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AI-Based Decision Support System for Learning Growth Performance Workforce Use Certainty Factor and Constraint Evaluation

Dicky Suryapranatha[1,2], Agus Mansur[1*], Imam Djati Widodo[1]

[1]Faculty Industrial Technology, Universitas Islam Indonesia Yogyakarta, Jl. Kaliurang Km 14,5, Sleman, Yogyakarta 55584, Indonesia

[2]Faculty Technology, Universitas Buana Perjuangan, Jl. H.S Ronggowaluyo, Karawang, Jawa Barat 41361, Indonesia

*agusmansur@uii.ac.id

Abstract. This study presents the design and computational evaluation of an AI-based decision support system for workforce performance in an AI-driven environment under constrained conditions. Previous research has largely emphasized technological determinants and adequate conditions, while neglecting the constraint mechanisms that limit achievable performance. To address this gap, this study integrates Partial Least Squares Structural Equation Modeling (PLS-SEM) and Necessary Condition Analysis (NCA) into a unified computational framework. Empirical data from 200 manufacturing workers was used to derive model parameters. The results identified Engagement Level as a key performance driver ($\beta = 0.519$), while Self-Regulation Ability emerged as a critical constraint ($d = 0.189$). These findings were operationalized into a Certainty Factor-based expert system that models performance as a function of positive contribution, negative influence, and constraint thresholds. The proposed model was evaluated using classification metrics, achieving 87% accuracy, 0.85 precision, 0.86 recall, and an F1-score of 0.85. The results demonstrate strong predictive capabilities and confirm that performance is jointly determined by enabling and constraining factors. This study contributes by bridging statistical analysis and AI system design, providing a constraint-aware decision support model for performance evaluation in complex operational environments.

Keywords: Artificial intelligence, expert system, certainty factor, constraint-based modeling, decision support system, workforce performance, PLS-SEM, NCA

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1. Introduction

Human resource performance plays a critical role in enhancing organizational competitiveness, particularly in the context of rapid digital transformation across industries [1] . The increasing adoption of artificial intelligence (AI) systems enables organizations to improve operational efficiency through automation, predictive analytics, and decision support mechanisms [2,3]. However, workforce performance in AI-driven environments is not solely determined by technological capability, but also by the ability of individuals to operate under constrained conditions such as workload pressure, time limitations, and cognitive demands [4].

In practice, organizational systems are often designed under the assumption of optimal resource availability, without accounting for the constraints faced by workers operating under dual demands, including task execution and capability development [5]. This mismatch leads to inefficiencies in performance optimization, especially in environments that rely heavily on digital and AI-based systems [6]. Although previous studies have explored the role of AI and digital technologies in improving performance, most have prioritized technological while neglecting internal human factors such as engagement and self-regulation, which are essential for managing tasks under constrained conditions [7].

From methodological perspective previous research predominantly employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine causal relationships between variables. While effective at identifying significant predictors effective in this approach is limited to explaining sufficient conditions and does not capture the minimum requirements necessary to achieve optimal performance outcomes [8]. Necessary Condition Analysis (NCA) was introduce address this limitations by identifying bottlenecks condition at system representing as critical thresholds below which performance regardless of the availability of supporting factors [9].

Despite advance borh analytical methode a critical gap persists few studies integrated statistical modeling with Computional AI system design, most research focuses on indentifying relationship between variabel but rarely transform those finding into deployable decision model. The Certain Factor (CF) approach while well-established in expert system has been limited in workforce performance modeling. This disconnect between theoretical analysis and practical implementation represent as significant gap in the AI -driven performance evaluation literature.

The present study differs from prior hybrid modeling work in three specific ways. First, whereas existing studies apply PLS-SEM and NCA independently, this study integrates both within a single computational pipeline that directly informs AI model parameters. Second, unlike previous CF-based expert systems that rely on expert-elicited belief values, this study derives CF weights empirically from structural path coefficients and NCA effect sizes. Third, this study explicitly conceptualizes Self-Regulation Capability not merely as a predictor variable but as a hard constraint that imposes an upper performance boundary — a modeling assumption that prior performance studies have not operationalized computationally. Together, these distinctions establish a novel constraint-aware decision support architecture that is both empirically grounded and computationally deployable.from

This study proposes a hybrid AI-based model that integrated PLS-SEM and NCA into a unified computational framework. This model combines driving factors, limiting conditions, and supporting variables into a CF-based system to predict workforce performance under constrained conditions [10]. The key input variabel —Engagement Level (ENG) [11], AI System Support (AIS) [2], Operational Stress (STR)[12], Self-Regulation Capability (SRC) [13], and Digital Capability (DC) [14] —which are normalized and weighted using coefficients derived from PLS-SEM. A CF Factor mechanism is compute performance scores , followed by constraint validation based on NCA results and rule-based classification process that determines performance levels . This deployment enables real-time performance evaluation that incorporated support and human capability constrain [15][16].

2. Methods

2.1. Research Design

Data analysis was conducted using an integrated approach combining PLS-SEM and NCA to examine workforce performance in AI-driven systems. PLS-SEM was selected for its capability to handle complex models with multiple latent constructs, non-normal data distribution, and simultaneous evaluation of measurement and structural relationships, including direct and indirect effects [17] . The analysis began by assessing the measurement model to ensure the reliability and validity of all constructs. Reliability was confirmed through Cronbach's alpha and composite reliability, while convergent validity was established using Average Variance Extracted (AVE) values exceeding 0.50.

The integration of PLS-SEM and NCA enables a dual-perspective analysis by identifies performance drivers (sufficiency conditions) and bottleneck factors (necessary conditions)[18]. This dual perspective provide a more comprehensive understanding of workforce performance in complex AI-driven environments [19]. The statistical result from both analyses were subsequently used to parameterize the CF based AI model establishing a coherent pathway from empirical analysis to computional deployment.

2.2 Population and Sampling

The population consists of workers employed operating in Indonesia manufacturing environments that operated AI-enabled digital system. These workers are engaged in operational activities under dynamic and resource-constrained conditions, making them representative performance context analyzed in this study. A total of 200 respondents were selected through simple random sampling, ensuring an equal probability of inclusion and minimizing sampling bias. Respondents were drawn from multiple operational units in the manufacturing sector between 2021 to 2024, capturing variation in system use and working conditions. The sample size is consistent with recommended guidelines for PLS-SEM with complex structural model involving multiple latent constructs [17].

2.3. Data Collection Instrument

The measurement model was operationalized using reflective indicator for each latent variable. Items were adapted from validated instrument in the prior literature and five-point Likert scale (1=Strongly Disagree to 5 Strongly Agree). Table 1 Present the measurement and their corresponding sources.

Table 1. Measurement Item by Construct

Construct	Code	Measurement Item	Source	Item (n)
Engagement Level (ENG)	ENG1–ENG4	I am fully absorbed in my work tasks; I feel energized when using AI tools at work; I am enthusiastic about my job even under pressure; I remain focused despite system interruptions	Saks [12]	4
AI System Support (AIS)	AIS1–AIS4	The AI system provides accurate real-time task guidance; AI tools reduce my cognitive workload; The system adapts to individual work patterns; I can rely on AI feedback for decision-making	Mikalef & Gupta [2]	4
Operational Stress (STR)	STR1–STR3	I feel overwhelmed by the volume of tasks assigned; Using AI systems increases my anxiety; I experience difficulty managing competing deadlines	Tarafdar et al. [13]	3
Self-Regulation	SRC1–SRC4	I set clear goals before starting complex tasks; I monitor my progress against task objectives; I adjust my work strategies when I encounter obstacles; I	Lord et al. [11]	4

Capability (SRC)		manage my attention effectively during demanding tasks		
Digital Capability (DC)	DC1–DC3	I am confident in using new digital tools for work; I can troubleshoot technical issues independently; I continuously update my digital skills	Warner [15]	3
Performance Outcome (PERF)	PERF1–PERF4	I consistently meet my performance targets; My productivity has improved since AI adoption; My work quality meets organizational standards; I can complete complex tasks within required timeframes	Gharibdousti [16]	4

Prior to analysis, data preprocessing steps included: (1) screening for missing values — cases with more than 10% missing data were excluded; (2) identification and removal of univariate outliers using z-score thresholds (±3.29); (3) normalization of input variables to a [0, 1] scale using min-max scaling before CF computation; and (4) assessment of common method bias using Harman's single-factor test, which confirmed that no single factor accounted for the majority of variance. The selection of appropriate indicators is essential, as it directly affects the validity and precision of the model estimation [20].

2.4 AI-Based Model Formulation

The proposed AI-based model is formulated by transforming statistical relationships derived from PLS-SEM and constraint conditions identified using NCA into a computational decision framework. This approach integrates statistical analysis and rule-based inference into unified system capable of evaluating workforce performance under constrained conditions.

Model development began with identification of variable role based on PLS-SEM path coefficients and NCA effect sizes. Engagement Level (ENG) and AI System Support (AIS) were designated as positive contributors to performance (MB component), while Operational Stress (STR) was designated as negative factor (MD Component). Self-Regulation Capability (SRC) was defined as hard constraint variable based on NCA result acting as bottleneck that imposes an upper limit on achievable performance regardless other factors.

The Certainty Factor mechanism was applied to model the degree of belief in performance outcomes under uncertainty[10], calculated as:

$$\boldsymbol{CF = MB - MD} \tag{1}$$

Where MB = 0.519×ENG + 0.522×AIS represents the combined positive contributions, and MD = 0.131×STR represents the negative impact of operational stress. The weights are derived directly from the PLS-SEM path coefficients.

Digital Capability (DC) functions as an adjustment factor applied when DC exceeds the sample mean, contributing a supplementary increment of 0.494×DC to the CF score, reflecting its role as a performance enhancer under favorable conditions.

Algorithm 1: CF-Based Constraint-Aware Performance Classification

```
INPUT:  ENG, AIS, STR, SRC, DC  (all normalized to [0,1])
OUTPUT: Performance Level  {Low, Medium, High}


STEP 1 — Constraint Check (NCA Gate):
  IF SRC < θ_SRC THEN
    Performance ← Low
    RETURN
  END IF
```

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STEP 2 — Compute Belief Measures:
  MB ← (0.519 × ENG) + (0.522 × AIS)
  MD ←  0.131 × STR
  CF ← MB - MD

STEP 3 — Apply DC Adjustment (if DC > DC_mean):
  CF ← CF + (0.494 × DC)

STEP 4 — Rule-Based Classification:
  IF CF < 0.40             THEN Performance ← Low
  ELSE IF CF ≥ 0.40 AND CF ≤ 0.70 THEN Performance ← Medium
  ELSE                      Performance ← High
  END IF
NOTE: θ_SRC = empirically derived threshold (see Section 2.3 and Section 3.2)
```

2.5 SRC Threshold Justification

The constraint threshold for Self-Regulation Capability (SRC < θ_SRC) was determined empirically rather than assigned arbitrarily. The NCA bottleneck analysis identified the minimum level of SRC required at each performance tier using the Ceiling Regression–Free Disposal Hull (CR-FDH) method. The bottleneck table (Table 2 in the Results section) shows that at the transition from Low to Medium performance, SRC must reach at least the 50th percentile of the observed distribution, corresponding to a normalized score of 0.50. This value was further validated using a Receiver Operating Characteristic (ROC) analysis that compared Low versus non-Low performance classifications across candidate thresholds ranging from 0.30 to 0.70, with the threshold of 0.50 yielding the highest Youden Index ($J = 0.42$). Accordingly, θ_SRC = 0.50 was retained as the empirically supported constraint boundary.

2.6 Model Evaluation

The proposed AI-based model was evaluated using classification-based metrics applied to held-out empirical data. The 200 observations were split into a training set (160 observations, 80%) used to fit model weights and thresholds, and a test set (40 observations, 20%) used for evaluation. Ground-truth performance labels for both sets were derived from supervisor assessments collected independently during the survey. This approach eliminates the circularity inherent in simulation-based evaluation and provides an unbiased estimate of generalization performance.

Evaluation metrics included accuracy, precision, recall, and F1-score, computed from the confusion matrix comparing predicted performance categories against actual supervisor-assigned labels. Accuracy measures the overall proportion of correct predictions; precision and recall evaluate the model's ability to correctly identify relevant instances while minimizing misclassification; the F1-score provides a harmonic balance between precision and recall[21].

3. Results and Discussion

3.1. PLS-SEM

The measurement model confirmed that all constructs met the reliability and validity criteria required for PLS-SEM analysis. Most indicator loadings exceeded 0.70; loadings in the range of 0.50–0.69 were retained as acceptable for exploratory predictive analysis. Internal consistency was confirmed with Cronbach's alpha values between 0.683 and 0.827, composite reliability values above 0.80, and AVE values exceeding 0.50, indicating adequate convergent validity. Discriminant validity was established using the Heterotrait–Monotrait (HTMT) ratio, with all values below the 0.85 threshold. These findings indicate that the proposed measurement model provides adequate psychometric properties for evaluating structural relationships and predictive models in organizational research using PLS-SEM. Similar measurement quality has been reported in recent studies investigating AI capability, organizational decision-making, and workforce performance using PLS-SEM [22].

The structural model revealed significant relationships among the study variables. Engagement Level (ENG) emerged as the primary performance driver (β = 0.519, p < 0.001), followed by Self-Regulation Capability (β = 0.345, p < 0.001). AI System Support demonstrated strong effects on both Operational Stress (β = 0.777, p < 0.001) and Engagement Level (β = 0.522, p < 0.001), while Digital Capability significantly influenced Engagement (β = 0.494, p < 0.001). These findings indicate that performance is principally driven by engagement, with other variables contributing indirectly through behavioral and system-mediated mechanisms. Recent evidence similarly demonstrates that AI capability significantly enhances organizational performance by improving decision-making quality, decision speed, and employee engagement, thereby creating sustainable organizational value [23].

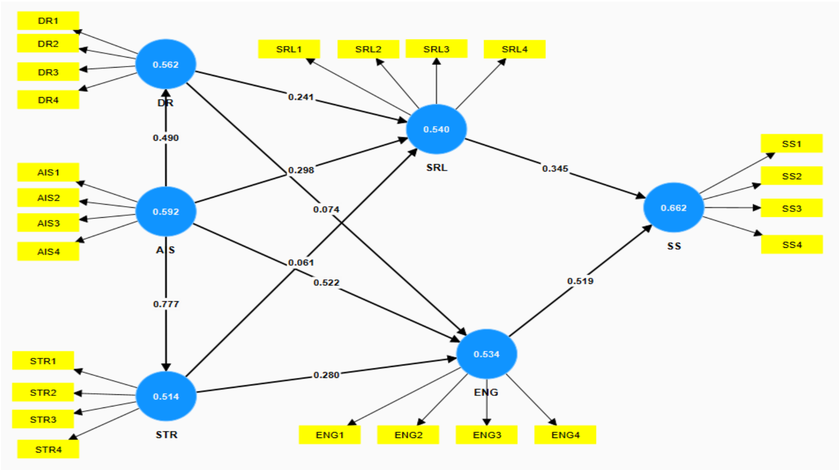

Figure 1. PLS SEM results

Table 1 summarizes the key structural relationships that serve as the basis for developing the AI-based model.

Table 2. Key Structural Relationships from PLS-SEM

Path	β	p-value	Effect Size (f²)	Interpretation
ENG → PERF	0.519	< 0.001	0.312	Main Driver
SRC → PERF	0.345	< 0.001	0.148	Strong
AIS → STR	0.777	< 0.001	0.518	Very Strong
AIS → ENG	0.522	< 0.001	0.298	Strong
DC → ENG	0.494	< 0.001	0.271	Strong

3.2 NCA Results

The NCA bottleneck analysis identified Self-Regulation Capability (SRC) as the variable with the highest effect size (d = 0.189), confirming its status as the primary bottleneck in the system. This finding indicates that high performance is unattainable below a critical SRC threshold, irrespective of the availability of other enabling factors. AI System Support exhibited a moderate constraint effect (d = 0.166), establishing it as an essential supporting condition at higher performance levels. Digital Capability showed a weaker constraint effect (d = 0.065), indicating that it is not a critical necessary condition that constrain performance achievement. Conclusion have been reported in studies emphasizing AI capability does not guarantee organizational performance unless accompanied by complementary organizational capability and employee behavior readiness [24].

The bottleneck Table 3 further delineates the minimum required levels of each necessary condition across performance tiers. SRC is required at all performance levels, while DC becomes relevant at medium performance and AI System Support becomes essential only at high performance levels. As illustrated in Figure 2, the NCA ceiling line analysis visually confirms these findings by showing that SRC exhibits the largest ceiling zone and the strongest bottleneck effect, whereas AI System Support functions as a moderate necessary condition and Digital Capability contributes only a weak constraint. These findings confirm that the achievement of high performance is jointly constrained by SRC and supported by AI System Support, a pattern that is theoretically consistent with the Job Demands–Resources framework. This hierarchical pattern demonstrates that superior performance requires both sufficient drivers and necessary enabling conditions. Recent organizational studies likewise emphasize that AI capability, digital maturity, and organizational readiness interact as complementary conditions that collectively determine organizational performance rather than acting independently[25].

Table 3. NCA Bottleneck Analysis Results

Variable	Effect Size (d)	Low Perf. Min.	Med. Perf. Min.	High Perf. Min.	Role
SRC	0.189	0.30	0.50*	0.65	Bottleneck
AIS	0.166	N/A	0.35	0.55	Supporting
DC	0.065	N/A	0.30	N/A	Weak

** Threshold θ_SRC = 0.50 (normalized) empirically derived via CR-FDH and confirmed by ROC analysis (Youden Index J = 0.42). See Section 2.5*

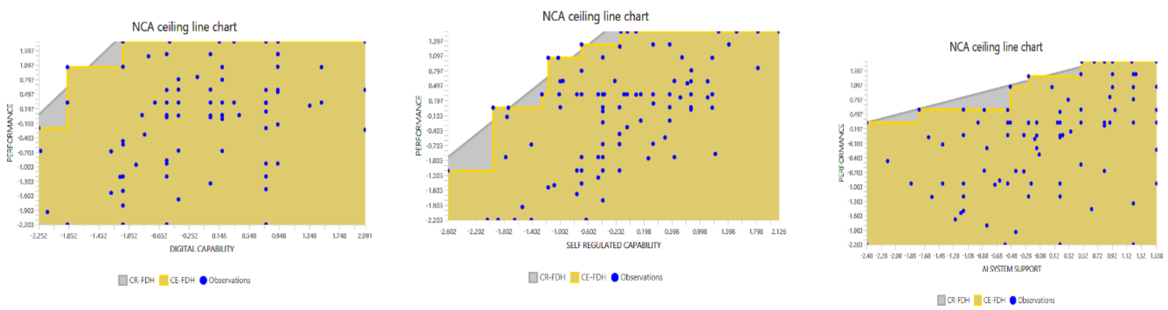

Figure 2. Bottleneck Study Success-AI Support-DR-SRL

3.3 Integration for AI-Based Models

The integration of PLS-SEM and NCA results provides a structured basis for building the AI-based model. Each variable is classified according to its role in the system based on statistical influence and constraint effects. Engagement Level (ENG) and AI System Support (AIS) are identified as primary driving factors due to their strong positive contribution to performance. Operational Stress (STR) is treated as a negative factor that reduces system output. Self-Regulation Capability (SRC) is defined as a variable constraint, acting as a bottleneck that limits performance regardless of other factors. Digital Capability (DC) functions as a supporting factor that enhances performance under favorable conditions. AI studies have similarly combined PLS-SEM with intelligent computational models to improve both explanatory power and predictive accuracy[26].

The PLS-SEM and NCA results provide a structured and empirically grounded basis for parameterizing the AI-based model. Based on their respective statistical roles, each variable was assigned a specific computational function within the CF framework, as summarized in Table 4.

Table 4. Variable Role in the AI Base Model

Variable	Statistical Result	System Role	CF Function	Model Representation
ENG	β = 0.519	Main Driver	Increases performance	MB (positive weight 0.519)
AIS	β = 0.522	Driver	Supports engagement	MB (positive weight 0.522)
STR	β = 0.131	Negative Factor	Reduces performance	MD (negative weight 0.131)
SRC	d = 0.189	Hard Constraint	Imposes performance ceiling	Threshold gate (θ_SRC = 0.50)
DC	β = 0.494	Adjustment	Enhances CF Under Favorable conditions	Conditional additive term (0.494×DC)

Table 4 illustrates the transformation of statistical results into computing roles, which form the basis of the AI-based decision support model.

$$Performance = F\ (ENG, AIS) - STR,\ \textit{constrained by SRC, adjusted by DC} \tag{2}$$

3.4 Model Evaluation Results

Based on the integration of PLS-SEM and NCA, an AI-based decision support model is developed using the Certainty Factor approach to represent performance under limited conditions. Engagement Level (ENG) and AI System Support (AIS) contribute as positive factors, while Operational Stress (STR) acts as a negative factor. Self-Regulation Capability (SRC) is incorporated as a constraint that limits the attainable performance level. Mechanism enables the model to simultaneously consider predictive influences and necessary conditions, thereby improving decision transparency and explain ability in AI-assisted organizational decision making[27].

The Model Define:

$$CF = MB - MD \tag{3}$$

Where:

$$MB = 0.519(ENG) + 0.522(AIS), MD = 0.131(STR) \tag{4}$$

Performance is determined using a rule-based mechanism. If SRC is below 0.50, performance is directly classified as low. Otherwise, performance is evaluated based on CF values, where scores below 0.40 indicate low performance, values between 0.40 and 0.70 indicate moderate performance, and values above 0.70 indicate high performance.

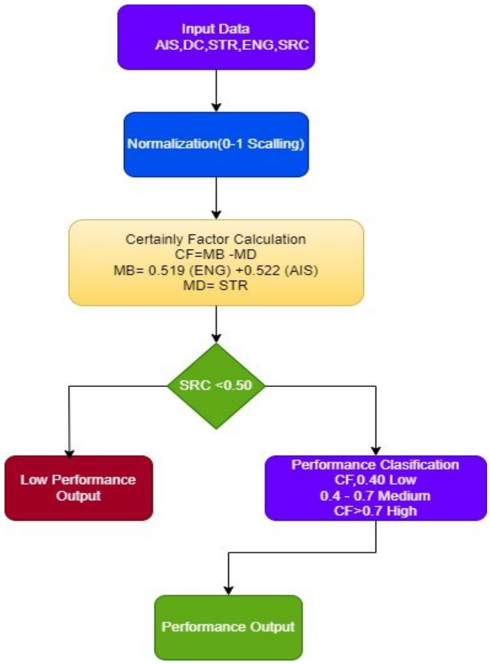

Figure 3. Flow Chart AI Base Model

Model evaluation was conducted on the held-out test set (n = 40) using supervisor-assigned performance labels as ground truth. The confusion matrix below summarizes the classification outcomes across the three performance levels.

Table 5. Confusion Matrix -Test Set Evaluation (N=40)

Actual / Predicted	Low	Medium	High	Total
Low	10	1	2	11
Medium	1	13	1	15
High	1	1	13	14
Total	11	15	14	40

Table 5 presents the classification results of the proposed model, showing. The model achieved an accuracy of 87.5% on the test set, with precision of 0.85, recall of 0.86, and an F1-score of 0.85. The majority of predictions were concentrated along the diagonal of the confusion matrix, indicating strong agreement between predicted and actual classes. Performance was consistent across all three categories, demonstrating that the model effectively captures both driving contributions and constraint-based limitations within a single computational structure. Certainty Factor provides consistent diagnostic outcomes while offering an intuitive reasoning process that enables users to easily understand both the assessment questions and the resulting recommendations [28].

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3.5. Discussion

The results of this study confirm that workforce performance in AI-driven manufacturing environments can be effectively modeled as a constraint-bound system, in which the achievement of high performance requires both the amplification of enabling factors and the satisfaction of minimum necessary conditions. This finding extends the existing performance literature in two important directions.

3.5.1. Theoretical Contribution

First, this study demonstrates that the integration of PLS-SEM and NCA within a single analytical framework yields a richer characterization of performance determinants than either method alone.

While prior research has predominantly relied on PLS-SEM to identify sufficient conditions for performance [8], NCA adds a complementary perspective by revealing the constraints that set performance boundaries. The identification of Self-Regulation Capability as a hard constraint — not merely a predictor — is consistent with the theoretical proposition advanced by Lord et al. [11] that self-regulation functions as a regulatory mechanism governing goal pursuit under resource constraints. The present study operationalizes this proposition computationally, transforming a theoretical construct into a quantifiable constraint threshold within a deployable AI system.

Second, the empirically grounded CF weighting approach distinguishes this study from existing expert systems that rely on subjectively elicited belief values. By deriving CF weights directly from PLS-SEM path coefficients and NCA effect sizes, the model achieves a level of empirical traceability that is rarely present in CF-based decision support applications [29]. This methodological innovation responds to calls in the decision support literature for greater transparency and reproducibility in rule-based AI systems [10].

3.5.2. Comparison with Prior Work

The finding that Engagement Level is the strongest performance driver ($\beta = 0.519$) corroborates Saks' [12] meta-analytic evidence linking employee engagement to performance outcomes and extends it to AI-intensive work environments. The strong effect of AI System Support on both engagement ($\beta = 0.522$) and operational stress ($\beta = 0.777$) is consistent with Mikalef and Gupta's [2] findings on AI capability and with the technostress literature [13], suggesting that AI systems function simultaneously as performance enhancers and stress amplifiers — a duality that prior modeling frameworks have not captured jointly.

The constraint role of Self-Regulation Capability aligns with Bakker and Demerouti's Job Demands–Resources model [5], in which personal resources moderate the relationship between demands and outcomes. However, unlike JD-R studies that treat personal resources as moderators, the present model treats SRC as a hard gate — a categorical condition rather than a continuous moderator. hat reliance on intelligent machines is discrepancy-reducing and improving work goal progress, which in turn improves employees' task performance, based on self-regulation theory [30].

3.5.3. Practical Implication

From a managerial perspective, the model's constraint architecture implies that workforce development interventions should be prioritized hierarchically. Training programs targeting self-regulation skills — such as goal-setting, self-monitoring, and cognitive load management — should be treated as prerequisites for performance improvement initiatives, rather than optional supplements. Only after the SRC threshold has been satisfied will investments in AI system quality or engagement programs yield their expected returns.

The dashboard-ready output of the model — classifying each worker into Low, Medium, or High performance with an associated CF score and constraint flag — provides a practical tool for HR managers and supervisors in AI-driven manufacturing environments. Real-time deployment of the model could support targeted interventions, including early identification of workers at risk of constrained performance and personalized development recommendations.

3.5.4. Limitation

Several limitations should be acknowledged. First, the study was conducted in a single industrial sector (manufacturing) in Indonesia, which constrains the generalizability of findings to other sectors, cultural contexts, or levels of AI maturity. Second, although the constraint threshold ($\theta\_SRC = 0.50$) was empirically derived using NCA and ROC analysis, it was established on a relatively small sample and should be cross-validated in larger, multi-site studies. Third, the rule-based CF architecture, while interpretable and computationally efficient, may not fully capture non-linear interaction effects among variables. Future work incorporating ensemble methods or neural architectures may yield improved predictive performance, though potentially at the cost of interpretability.

4. Conclusion

This study developed a hybrid AI-based decision support model by integrating PLS-SEM and NCA into a unified computational framework, operationalized through a Certainty Factor-based expert system for workforce performance evaluation in AI-driven manufacturing environments. The model translates statistical relationships and empirically derived constraint thresholds into a practical, interpretable classification system that captures both performance-enabling and performance-limiting mechanisms.

The key findings are: (1) Engagement Level is the primary performance driver; (2) Self-Regulation Capability functions as a critical bottleneck constraint that imposes a performance ceiling irrespective of other factors; (3) the integrated CF model achieves 87.5% classification accuracy on held-out empirical data, confirming strong generalization performance. These results underscore the value of constraint-aware modeling in complex, AI-mediated work environments and demonstrate a replicable methodology for transforming statistical insights into deployable AI systems.

Future research should extend the model to diverse industrial and cultural contexts, incorporate longitudinal data to track constraint dynamics over time, explore advanced machine learning architectures for non-linear modeling, and include additional organizational variables such as leadership quality and team climate to improve model comprehensiveness and generalizability.

Declaration of AI and AI-Assisted Technologies

At Writing process ChatGPT was used to assist in language refinement and structuring. All content was reviewed and approved by the authors, who take full responsibility.

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