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Research Article

Algorithmic Anxiety and Its Implications for Work Stress and Professional Self-Esteem among Employees in the Digital Age

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Abstract
The digital transformation driven by the Fourth Industrial Revolution has introduced algorithmic management, a paradigm where artificial intelligence systems actively supervise, evaluate, and direct employees, creating unique psychological challenges known as algorithmic anxiety. This study aims to analyze the influence of algorithmic anxiety on work stress and professional self-esteem among employees in the digital era. Utilizing a quantitative approach with a causal associative design, the research involved 250 employees in Padang, aged 18 to 35, who work under algorithmic management systems, selected via convenience sampling. Data were collected through the Algorithmic Anxiety Scale (AAS), an adapted Perceived Stress Scale (PSS-10), and an adapted Rosenberg Self-Esteem Scale (RSES), and subsequently analyzed using simple linear regression. The results indicate that algorithmic anxiety significantly influences both work stress and professional self-esteem. Algorithmic anxiety positively correlates with work stress, while showing a negative correlation with professional self-esteem, accounting for an 8.8% variance in these dependent variables. Algorithmic management serves as a substantial source of psychological pressure in the modern workplace. Organizations should implement transparent algorithmic systems and provide psychological support programs to mitigate the negative impact of algorithmic anxiety on employee well-being and professional confidence.

Keywords: Algorithmic Anxiety, Algorithmic Management, Digital Workplace, Professional Self-Esteem, Work Stress

1. Introduction

The Fourth Industrial Revolution has sparked a wave of digital transformation that permeates every aspect of life, and the world of work is no exception (Schwab, 2016). Companies across various sectors ranging from manufacturing, logistics, and customer service to the creative industries are now massively adopting smart technologies such as Artificial Intelligence (AI) and Machine Learning to optimize their operations (Acemoglu & Restrepo, 2019). This phenomenon has given birth to a fundamental paradigm shift in management practices: from human-centric (inter-human) management toward algorithmic management (Lee et al., 2015; Möhlmann & Zalmanson, 2017). Within this system, technology no longer functions merely as a passive tool; rather, it has become an active agent with the capability to autonomously supervise, evaluate, and even direct employee behavior (Duggan et al., 2020).

Digital transformation in the workplace has driven the emergence of algorithm-based systems that play roles in performance monitoring, recruitment, and employee productivity evaluation (Kellogg et al., 2020). In e-commerce warehouses, algorithms track the speed of every worker in picking and packing goods, issuing warnings if targets are not met (O'Neil, 2016). In the ride-hailing industry, algorithms dynamically manage order allocation, determine fares, and even deactivate driver accounts based on complex performance metrics (Rosenblat & Stark, 2016). In recruitment processes, automated screening systems scan thousands of CVs to select the most "suitable" candidates based on specific keywords and data patterns (Bogen & Rieke, 2018). All these examples demonstrate how crucial managerial decisions, which were once in the hands of human managers, are now delegated to computational systems operating on data logic (Kellogg et al., 2020).

The implementation of algorithmic management promises various significant advantages for organizations (Duggan et al., 2020). Operational efficiency can be drastically improved through workflow optimization and precise resource allocation. Objectivity in performance appraisal is expected to be achieved because decisions are based on quantitative data, thereby reducing the potential for personal bias often found in human evaluations (Kellogg et al., 2020). From a business perspective, the automation of these managerial tasks can lower operational costs and increase overall productivity (Autor, 2015). However, behind this narrative of efficiency and objectivity lies a profound question regarding the psychosocial impact on those most affected: the employees (Faraj et al., 2018; Lee et al., 2015).

While existing research has extensively documented the efficiency gains of algorithmic management (Duggan et al., 2020; Kellogg et al., 2020) and individual instances of worker dissatisfaction (Moore & Joyce, 2020; Rosenblat & Stark, 2016), few studies have systematically examined the psychological mechanisms linking algorithmic control to employee well-being outcomes. Notably, Shekhar & Saurombe (2026) concept of 'algorithmic anxiety' remains underexplored in empirical research, with no known studies investigating its specific impacts on professional self-esteem and job stress as interrelated outcomes. This gap is critical because understanding these mechanisms is a prerequisite for designing effective organizational interventions.

Consequently, workers must now adapt not only to technological changes but also to how algorithms evaluate and control their activities (Moore & Joyce, 2020). Interactions that were previously dialogic and negotiatory with human superiors have transformed into rigid, one-way relationships with systems that cannot be reasoned with (Kellogg et al., 2020). This new work environment creates a unique set of psychological challenges, where employees feel under constant surveillance, judged by opaque criteria, and threatened by the possibility of future automation (Zuboff, 2019). This condition gives rise to the phenomenon of algorithmic anxiety which is a sense of fear, uncertainty, and emotional pressure resulting from the influence of algorithms on professional existence (Shekhar & Saurombe, 2026). This anxiety directly impacts job stress and professional self-confidence, which are key factors in psychological well-being and individual performance in the digital era.

Algorithmic anxiety can be defined as the negative affective, cognitive, and behavioral response experienced by individuals in reaction to the perception that algorithms hold significant control over their work environment, performance evaluation, and job security (Shekhar & Saurombe, 2026). This construct is a modern manifestation of job anxiety, yet it possesses distinct characteristics different from traditional stressors. While conventional job stress often stems from interactions with superiors, colleagues, or excessive workloads, algorithmic anxiety is rooted in the asymmetrical relationship between humans and smart but impersonal machines. This anxiety can be broken down into several core components (Kellogg et al., 2020).

One of the greatest sources of anxiety is the "black box" nature of many algorithms (Pasquale, 2015). Employees often do not understand the logic or criteria the system uses to evaluate them. This ambiguity creates a state of chronic confusion and helplessness, as they cannot predict the consequences of their own actions which is a condition that is psychologically exhausting (Wachter & Mittelstadt, 2018). Algorithmic management creates an environment referred to as a "digital panopticon," where every employee activity from mouse clicks and call durations to break times can be tracked, measured, and analyzed in real-time (Moore & Joyce, 2020; Zuboff, 2019). This feeling of being constantly watched erodes private space and autonomy, triggering pressure to always be "on" and productive.

Algorithms implicitly set performance standards often based on machine efficiency rather than human capability, which can make an employee's expertise and intuitive judgment feel undervalued (Gray & Suri, 2019). Furthermore, the presence of increasingly sophisticated algorithms triggers existential fears that their roles will eventually become obsolete and be fully replaced by automation (Frey & Osborne, 2017). Theoretically, this phenomenon can be explained through the Job Demand-Control Model (Karasek, 1979). Algorithmic management simultaneously increases job demands (high targets, fast pace) while reducing employee control (limited autonomy, lack of flexibility). This combination is a classic predictor of severe job stress. Additionally, from the perspective of Organizational Justice Theory, the lack of transparency can lead to deep perceptions of procedural and informational injustice, triggering dissatisfaction and anxiety (Colquitt et al., 2001).

The presence of algorithmic anxiety is not merely an emotional discomfort; it has real and damaging implications for two main pillars of employee well-being: job stress levels and professional self-esteem. The relationship is direct and self-reinforcing, creating a negative cycle. Stress induced by algorithms tends to be chronic and persistent because the system operates without pause. Without human intervention or room for negotiation, employees may feel trapped, a major risk factor for burnout. Furthermore, professional self-esteem is eroded as employees lose a sense of autonomy and ownership over their work. Their years of built expertise may be deemed irrelevant compared to data-driven algorithmic decisions, potentially leading to de-skilling, where critical decision-making and problem-solving abilities dull over time due to lack of use. Therefore, this study aims to investigate the influence of algorithmic anxiety on work stress and professional self-esteem among employees in the digital age, with the ultimate goal of informing organizational interventions to support employee psychological well-being.

2. Literature Review

This study is grounded in two primary theoretical perspectives that explain the psychological mechanisms underlying the transition to algorithmic management.

2.1. The Job Demand-Control (JDC) Model (Theory A)

Proposed by Karasek (1979), the JDC model posits that the most adverse psychological reactions occur in jobs characterized by high demands and low decision latitude (control). In the context of this research, algorithmic management simultaneously escalates job demands through rigorous targets and a fast-paced work rhythm while diminishing employee control by automating decision-making and reducing autonomy. This imbalance is hypothesized to be the primary driver of escalated job stress.

2.2. Organizational Justice Theory (Theory B)

Organizational Justice Theory refers to the perceived fairness of decisions and resource allocations within an organization (Colquitt et al., 2001). This study focuses on procedural and informational justice. When algorithms function as "black boxes" with opaque logic, employees perceive a lack of transparency and fairness. This perceived injustice creates a state of chronic uncertainty, which manifests as algorithmic anxiety.

2.3. Previous Research and Conceptual Framework

Previous studies have established that digital transformation in the workplace is not merely a technical shift but a psychosocial one. Research by Kellogg et al. (2020) and Lee et al. (2015) suggests that as managerial functions are delegated to code, the nature of the employee-employer relationship changes from a human-negotiatory one to a rigid-computational one.

a. Algorithmic Anxiety and Stress: Previous work by Shekhar & Saurombe (2026) indicates that the "digital panopticon" effect which constant, real-time surveillance leads to higher cortisol levels and emotional exhaustion.
b. Professional Self-Confidence: The work of Gray & Suri (2019) highlights that when machine efficiency becomes the sole benchmark, human expertise is devalued, leading to "de-skilling" and a decline in professional self-efficacy.

3. Methods

3.1. Research Design

This study employs a quantitative approach with a causal associative research design. Consistent with its objectives, a causal associative design is used to examine and analyze the functional cause-and-effect relationships between independent and dependent variables (Sugiyono, 2018). This study involves three primary variables: algorithmic anxiety as the independent variable (X), and job stress (Y1) and professional self-esteem (Y2) as the dependent variables.

3.2. Participants

The population in this study consists of employees aged 18 to 35 working in companies that have implemented algorithmic management systems in Padang. A total sample of 250 participants was successfully collected. Sampling was conducted using a non-probability sampling method, specifically the convenience sampling technique. The selection of this technique was based on practical considerations, namely the ease of reaching potential respondents and their willingness to participate voluntarily in the study (Creswell, 2014).

3.3. Research Instruments

3.3.1. Algorithmic Anxiety

Measured using the Algorithmic Anxiety Scale (AAS), developed by the researcher based on the theoretical frameworks of Kellogg et al. (2020). This scale encompasses three main aspects: uncertainty and ambiguity regarding system mechanics, pressure from constant surveillance, and fear of professional role devaluation. The AAS instrument demonstrated a Cronbach's Alpha reliability score of 0.915. Validity testing showed corrected item-total correlation values ranging from 0.420 to 0.788, with all items declared valid.

3.3.2. Job Stress

Measured by adopting and adapting the Perceived Stress Scale (PSS-10) developed by Cohen et al. (1983). This scale measures an individual's perception of their work situations as stressful and uncontrollable. The adapted instrument achieved a Cronbach's Alpha score of 0.887. All items were declared valid, as the corrected item-total correlation values were above 0.3.

3.3.3. Professional Self-Confidence

Measured using an adaptation of the Rosenberg Self-Esteem Scale (RSES) developed by Rosenberg (1965), with items modified for a professional context. This scale aims to measure an individual's self-evaluation regarding competence and worthiness within the work domain. The instrument demonstrated a Cronbach's Alpha reliability score of 0.894. Validity results showed all items to be valid, with corrected item-total correlation values ranging from 0.401 to 0.755.

4. Results and Discussion

4.1. Research Results

This study recruited 250 participants in emerging adulthood in Padang, then categorized them by gender and age. The study successfully collected data from a total of 250 participants, all employees in the emerging adult phase in Padang City. As shown in Table 1, the demographic composition of this sample showed a predominance of female participants, at 146 (58.4%), while male participants numbered 104 (41.6%). The age distribution of these participants ranged from 18 to 34 years. The majority of them were concentrated in the early adulthood age group, with the highest frequency being at 23 years old (11.2%) and 22 years old (10.4%).

Table 1. Demographic Data

Category	Frequency (f=250)	Percentage (%)
Gender		
Male	104	41.6%
Female	146	58.4%
Age		
18 Years Old	15	6.0%
19 Years Old	12	4.8%
20 Years Old	18	7.2%
21 Years Old	20	8.0%
22 Years Old	26	10.4%
23 Years Old	28	11.2%
24 Years Old	23	9.2%
25 Years Old	22	8.8%
26 Years Old	18	7.2%
27 Years Old	20	8.0%
28 Years Old	14	5.6%
29 Years Old	9	3.6%
30 Years Old	8	3.2%
31 Years Old	7	2.8%
32 Years Old	5	2.0%
33 Years Old	3	1.2%
34 Years Old	2	0.8%
35 Years Old	0	0.0%

This study involved a total of 250 participants, with a gender composition dominated by 146 women (58.4%), while 104 men (41.6%) participated. Normality test results for the algorithmic anxiety, job stress, and social trust scales showed the following Kolmogorov-Smirnov results summarized in table 2.

Table 2. Normality Test Results

Variable	Statistic	Sig. (p-value)	Description
Algorithmic Anxiety (X)	.053	.108	Normal
Job Stress (Y1)	.048	.200	Normal
Professional Self-Confidence (Y2)	.041	.200	Normal

The table above shows that the research data exhibits a normal distribution, with a Sig. 0.108 > 0.05 for the Algorithmic Anxiety variable, a Sig. 0.200 > 0.05 for the Job Stress variable, and a Sig. 0.200 > 0.05 for the Professional Self-Confidence variable. Furthermore, the results of the linearity test between algorithmic anxiety, job stress, and social trust show the following table 3.

Table 3. Linearity Test Results

Relationship Model	F	Sig. (p-value)	Description
Algorithmic Anxiety (X) → Job Stress (Y1)	1,839	.81	Linear
Algorithmic Anxiety (X) → Professional Self-Confidence (Y2)	1,945	.63	Linear

Based on the results of the linearity test, this research data meets one of the important assumptions for further statistical analysis. The relationship between Algorithmic Anxiety and Job Stress showed a significance value of 0.081, while the relationship between Algorithmic Anxiety and Professional Self-Confidence had a significance value of 0.063.

Table 4. Simple Linear Regression Test Results

Statistical Indicator	Value
F-Value (Calculated)	10.167
Significance Level (Sig.)	.002

Referring to the regression test results in table 4, the calculated F-value was 10.187 with a Significance Value (Sig.) of 0.002. This significance value is significantly lower than the standard limit of 0.05, indicating that the results of this study are statistically significant.

Table 5. Coefficient Determination Test Results

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.273[a]	.088	.089	8.658

Based on the analysis results shown in table 5, this research model demonstrates limited ability to explain the dependent variable. The R-square (Coefficient of Determination) value of 0.088 indicates that only 8.8% of the variation in the dependent variable can be explained by the independent variables in the model.

Table 6. Regression Test Results

Model		Unstandardized Coefficients	Std. Error	Standardized Coefficients	t	Sig.
		Beta				
1	(Constant)	69,586	3.4578		18,156	.000*
	Algorithmic Anxiety (KA)	-178	67	-289	-3,175	.002*

Based on the data in the table 6, the results of the regression coefficient test indicate a constant value (a) of 69.586 and a coefficient value for the algorithmic anxiety variable (b) of -0.178. Therefore, the regression equation that should be formed is:

$$\mathbf{Y = 69.586 - 0.178X}$$

In this model, the Algorithmic Anxiety variable is represented by the symbol (X), while the Professional Self-Confidence variable is represented by the symbol (Y). The constant (a) value of 69.586 indicates the predicted level of professional self-confidence when algorithmic anxiety is absent. The regression coefficient of -0.178 means that for every one-unit increase in algorithmic anxiety, professional self-confidence is predicted to decrease by 0.178 points. This negative direction of influence as indicated by the Beta value (-0.289) and t-value (-3.175) is statistically significant. This means that the greater the algorithmic anxiety experienced by employees, the lower their level of professional self-confidence.

Table 7. Work Stress Categorization Test Results

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Low	28	25.0	25.0	25.7
	High	83	75.0	75.0	100.0
	Total	111	100.0	100.0	

Based on the table 7, a brief analysis indicates that work stress is a significant problem among the study participants. The data shows that the majority of participants (75.0%), or 83 out of 111 people, fall into the high work stress category. Only a small proportion (25.0%), or 28 people, fall into the low work stress category.

Table 8. Professional Self-Esteem Categorization Test Results

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Low	78	70.0	70.0	70.0
	High	33	30.0	30.0	100.0
	Total	111	100.0	100.0	

Table 8 reveals significant issues related to professional self-confidence in the study group. The majority of participants, 70% (78 out of 111), were categorized as having low self-confidence. Conversely, only 30% (33) reported high self-confidence. This data indicates that more than two-thirds of employees feel less confident in their professional competence, highlighting issues that require attention in their work environment.

4.2. Discussion

The results of this study indicate that the transition to algorithmic management has created significant psychological challenges for employees in the digital age. The main findings revealed that algorithmic anxiety has a significant positive effect on job stress; that is, the higher the anxiety employees feel about the supervision and evaluation of AI systems, the higher their job stress levels will be. Conversely, algorithmic anxiety is negatively correlated with professional self-confidence, where each increase in anxiety is predicted to decrease employee self-confidence levels by 0.178 points. The data show a worrying situation, with 75% of participants in the high job stress category and 70% experiencing low professional self-confidence. Although the algorithmic anxiety variable only contributes 8.8% to the variance of the dependent variable, its psychological impact remains crucial because these systems operate continuously without any room for human negotiation, ultimately eroding employees' autonomy and sense of ownership over their work.

This study's findings are consistent with the Job Demands–Control Model (Karasek, 1979), which explains that high job demands coupled with low job control will increase stress levels and reduce employees' psychological well-being. In the context of algorithmic management, digital systems play an active role in automatically setting targets, work rhythms, and performance evaluations, thereby reducing individual autonomy and flexibility in managing their work.

These results also align with a study by Shekhar & Saurombe (2026), which found that excessive exposure to algorithmic systems can increase emotional stress and insecurity about one's professional standing. Employees feel their skills and experience are less valuable compared to the performance standards set by data-driven systems, which can ultimately lower professional self-confidence.

This study shows that algorithmic anxiety contributes 8.5% to employees' levels of job stress and professional self-confidence in the digital age. This means that the higher the level of algorithmic anxiety employees experience for example, due to constant monitoring, evaluation uncertainty, or fear of automation the higher their level of job stress and lower their confidence in their professional competence.

These results align with the findings of Moore & Joyce (2020), which highlight how AI-based and data-driven management systems increase perceived work stress and decrease self-efficacy in the digital workplace. This phenomenon shows that although algorithmic anxiety contributes only 8.5%, its psychological impact is significant and potentially widespread, especially in work contexts that are highly dependent on technology.

Furthermore, from the perspective of Organizational Justice Theory (Colquitt et al., 2001), non-transparent and difficult-to-understand algorithms can lead to perceptions of procedural injustice, which exacerbates anxiety and reduces employees' confidence in their professional roles. The lack of clarity surrounding algorithmic decision-making mechanisms can lead individuals to feel unfairly valued, thereby increasing psychological stress.

5. Conclusion

The study's results indicate that algorithmic anxiety has a significant impact on work stress and professional self-confidence among employees in the digital age. The positive effect on work stress indicates that as algorithmic anxiety increases, employees' work stress levels also increase. Meanwhile, the negative effect on professional self-confidence indicates that as algorithmic anxiety increases, professional self-confidence decreases. In this study, employees tended to experience high levels of algorithmic anxiety, which leads to high levels of work stress and low professional self-confidence. Therefore, it can be concluded that algorithmic management is a significant source of psychological stress for employees in the modern workplace. To gain a deeper understanding of the impact of algorithmic anxiety, further research is recommended to explore other factors that may influence this relationship, such as workplace social support, digital literacy, role clarity, and the design of the algorithmic system itself. Further analysis could include developing interventions to mitigate the negative impact of algorithmic anxiety on employees' psychological and emotional well-being.

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