Algorithmic Management: An MCDA-Based Comparison of Key Approaches

Research Paper

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Abstract. Algorithmic management systems are increasingly used to control and coordinate work, presenting both opportunities and challenges for organizations and workers. This study employs Multi-Criteria Decision Analysis (MCDA) to evaluate and compare four distinct approaches to the governance of these systems: principle-based, rule-based, risk-based, and auditing-based. A structured questionnaire elicited preferences from 27 experts regarding the effectiveness, feasibility, adaptability, and stakeholder acceptability of each approach. A Weighted Sum Model (WSM) aggregated these preferences. Results, supported by statistical testing and sensitivity analysis, consistently indicated a strong preference for the hybrid, risk-based approach. This approach was perceived as the most effective in mitigating risks, while also demonstrating good adaptability and stakeholder acceptability. The findings highlight the importance of prioritizing risk mitigation in the design of algorithmic management governance frameworks and provide a structured methodology for evaluating and comparing different governance strategies. This study offers valuable, evidence-based insights for research, organizations and policymakers.

Keywords: Algorithmic Management, Multi-Criteria Decision Analysis (MCDA), Risk Management, Organizational Control.

1 Introduction

The increasing integration of Artificial Intelligence (AI) into organizational processes has given rise to algorithmic management, where algorithms significantly assist in, or make, decisions traditionally made by human managers (Recker et al., 2021). This phenomenon spans diverse sectors, from ride-hailing and e-commerce to logistics (Möhlmann et al., 2021; Tarafdar et al., 2023; Wiener et al., 2023), where algorithms coordinate work, allocate tasks, monitor performance, provide feedback, and influence hiring/firing decisions (Kellogg et al., 2020; Möhlmann et al., 2021). This shift presents a duality of opportunities and challenges. Algorithmic management offers potential gains

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in efficiency, scalability, and objectivity (Benlian et al., 2022). Algorithms can process vast datasets, identify patterns, and make decisions with speed and consistency surpassing human capabilities, particularly beneficial in dynamic environments requiring real-time responsiveness (Wiener et al., 2023). This can optimize resource allocation, improve productivity, and reduce costs.

However, reliance on algorithmic management raises concerns about worker autonomy, well-being, fairness, and transparency (Möhlmann and Henfridsson, 2019). Algorithmic control can diminish autonomy (Wiener et al., 2023), increase stress (Cram et al., 2022), and cause role conflict (Tarafdar et al., 2023). The opacity of many algorithms ("black box" problem) hinders worker understanding of decision rationales, fostering powerlessness and distrust (Meijerink et al., 2021). Workers sometimes respond through "algoactivism," resisting or manipulating the algorithms governing their work (Jiang et al., 2021; Kellogg et al., 2020).

The academic discourse has responded to these challenges with a foundational call to establish "algorithmic governance" as a distinct field of inquiry, focusing on the design and legitimacy of systems that regulate organizational and social order (Danaher et al., 2017). In response, a spectrum of governance philosophies has emerged. On one end, ethicists and policymakers advocate for high-level, principle-based frameworks (Floridi, 2019; Jobin et al., 2019). On the other end, legal scholars propose detailed, rule-based regulatory "blueprints" that emphasize enforceable rights and transparency mandates (Adams-Prassl et al., 2023; Yeung, 2018). Bridging these are hybrid, risk-based models, similar to approaches in cybersecurity or finance, which tailor governance intensity to the level of potential harm (European Commission, 2021). However, while these distinct governance archetypes are debated on their conceptual merits, a significant research gap persists: there is a lack of empirical research that systematically compares them. It remains unclear how experts and decision-makers perceive the practical trade-offs between competing criteria like effectiveness, feasibility, and adaptability. We do not yet know which approach is considered most promising for balancing innovation with responsibility in practice.

This study addresses this gap using MCDA to evaluate four distinct governance archetypes: proactive/principle-based, reactive/rule-based, hybrid/risk-based, and self-regulation/auditing-based. A structured questionnaire elicited preferences from 27 experts with diverse backgrounds. Experts rated and ranked these approaches across four criteria: Effectiveness, Feasibility, Adaptability, and Stakeholder Acceptability. A weighted sum model, statistical testing (Friedman and Wilcoxon signed-rank tests), and sensitivity analysis were used to ensure reliability and robustness.

The central research question is:

Which approach to governing algorithmic management systems is most preferred and how robust is this preference?

This study's novelty lies in its empirical evaluation of the trade-offs between these key governance archetypes. By moving beyond conceptual debate to structured, evidence-based comparison, it provides urgently needed insights for organizations implementing algorithmic management responsibly and ethically, and for policymakers/researchers concerned with broader societal implications. This research contributes a structured, evidence-based comparison, informing more effective and equitable governance strategies. The remainder of this paper is structured as follows. Section 2 reviews the theoretical background of algorithmic management. Section 3 details the methodological approach based on Multi-Criteria Decision Analysis (MCDA). Subsequently, Section 4 presents the results of our empirical study. In Section 5, we discuss the theoretical and practical implications of these findings, before the paper concludes in Section 6 with a summary, a discussion of limitations, and an outlook on future research.

2 Foundations

Algorithmic management represents a shift from hierarchical structures to decentralized, data-driven approaches (Santana and Cobo, 2020). It is defined as the use of algorithms to execute, or significantly assist in, managerial decisions traditionally handled by humans (Recker et al., 2021). This includes tasks like workflow optimization, performance monitoring, and strategic decisions (hiring, firing, promotions, compensation) (Santana and Cobo, 2020).

The defining characteristic is automated data processing and decision-making by algorithms, impacting organizational structures, managerial roles, and the nature of work (Gal et al., 2020). Algorithms streamline workflows (Kellogg et al., 2020; Möhlmann et al., 2021), monitor performance (Myhill et al., 2021), provide decision support (Kellogg et al., 2020), offer feedback (Myhill et al., 2021), and facilitate communication (Tarafdar et al., 2023).

Technological foundations include: (1) "big data" from digital platforms (Möhlmann et al., 2021); (2) increased computing power and data storage (Kellogg et al., 2020); (3) internet/mobile technologies for communication (Möhlmann and Henfridsson, 2019); and (4) AI/machine learning advancements (Wurm et al., 2023). These technologies have shaped the evolution and applications of algorithmic management (Cameron and Rahman, 2022; Veen et al., 2020; Wiener et al., 2023).

Implementation varies across contexts (Myhill et al., 2021). Key dimensions are algorithmic coordination (optimizing resource allocation, matching tasks – e.g., ride-hailing (Möhlmann et al., 2021), online labor platforms (Kellogg et al., 2020)) and algorithmic control (monitoring behavior, enforcing standards, providing feedback – e.g., logistics, warehousing (Waldkirch et al., 2021)). Algorithmic control systems often operate with high opacity, making it difficult for workers to understand decision-making (Tarafdar et al., 2023).

Implications are profound. For organizations, potential benefits include increased efficiency, scalability, and objectivity (Waldkirch et al., 2021). Real-time data analytics can optimize resource allocation (Waldkirch et al., 2021). The perceived objectivity of algorithms can, in theory, enhance fairness (Benlian et al., 2022).

However, challenges arise, particularly for workers (Myhill et al., 2021). Concerns include reduced autonomy, well-being, and job satisfaction (Möhlmann and Henfridsson, 2019). Constant monitoring can lead to stress and perceived lack of control (Waldkirch et al., 2021; Wiener et al., 2023). Lack of transparency creates distrust and powerlessness (Tarafdar et al., 2023). Ethical and legal concerns include algorithmic bias, data privacy, and accountability (Benlian et al., 2022; Parente et al., 2024). Algorithms trained on biased data may perpetuate inequalities (Myhill et al., 2021). Data collection raises privacy concerns (Cameron and Rahman, 2022).

3 Methods

To address our research question, this study required a method capable of systematically evaluating pre-defined alternatives against multiple, often conflicting, criteria. We chose Multi-Criteria Decision Analysis (MCDA) because it is specifically designed for such complex decision problems. While alternative methods like qualitative case studies could provide rich context, they would lack a structured, comparative framework. Methods like vignette or scenario-based studies often focus on isolated decision points rather than a holistic comparison of entire governance systems. MCDA, in contrast, allows for the explicit and quantifiable comparison of governance archetypes by making the inherent trade-offs between criteria—such as Effectiveness versus Feasibility—transparent. This structured approach is essential for providing clear, evidence-based insights into the preferences of experts, which is the core objective of this research.
The study adopts a prescriptive decision-making framework, which focuses on how decisions should be made to achieve optimal outcomes based on a decision-maker's objectives and preferences (Bell et al., 1988; Keeney and Raiffa, 1993). MCDA provides a formal process for this by: (1) identifying objectives (our criteria); (2) defining feasible alternatives (our governance approaches); and (3) evaluating these alternatives based on expert preferences to find the most suitable solution. This study uses a Weighted Sum Model (WSM), a common MCDA method chosen for its simplicity, transparency, and ease of interpretation (Fishburn, 1967). In the WSM, experts assign weights to criteria based on their importance and rate the performance of each alternative against each criterion. These are combined to produce an overall score, with the highest-scoring alternative being the most preferred.

3.1 Alternatives: Governance Approaches for Algorithmic Management

Four distinct alternatives, representing archetypes of governance, were synthesized from a comprehensive review of current literature in AI ethics, technology policy, and regulatory studies. These were designed to reflect the dominant philosophical and practical approaches currently under discussion. The selection was informed by foundational work on AI ethics (Jobin et al., 2019; Mittelstadt et al., 2016), regulatory theory (Yeung, 2018), and concrete policy proposals (European Commission, 2021; OECD, 2019).

- The **Principle-Based** approach reflects the numerous ethics guidelines that form the core of the AI ethics field (Jobin et al., 2019).
- The **Rule-Based** approach captures the logic of legally binding regulations, as exemplified by recent "blueprint" proposals (Adams-Prassl et al., 2023) and theories of algorithmic regulation (Yeung, 2018).

- The **Risk-Based** approach is central to recent major policy initiatives, most notably the European Commission's AI Act (2021), which tailors obligations to risk levels.
- The **Auditing-Based** approach reflects calls for industry self-regulation and third-party certification to ensure accountability (Hagendorff, 2020).

Table 1 outlines these alternatives, highlighting their inherent tensions.

Table 1. Alternatives for Algorithmic Management Governance

Alternative (A)	Description	Key Characteristics and Examples
A1: Proactive, Principle-Based	Focuses on establishing high-level ethical principles and guidelines before system deployment. Emphasizes prevention through "ethics by design". Can be abstract and difficult to enforce.	Embedding ethical principles (fairness, transparency, accountability) into design specifications. Conducting ethical impact assessments prior to deployment.- Developing internal ethical review boards for algorithmic systems.(e.g.,Mittelstadt et al., 2016)
A2: Reactive, Rule-Based	Relies on establishing specific, legally binding rules and regulations after harms or risks have been identified. Emphasizes enforcement and accountability. Can be rigid and slow to adapt to new technologies.	Implementing regulations mandating transparency requirements (e.g., explanations for decisions). Establishing legal liability for harms caused by systems. (e.g.,Citron and Pasquale, 2014)
A3: Hybrid, Risk-Based	Combines principle-based and rule-based approaches. Focuses on identifying, assessing, and mitigating specific risks, using a tiered approach based on risk level. Requires complex risk assessment capabilities.	Conducting risk assessments to identify potential harms (bias, discrimination, privacy violations).- Implementing risk mitigation measures proportionate to risks (e.g., enhanced monitoring for high-risk systems).- Adapting regulations based on ongoing risk monitoring.(e.g.,Scherer et al., 2016)
A4: Self-Regulation, Auditing-Based	Emphasizes industry self-regulation through voluntary codes of conduct, industry-specific standards, and independent audits, with limited direct government oversight. Risks being ineffective if not	Developing industry-specific codes of conduct.- Establishing independent certification programs.- Conducting regular audits to assess compliance with guidelines and standards. (e.g.,Hagendorff, 2020)

	widely adopted or rigorously enforced.	

These alternatives represent a spectrum of governance approaches, reflecting different philosophies and strategies.

3.2 Criteria: Evaluating Governance Approaches

Four evaluation criteria were selected to assess performance. Selection was guided by relevance to core challenges, ability to capture key dimensions, alignment with AI ethics/governance frameworks (Jobin et al., 2019; Morley et al., 2020; OECD, 2019), and measurability using expert judgment. Table 2 describes each criterion.

Table 2. Evaluation Criteria

Criterion (C)	Description	Factors Considered
C1: Effectiveness	The extent to which the approach prevents/mitigates risks and harms associated with algorithmic management systems.	Prevention of bias/discrimination. Transparency/explainability. Worker privacy/data security. Robustness against manipulation. Accountability for harms.
C2: Feasibility	The practicality and realism of implementing the approach, considering technical, legal, economic, and organizational constraints.	Technical complexity. Legal/regulatory compliance. Economic costs. Availability of expertise/resources. Organizational capacity/culture.
C3: Adaptability	The ability of the approach to adapt to rapid technological advancements and new/emerging risks.	Flexibility for new techniques/applications. Scalability. Capacity to address unforeseen risks. Long-term viability/sustainability.
C4: Stakeholder Acceptability	The extent to which the approach is acceptable to stakeholders (workers, managers, shareholders).	Perceived fairness/equity. Alignment with ethical values. Impact on worker autonomy/well-being. Support from stakeholder groups. Public trust/confidence.

These criteria provide a comprehensive, balanced framework for evaluating algorithmic management governance approaches, encompassing technical effectiveness, practical implementability, adaptability, and stakeholder acceptance.

3.3 Expert Elicitation

To gather informed judgments on the governance approaches, a structured expert elicitation process was employed. Expert elicitation is a systematic method for obtaining and quantifying expert knowledge, particularly valuable when empirical data are scarce (Keeney and Winterfeldt, 1991; O'Hagan et al., 2006). A panel of 27 experts was assembled, representing a diverse range of relevant disciplines and reflecting a primarily European/German context. The panel composition included 26% academics (professors and researchers), 41% industry professionals from sectors including technology, consulting, and manufacturing, 18% from government/regulatory bodies, and 15% from NGOs/civil society organizations.

Expert experience, measured in years within their respective fields, ranged from 3 to 22 years, with a mean of 10.1 years and a standard deviation of 5.8 years. This distribution ensures a balance between established expertise and more recent perspectives. The selection criteria prioritized demonstrated expertise in areas directly relevant to algorithmic management governance, including AI ethics, policy, risk management, and societal impact. To ensure representation across key areas, the panel was designed to include at least three experts from each of the four main sectors (academia, industry, government/regulatory, and NGO/civil society). This diverse composition mitigates potential biases associated with any single viewpoint and enhances the credibility and robustness of the elicited judgments (Clemen and Winkler, 1999). Ethical approval for the study was granted by the authors' institutional review board, and all participants provided informed consent. Experts were provided with detailed descriptions of the governance approaches and evaluation criteria before completing the structured questionnaire.

4 Results

This section presents the Multi-Criteria Decision Analysis results, evaluating four algorithmic management governance approaches. Data were gathered from 27 respondents. Analysis includes descriptive statistics, weighted scores, ranking analysis, statistical significance testing, and sensitivity analysis.

4.1 Descriptive Statistics: Unveiling Initial Preferences

Table 4.1 summarizes descriptive statistics of respondent ratings. Alternatives (A1: Principle-Based, A2: Rule-Based, A3: Risk-Based, A4: Auditing-Based) were evaluated on four criteria (C1: Effectiveness, C2: Feasibility, C3: Adaptability, C4: Stakeholder Acceptability) using a 5-point Likert scale (1 = Very Low, 5 = Very High).

Mean rating (μ_{ij}) was calculated as:

$$\mu_{ij} = \frac{1}{N}\sum_{k=1}^{N} R_{ijk} \tag{1}$$

(N=27, R_{ijk} = rating by respondent k for alternative i on criterion j).

Standard deviation σ_{ij} was calculated as:

$$\sigma_{ij} = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}\left(R_{ijk} - \mu_{ij}\right)^2} \tag{2}$$

Table 3. Descriptive Statistics of Ratings (N=27)

Alternative / Criterion	Mean μ_{ij}	Standard Deviation σ_{ij}
A1: Principle-Based		
C1: Effectiveness	3.81	0.75
C2: Feasibility	2.89	0.78
C3: Adaptability	4.11	0.77
C4: Stakeholder Accept.	3.22	0.83
A2: Rule-Based		
C1: Effectiveness	3.22	0.75
C2: Feasibility	3.52	0.91
C3: Adaptability	2.67	0.88
C4: Stakeholder Accept.	2.78	0.85
A3: Risk-Based		
C1: Effectiveness	4.30	0.67
C2: Feasibility	3.78	0.70
C3: Adaptability	3.89	0.83
C4: Stakeholder Accept.	3.67	0.73
A4: Auditing-Based		
C1: Effectiveness	2.48	0.85
C2: Feasibility	3.96	0.84
C3: Adaptability	3.26	0.86
C4: Stakeholder Accept.	2.96	0.89

The Risk-Based approach (A3) consistently had the highest mean ratings for Effectiveness (4.30), Adaptability (3.89), and Stakeholder Acceptability (3.67), with relatively low standard deviations, indicating higher consensus. The Auditing-Based approach (A4) scored highest on Feasibility (3.96) but lowest on Effectiveness (2.48). The Principle-Based approach (A1) was strong on Adaptability (4.11) but weaker on Feasibility (2.89). The Rule-Based approach (A2) received lower ratings across most criteria, especially Adaptability (2.67).

4.2 Weighted Scores: Incorporating Criterion Importance

Respondents assigned weights (totaling 100%) to the four criteria. Average weights Average Weight_j were calculated:

$$\text{Average Weight}_j = \frac{1}{N}\sum_{k=1}^{N} W_{jk} \tag{3}$$

(W_{jk} = weight assigned to criterion j by respondent k).

Average weights were: Effectiveness (34.8%), Feasibility (24.6%), Adaptability (20.2%), and Stakeholder Acceptability (20.4%). Effectiveness was most emphasized. Weighted scores WS_{ik} for each alternative i for a given respondent k were calculated, and averaged over all respondents $\text{Average Weighted Score}_i$:

$$\mathrm{WS}_{ik} = \sum_{j=1}^{4}\left(R_{ijk} \times \frac{W_{jk}}{100}\right) \tag{4}$$

$$\text{Average Weighted Score}_i = \frac{1}{N}\sum_{k=1}^{N}\mathrm{WS}_{ik} \tag{5}$$

Table 4. Average Weighted Scores

Alternative	Average Weighted Score
A1: Principle-Based	3.53
A2: Rule-Based	3.07
A3: Risk-Based	4.00
A4: Auditing-Based	3.12

The Risk-Based approach (A3) had the highest average weighted score (4.00), reinforcing its leading position.

4.3 Ranking Analysis: Direct Preference Elicitation

Respondents ranked alternatives from most preferred (1) to least preferred (4).

Table 5. Distribution of Rankings

Alternative	Rank 1	Rank 2	Rank 3	Rank 4	Average Rank
A1: Principle-Based	4	7	10	6	2.63
A2: Rule-Based	1	6	7	13	3.15
A3: Risk-Based	21	4	2	0	1.78
A4: Auditing-Based	1	10	8	8	2.44

The Risk-Based approach (A3) was ranked first by 78% of respondents (21/27). The Rule-Based approach (A2) was most frequently ranked last.

4.4 Statistical Significance Testing and Sensitivity Analysis: Establishing Robustness

Friedman tests (non-parametric repeated-measures ANOVA) assessed differences in ratings and rankings (Siegel and Castellan, 1988). A Bonferroni correction was applied (alpha = 0.0125). Post-hoc Wilcoxon signed-rank tests (with Bonferroni correction) identified pairwise differences.

Effectiveness Ratings: Significant difference $\chi^2(3) = 38.74$, $p < .001$. A3 was rated significantly higher than all others (p < .001). A1 was rated higher than A4 (p = .002).

Feasibility Ratings: Significant difference $\chi^2(3) = 19.23$, $p < .001$. A4 was rated significantly higher than A1 (p < .001).

Adaptability Ratings: Significant difference $\chi^2(3) = 37.84$, $p < .001$. A1 was rated significantly higher than A2 and A4 (p < .001). A3 was rated higher than A2 (p < .001). Stakeholder Acceptability Ratings: Significant difference $\chi^2(3) = 11.39$, $p = .010$. A3 was rated significantly higher than A2 (p=0.006).
Overall Rankings: Significant difference $\chi^2(3) = 38.182$, $p < .001$. A3 was ranked significantly better than all others (p < .001). A4 was ranked better than A2 (p = .011). These results strongly support A3 as the most preferred approach overall, with statistical significance.

4.5 Sensitivity Analysis: Evaluating the Impact of Weight Variations

One-way sensitivity analysis assessed the impact of varying criterion weights (Hillier et al., 2005). Each criterion's weight was increased and decreased by 10 percentage points, recalculating weighted scores.

Table 6. Sensitivity Analysis Results (Average Weighted Scores)

Criterion Varied	Weight Change	A1	A2	A3	A4
Baseline	-	3.53	3.07	4.00	3.12
Effectiveness	+10%	3.61	3.09	4.07	3.04
	-10%	3.45	3.04	3.94	3.20
Feasibility	+10%	3.44	3.17	3.92	3.22
	-10%	3.62	2.98	4.07	3.02
Adaptability	+10%	3.62	2.99	3.98	3.14
	-10%	3.44	3.15	4.02	3.10
Stakeholder	+10%	3.54	3.00	3.97	3.11
	-10%	3.52	3.14	4.03	3.13

The Risk-Based approach (A3) consistently maintained the highest average weighted score across all scenarios, demonstrating robustness to weight variations.

5 Discussion

The results of this study, employing Multi-Criteria Decision Analysis with a Weighted Sum Model, provide compelling evidence for the preference of a hybrid, risk-based approach (A3) to the governance of algorithmic management systems within organizations. This preference emerged consistently across a range of scenarios in the sensitivity analysis, demonstrating its robustness to variations in the relative importance assigned to the evaluation criteria (Effectiveness, Feasibility, Adaptability, and Stakeholder Acceptability). Specifically, the risk-based approach achieved the highest average weighted score (4.00, as shown in Table 4), significantly outperforming the other alternatives. This finding suggests that experts do not favor a single governance philosophy but rather a pragmatic synthesis that balances proactive principles with reactive rules, tailored to specific levels of risk.
Our findings offer several significant theoretical implications. First, they provide a direct empirical response to the call for a research agenda on algorithmic governance

(Danaher et al., 2017). While the field has established the importance of the topic, our study provides one of the first comparative, empirical data points on which governance archetypes are actually preferred by practitioners, moving the discussion from the conceptual to the empirical realm. The strong preference for a hybrid model suggests that future governance theories should focus on integrative frameworks rather than promoting singular solutions.

Second, this study helps to mediate the ongoing debate between principle-based (Floridi, 2019) and rule-based governance (Adams-Prassl et al., 2023; Yeung, 2018). Our results indicate that experts see both pure approaches as flawed in isolation. This is evident in the inherent trade-offs revealed by our data (Table 3): The Rule-Based approach (A2), while perceived as relatively feasible (μ=3.52), scored poorly on Adaptability (μ=2.67), suggesting it is seen as too rigid for a rapidly evolving technological landscape. Conversely, the Principle-Based approach (A1) was rated as highly adaptable (μ=4.11) but was penalized on Feasibility (μ=2.89), indicating concerns about its practical enforceability. The clear preference for the Risk-Based approach (A3) can thus be interpreted as a pragmatic search for a 'sweet spot' that balances the flexibility of principles with the clarity of rules, thereby contributing a nuanced perspective to the governance discourse.

Third, the results lend empirical support to theories of "responsive" or "smart" regulation, which argue for a pyramid of regulatory strategies rather than a one-size-fits-all approach. The risk-based model is a direct embodiment of this philosophy, applying stricter, rule-like controls only where risks are high, and allowing for more principle-based flexibility where risks are low. This advances our understanding of how broader governance theories can be effectively applied to the specific domain of algorithmic management.

Beyond its theoretical contributions, this study offers actionable insights for managers and policymakers. The primary recommendation is to move away from a uniform governance strategy for all algorithmic systems within an organization. Instead, managers should adopt a differentiated, risk-based portfolio approach.

This involves two practical steps:

Classify Algorithmic Systems: Organizations must first assess and classify their algorithmic management systems based on their potential for harm. For example, an algorithm that optimizes delivery routes or schedules warehouse shifts poses a different level of risk than an algorithm used for automated performance reviews, disciplinary actions, or hiring and firing decisions.

Tailor Governance Intensity: The intensity of governance should be proportional to the risk level. For a low-risk system (e.g., route planning), governance could be lighter, focusing on principles of efficiency and transparency, regular monitoring, and feedback channels (aligning with A1 and A4). In contrast, a high-risk system (e.g., automated firing) would trigger a far more stringent governance regime. This would include mandatory human-in-the-loop oversight for final decisions, regular bias and fairness audits, full transparency regarding the logic used, and the establishment of clear, accessible appeal processes for affected workers (incorporating the robust elements of A2).

To illustrate, consider a logistics company. An algorithm assigning delivery routes would be 'low-risk'. A system that monitors driver behavior (e.g., speed, braking) for performance ratings would be 'medium-risk' and require more oversight. An algorithm with the autonomy to deactivate a driver's account based on performance metrics would be 'high-risk', demanding the strictest level of scrutiny and human control. This tiered approach allows organizations to innovate responsibly without stifling low-risk applications with excessive bureaucracy, while ensuring that the most impactful decisions are subject to rigorous oversight. This directly addresses the need for governance to adapt to different application areas.

6 Conclusion, Limitations and Future Research

This study makes a substantial contribution to the burgeoning field of algorithmic management by providing a novel, empirically-grounded framework for evaluating and comparing different governance approaches. The rigorous application of MCDA, coupled with comprehensive statistical testing and sensitivity analysis, provides strong evidence supporting the preference for a hybrid, risk-based approach to governing algorithmic management systems within organizations. This approach demonstrably balances the strengths of proactive, principle-based guidelines with the reactive, enforcement-oriented nature of rule-based systems.

The findings underscore the critical need for organizations and policymakers to move beyond simplistic, one-size-fits-all solutions and embrace a more nuanced, context-sensitive approach to governing these powerful technologies. The risk-based approach, with its emphasis on identifying, assessing, and mitigating specific harms associated with particular algorithmic implementations, offers a practical and adaptable pathway for navigating the complex ethical, legal, and operational challenges of algorithmic management.

The study’s emphasis on stakeholder acceptability and adaptability also highlights the importance of inclusive and forward-looking governance strategies. This research offers actionable insights for organizations seeking to implement algorithmic systems responsibly, ethically, and effectively, and for policymakers aiming to craft regulatory frameworks that foster innovation while safeguarding fundamental rights and values. By providing a clear, evidence-based comparison of alternative governance strategies, this study significantly advances the discourse on algorithmic management and contributes to the development of more effective and equitable socio-technical systems.

While this study provides valuable insights and a robust methodological framework, certain limitations should be acknowledged, offering opportunities for future research. The generalizability of the findings could be further enhanced by expanding the sample size and broadening the range of stakeholders involved, most critically by incorporating the direct perspectives of workers who are subject to algorithmic management daily. Their lived experience represents a crucial viewpoint that is underrepresented in our expert panel, a key avenue for future research. Although the Weighted Sum Model provides a transparent and interpretable approach, exploring alternative MCDA methods (e.g., AHP, ELECTRE, as discussed by Greco et al. (2016)) could offer complementary perspectives and test the robustness of the findings across different preference elicitation and aggregation techniques.

Furthermore, while the four governance approaches studied represent dominant perspectives in the literature (e.g., Jobin et al., 2019; Mittelstadt et al., 2016), future research could explore novel hybrid approaches or entirely new models. Complementing the study's reliance on stated preferences with experimental designs or field studies examining the actual implementation of governance approaches would also be beneficial. Investigating societal implications beyond the organizational level is a crucial next step. Finally, the dynamic nature of AI necessitates continuous research to keep pace with technological advancements and refine governance strategies, ensuring the responsible development of algorithmic management systems.

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