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WHEN METRICS REPLACE MANAGERS: ALGORITHMIC PERFORMANCE EVALUATION AND SUPERVISOR TRUST

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Abstract
The increasing use of algorithmic systems to monitor, quantify, and evaluate employee performance is changing the traditional relationship between employees and their immediate supervisors. Although prior research has investigated employee trust in algorithms and perceptions of algorithmic fairness, considerably less attention has been given to whether metric-driven performance evaluation changes trust in the human supervisor who remains responsible for communicating and implementing performance decisions. This study examines six direct predictors of supervisor trust in algorithmically managed performance environments: algorithmic performance evaluation reliance, perceived algorithmic fairness, evaluation transparency, perceived supervisor discretion, perceived evaluation accuracy, and employee voice. Reliability and validity assessments were conducted before the hypotheses were tested using multiple regression. The results indicate that algorithmic performance evaluation reliance is negatively associated with supervisor trust ($\beta = -.177$, $p < .001$), whereas perceived fairness ($\beta = .210$, $p < .001$), supervisor discretion ($\beta = .245$, $p < .001$), evaluation accuracy ($\beta = .193$, $p < .001$), and employee voice ($\beta = .138$, $p = .004$) are positively associated with trust. Transparency does not retain a statistically significant unique relationship after the other evaluation characteristics are considered ($\beta = .077$, $p = .107$). Collectively, the predictors explain 42.5% of the variance in supervisor trust. The study extends algorithmic-management research by shifting attention from trust in technology to trust in the human manager operating within algorithmically structured performance systems. The findings suggest that organizations should avoid reducing supervisors to passive transmitters of metric-based judgments and should preserve meaningful managerial discretion, fairness, accuracy, and opportunities for employee voice.

Keywords: Algorithmic Management; Performance Evaluation; Supervisor Trust; Algorithmic Fairness; Managerial Discretion; Employee Voice; Artificial Intelligence; Performance Management.

1. Introduction
More and more organizations are transforming employee performance into digital data, scores, rankings, dashboards and predictive indicators. Previously measured by supervisory observation and judgment, activities can now be measured using productivity software, customer ratings, workflow systems, electronic monitoring, enterprise analytics, and systems that use artificial intelligence. Algorithmic management is more than just the addition of another tool or space for work in the workplace. It alters the way managerial responsibilities like directing, monitoring, evaluating, rewarding and disciplining employees are undertaken. For instance, according to Kellogg et al. (2020), the basic functions of algorithms by which they affect organizational control include recording and

rating. By a similar argument, Duggan et al. (2020) show that algorithmic management has direct implications for performance management and employment relationships. App-based workers, from the worker side, feel the impact of these systems as a different type of algorithmic HRM control (Duggan et al., 2023). The initial studies of algorithmic management have come from platform-mediated and gig work. Research on ride-hailing and online labor platforms showed that organizations have a significant capacity to exert control without directly supervising people (Möhlmann & Zalmanson, 2017; Rosenblat & Stark, 2016; Wood et al., 2019). However, algorithmic management is not limited to platform jobs. Algorithmic control is an organizational phenomenon, as it is becoming more common within conventional workplaces (Jarrahi et al., 2021). More recently, AI and predictive analytics are also playing a growing role in HR tasks such as recruitment, performance management, talent management, and workforce forecasting (Tambe et al., 2019). Similarly, electronic performance monitoring has spread to traditional occupations (Ravid et al., 2020), and algorithmic management is theorized as a part of mainstream HRM systems, not just gig work (Meijerink & Bondarouk, 2023; Strohmeier & Piazza, 2015).

This change gives rise to a question which has been given relatively little empirical consideration. When the performance evaluation relies more and more on algorithms, how will employees' trust in their supervisors be affected?

The question is important because the algorithm does not normally replace the human supervisor completely. In many organisations, the algorithm is used to record performance, to provide indicators, to make comparisons, to suggest ratings, and to flag deviations. However, the supervisor still communicates with them, holds appraisal meetings, suggests rewards, discusses development, and sets consequences. Staff are thus faced with a mixed system of leadership. There is a certain evaluative authority within the technological system, and interpersonal accountability is still with the supervisor. This means there is a managerial paradox created. Supervisors can have increasingly diminished real authority but still have a formal mandate to make decisions. This could be communicated to an employee as a low rating due to a dashboard, productivity score, automated quality measure, or model-generated recommendation. However, the employee may still think that the supervisor is expected to know and understand the situation of the work, interpret odd occurrences, rectify incorrect information, take into account the qualitative aspects of the work, and intervene when the standard measures give unreasonable results. If managers cannot or do not do these, employees may re-evaluate the worth and reliability of the supervisory relationship.

Leavitt et al. (2025) reject the assumption that the algorithm replaces human managers and talk about human managers as crucial trust actors in algorithmic performance-management systems. Their framework highlights that human managers are able to interpret, translate, question and fill in algorithmic output. This is because it is a different perspective from the one that is often studied, which is whether employees trust algorithms or not, but rather about the connection between algorithmic systems and trust in human managers. Trust is essential in the supervisor/employee relationship. Mayer et al. (1995) define trust as a willingness to place oneself at the other party's mercy, stemming from positive expectations of the other party, and believe that ability, benevolence, and integrity are core constructs of perceived trustworthiness. Trust in the leadership has been shown to be correlated with significant employee outcomes in the organization, and the relationship between the direct supervisor and the leader is a significant trust referent (Dirks & Ferrin, 2002). Trust is also tightly linked to the issue of performance evaluation because performance evaluations are also related to consequential managerial judgments about the contribution of employees, rewards, employee development, and promotion.

Research in performance appraisal has always shown that ratings are not the only criteria used when conducting an appraisal evaluation. They are sensitive to the social dimensions of assessment such as fairness, involvement, supervisor-employee relations, opportunity for voice, and belief in the accuracy of the assessment (Cawley et al., 1998; Levy & Williams, 2004). Fulk et al. (1985) specifically related trust in supervisors to employees' perceptions of fairness and accuracy of their performance evaluations. Research on procedural justice also shows that attitudes towards organizational authorities are influenced by the features of decision processes (Colquitt, 2001; Folger & Konovsky, 1989). This social context is altered when an algorithm is used to assess performance. Algorithms can often be relied on to be consistent, quantitative, and less susceptible to some human biases. Algorithms seem to be

consistent, quantitative, and less prone to certain human biases. There are instances where people will choose to accept algorithmic advice over human judgment, as shown in research on algorithm appreciation by Logg et al. (2019). Conversely, workers might see algorithmic decisions as unhelpful, impenetrable, out-of-context, or lacking in qualitative aspects of performance. Newman et al. (2020) have uncovered that algorithmic decisions in the HR realm can be seen as less procedurally fair when employees feel that some aspects of human performance are becoming "simplified" to a limited amount of quantitative data. Similarly, Lee (2018) has shown that fairness and trust reactions to algorithmic managerial decisions differ according to the nature of the managerial decision.

The current study brings these lines together and analyzes the six direct determinants of algorithmically evaluated workplaces with regard to supervisor trust. Namely, it examines the algorithms' performance evaluation reliance, perceived algorithms' fairness, evaluation transparency, perceived supervisor discretion, perceived evaluation accuracy, and employee voice. The paper has three contributions to make. It brings the trust referent from the algorithm to the human supervisor, first. The bulk of algorithmic-management research focuses on trust in automated systems, acceptance of algorithmic recommendations or perceived fairness of algorithmic decisions. The question in this study, however, is how technology-based assessment impacts trust in the human authority that functions in that system. Second, the study differentiates between the reliance on algorithms and particular properties of the assessment context. A workplace can be highly algorithmic in its measurement of employee performance, but be fair in its procedures, accurate in its indicators, allow for managerial discretion, and even give employees voice. Addressing these dimensions separately makes it possible to focus on the issue of algorithmic evaluation as an algorithmic problem or on how the evaluation is institutionally performed. Third, the study brings into focus the dimension of perceived supervisor discretion as an important attribute of the performance management system in the present day. It is the central premise of the book that the employees may evaluate the performance of the managers in terms of the output of the algorithms that they communicate to them, but also on whether or not the employees have any authority to interpret, contextualize, question and revise algorithmically generated judgments.

2. Theoretical Background and Hypotheses

2.1 Algorithmic Management and Performance Evaluation

In general, algorithmic management is the use of computer systems to execute, inform or organize managerial aspects. Kellogg et al. (2020) outline algorithms in terms of 6 mechanisms: recommending, restricting, recording, rating, replacing and rewarding. The mechanisms are examples of the ways that digital technologies can expand organizational control over task direction, employee evaluation, and discipline. As algorithmic management is a sociotechnical phenomenon, Jarrahi et al. (2021) stress this. An algorithm is not autonomous of organizational choices. The types of data that are collected, the significance of the various indicators, the interpretation of scores, when decisions based on the automated recommendations are implemented, and opportunities for employees to challenge a decision are determined by the manager or organization. Thus, the same technology can create different employee experiences, as a function of the managerial context. Parent-Rocheleau and Parker (2022) also question the deterministic approach – they demonstrate that algorithmic monitoring, goal setting and performance management alter aspects of the job, including autonomy, and that transparency, fairness, and human control of the system account for these effects. In the case of performance evaluation, this distinction is very significant. Algorithmic performance evaluation may be defined as the process of using computed data, ratings, classifications, scores or recommendations to evaluate employee performance and inform employee performance-related decision-making that are generated by a computer program. It includes a range of basic digital productivity indicators, but also has more complex machine-learning models.

As humans become more quantifiable, HR analytics becomes more prevalent, which makes it more convenient for employers to assign numbers to employee behavior so they can be compared with others over time, teams, locations, and supervisors. The quality and use of the underlying data are still important considerations for evidence-based decision-making; HR analytics can have the potential to improve these processes (Marler & Boudreau, 2017). This is echoed by Tambe et al. (2019), who state that AI usage in HR has similar concerns such as data constraints, fairness and accountability, and

employee reactions. The use of algorithms thus alters information available to supervisors, and the sense of where decision-making power lies. Traditional appraisal systems tend to give employee performance ratings mainly to the supervisor. In highly algorithmic evaluation, responsibility shifts from the technological system to the system's designer and/or its adopter, and to the manager(s) who use its outputs.

2.2 Supervisor Trust in Algorithmically Managed Workplaces

Trust is defined as a willingness to be vulnerable to another party with positive expectations of the party's actions (Mayer et al., 1995). They believe that ability, benevolence and integrity are important dimensions of perceived trustworthiness and have an influential model to this end. Later meta-analytic and conceptual research also substantiates this; ability, benevolence and integrity all contribute to trust, and to trust-related outcomes in unique ways (Colquitt et al., 2007; Schoorman et al., 2007).

These dimensions are particularly important for algorithmic performance management.

Ability: Worrying that supervisors lack the capabilities to know what employees are doing and make the correct decisions. Reliance on automated metrics could make questions about the supervisor's ability to assess performance on his/her own arise.

Benevolence means the level of management support for the employee's interest felt by the employee. If a supervisor is unwilling to take a look at factors that cannot be enumerated on an automated score, he or she seems less benevolent. Höddinghaus et al. (2021) discovered that workers saw automated leadership agents as more transparent and more trustworthy than human leaders, but saw human leaders as more benevolent and flexible, suggesting benevolence is still a distinctly human source for trust.

Integrity concerns following acceptable principles. If employees ask themselves why the integrity of their managers in applying algorithmic judgments is flawed when the managers are aware of and are making inaccurate or unfair algorithmic judgments while they are distancing themselves from responsibility, they may question the integrity of the manager.

Trust also has a relational aspect. McAllister (1995) highlights two types of trust, with one being based on cognition and the other on affect: Trust in the workplace is tied to judgments of reliability as well as to relational bonds. Algorithmic systems can provide information, but they cannot take the place of all interpersonal functions of supervisors. Also, Dirks and Ferrin's (2002) meta-analysis indicates that there is a relationship between leader trust and job attitudes and behavioral outcomes, and that trust relationships vary based on the leader referent. It emphasizes the importance of investigating supervisor trust specifically and not as a synonym for trust in AI, trust in the organization, and trust in the immediate supervisor.

2.3 Algorithmic Performance Evaluation Reliance and Supervisor Trust

Reliance on algorithmic performance evaluations means the extent to which workers believe that systems created by algorithms or computers significantly influence performance evaluations and related decisions. Reliance is not just the use of technology. An organization can gather a lot of data that managers can rely on as one of many inputs. On the other hand, an organization can create a score that is automatically given to the supervisor, which gives little discretion. Raisch and Krakowski (2021) define automation as when machines replace human labour, and augmentation as when machines help humans. They believe that the two go hand in hand and can lead to some organizational conflict. When applied to the evaluation of performance, reliance is an issue when a metric-based system supplants management's judgment. Langer and Landers (2021) overview research related to workers targeted by automated and augmented decisions and stress the reactions that are dependent on how decision authority is split between the human and the system. Supervisors' trust may be negatively impacted for a number of reasons if they rely heavily on the resources. The supervisor's reliance on algorithmic results can be seen as a sign of diminished knowledge, skill, or expertise by the employees. They might sense managers are not dedicated to taking personal responsibility for consequential decisions. They also may doubt the kindness of supervisors who focus on objective measures rather than subjective understanding of the effort they are putting in. Algorithmic systems may also be able to generate informational and power imbalances. Studies of the ride-hailing platforms reveal that the drivers might have a great deal of algorithmic control, even if they are not aware of how the algorithms create certain results (Rosenblat & Stark, 2016; Möhlmann & Zalmanson, 2017). In spite of the different institutional settings in which conventional employees work, comparable attributional processes can occur when supervisors use automated scores as a basis for their authority.

Accordingly:

H1: Algorithmic performance evaluation reliance is negatively associated with employee trust in the immediate supervisor.

2.4 Perceived Algorithmic Fairness and Supervisor Trust

Favoritism is one of the key factors that employees look at when examining performance management systems. Based on organizational-justice research, there are three types of justice: distributive justice, procedural justice, and interpersonal justice and informational justice (Colquitt, 2001). While these dimensions are interrelated, they differ in their relationship to attitudes and evaluations of authorities within the organization (Colquitt et al., 2001). In some cases, it is hoped that algorithmic systems will be fairer because of the consistent application of rules and reduction of idiosyncratic human judgment. However, algorithms are not necessarily neutral. They can have unequal or undesirable effects from their design decisions, training data, feature selection, thresholds and optimization goals. Köchling and Wehner (2020) provide a review that shows that issues of fairness and discrimination have been shown to be relevant concerns in algorithmic HR decision-making. However, as shown by Kochling et al. (2021), the same algorithm can be both highly accurate and discriminatory, suggesting that accuracy and fairness are distinct evaluative criteria. The same justice rules for selection systems (consistency, job relatedness, opportunity to perform) apply to algorithmic evaluation (Gilliland, 1993).

Staff attitudes come into particular focus. Technically correct algorithms can be considered unfair when they limit the performance of an algorithm to a small number of metrics. This problem is referred to as algorithmic reductionism by Newman et al. (2020). Employees might feel contextual and/or qualitative information is not being considered in the decision-making process. An algorithmic evaluation's fairness can also impact a supervisor's perception due to the fact that supervisors are still visible organizational representatives. Procedural justice was especially important to trust in supervisors, as was found by Folger and Konovsky (1989). Employees can also give credit to managers who implement, recommend, explain, or fix the system of evaluation for the fairness of the evaluation process in algorithmic contexts.

Thus:

H2: Perceived fairness of algorithmic performance evaluation is positively associated with employee trust in the immediate supervisor.

2.5 Evaluation Transparency and Supervisor Trust

Transparency is the level of clarity that employees have about the principles behind algorithmic assessments. To enable employees to see what information is collected, what criteria are assessed, how their scores can affect decisions and what they can do to change their performance, a transparent performance system should be used. Transparency is an important aspect since computational systems may be opaque for several reasons. Burrell (2016) describes opacity as being due to deliberate secrecy, to variation in technical expertise, or to the intrinsic difficulty of a machine-learning system. However, there is no linear relationship between transparency and trust. When the outcomes differed from expectations, Kizilcec (2016) discovered that a moderate level of procedural explanation led to a higher level of trust, whereas more information reduced trust. Performance evaluation is consequential, and opacity creates problems for employees. Feedback cannot be acted upon when the employee does not know how the feedback was produced. Accountability can also be diminished due to the absence of transparency. If the employee and supervisor cannot provide information about what caused a specific result, it is hard to assign responsibility. The theory of fairness, accountability and transparency indicates that these perceptions are tightly linked to trust in an algorithmic context. Similarly, Lee (2018) demonstrates a distinction between the basis on which algorithmic and human decision-makers are judged, indicating that knowledge of the decision-making process is important for reactions. Schlicker et al. (2021) also observed that people perceived that HVs are more just in terms of interpersonal justice and more voice-giving, while the lack of explanations had a different impact on HVs than on AAs.

Oftentimes, supervisors are the first place supervisors turn to for explanations regarding performance. As a result, employees might interpret a supervisor's competency and integrity in using metrics as a way of assessing them as a tool. Consequently, an employee's perception of their supervisor's competency and integrity in explaining how metric-based evaluation is used as a tool might be a sign of their supervisor's competency and integrity as a person.

Accordingly:

H3: Perceived transparency of algorithmic performance evaluation is positively associated with employee trust in the immediate supervisor.

2.6 Perceived Supervisor Discretion and Supervisor Trust

This paper refers to perceived supervisor discretion as the employee's sense that the immediate manager has the authority to interpret, contextualize, question, supplement or adjust algorithmically generated information about his or her work performance. Theoretically important because algorithmic performance management can change the allocation of managerial power but not the power itself. A supervisor does not necessarily need to have the authority to alter an automatically generated appraisal rating, but may have the authority to hold appraisal meetings and provide performance consequences. These could reduce managers' confidence in their capabilities. If management cannot make an actual change to a clearly substandard or incorrect evaluation, employees may wonder why it is important for the manager to make a judgment. Also, lowered discretion can diminish perceptions of benevolence, as supervisors will lack any ability to prevent inappropriate results. Leavitt et al. (2025) focus on human managers as the key in forming trust within the algorithmic performance-management system. Their theorizing implies that managers can interpret and enrich algorithmic outputs, rather than simply being a conduit. The automation-augmentation distinction also supports this argument. Algorithms supplement and do not replace managerial judgment, meaning supervisors still can integrate the standardized information with the context (Raisch & Krakowski, 2021). This means that employees must be more confident in the supervisor's ability to understand and use the system independently and make judgments.

H4: Perceived supervisor discretion over algorithmic performance evaluations is positively associated with employee trust in the immediate supervisor.

2.7 Perceived Evaluation Accuracy and Supervisor Trust

Accuracy is related to the degree to which performance indicators accurately represent employee contribution. Performance may seem accurate but not capture the performance. This is especially an issue for quantitative systems if employees do multi-dimensional work. A productivity measure may reflect output volume but not quality, mentoring, cooperation, creativity, emotional labor, problem solving and/or tasks that have delayed outcomes. The relationship between perceived accuracy and employee reactions has been related to performance-appraisal research that has been conducted for years. Fulk et al. (1985) looked at perceived fairness and accuracy and their relationship to supervisor trust; they found that there is a relationship between how perceived appraisals relate to the interpersonal relationship between supervisor and employee. Algorithmic systems can exacerbate accuracy issues, since it may lead to a sense of objectivity when numbers are used. However, employees can make a distinction between numerical exactness and content validity. The right dimensions of performance are often measured with a score that has only a few decimal places. If supervisors use indicators that the employees think are incorrect, they might doubt the supervisor's ability and decision-making. On the other hand, the measurement tools that align with what the employees do could help to establish trust in the supervisor's decision-making.

Thus:

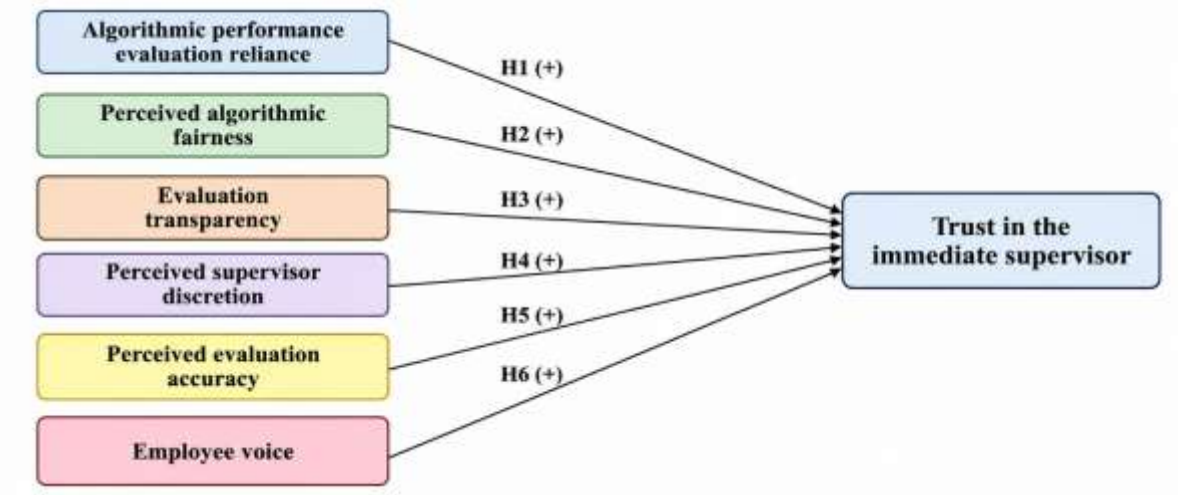
H5: Perceived accuracy of algorithmically generated performance evaluations is positively associated with employee trust in the immediate supervisor.

2.8 Employee Voice and Supervisor Trust

Employee voice in performance evaluation is about allowing an employee to give information, clarify situations, challenge inaccurate information and share opinions before and after a performance decision is made. Voice is firmly rooted in procedural-justice research, as people are not just interested in the outcomes, but also in whether they have the opportunity to participate in decision processes. With regard to performance appraisal, Cawley et. Al. (1998) conducted a meta-analysis of 27 studies and discovered that the involvement of appraisal and employee reactions had a significant positive relationship. Value-expressive participation – an opportunity to express opinions – was especially important. Upward voice is defined as employees' voluntary sharing of suggestions as well as problems, concerns and opinions about work with a superior in the organization (Morrison, 2014). Voice could be even more significant in algorithmic performance systems. Algorithms always work with certain variables. Some employees have information about the system that is not part of the data set (e.g., system downtime, unusual

customer orders, temporary resource shortages, team support activities, or work responsibilities that are hard to measure). When a supervisor hears such explanations, he or she conveys the message that the employee is a subject, not an object of measurement. Voice can thus foster the sense of respect, benevolence, and integrity by the supervisor.
Accordingly:
H6: Employee voice in the algorithmic performance evaluation process is positively associated with employee trust in the immediate supervisor.
Figure 1 summarizes the proposed research model. All six relationships are specified as direct effects on trust in the immediate supervisor.

Figure 1 Proposed Research Model



Note. Arrows represent hypothesized direct effects; signs indicate the expected direction. No mediating or moderating paths are specified.

3. Method

3.1 Research Design
The study employed a cross-sectional quantitative employee-survey design to examine direct relationships between six characteristics of algorithmic performance evaluation and trust in the immediate supervisor. The final analytical sample comprised 345 employee responses.

3.2 Study Population and Eligibility Criteria
The study population comprised employees who:

1. are at least 18 years old;
2. work under an identifiable immediate supervisor;
3. have sufficient experience with that supervisor to evaluate the relationship; and
4. are subject to performance evaluation that relies at least partly on digitally generated or algorithmically processed indicators.

The sample included employees whose organizations used productivity dashboards, automated quality scores, electronic performance monitoring, customer-rating systems, AI-assisted evaluation, workflow analytics, or algorithmically generated performance recommendations. Respondents represented IT/ITES, banking and financial services, sales and retail, logistics and e-commerce, manufacturing, and other service activities.

3.3 Sample Profile
The final analytical sample comprised 345 respondents. Table 1 summarizes the demographic and employment profile of the sample.

Table 1 Demographic Profile (N = 345)

Characteristic	Category	n	%

Gender	Male	188	54.5
	Female	147	42.6
	Other/prefer not to say	10	2.9
Age	21–30 years	129	37.4
	31–40 years	133	38.6
	41–50 years	60	17.4
	51+ years	23	6.7
Organizational tenure	< 2 years	70	20.3
	2–5 years	139	40.3
	6–10 years	92	26.7
	> 10 years	44	12.8
Sector	IT/ITES	82	23.8
	Banking/financial services	58	16.8
	Sales/retail	58	16.8
	Logistics/e-commerce	48	13.9
	Manufacturing	53	15.4
	Other services	46	13.3

Note. Percentages may not total 100 because of rounding.

3.4 Measures

All constructs were represented using multi-item measures scored on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

Table 2 Construct Definitions, Hypothesized Direction, and Theoretical Anchors

Construct	Working definition	Items	Sign	Key sources
Algorithmic performance evaluation reliance	Degree to which automated or digitally generated indicators substantially determine performance assessments	4	−	Kellogg et al. (2020); Raisch & Krakowski (2021)
Perceived algorithmic fairness	Belief that the algorithm-supported evaluation is fair and consistently applied	4	+	Colquitt (2001); Lee (2018); Newman et al. (2020)
Evaluation transparency	Understanding of what is measured and how scores are calculated and used	4	+	Burrell (2016); Kizilcec (2016)
Perceived supervisor discretion	Belief that the supervisor can interpret, contextualize, question, or revise algorithmic outputs	4	+	Leavitt et al. (2025); Parent-Rocheleau & Parker (2022)
Perceived evaluation accuracy	Correspondence between metric-based assessment and actual contribution	4	+	Fulk et al. (1985); Levy & Williams (2004)
Employee voice	Opportunity to provide information, explain circumstances, and challenge metrics	4	+	Cawley et al. (1998); Morrison (2014)
Supervisor trust (DV)	Willingness to be vulnerable to the immediate supervisor based on positive expectations	5	—	Mayer et al. (1995); McAllister (1995)

Note. All items are rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). DV = dependent variable.

Algorithmic Performance Evaluation Reliance

Four items captured the perceived extent to which automated metrics drove performance judgments. Example items included:

- "Automated performance metrics play an important role in my performance evaluation."
- "My performance rating depends heavily on digitally generated measures."
- "My supervisor relies extensively on system-generated performance information."
- "Automated indicators strongly influence decisions about my performance."

The construct was designed to capture decision reliance rather than mere technology availability.

Perceived Algorithmic Fairness

Four items assessed whether the algorithm-supported evaluation process was perceived as fair and consistently applied. Example items included:

- "The performance evaluation system treats employees fairly."
- "The criteria used by the system are applied consistently."
- "The system produces fair performance judgments."
- "Employees are evaluated according to appropriate performance criteria."

The conceptualization was informed by organizational-justice research (Colquitt, 2001) and research on fairness perceptions in algorithmic decision-making (Lee, 2018; Newman et al., 2020).

Evaluation Transparency

Four items captured employee understanding of the basis of algorithmic evaluations:

- "I understand how my system-generated performance rating is determined."
- "I know which indicators are used to evaluate my performance."
- "The organization clearly explains how automated performance metrics are calculated."
- "I understand how algorithmic scores influence my performance appraisal."

Perceived Supervisor Discretion

Four items measured the extent to which the supervisor was perceived to retain meaningful judgment:

- "My supervisor can adjust a system-generated performance assessment when necessary."
- "My supervisor can consider factors that are not captured by performance metrics."
- "My supervisor has meaningful authority over my final performance evaluation."
- "My supervisor can question system-generated performance information."

Evaluation Accuracy

Four items assessed correspondence between metric-based assessment and actual work:

- "The performance system accurately reflects my actual contribution."
- "My digital performance indicators represent the quality of my work."
- "Automated performance measures provide an accurate picture of my performance."
- "The system rarely misrepresents my work performance."

Employee Voice

Four items assessed employee opportunities to contribute to the appraisal process:

- "I can explain circumstances that affect my system-generated performance scores."
- "I have an opportunity to challenge an inaccurate performance rating."
- "My supervisor listens when I question system-generated performance information."
- "I can provide additional information before a final performance decision is made."

Supervisor Trust

Supervisor trust was represented by five items grounded in established interpersonal-trust research (Mayer et al., 1995; McAllister, 1995). The items assessed trust specifically in the respondent's immediate supervisor rather than in management or the organization more generally, preserving the intended trust referent of the study.

3.5 Analytical Strategy

Analysis proceeded in four stages.

First, descriptive statistics and Pearson correlations were examined to summarize the variables and their bivariate relationships.

Second, internal consistency and convergent validity were assessed using Cronbach's alpha, standardized item loadings, composite reliability (CR), and average variance extracted (AVE). CR and AVE were calculated from the standardized item loadings reported for each construct.
Third, discriminant validity was assessed using the Fornell-Larcker criterion together with inspection of the inter-construct correlation matrix.
Fourth, H1-H6 were tested simultaneously using multiple linear regression with supervisor trust as the dependent variable. Standardized coefficients, 95% confidence intervals, variance inflation factors (VIFs), R^2, adjusted R^2, and the omnibus F statistic were used to evaluate the direct relationships and the overall regression model.
All hypothesis tests were two-tailed. Because the theoretical model specifies direct effects only, no mediation, moderation, indirect effects, interaction terms, or conditional-process analyses were conducted

4. Results

4.1 Measurement Properties

The measurement results indicated acceptable internal consistency across all seven constructs.

Table 3 Measurement Properties of the Study Constructs

Construct	Items	Loading range	Cronbach's α	CR	AVE
Algorithmic evaluation reliance	4	.794–.838	.842	.894	.678
Algorithmic fairness	4	.766–.865	.849	.898	.687
Transparency	4	.796–.859	.849	.898	.687
Supervisor discretion	4	.771–.854	.821	.881	.650
Evaluation accuracy	4	.805–.818	.823	.883	.654
Employee voice	4	.766–.884	.844	.894	.679
Supervisor trust	5	.803–.852	.891	.920	.696

Note. CR = composite reliability; AVE = average variance extracted. CR and AVE were calculated from the standardized item loadings. Recommended thresholds: α and CR ≥ .70; AVE ≥ .50.

All Cronbach's alpha coefficients exceeded .80. Composite reliability values ranged from .881 to .920, and all AVE values exceeded .50. The reported item loadings, reliability coefficients, and AVE values therefore indicated satisfactory internal consistency and convergent validity. Discriminant validity was assessed using the Fornell-Larcker (1981) criterion, which requires the square root of each construct's AVE to exceed its correlations with every other construct. As Table 4 shows, the smallest square root of AVE (.806, supervisor discretion) is substantially larger than the largest inter-construct correlation (.448, between supervisor discretion and supervisor trust), supporting discriminant validity.

Table 4 Discriminant Validity: Fornell–Larcker Criterion

Construct	1	2	3	4	5	6	7
1. Algorithmic reliance	**.823**						
2. Fairness	−.139	**.829**					
3. Transparency	−.122	.307	**.829**				
4. Supervisor discretion	−.150	.272	.324	**.806**			
5. Evaluation accuracy	−.240	.375	.285	.250	**.809**		
6. Employee voice	−.213	.292	.403	.333	.249	**.824**	
7. Supervisor trust	−.328	.438	.353	.448	.432	.398	**.834**

Note. Bold diagonal values are the square roots of AVE; off-diagonal values are inter-construct correlations.

4.2 Descriptive Statistics and Correlations

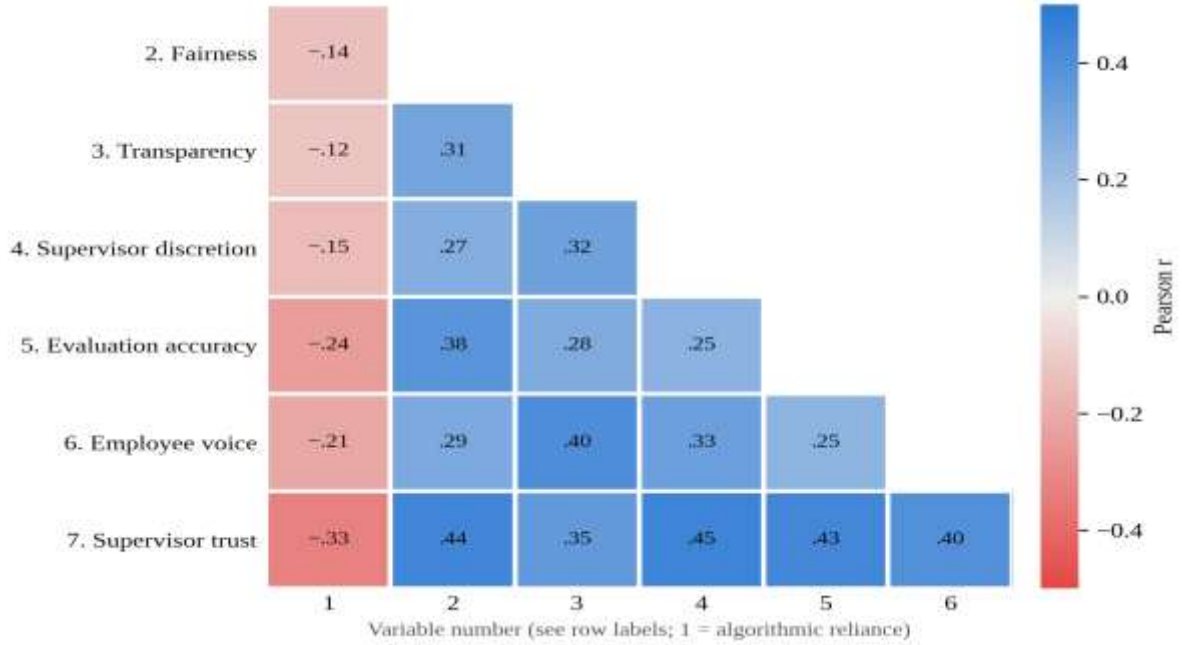
Table 5 Means, Standard Deviations, and Correlations Among Study Variables

Variable	M	SD	1	2	3	4	5	6	7
1. Algorithmic reliance	3.00	1.09	—						
2. Fairness	3.01	1.08	−.139	—					
3. Transparency	2.99	1.08	−.122	.307	—				
4. Supervisor discretion	3.01	1.06	−.150	.272	.324	—			
5. Evaluation accuracy	3.00	1.07	−.240	.375	.285	.250	—		
6. Employee voice	3.03	1.07	−.213	.292	.403	.333	.249	—	
7. Supervisor trust	3.00	1.10	−.328	.438	.353	.448	.432	.398	—

Note. N = 345. Entries are Pearson correlations; significance tests are two-tailed.

The zero-order correlations were consistent with the general theoretical expectations. Algorithmic performance evaluation reliance was negatively correlated with supervisor trust (r = −.328). Fairness (r = .438), transparency (r = .353), supervisor discretion (r = .448), evaluation accuracy (r = .432), and employee voice (r = .398) were positively correlated with supervisor trust. Correlations among the independent variables were moderate rather than extreme, suggesting that the constructs captured related but distinguishable aspects of algorithmic performance evaluation. Figure 2 presents the correlation pattern visually.

Figure 2 Heat Map of Inter-Construct Correlations



Note. Lower triangle of the Pearson correlation matrix (N = 345). Red cells denote negative and blue cells positive correlations; shading intensity reflects magnitude.

4.3 Hypothesis Testing

The six predictors were entered simultaneously into a multiple regression model predicting supervisor trust.

The overall regression equation was statistically significant:

$F(6, 338) = 41.66$, $p < .001$.

The model explained 42.5% of the variance in supervisor trust ($R^2 = .425$; adjusted $R^2 = .415$).

Multicollinearity was not a concern: variance inflation factors ranged from 1.09 to 1.33, well below conventional thresholds. The standardized coefficients and their 95% confidence intervals are displayed in Figure 3.

Table 6 Multiple Regression Predicting Supervisor Trust

Predictor	β	t	p	95% CI for β	VIF	Hypothesis
Algorithmic evaluation reliance	−.177	−4.10	< .001	[−.261, −.092]	1.09	H1 supported
Algorithmic fairness	.210	4.52	< .001	[.119, .302]	1.27	H2 supported
Transparency	.077	1.62	.107	[−.017, .170]	1.32	H3 not supported
Supervisor discretion	.245	5.37	< .001	[.155, .335]	1.23	H4 supported
Evaluation accuracy	.193	4.15	< .001	[.102, .285]	1.27	H5 supported
Employee voice	.138	2.91	.004	[.045, .232]	1.33	H6 supported

Note. Dependent variable: supervisor trust. $R^2 = .425$, adjusted $R^2 = .415$, $F(6, 338) = 41.66$, $p < .001$. β = standardized coefficient; CI = confidence interval; VIF = variance inflation factor.

H1

Algorithmic performance evaluation reliance was negatively associated with supervisor trust (β = −.177, p < .001). H1 was therefore supported.

H2

Perceived algorithmic fairness showed a positive relationship with supervisor trust (β = .210, p < .001). H2 was supported.

H3

Transparency had a positive zero-order relationship with trust but did not make a statistically significant unique contribution after the remaining evaluation characteristics were controlled (β = .077, p = .107). H3 was therefore not supported.

H4

Perceived supervisor discretion had the largest positive standardized coefficient in the full model (β = .245, p < .001). H4 was supported.

H5

Perceived evaluation accuracy was positively associated with supervisor trust (β = .193, p < .001), supporting H5.

H6

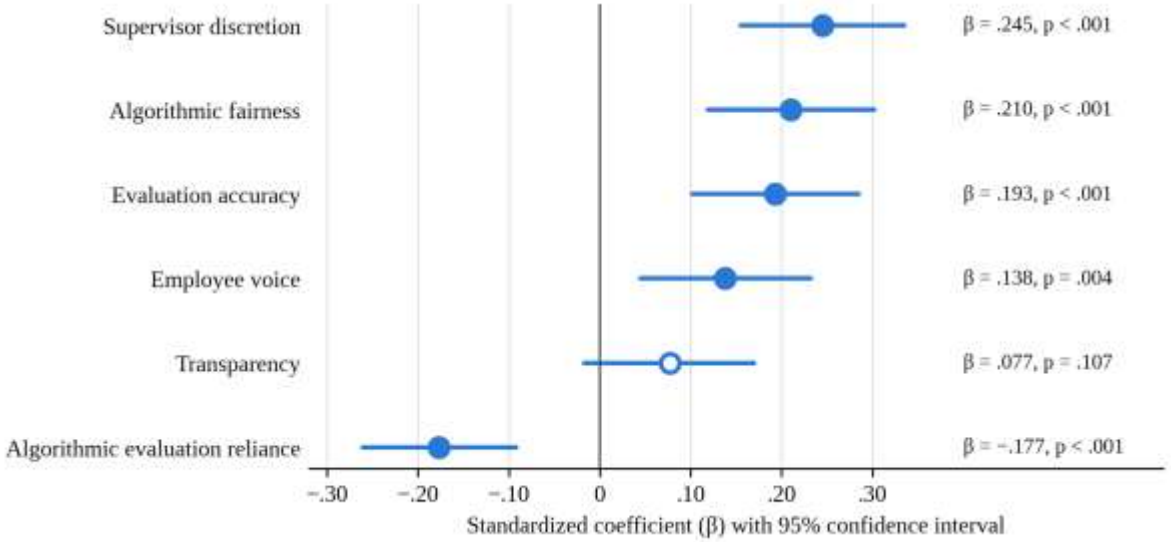
Employee voice was positively associated with supervisor trust (β = .138, p = .004), supporting H6. Overall, five of the six hypotheses received support in the analysis.

Table 7 Summary of Hypothesis Testing

Hypothesis	Relationship	Expected	β	Decision
H1	Algorithmic evaluation reliance → Supervisor trust	−	−.177***	Supported
H2	Algorithmic fairness → Supervisor trust	+	.210***	Supported
H3	Evaluation transparency → Supervisor trust	+	.077 (ns)	Not supported
H4	Supervisor discretion → Supervisor trust	+	.245***	Supported
H5	Evaluation accuracy → Supervisor trust	+	.193***	Supported
H6	Employee voice → Supervisor trust	+	.138**	Supported

Note. *** p < .001; ** p < .01; ns = not significant.

Figure 3 Standardized Regression Coefficients With 95% Confidence Intervals



Note. Filled markers indicate coefficients whose 95% confidence interval excludes zero; the hollow marker (transparency) is not statistically significant. Predictors are ordered by coefficient size.

5. Discussion

This study aimed to explore the relationship between the immediate supervisor's performance assessment using an algorithm and employee trust in the immediate supervisor. The study used interpersonal consequences of moving the evaluative authority from interpersonal to metric-based systems as the outcome variable, rather than trust in algorithms.

The results yield a number of theoretically significant patterns.

The reliance on algorithmic performance measures was negatively associated with the supervisor's trust, even when evaluating algorithmic fairness, transparency, discretion, accuracy and voice was conducted at the same time. This is in line with the assumption that employees differentiate between the use of technology to facilitate management and technology that takes over managerial judgment. It is a difference that matters. Digital performance information is never actually incompatible with trust. There have been long-standing practices for organizations to apply quantitative information to performance management. The concern is raised when the employees think that the metrics have taken the place of the management's judgments instead of guiding it. In these instances, the supervisor can come across as lacking one of the fundamental duties of a manager: sound judgment in circumstances that a set of scales can not capture. This therefore follows the automation-augmentation approach proposed by Raisch and Krakowski (2021). While technology can be useful for decision support, it can also create relational costs as employees feel they are being replaced by technology. The discovery also confirms previous studies that have demonstrated that algorithmic management can challenge traditional authority structures. Kellogg et al. (2020) demonstrate the ways in which algorithmic systems can document, rate, recommend, limit, reward, and replace facets of managerial control. Similarly, Jarrahi et al. (2021) highlight power and social transformation shifting because of algorithmic management. The current model adds these insights by proposing that one interpersonal outcome of this restructuring of authority is that employees' trust in the manager may decrease.

Second, the largest positive standardized coefficient in the full model was the generated by perceived supervisor discretion. This is likely the most theoretically unique outcome of the model. There is a lot of talk about transparency, fairness or explainability in the discussion about responsible AI. Those dimensions are certainly relevant, but they do not go far enough in discussing the contribution of the human manager. Workers might know exactly why an algorithm has been created and yet be suspicious of the supervisor who cannot fix an unfair result. Discretion implies that the supervisor is truly a decision-maker. Continued managerial agency is evidenced by a manager who is able to bring in contextual information, by recognizing unusual circumstances, questioning automated decisions, and by changing a final evaluation. This could reinforce the supervisor's ability to earn trust with employees

since the supervisor is able to make independent decisions. It is possible to foster benevolence as the supervisor will be able to shield the employee from the undesirable effects. It can also help build integrity since the manager takes full responsibility for the outcome of the decision, not leaving the responsibility to a system. This interpretation aligns with the argument by Leavitt et al. (2025), who claim that managers are still important trust actors in algorithmic performance-management systems. Managers can be more than mere interpreters of automatic products; they can be enhancers.

Third, there was a strong positive correlation between perceived algorithmic fairness and supervisor trust. The finding links up old and new research on organizations and algorithms. Colquitt (2001) illustrates that employees differentiate between various dimensions of justice, and Folger and Konovsky (1989) argue that procedural justice is particularly important in shaping attitudes toward authorities, such as trust in a supervisor. The idea is that there might be relational spillover effects of algorithmic fairness. That does not mean that staff do not regard an algorithm as a wholly different entity from the manager. Use or endorsement by a supervisor can lead to some degree of identification of a supervisor with a system and, therefore, with its fairness or lack of it. This is important because statements of technological objectivity alone do not create the perceptions of fairness. The authors Kochling and Wehner (2020) report a wide range of worry about discriminatory and fair uses of algorithmic HR. Newman et al. (2020) also demonstrate the perception of procedural unfairness when the algorithmic decision-making is seen as a process that omits human qualities and makes them more limited quantitative representations.

Fourth, there was a positive correlation between the evaluation accuracy and supervisor trust. This finding demonstrates the difference between algorithm sophistication and employee perceptions of validity. Even in the case of an advanced analytical system, the actual performance can be different. The evaluation of performance is a measurement problem. Organizations measure performance in signs and not the whole thing. The problem gets more serious when the organisations focus on "observable indicators" as "all indicators". Employees will accept quantitative assessment if the requirements of their jobs can be measured and quantified. However, if the requirements are more visible tasks, and the less visible tasks are being overlooked, then there is a problem. In knowledge work, professional positions, or within work groups, the contribution may be a performance that involves creativity, mentoring, judgment, problem solving, relationship management and long-term contributions. Managers who unthinkingly follow incomplete metrics can thus compromise the trust in their judgment.

Fifth, employee voice continued to be a positive correlate with supervisor trust. This finding is in line with much performance-appraisal research. Cawley et al. (1998) determined that employee reactions to appraisal processes were highly correlated with participation, especially if participation is provided as a means for employees to voice their opinion. Under algorithmic evaluation, it may be even more important that voice has information that is not available to the system, as it is often the case. An employee may be aware of a system failure which resulted in a decrease in output, have noticed that customer satisfaction was impacted by an unusually challenging clientele list, or have measured the individual productivity shortfall that occurred when some of his time was spent supporting others on his team. If employees can add such information there, then the data is not the only source for the organization's reality.

Lastly, transparency was not significantly associated with a unique effect on the multivariate model even though it had a positive bivariate correlation with supervisor trust. This is not a significant finding; do not read into it as transparency not mattering. Rather, the disclosure that one knows how the system operates might not be enough to create trust if employees assess whether the system is fair, accurate, open to voice, and fair to meaningful supervisory judgment. An employee can have a clear understanding of how his or her performance is measured by a specific productivity measure, yet still consider the process unfair or inaccurate. Transparency can expose the logic of a system, and it does not make it acceptable. This is important since it does not allow the study to focus only on explainability as a way of describing algorithmic management. While Burrell (2016) shows that opacity can be manifested in a number of ways, the lack of opacity does not necessarily address the normative and relational outcomes of a system. This is supported by experimental evidence in which the more information that an algorithm contains, the less trust it can engender (Kizilcec, 2016).

6. Theoretical Implications

6.1 From Trust in Algorithms to Trust Around Algorithms

The first theoretical contribution has to do with the site of trust.

Research into the capabilities of AI and automation has naturally focused on whether humans trust systems with technology. Obviously, when it comes to AI and automation research, the focus has been on whether or not humans trust technological systems. Trust is identified as a key element of the proper use of automation by Lee and See (2004), and Glikson and Woolley (2020) review the evidence on human trust in AI.

However, organizational staff members do not deal with technological systems alone; they also deal with the people who are responsible for designing, authorizing, interpreting, and enforcing them. In this study, we thus propose a more general concept, that of trust in algorithms.

An employee may simultaneously:

- trust the statistical accuracy of an algorithm,
- distrust the fairness of the process,
- trust the organization,
- distrust the supervisor,
- Alternatively, trust the supervisor precisely because the supervisor questions the algorithm.

Trust is therefore referent-specific.

The difference between this and the previous findings of algorithm aversion and algorithm appreciation is reconciled. Dietvorst et al. (2015) show that people can become reluctant to use algorithms after seeing mistakes, and Logg et al. (2019) illustrate that sometimes people prefer to take algorithmic advice over human advice. Working with technology does not mean that the individual has to turn down use of technology in order to be treated responsibly as a human being.

6.2 Managerial Discretion as a Trust Resource

The second contribution is the notion of managerial discretion as a resource that facilitates a trust relationship. Commonly, the understanding of discretion in algorithmic management is couched in terms of efficiency. Humans have the potential to add bias, inconsistency, favoritism or error. Thus, the standardization of algorithms can be done specifically to minimize managerial discretion.

The existing system proposes relationship-based compensation.

A bit of discretion may be required, as standardized systems are unable to foresee all situations that may impact human performance. Minimizing discretion can lead employees to be more susceptible to measurement error, and also reduce the manager's ability to be competent, benevolent and honest. The question of managing with discretion then is not whether the manager should be in possession of discretion, but rather what they should be allowed to do, and how. This is what it takes to establish responsible authority. Organisations may allow managers to review algorithmic outcomes, but must be able to explain and record their choices, conduct audits, and review on a regular basis. This way, standardized data is preserved, but it is not considered an “automated command.”

6.3 Performance Evaluation as a Sociotechnical Relationship

Third, the study confirms that the performance evaluation of algorithms is not just a measurement system. It is a relationship of the social and the technical.

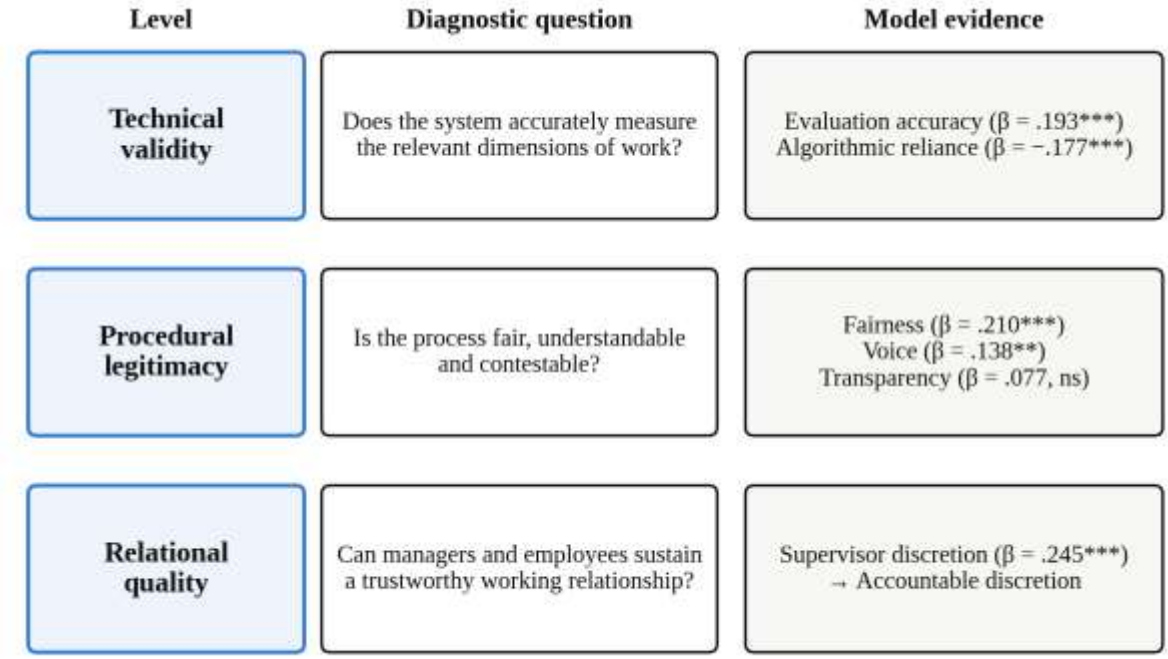
One way that algorithms influence organizational outcomes is by changing how people communicate, who has authority, who is accountable, and how people interpret each other. Jarrahi et al. (2021) explicitly focus on algorithmic management as a sociotechnical practice, and Rosenblat and Stark (2016) show how the presence of information asymmetries influences worker-management relationships.

This suggests that organizations should evaluate algorithmic performance systems at three levels:

1. technical validity: Does the system accurately measure relevant dimensions?
2. procedural legitimacy: Is the process fair, understandable, and contestable?
3. relational quality**:** Does the system allow managers and employees to sustain trustworthy working relationships?

A system can perform well at one level and poorly at another. Figure 4 maps the model’s constructs onto these three levels.

Figure 4 Three-Level Framework for Evaluating Algorithmic Performance Systems



Note. Coefficients are standardized estimates from the reported model (Table 6). *** p < .001; ** p < .01; ns = not significant.

7. Practical Implications

The findings have several practical implications for organizations implementing algorithm-supported performance management.

7.1 Avoid Turning Supervisors into Messengers of Scores

There should not be a case where the decision is made entirely by software and the supervisor's role is simply to transmit the decisions.

Statements such as:

This is the score the system produced, I didn't do it, it's the system.

may be convenient for the organization but detrimental to the relationship.

The supervisor, instead, should have a clear idea of how the score was computed, know if there are missing pieces of information, take into account the context of the situation, and clarify the decision made.

7.2 Preserve Human Review

Performance systems should contain clearly defined mechanisms for human review.

This does not mean permitting managers to arbitrarily ignore data. Human review should be structured and auditable. A useful process would allow a supervisor to:

- examine the underlying metrics;
- identify abnormal circumstances;
- consider qualitative evidence;
- request recalculation when data are wrong;
- adjust ratings when justified;
- record reasons for overrides.

Such mechanisms create a genuine human-in-the-loop system rather than a nominal human presence.

7.3 Validate What Is Being Measured

Organizations need to differentiate between what is measurable and what is important in affecting the performance. There should be periodic reviews of the criterion-relevancy and criterion-deficiency of metrics. A system that only measures output that is readily quantifiable can systematically misrepresent performance when working in teams, serving customers, recovering service, mentoring, being creative,

making professional judgments, or building long-term relationships are part of an employee's job. It's important that employee and supervisor feedback be incorporated into metric validation.

7.4 Build Voice into the Evaluation Process

Employees should have formal opportunities to challenge or contextualize algorithmically generated information.

An appropriate process could include:

1. access to the relevant performance indicators before the appraisal meeting;
2. an opportunity to identify incorrect data;
3. a mechanism for explaining contextual circumstances;
4. supervisory review;
5. documented resolution of contested information;
6. an escalation or appeal route when disagreement remains.

Voice does not require employees to control the outcome. It requires that relevant employee information can enter the decision process.

7.5 Do Not Treat Transparency as a Complete Solution

When algorithms are a concern, organisations tend to do so by making them more transparent.When organisations have concerns about algorithms they often do this by making the algorithms more transparent. Transparency is good, but not a substitute for the results.

There's no justification for an unfair process that is not fair.

It's one thing to explain a measurement that is not accurate and quite another to make it accurate.

While it is true a supervisor lacks authority, that doesn't return managerial discretion.

Transparency should, then, be used in conjunction with, and not as a replacement for, fairness, validation, contestability and human judgement.

8. Conclusion

This research investigated the relationship between algorithmic performance evaluation and trust in the immediate supervisor for six characteristics of the performance evaluation environment. The findings reveal that a higher algorithmic dependence on performance assessment is negatively related to supervisor trust, and perceived fairness, supervisor discretion, assessment accuracy, and employee voice are positively related to supervisor's trust. At the bivariate level, transparency is positively related to trust, but this association is not statistically significant for the unique effect of transparency, after controlling for the rest of the evaluation characteristics. The results place supervisor trust as a crucial relational outcome of algorithmic management. They argue that the question isn't just whether performance information is algorithmically generated, but whether managers maintain a legitimate authority to make sense of it, employees feel fair, accurate, and that they are getting meaningful information, and employees are given a chance to give context. The results confirm the perspective that a strong supervisor-employee relationship is fostered when technology provides supervision information to guide rather than replace managerial decisions.

9. Limitations and Future Research

The results should be interpreted with the following limitations in mind. Firstly, the cross-sectional design of the study makes causal inference difficult and it does not allow for temporal ordering, so reciprocal relationships between supervisor trust and perceptions of algorithmic evaluation could exist. Secondly, the same self-report instrument was used to measure all focal variables which precludes the possibility of common method variance (Podsakoff et al., 2003). Third, the sample is across sectors, but not every sector-specific difference was explored here, and algorithmic assessment could vary by occupation and/or industry. Fourth, the study acknowledges that performance evaluation for algorithms is quite general, and that responses to algorithms, such as those based on rules, may differ from algorithmic responses based on machine learning, customer ratings, biometric monitoring, Generative-AI assessments, and productivity analytics. Supervisor characteristics, such as technological competency and challenge of automated decisions should also be studied further. One possible avenue for study is the way trust builds or breaks over multiple appraisal cycles in a longitudinal study. Lastly, future studies may expand the model to behavioral and attitudinal outcomes like employee voice,

employee withdrawal, knowledge hiding, intention to quit the organization, organizational citizenship behavior, resistance to monitoring, and job performance.

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