND INDIRECT EFFECTS OF X ON Y **********

Direct effect of X on Y

Effect	se(HC4)	t	p	LLCI	ULCI
-,0044	,0935	-,0469	,9627	-,1900	,1812

Conditional indirect effects of X on Y:

INDIRECT EFFECT:

AGS_mean -> SJC_mean -> JS_Mean

Consiste	Effect	BootSE	BootLLCI	BootULCI
-1,2511	-,1163	,0571	-,2438	-,0201
,0000	-,1092	,0445	-,2015	-,0286
1,2511	-,1020	,0559	-,2168	-,0004

Index of moderated mediation:

	Index	BootSE	BootLLCI	BootULCI
Consiste	,0057	,0279	-,0454	,0680

Pairwise contrasts between conditional indirect effects (Effect1 minus Effect2)

Effect1	Effect2	Contrast	BootSE	BootLLCI	BootULCI
-,1092	-,1163	,0071	,0349	-,0568	,0851
-,1020	-,1163	,0142	,0697	-,1135	,1701
-,1020	-,1092	,0071	,0349	-,0568	,0851

********** ANALYSIS NOTES AND ERRORS **********

Level of confidence for all confidence intervals in output:

95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

10000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: A heteroscedasticity consistent standard error and covariance matrix estimator was used.

NOTE: The following variables were mean centered prior to analysis:

Consiste AGS_mean

Adaptability Moderated Mediation Analysis

Model : 7

Y : JS_Mean

X : AGS_mean

M : SJC_mean

W : Adaptabi

Sample

Size: 102

****

OUTCOME VARIABLE:

SJC_mean

Model Summary

R	R-sq	MSE	F(HC4)	df1	df2	p
,4348	,1890	,8314	6,6781	3,0000	98,0000	,0004

Model

	coeff	se(HC4)	t	p	LLCI	ULCI
constant	5,4061	,0925	58,4707	,0000	5,2226	5,5896
AGS_mean	-,2444	,0736	-3,3188	,0013	-,3906	-,0983
Adaptabi	,1969	,0732	2,6901	,0084	,0516	,3421
Int_1	,0563	,0624	,9020	,3692	-,0676	,1802

Product terms key:

Int_1 : AGS_mean x Adaptabi

Test(s) of highest order unconditional interaction(s):

	R2-chng	F(HC4)	df1	df2	p
X*W	,0117	,8137	1,0000	98,0000	,3692

Focal predict: AGS_mean (X)

Mod var: Adaptabi (W)

```
DATA LIST FREE/
  AGS_mean   Adaptabi   SJC_mean   .
BEGIN DATA.
   -1,3676    -1,4503     5,5666
     ,0000    -1,4503     5,1206
    1,3683    -1,4503     4,6744
   -1,3676     ,0000     5,7404
     ,0000     ,0000     5,4061
    1,3683     ,0000     5,0717
   -1,3676     1,4503     5,9143
```

,0000 1,4503 5,6917

1,3683 1,4503 5,4690

END DATA.

GRAPH/SCATTERPLOT=

AGS_mean WITH SJC_mean BY Adaptabi .

OUTCOME VARIABLE:

JS_Mean

Model Summary

R	R-sq	MSE	F(HC4)	df1	df2	p
,4165	,1735	1,0258	7,4243	2,0000	99,0000	,0010

Model

	coeff	se(HC4)	t	p	LLCI	ULCI
constant	2,8386	,7934	3,5776	,0005	1,2642	4,4129
AGS_mean	-,0044	,0935	-,0469	,9627	-,1900	,1812
SJC_mean	,4586	,1441	3,1821	,0020	,1726	,7446

********** DIRECT AND INDIRECT EFFECTS OF X ON Y **********

Direct effect of X on Y

Effect	se(HC4)	t	p	LLCI	ULCI
-,0044	,0935	-,0469	,9627	-,1900	,1812

Conditional indirect effects of X on Y:

INDIRECT EFFECT:

AGS_mean -> SJC_mean -> JS_Mean

Adaptabi	Effect	BootSE	BootLLCI	BootULCI
-1,4503	-,1496	,0548	-,2473	-,0350
,0000	-,1121	,0395	-,1904	-,0352
1,4503	-,0746	,0449	-,1800	-,0066

Index of moderated mediation:

	Index	BootSE	BootLLCI	BootULCI
Adaptabi	,0258	,0212	-,0248	,0597

Pairwise contrasts between conditional indirect effects (Effect1 minus Effect2)

Effect1	Effect2	Contrast	BootSE	BootLLCI	BootULCI
-,1121	-,1496	,0375	,0308	-,0360	,0866
-,0746	-,1496	,0749	,0615	-,0719	,1731
-,0746	-,1121	,0375	,0308	-,0360	,0866

********** ANALYSIS NOTES AND ERRORS **********

Level of confidence for all confidence intervals in output:

95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

10000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: A heteroscedasticity consistent standard error and covariance matrix estimator was used.

NOTE: The following variables were mean centered prior to analysis:

Adaptabi AGS_mean

Mission moderated mediation analysis

Model : 7

Y : JS_Mean

X : AGS_mean

M : SJC_mean

W : Mission_

Sample

Size: 102

****

OUTCOME VARIABLE:

SJC_mean

Model Summary

R	R-sq	MSE	F(HC4)	df1	df2	p
,3914	,1532	,8682	3,9385	3,0000	98,0000	,0106

Model

	coeff	se(HC4)	t	p	LLCI	ULCI
constant	5,3947	,0961	56,1405	,0000	5,2040	5,5854
AGS_mean	-,2593	,0823	-3,1490	,0022	-,4227	-,0959
Mission_	,1532	,0837	1,8296	,0703	-,0130	,3193
Int_1	,0831	,0750	1,1075	,2708	-,0658	,2319

Product terms key:

Int_1 : AGS_mean x Mission_

Test(s) of highest order unconditional interaction(s):

	R2-chng	F(HC4)	df1	df2	p
X*W	,0182	1,2266	1,0000	98,0000	,2708

Focal predict: AGS_mean (X)

Mod var: Mission_ (W)

Data for visualizing the conditional effect of the focal predictor:

Paste text below into a SPSS syntax window and execute to produce plot.

```
DATA LIST FREE/
  AGS_mean   Mission_   SJC_mean   .
BEGIN DATA.
   -1,3676    -1,2884     5,6983
    ,0000    -1,2884     5,1973
    1,3683    -1,2884     4,6961
   -1,3676     ,0000     5,7493
    ,0000     ,0000     5,3947
    1,3683     ,0000     5,0399
   -1,3676     1,2884     5,8003
    ,0000     1,2884     5,5920
    1,3683     1,2884     5,3837
END DATA.
GRAPH/SCATTERPLOT=
 AGS_mean WITH     SJC_mean BY       Mission_ .
```

****

OUTCOME VARIABLE:

JS_Mean

Model Summary

R	R-sq	MSE	F(HC4)	df1	df2	p
,4165	,1735	1,0258	7,4243	2,0000	99,0000	,0010

Model

	coeff	se(HC4)	t	p	LLCI	ULCI
constant	2,8386	,7934	3,5776	,0005	1,2642	4,4129
AGS_mean	-,0044	,0935	-,0469	,9627	-,1900	,1812
SJC_mean	,4586	,1441	3,1821	,0020	,1726	,7446

********** DIRECT AND INDIRECT EFFECTS OF X ON Y **********

Direct effect of X on Y

Effect	se(HC4)	t	p	LLCI	ULCI
-,0044	,0935	-,0469	,9627	-,1900	,1812

Conditional indirect effects of X on Y:

INDIRECT EFFECT:

AGS_mean -> SJC_mean -> JS_Mean

Mission_	Effect	BootSE	BootLLCI	BootULCI
-1,2884	-,1680	,0697	-,2957	-,0266
,0000	-,1189	,0428	-,2003	-,0334

1,2884 -,0698 ,0430 -,1572 ,0143

Index of moderated mediation:

	Index	BootSE	BootLLCI	BootULCI
Mission_	,0381	,0303	-,0219	,0979

Pairwise contrasts between conditional indirect effects (Effect1 minus Effect2)

Effect1	Effect2	Contrast	BootSE	BootLLCI	BootULCI
-,1189	-,1680	,0491	,0390	-,0282	,1261
-,0698	-,1680	,0982	,0781	-,0564	,2522
-,0698	-,1189	,0491	,0390	-,0282	,1261

********** ANALYSIS NOTES AND ERRORS **********

Level of confidence for all confidence intervals in output:

95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

10000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: A heteroscedasticity consistent standard error and covariance matrix estimator was used.

NOTE: The following variables were mean centered prior to analysis:

Mission_ AGS_mean

------ END MATRIX ----