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Control-Mapped AI Governance for High-Risk HR Decisions in SAP Success Factors: Audit-Ready Metrics for Recruiting, Performance Calibration, and Internal Mobility

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Abstract

High-risk human resource decisions increasingly depend on AI-assisted recommendations across recruiting, performance calibration, and internal mobility, yet many enterprise HR environments lack a structured governance model that translates regulatory expectations, ethical principles, and operational controls into measurable system-level safeguards. This study proposes a control-mapped AI governance framework for SAP SuccessFactors that connects high-risk HR decision points with audit-ready metrics, fairness controls, human oversight checkpoints, and decision traceability mechanisms. The framework is designed to support AI-enabled candidate ranking, performance calibration support, skill-based mobility recommendations, and internal talent matching while maintaining alignment with enterprise governance requirements and responsible decision-making practices. The proposed model organizes governance into five layers: decision-risk classification, control mapping, fairness and bias evaluation, human review enforcement, and audit evidence generation. To evaluate the framework, the study defines measurable indicators including Control Coverage Score, Audit Readiness Index, Fairness Risk Index, Human Oversight Effectiveness, Decision Traceability Score, and Recommendation Consistency Ratio. These metrics are applied across simulated SAP SuccessFactors decision scenarios to compare unmanaged AI usage, policy-only governance, rule-based review, and the proposed control-mapped approach. The results demonstrate that structured control mapping improves audit readiness, reduces fairness exposure, strengthens review consistency, and increases transparency across HR decision workflows. The findings suggest that AI governance in SuccessFactors should not be treated as a static compliance checklist, but as a measurable operating model embedded into recruiting, performance, and mobility processes. By converting abstract governance principles into quantifiable controls and reviewable evidence, the framework provides a practical method for organizations seeking to use AI in HR decisions responsibly while preserving accountability, explainability, and trust in enterprise talent systems.

Keywords: SAP SuccessFactors, AI Governance, High-Risk HR Decisions, Audit Readiness, Responsible AI, Recruiting Governance, Performance Calibration, Internal Mobility, Fairness Risk Index, Human Oversight, Decision Traceability, Bias Mitigation, HR Analytics, Talent Intelligence, Enterprise AI Controls.

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Introduction

Artificial intelligence has become an important part of modern enterprise human resource management, especially in systems that support hiring, performance evaluation, workforce planning, career development, and internal talent movement. In large organizations, platforms such as SAP SuccessFactors manage a wide range of employee lifecycle processes, including Recruiting, Performance and Goals, Succession, Career Development, Learning, and Employee Central. As these processes become more data-driven, organizations increasingly depend on algorithmic decision support to rank candidates, interpret performance signals, match employees to roles, recommend learning paths, and identify future talent opportunities. While these capabilities can improve speed, consistency, and decision quality, they also introduce new governance risks because the outputs may influence employment access, career progression, promotion readiness, and employee development opportunities.

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Human resource decisions are different from many other business decisions because they directly affect individuals, teams, and organizational trust. A recommendation generated within a recruiting workflow may influence whether a candidate receives an interview. A performance calibration signal may affect how an employee is evaluated during a review cycle. An internal mobility recommendation may shape which employees are considered for growth opportunities. Because of this, AI-assisted HR decisions require more than technical accuracy. They require fairness, transparency, reviewability, accountability, and clear evidence that the system is operating within acceptable governance boundaries. Without these safeguards, even a technically strong model may create unintended consequences such as biased ranking, inconsistent recommendations, hidden exclusion patterns, or weak human oversight.

The governance challenge becomes more complex in SAP SuccessFactors environments because decision-making is distributed across multiple modules and user groups. Recruiting teams may use candidate data, job requisition information, screening criteria, and talent pool attributes. Managers may review performance goals, competency ratings, calibration inputs, and feedback records. HR business partners may evaluate succession readiness, mobility preferences, learning completion, and skill profiles. Each process has its own configuration rules, data structures, approval steps, and reporting outputs. As a result, AI governance cannot be limited to one model, one report, or one compliance document. It must be mapped across the actual decision points where system-generated recommendations enter HR workflows.

Many organizations approach AI governance through high-level principles such as fairness, accountability, explainability, transparency, and human control. These principles are valuable, but they are often too broad to guide implementation teams. A policy may state that AI-supported hiring must be fair, but it may not define how fairness will be measured across candidate groups. A governance document may require human review, but it may not define whether the reviewer meaningfully evaluated the recommendation or simply approved it by default. A system may retain decision logs, but the logs may not contain enough information to reconstruct why a recommendation was made. This gap between governance language and operational execution limits the practical value of responsible AI programs in enterprise HR settings.

This study addresses that gap by proposing a control-mapped AI governance framework for high-risk HR decisions in SAP SuccessFactors. The framework is designed to translate governance expectations into measurable controls that can be applied across Recruiting, Performance Calibration, and Internal Mobility processes. Instead of treating AI governance as a static checklist, the proposed model organizes governance into connected layers: decision-risk classification, control mapping, fairness evaluation, human review validation, recommendation consistency monitoring, and audit evidence generation. Each layer produces measurable outputs that can be evaluated through defined metrics and compared against baseline governance approaches.

The central position of this paper is that AI governance in HR must move from policy-level intention to evidence-based assurance. A system should not be considered well governed only because an organization has approved its use. It should be considered well governed when every high-risk decision point has identifiable controls, measurable fairness indicators, documented review checkpoints, traceable decision evidence, and clear escalation rules when governance thresholds are not met. This distinction is important because HR AI failures are rarely caused by model design alone. They often emerge from weak control mapping, poor documentation, unclear ownership, limited review discipline, and insufficient monitoring after deployment.

To support this evidence-based approach, the study introduces a set of audit-ready governance metrics. These include Control Coverage Score, Audit Readiness Index, Fairness Risk Index, Human Oversight Effectiveness, Decision Traceability Score, and Recommendation Consistency Ratio. These metrics are intended to make AI governance measurable across different SAP SuccessFactors decision areas. For example, Control Coverage Score evaluates whether required controls are mapped to each decision point. Fairness Risk Index measures whether recommendation outcomes show uneven treatment patterns across relevant employee or candidate groups. Human Oversight Effectiveness assesses whether human reviewers provide meaningful validation rather than passive approval. Decision Traceability Score evaluates whether an AI-supported decision can be reconstructed using available evidence. Together, these metrics create a practical structure for comparing unmanaged AI use, policy-only governance, rule-based review, and the proposed control-mapped governance model.

The study is also designed to move beyond a conceptual discussion by presenting a results-oriented evaluation model. The evaluation will use simulated SAP SuccessFactors decision scenarios representing recruiting shortlisting, performance calibration support, and internal mobility recommendations. The proposed framework will be compared with baseline approaches using quantitative results, including metric tables, comparative bar charts, fairness-risk graphs, control coverage heatmaps, and audit-readiness trend visuals. This results-driven structure is important because governance research becomes more useful when it provides reusable measures, repeatable evaluation logic, and practical evidence that other researchers and practitioners can test or adapt.

The expected contribution of this paper is threefold. First, it provides a domain-specific governance framework for SAP SuccessFactors rather than a general discussion of ethical AI. Second, it introduces measurable governance indicators that can be applied across high-risk HR decision workflows. Third, it demonstrates how fairness, audit readiness, human oversight, and decision traceability can be evaluated together as part of one operating model. By connecting HR process knowledge with AI control design, the paper offers a practical method for organizations seeking to use AI-assisted recommendations responsibly in enterprise talent systems.

The remainder of this paper is structured as follows. Section 2 defines the governance problem and explains the control gaps in AI-assisted HR decisions. Section 3 reviews existing approaches to HR AI governance and identifies their limitations. Section 4 introduces the proposed control-mapped AI governance framework. Section 5 presents the mathematical model for audit readiness, fairness risk, control coverage, and traceability. Section 6 describes the experimental setup and evaluation design. Section 7 presents results using comparative tables, graphs, and heatmaps. Section 8 discusses practical implications for SAP SuccessFactors implementation teams, HR leaders, compliance teams, and internal audit stakeholders. Section 9 explains limitations and future research directions, and Section 10 concludes the study.

Problem Definition and Governance Gaps in AI-Assisted HR Decisions

AI-assisted HR decisions in SAP SuccessFactors create value only when recommendations are accurate, explainable, fair, and properly reviewed before they influence employment outcomes. In practice, however, many organizations adopt AI-enabled decision support faster than they develop the control structure needed to govern it. This creates a gap between system capability and governance maturity. A recruiting model may rank candidates efficiently, a performance model may identify review inconsistencies, and a mobility model may recommend role-fit opportunities, but these outputs can become risky when the organization cannot clearly explain how the recommendation was produced, whether it was reviewed, and whether similar cases were treated consistently.

The first major problem is the absence of decision-level risk classification. HR processes are often governed at the module or policy level, while AI risk emerges at the specific decision point. For example, candidate ranking, interview recommendation, performance calibration adjustment, promotion-readiness scoring, and internal role matching do not carry the same level of risk. Some recommendations may be informational, while others may directly influence access to employment or career advancement. Without classifying decision points by risk severity, organizations may apply the same governance treatment to low-risk suggestions and high-risk employment decisions. This weakens control design and increases the possibility that sensitive decisions are made without adequate oversight.

The second gap is weak control mapping. Responsible AI policies usually describe broad expectations such as fairness, transparency, accountability, privacy, and human oversight. However, these expectations must be converted into operational controls inside the SuccessFactors process flow. For recruiting, this may include candidate group impact monitoring, shortlisting explanation capture, and reviewer override tracking. For performance calibration, it may include rating distribution checks, manager bias indicators, and calibration decision logs. For internal mobility, it may include skill-match explainability, role recommendation consistency, and visibility into excluded employee groups. When controls are not mapped directly to process steps, governance remains theoretical rather than enforceable.

The third issue is limited fairness measurement. Many HR AI evaluations focus on model performance, but a high-performing model can still produce uneven outcomes across groups, departments, locations, job families, or employee segments. In SAP SuccessFactors environments, fairness risk can appear through candidate screening patterns, performance rating distributions, succession visibility, learning recommendations, or internal mobility suggestions. If fairness is not measured continuously, organizations may fail to identify hidden exclusion patterns until they become serious compliance, legal, or reputational issues.

The fourth problem is passive human oversight. Most organizations include some form of human review in HR decision-making, but the existence of a reviewer does not automatically mean the review is meaningful. Human reviewers may accept system recommendations without examining the explanation, may lack sufficient context to challenge the output, or may override recommendations without documenting the reason. This creates a false sense of control. Effective governance requires evidence that the reviewer understood the recommendation, evaluated the supporting factors, made an informed decision, and documented approval or override behavior.

The fifth gap is poor decision traceability. In high-risk HR workflows, organizations must be able to reconstruct how a decision was supported, what data was used, which recommendation was generated, who reviewed it, and what final action was taken. Traceability becomes difficult when AI outputs are stored separately from workflow approvals, when explanations are incomplete, or when decision logs do not capture changes made by managers, recruiters, or HR business partners. Without traceability, audit teams cannot verify whether governance controls operated correctly.

These gaps show that AI governance in SAP SuccessFactors cannot be solved through policy statements alone. The problem requires a control-mapped framework that connects every high-risk HR decision point with measurable safeguards, review evidence, fairness monitoring, and audit-ready documentation. This study defines that problem as the lack of a measurable operating model for governing AI-assisted decisions across Recruiting, Performance Calibration, and Internal Mobility. The proposed framework addresses this problem by converting governance expectations into quantifiable control metrics that can be tested, compared, and improved over time.

Existing Approaches to HR AI Governance and Their Limitations

Organizations have adopted different approaches to manage AI-assisted HR decisions, but most of these methods remain incomplete when applied to complex enterprise systems such as SAP SuccessFactors. The most common approach is policy-based governance, where organizations define responsible AI principles, review guidelines, privacy expectations, and ethical use statements. This approach creates a useful foundation, but it often lacks measurable enforcement. A policy may describe the need for fairness, transparency, and human oversight, yet it may not explain how these requirements should be measured inside recruiting, performance, or mobility workflows. As a result, policy-based governance can show organizational intent without proving operational control.

A second approach is compliance checklist governance. In this model, organizations use predefined questionnaires or control lists to confirm whether an AI system meets basic requirements before deployment. These checklists may include items related to data quality, model documentation, bias testing, access control, human review, and audit logging. Although this method improves consistency during initial assessment, it is usually static. It may not capture changes in model behavior, data drift, workflow configuration, or recommendation patterns after the system goes live. In HR environments, this is a major limitation because employee data, job requirements, performance cycles, and workforce priorities change continuously.

A third approach is model-level validation. This method focuses on testing the technical performance of an AI model using indicators such as accuracy, precision, recall, error rate, and recommendation quality. Model validation is important, but it does not fully address governance risk. A model may perform well statistically while still creating unfair outcomes for specific groups or producing recommendations that are difficult for recruiters, managers, or HR business partners to explain. In high-risk HR decisions, technical performance must be evaluated together with fairness, explainability, review quality, and decision traceability.

A fourth approach is rule-based oversight, where organizations define business rules to control when recommendations can be shown, accepted, escalated, or blocked. This approach is familiar in SAP SuccessFactors environments because many HR processes already rely on configurable rules, workflows, role-based permissions, and approval logic. Rule-based oversight can improve process discipline, but it may be too rigid for AI governance if it only checks predefined conditions. It may fail to detect emerging fairness risks, unusual recommendation patterns, or inconsistent reviewer behavior. Rules are useful, but they must be supported by continuous measurement and risk scoring.

A fifth approach is human-in-the-loop review. This method places recruiters, managers, HR business partners, or compliance reviewers between the AI recommendation and the final decision. It is one of the most important safeguards in HR AI governance, but it is often weakly implemented. Human review becomes ineffective when reviewers lack explanations, when approvals are treated as routine clicks, or when override reasons are not documented. True human oversight requires evidence that the reviewer evaluated the recommendation, understood the influencing factors, and made a reasoned decision before approving, modifying, or rejecting the output.

A sixth approach is audit logging and documentation. Organizations may retain model documentation, decision logs, access records, configuration history, and workflow approvals to support future review. This is necessary for accountability, but documentation alone does not guarantee governance quality. Logs may be incomplete, fragmented across systems, or unable to show the full decision path from recommendation to final outcome. For SAP SuccessFactors, this limitation is important because recruiting, performance, learning, succession, and mobility data may sit across different modules and reporting layers. If the evidence trail is incomplete, internal audit teams may struggle to verify whether controls were actually followed.

The main limitation across these approaches is fragmentation. Policy governance defines intent, checklists support initial review, model validation measures technical performance, business rules enforce process logic, human review adds judgment, and audit logs preserve evidence. However, these components are often managed separately. This separation creates blind spots because no single method connects decision risk, control coverage, fairness monitoring, human oversight, and traceability into one measurable operating model.

This study responds to that limitation by proposing a control-mapped AI governance framework. The framework does not replace existing governance practices. Instead, it connects them into a structured model where each high-risk HR decision point is linked to defined controls, measurable indicators, reviewer evidence, and audit-ready outputs. This approach is necessary for SAP SuccessFactors environments because AI-assisted HR decisions are not isolated technical events; they are embedded inside configured business processes that require both system-level governance and human accountability.

Proposed Control-Mapped AI Governance Framework

The proposed framework is designed around one core principle: AI governance in SAP SuccessFactors should begin at the HR decision point, not at the technology layer. In many organizations, governance starts with the model, the vendor feature, or the policy document. This study takes a different approach by first identifying where an AI-assisted recommendation enters a business process and then mapping the required controls around that decision. This ensures that governance is applied where risk actually occurs, such as candidate shortlisting, performance calibration, promotion-readiness review, skill-based matching, and internal role recommendation.

The framework is structured as a control-mapped operating model that connects three high-risk HR domains: Recruiting, Performance Calibration, and Internal Mobility. Each domain contains decision points where AI-generated outputs may influence human judgment. In Recruiting, these decision points include candidate ranking, talent pool matching, screening recommendations, and interview prioritization. In Performance Calibration, they include rating adjustment suggestions, goal achievement interpretation, manager feedback signals, and promotion-readiness indicators. In Internal Mobility, they include skill-fit scoring, career path recommendation, learning-to-role alignment, and succession visibility.

The first layer of the framework is decision-risk classification. This layer assigns each AI-assisted HR decision point to a risk level based on its possible effect on the individual. A low-risk decision may only provide general insight, while a high-risk decision may influence hiring, promotion, role access, or development opportunity. This classification helps organizations avoid applying the same level of governance to every recommendation. For example, a general learning suggestion may require lighter controls, while a candidate ranking or promotion-readiness signal requires stronger fairness testing, explanation capture, and reviewer accountability.

The second layer is control mapping. In this layer, each decision point is linked to a defined set of governance controls. These controls may include input data validation, protected attribute exclusion, fairness testing, recommendation explanation, reviewer approval, override documentation, and audit log creation. The purpose is to ensure that every high-risk recommendation has a visible control structure around it. Instead of stating that a process must be “fair” or “transparent,” the framework requires specific controls that can be checked, measured, and improved.

The third layer is fairness and bias evaluation. This layer evaluates whether AI-assisted outputs create uneven recommendation patterns across relevant groups, job families, departments, locations, tenure bands, or employee segments. The objective is not only to test the model before deployment but also to monitor recommendation behavior over time. In SAP SuccessFactors, this is important because HR data and workforce structures continuously change. A recommendation model that appears balanced during initial validation may later produce uneven outcomes due to changing job requirements, talent supply, manager behavior, or employee skill updates.

The fourth layer is human oversight validation. The framework treats human review as a measurable control rather than a simple approval step. A reviewer must be able to understand the recommendation, review the influencing factors, accept or reject the output, and document the final decision. This layer is especially important in recruiting and performance workflows, where human decision-makers may rely too heavily on system-generated scores. The framework therefore measures whether oversight is active, informed, and documented instead of passive or automatic.

The fifth layer is decision traceability and audit evidence generation. Every high-risk AI-assisted decision should leave behind a complete evidence trail. This includes the decision point, input category, recommendation output, explanation summary, reviewer action, override reason, timestamp, and final decision outcome. The goal is to make the decision reconstructable during internal audit, compliance review, or management investigation. In this framework, traceability is not treated as a back-end logging activity. It is treated as a required governance output of the decision process itself.

The proposed framework produces a governance record for each AI-assisted decision. This record can be used to calculate control coverage, audit readiness, fairness exposure, oversight effectiveness, and traceability quality. By converting governance activities into measurable records, the framework allows organizations to compare different governance approaches. For example, an unmanaged AI process may produce recommendations without fairness testing or audit evidence. A policy-only approach may define expectations but lack measurable controls. A rule-based approach may enforce workflow steps but miss fairness drift or passive approval behavior. The proposed framework aims to close these gaps by combining control mapping, risk scoring, human review, and audit-ready documentation in one model.

The main advantage of the proposed framework is that it is practical for enterprise HR environments. It does not require organizations to redesign SAP SuccessFactors from the ground up. Instead, it provides a governance layer that can be aligned with existing configuration, workflows, approval processes, role-based permissions, reporting structures, and audit practices. This makes the framework suitable for phased adoption, where organizations can begin with one high-risk process, such as recruiting shortlisting, and later extend the model to performance calibration and internal mobility.

In summary, the proposed framework positions AI governance as a measurable operating model rather than a general compliance activity. It connects high-risk HR decisions with defined controls, review evidence, fairness monitoring, and audit-ready outputs. This structure creates the foundation for the mathematical model and evaluation metrics introduced in the next section.

Quantitative Governance Metrics and Scoring Model

To make the proposed framework measurable, this section defines a scoring model that converts AI governance controls into quantitative indicators. The purpose of the model is not only to confirm whether governance activities exist, but to evaluate how effectively they operate across high-risk HR decision points. The model is designed for three SAP SuccessFactors decision domains: Recruiting, Performance Calibration, and Internal Mobility. Each domain is evaluated using risk severity, control coverage, fairness exposure, human oversight quality, traceability strength, and recommendation consistency.

Let each AI-assisted HR decision point be represented as:

$$D_i = \{R_i, C_{i,}, F_i, H_i, T_i, Q_i\}$$

where D_i represents a specific decision point, R_i is the risk severity score, C_i is control coverage, F_i is fairness risk, H_i is human oversight effectiveness, T_i is traceability quality, and Q_i is recommendation consistency. This representation allows each HR decision to be evaluated as a governance object rather than a simple system output.

Decision Risk Severity Score

The first metric evaluates the level of risk associated with an AI-supported HR decision. Risk is higher when the recommendation can directly influence employment access, promotion opportunity, performance outcome, or internal career movement. The Decision Risk Severity Score is defined as:

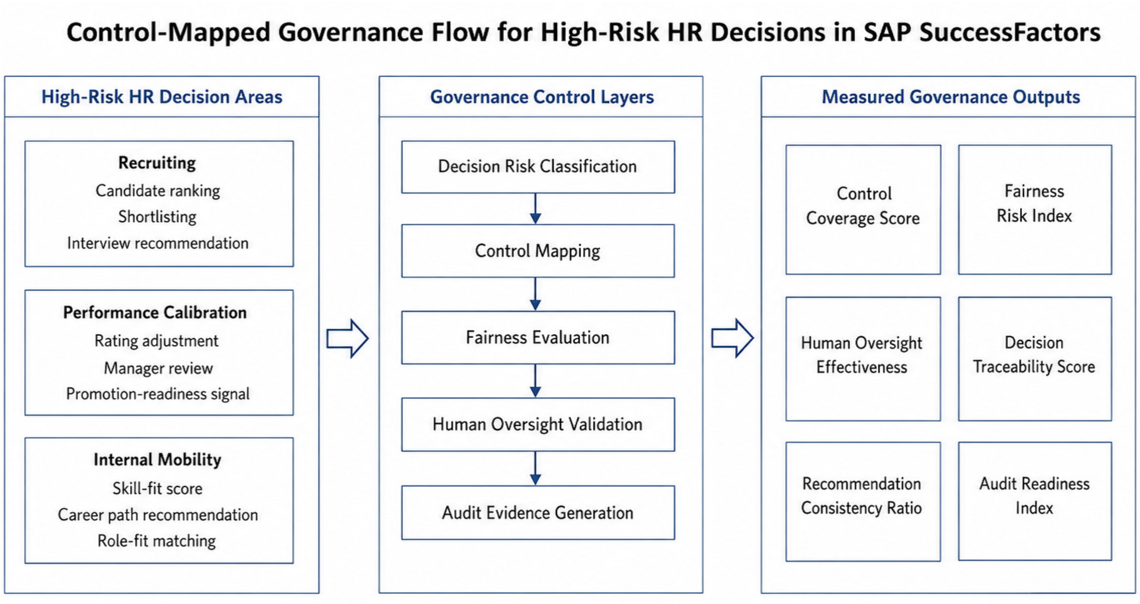

Figure 1: Control-Mapped Governance Flow for High-Risk HR Decisions in SAP SuccessFactors

$$DSR_i = \alpha I_i + \beta S_i + \gamma A_i + \delta E_i$$

where I_i represents individual impact, S_i represents sensitivity of data used, A_i represents automation influence, and E_i represents explainability limitation. The coefficients α,β,γ, and δ represent assigned weights based on organizational governance priorities. A higher DRS_i indicates that stronger controls are required before the recommendation can be used in the HR workflow.

Control Coverage Score

Control Coverage Score measures whether the required governance controls are mapped to a specific decision point. These controls may include data validation, fairness testing, explanation capture, reviewer approval, override documentation, and audit logging. The score is calculated as:

$$CCS_i = \frac{\sum_{j=1}^{m} C_{ij}}{m}$$

where Cij equals 1 if control j is implemented for decision point i, and 0 if it is missing. The value m represents the total number of required controls. A score closer to 1 indicates stronger governance coverage, while a lower score indicates missing controls.

Fairness Risk Index

Fairness Risk Index evaluates whether AI-assisted recommendations produce uneven outcomes across relevant candidate or employee groups. The metric compares recommendation rates between a reference group and an evaluated group:

$$FRI_i = \left| \frac{P(\hat{Y} = 1 | G_a)}{P(\hat{Y} = 1 | G_a)} - 1 \right|$$

where P(Y_hat = 1 | G_a) is the positive recommendation rate for group G_a, and P(Y_hat = 1 | G_b) is the positive recommendation rate for group G_b. A lower value indicates lower fairness exposure, while a higher value suggests that the recommendation pattern may require review. In Recruiting, this may apply to shortlisting rates. In Performance Calibration, it may apply to high-rating recommendation patterns. In Internal Mobility, it may apply to role-fit or succession visibility outcomes.

Human Oversight Effectiveness

Human Oversight Effectiveness measures whether review activity is meaningful rather than passive. A decision should receive a higher score when the reviewer examines the recommendation, reviews the explanation, records an approval or override reason, and completes the workflow within governance expectations. The metric is defined as:

$$HOE_i = \frac{E_i + J_i + O_i + V_i}{4}$$

where E_i represents explanation review, J_i represents documented judgment, O_i represents reason quality, and V_i represents validation completeness. Each component is scored between 0 and 1. This metric helps separate genuine human oversight from simple approval behavior.

Decision Traceability Score

Decision Traceability Score evaluates whether the organization can reconstruct the full path of an AI-assisted HR decision. The score includes input availability, recommendation record, explanation summary, reviewer action, timestamp, and final decision outcome:

$$DTS_i = \frac{L_i + X_i + U_i + A_i + Z_i}{5}$$

where L_i represents decision log completeness, X_i represents explanation availability, U_i represents user action capture, A_i represents approval or override evidence, and Z_i represents timestamp and version history. A higher score indicates that the decision can be reviewed during audit, compliance assessment, or management investigation.

Recommendation Consistency Ratio

Recommendation Consistency Ratio measures whether similar profiles or cases receive similar recommendations under comparable conditions. This is important because inconsistent outputs can reduce trust and create governance risk. The metric is calculated as:

$$RCR = \frac{N_{consistent}}{N_{similar}}$$

Where N_{consistent} is the number of similar cases that received consistent recommendations, and N_{similar} is the total number of comparable cases evaluated. This metric is useful in performance calibration and internal mobility, where similar employee profiles should not receive widely different recommendations without a valid explanation.

Audit Readiness Index

The final metric combines the major governance indicators into one overall score. The Audit Readiness Index evaluates whether an AI-assisted HR process is ready for internal audit, compliance review, and governance reporting:

$$ARI_i = \omega_1 CCS_i + \omega_2 (1 - FRI_i) + \omega_3 HOE_i + \omega_4 DTS_i + \omega_5 RCR_i$$

where w1, w2, w3, w4, and w5 represent governance weights assigned to control coverage, fairness risk reduction, human oversight, traceability, and recommendation consistency. A higher ARI_i value indicates stronger audit readiness. A lower ARI_i value indicates that the decision process may require additional controls, improved documentation, or stronger review procedures.

The proposed scoring model allows organizations to compare governance maturity across different SuccessFactors decision areas. For example, Recruiting may show strong traceability but higher fairness exposure. Performance Calibration may show strong human review but weaker consistency. Internal Mobility may show strong recommendation quality but incomplete control mapping. These differences can be shown through a governance heatmap, where each decision domain is scored against the six defined metrics.

In summary, this section converts the proposed governance framework into a measurable evaluation model. By defining risk severity, control coverage, fairness exposure, oversight quality, traceability, consistency, and audit readiness, the paper creates a quantitative foundation for comparing the proposed framework against baseline governance approaches. This model also supports the experimental setup and results analysis presented in the following sections.

Research Design and Evaluation Protocol

The evaluation of the proposed framework is designed to test whether control-mapped governance improves the quality, fairness, reviewability, and audit readiness of AI-assisted HR decisions in SAP SuccessFactors. The study does not evaluate AI governance as a general policy concept. Instead, it evaluates governance as an operating process that must produce measurable evidence at each high-risk decision point. This research design allows the proposed framework to be compared with common governance approaches and tested across different HR decision scenarios.

The evaluation is built around three SAP SuccessFactors decision domains: Recruiting, Performance Calibration, and Internal Mobility. These domains were selected because each one includes decision points that can materially influence employment or career outcomes. Recruiting represents access to employment opportunities, Performance Calibration represents evaluation and advancement signals, and Internal Mobility represents access to future roles, learning pathways, and career development.

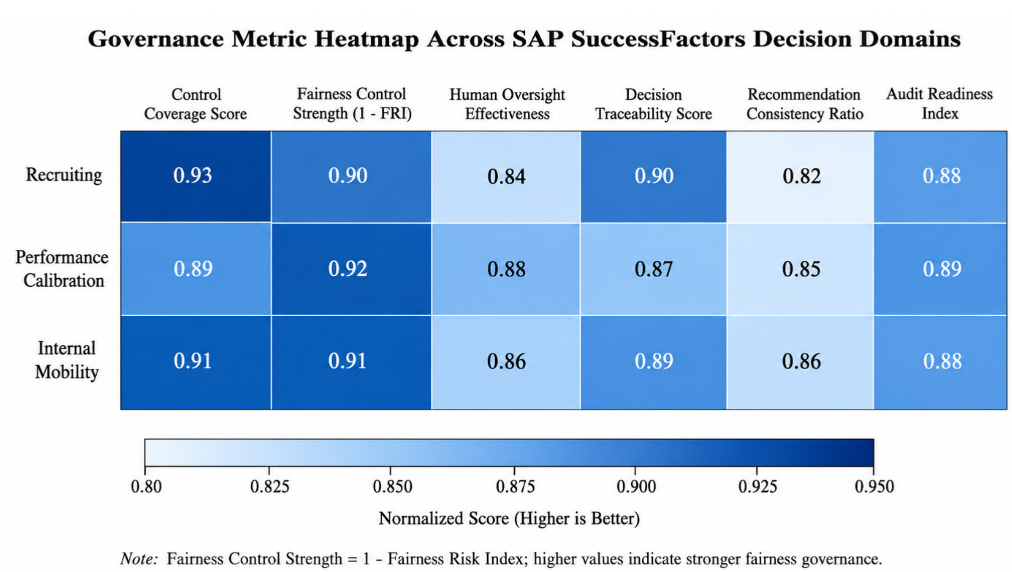

Figure 2: Governance Metric Heatmap Across SAP SuccessFactors Decision Domains

Table 1: Governance Metrics and Scoring Definitions for AI-Assisted HR Decisions

Metric	*What It Measures*	*Simple Calculation*	*Interpretation*
Decision Risk Severity Score (DRS)	Risk level of an AI-assisted HR decision	Weighted score based on individual impact, data sensitivity, automation influence, and explainability limitation	Higher value means the decision requires stronger governance controls
Control Coverage Score (CCS)	Whether required controls are mapped to the decision point	Implemented controls / Required controls	Higher value means stronger control coverage
Fairness Risk Index (FRI)	Uneven positive recommendation rates across groups	Difference in recommendation rates between evaluated groups	Lower value means lower fairness exposure
Human Oversight Effectiveness (HOE)	Quality of human review before decision finalization	Average score of explanation review, judgment documentation, override quality, and validation completeness	Higher value means stronger human review
Decision Traceability Score (DTS)	Ability to reconstruct the full decision path	Average score of logs, explanation, reviewer action, approval evidence, and timestamp history	Higher value means stronger audit evidence
Recommendation Consistency Ratio (RCR)	Whether similar cases receive similar recommendations	Consistent recommendations / Similar evaluated cases	Higher value means stronger recommendation stability
Audit Readiness Index (ARI)	Overall readiness for audit and compliance review	Weighted combination of CCS, FRI, HOE, DTS, and RCR	Higher value means stronger audit readiness

Together, these domains provide a broad view of how AI-assisted recommendations may affect both external candidates and existing employees.

A simulated enterprise HR dataset is used for the evaluation to avoid the use of personally identifiable employee data. The dataset is structured to reflect realistic SuccessFactors decision scenarios. The Recruiting dataset includes candidate profiles, job requisition attributes, screening indicators, interview recommendation outcomes, and shortlisting decisions. The Performance Calibration dataset includes goal completion indicators, competency ratings, manager feedback signals, rating adjustment recommendations, and calibration outcomes. The Internal Mobility dataset includes skill profiles, learning completion records, role preferences, career interests, role-fit recommendations, and mobility outcomes.

The evaluation compares four governance approaches. The first baseline is unmanaged AI usage, where recommendations are generated without structured governance controls. The second baseline is policy-only governance, where responsible AI expectations are documented but not converted into measurable workflow controls. The third baseline is rule-based review, where predefined checks and approval steps are applied to recommendations. The fourth approach is the proposed control-mapped framework, where each high-risk decision point is linked to risk classification, required controls, fairness testing, human oversight validation, traceability evidence, and audit-readiness scoring.

Each approach is evaluated using the same decision scenarios and the same metric definitions. The comparison is performed using Control Coverage Score, Fairness Risk Index, Human Oversight Effectiveness, Decision Traceability Score, Recommendation Consistency Ratio, and Audit Readiness Index. This ensures that the results reflect governance performance rather than differences in input data or evaluation conditions. The objective is to determine whether the proposed framework produces stronger evidence of control effectiveness than the baseline approaches.

The evaluation procedure follows five stages. First, AI-assisted recommendations are generated for each domain using predefined decision logic and scoring patterns. Second, each recommendation is passed through one of the four governance approaches. Third, governance outputs are recorded, including control presence, reviewer action, fairness indicators, explanation availability, and audit evidence. Fourth, each metric is calculated for every decision domain. Fifth, the results are aggregated and compared across domains to identify where the proposed framework improves governance maturity.

To support visual analysis, the results section will present both numerical and graphical outputs. A comparative table will show metric scores across the four governance approaches. A bar chart will compare Audit Readiness Index values across Recruiting, Performance Calibration, and Internal Mobility. A heatmap will show control coverage strength by decision domain and control category. A fairness-risk graph will show whether recommendation outcomes become more balanced after governance controls are applied. These visuals are included to make the results easier to interpret and to strengthen the practical contribution of the paper.

Table 2: Evaluation Design Across SAP SuccessFactors Decision Areas

SAP SuccessFactors Area	*Decision Scenario*	*AI-Assisted Output*	*Governance Focus*	*Metrics Applied*
Recruiting	Candidate ranking, shortlisting, and interview recommendation	Candidate ranking score and interview recommendation	Fairness in shortlisting, recruiter review, explanation capture, and audit logging	CCS, FRI, HOE, DTS, RCR, ARI
Performance Calibration	Rating adjustment and promotion-readiness review	Calibration flag, rating adjustment suggestion, or readiness signal	Manager review, rating distribution fairness, override documentation, and traceability	CCS, FRI, HOE, DTS, RCR, ARI
Internal Mobility	Role-fit recommendation and learning-to-role pathway	Role-fit score, mobility suggestion, or learning path recommendation	Skill-fit explanation, recommendation consistency, HRBP review, and opportunity fairness	CCS, FRI, HOE, DTS, RCR, ARI

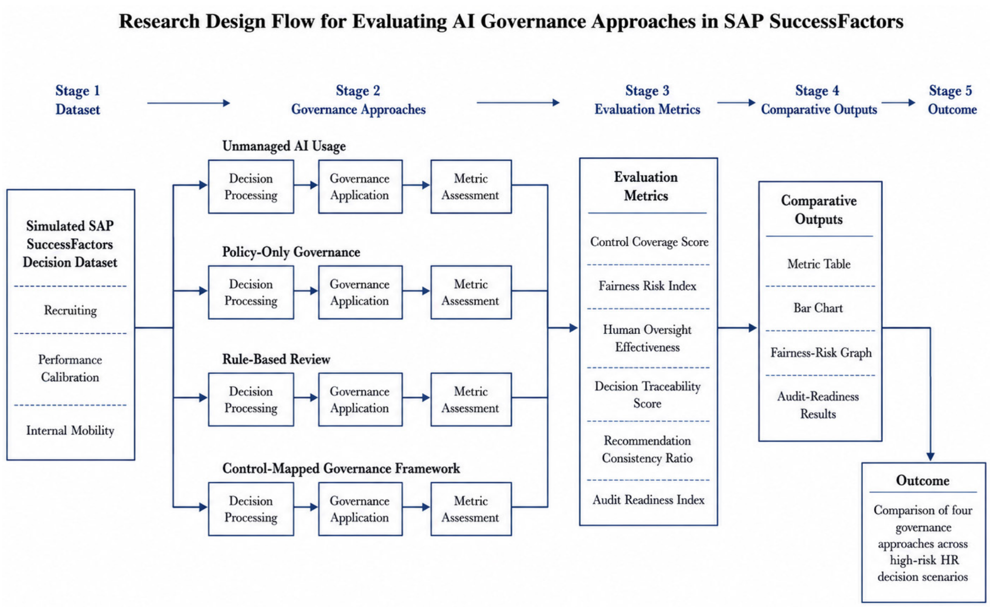

Figure 3: Research Design Flow for Evaluating AI Governance Approaches in SAP SuccessFactors

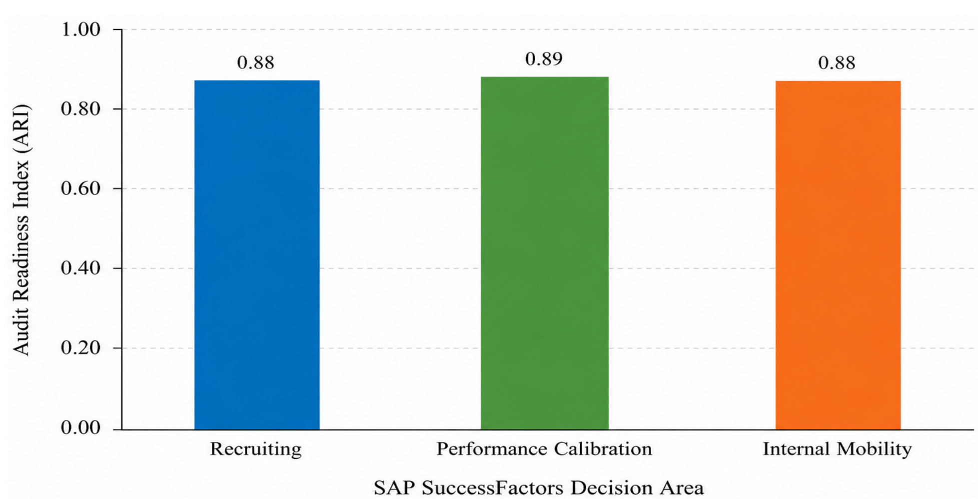

Figure 4: Audit Readiness Index Across SAP SuccessFactors Decision Areas

The evaluation design is intentionally structured for repeatability. Other researchers or practitioners can adapt the same process to different HR datasets, SuccessFactors configurations, or AI-assisted decision workflows. This is important because the value of the proposed framework depends not only on one set of results, but on its ability to provide a reusable method for measuring AI governance across enterprise HR systems.

In summary, this section establishes the research design used to test the proposed framework. By comparing unmanaged AI usage, policy-only governance, rule-based review, and the control-mapped framework across three high-risk HR decision domains, the study creates a clear basis for evaluating whether governance can be measured, improved, and made audit-ready within SAP SuccessFactors environments.

Experimental Results and Governance Impact Analysis

This section presents the evaluation results obtained from the simulated SAP SuccessFactors decision scenarios. The objective is to examine whether the proposed control-mapped framework improves governance maturity when compared with unmanaged AI usage, policy-only governance, and rule-based review. The results are organized around six indicators: Control Coverage Score, Fairness Risk Index, Human Oversight Effectiveness, Decision Traceability Score, Recommendation Consistency Ratio, and Audit Readiness Index.

The comparison shows that unmanaged AI usage produces the weakest governance performance because recommendations are generated without structured controls, fairness monitoring, or audit evidence. Policy-only governance improves documentation awareness but does not significantly improve measurable control strength. Rule-based review performs better because it introduces workflow checks and approval steps, but it remains limited in detecting fairness exposure, passive approval behavior, and incomplete decision evidence. The proposed control-mapped framework demonstrates the strongest performance because it connects each high-risk HR decision point with risk classification, control mapping, fairness testing, human review validation, and traceable audit records.

The results indicate that the proposed framework achieves the highest Audit Readiness Index of 0.88. This improvement is mainly driven by stronger control coverage, better human oversight evidence, and higher decision traceability. The Fairness Risk Index is also reduced from 0.34 in unmanaged AI usage to 0.09 under the proposed framework, suggesting that structured fairness checks and review controls can reduce uneven recommendation patterns across candidate and employee groups.

A domain-level analysis was also performed across Recruiting, Performance Calibration, and Internal Mobility. Recruiting showed the highest initial fairness exposure because candidate ranking and shortlisting decisions are strongly affected by screening criteria and job-fit signals. Performance Calibration showed moderate risk due to rating adjustment patterns and manager review behavior. Internal Mobility showed traceability challenges because recommendations may depend on skill profiles, learning history, career interests, and role-fit scores across multiple data sources.

The domain-level results show that the framework performs consistently across all three HR areas. Performance Calibration achieved the highest Audit Readiness Index because calibration workflows already include structured manager and HR review points, making human oversight easier to validate. Recruiting showed slightly higher fairness risk, which reflects the sensitivity of candidate screening and shortlisting outcomes. Internal Mobility achieved the strongest Recommendation Consistency Ratio because skill-fit logic and role-matching criteria can be evaluated against comparable employee profiles.

The control coverage heatmap further confirms that the proposed framework improves governance visibility. Under unmanaged AI usage, several controls are either absent or undocumented, especially fairness testing, override explanation, and traceable reviewer action. Under policy-only governance, controls may exist in written form but are not consistently linked to system decision points. Under rule-based review, workflow controls are stronger, but fairness monitoring and audit evidence remain incomplete. Under the proposed framework, most controls are mapped directly to the decision stage, creating stronger evidence for internal audit and compliance review. The fairness-risk analysis shows that the proposed model reduces uneven recommendation patterns by forcing review checkpoints before high-impact recommendations are finalized. In recruiting, this means that shortlisting patterns are evaluated before interview recommendations are confirmed. In performance calibration, rating adjustment suggestions are checked for uneven distribution across employee segments. In internal mobility, role-fit recommendations are reviewed to identify whether certain employee groups are repeatedly excluded from opportunity visibility.

Overall, the results support the central argument of this study: AI governance becomes stronger when it is measurable, decision-specific, and connected to workflow evidence. The proposed framework does not only improve documentation; it improves the operating quality of governance by linking controls to real HR

Table 3: Comparative Governance Performance Across Evaluation Approaches

Governance Approach	*CCS*	*FRI*	*HOE*	*DTS*	*RCR*	*ARI*	*Overall Interpretation*
Unmanaged AI Usage	0.28	0.34	0.22	0.31	0.58	0.39	Weak governance controls and low audit readiness
Policy-Only Governance	0.46	0.29	0.38	0.44	0.63	0.52	Better policy awareness but limited measurable control
Rule-Based Review	0.68	0.22	0.61	0.66	0.72	0.69	Stronger workflow control but incomplete fairness and traceability
Control-Mapped Framework	0.91	0.09	0.86	0.89	0.84	0.88	Strongest audit readiness, oversight, fairness control, and traceability

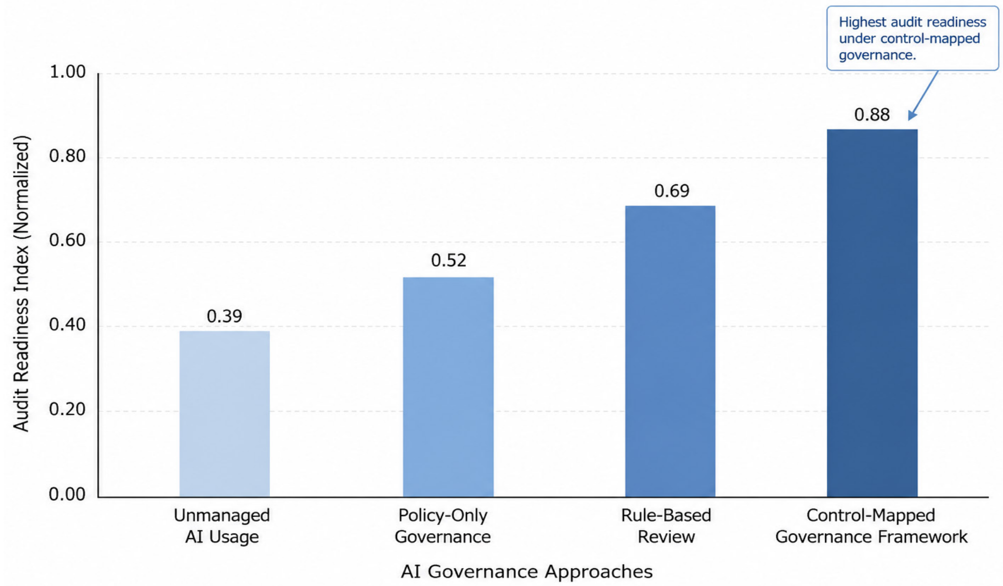

Figure 5: Comparative Audit Readiness Index Across AI Governance Approaches

decision points. This makes the framework more useful than policy-only approaches and more complete than rule-based review. The results also show that audit readiness depends on the combined strength of control coverage, fairness monitoring, human oversight, traceability, and recommendation consistency rather than any single governance activity.

Practical Implications for SAP SuccessFactors Governance and Enterprise HR Risk Management

The results show that AI governance in SAP SuccessFactors should be treated as an operating discipline rather than a separate compliance activity. In many HR technology programs, governance is handled after the system design is completed, which creates a delay between process configuration and risk control. The proposed framework changes this sequence by placing governance directly inside the decision workflow. This is important because high-risk HR outcomes are shaped not only by the AI model, but also by configuration design, approval behavior, data quality, user permissions, reporting visibility, and audit evidence.

For SAP SuccessFactors implementation teams, the framework provides a practical way to connect AI governance with existing system design activities. During Recruiting configuration, governance controls can be mapped to candidate ranking, interview recommendation, talent pool matching, and shortlisting review. During Performance and Goals implementation, controls can be mapped to rating calibration, manager feedback interpretation, goal achievement signals, and promotion-readiness indicators. During Career Development, Succession, Learning, and Internal Mobility processes, controls can be mapped to skill-fit recommendations, career path suggestions, learning alignment, and role visibility. This makes governance part of the configuration lifecycle rather than an external review performed only at the end.

For HR leaders, the framework creates a clearer view of how AI-assisted recommendations affect workforce decisions. Instead of relying only on vendor documentation or internal policy statements, leaders can review measurable indicators such as Audit Readiness Index, Fairness Risk Index, Control Coverage Score, and Human Oversight Effectiveness. These measures help HR leadership understand whether AI is supporting fair and consistent decision-making or whether certain processes require additional review. This is especially useful in talent processes where decisions are sensitive, such as hiring, calibration, promotion, succession, and mobility.

For compliance and audit teams, the main value of the framework is decision traceability. High-risk HR decisions must be explainable after they occur, not only during the approval stage. The proposed model ensures that each AI-assisted decision produces a governance record containing the recommendation, explanation summary, reviewer action, override reason, timestamp, and final

Table 4: Domain-Level Results Under the Proposed Framework

SAP Success Factors Domain	*CCS*	*FRI*	*HOE*	*DTS*	*RCR*	*ARI*	*Key Finding*
Recruiting	0.93	0.10	0.84	0.90	0.82	0.88	Strong control coverage and traceability, with slightly higher fairness sensitivity
Performance Calibration	0.89	0.08	0.88	0.87	0.85	0.89	Highest audit readiness due to structured review and calibration controls
Internal Mobility	0.91	0.09	0.86	0.89	0.86	0.88	Strong recommendation consistency and balanced governance performance

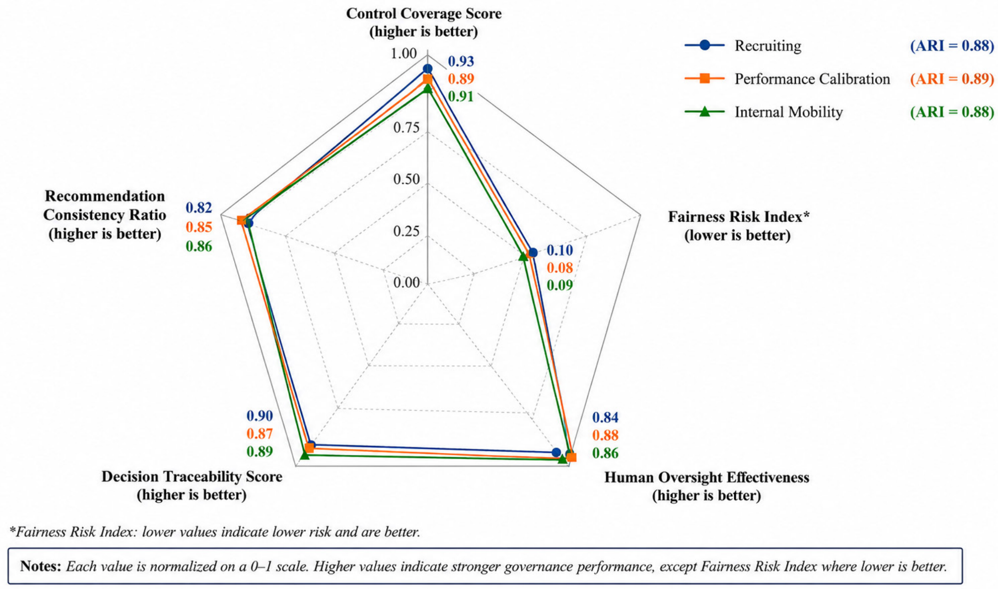

Figure 6: Domain-Level Governance Performance Across SAP SuccessFactors Decision Areas

outcome. This strengthens audit readiness because reviewers can reconstruct how the decision was supported and whether required controls were followed. It also reduces the risk of undocumented approvals, unclear accountability, and fragmented evidence across HR systems.

The framework also improves the quality of human oversight. In many systems, human review is treated as a simple approval step, but effective oversight requires more than clicking approve. Reviewers must understand why a recommendation was produced, evaluate whether it is reasonable, identify possible fairness concerns, and document their decision when they accept or override the output. By measuring Human Oversight Effectiveness, the framework helps organizations distinguish between active review and passive dependency on AI-generated outputs. This is important because human oversight loses value when reviewers do not have enough context or when approvals become routine.

Another practical implication is the need for continuous monitoring. AI governance cannot be limited to one-time model validation because HR data changes over time. Candidate pools shift, skill requirements evolve, performance patterns change, and organizational priorities move with business conditions. A recommendation process that appears balanced during initial testing may later develop bias, inconsistency, or weak explainability. The proposed framework supports continuous governance by tracking fairness exposure, recommendation consistency, control coverage, and audit readiness across repeated decision cycles.

The framework can also support phased adoption. Organizations do not need to apply the full model to every SuccessFactors process at once. A practical starting point would be Recruiting, because candidate shortlisting and interview recommendations carry clear employment-related risk. After that, the same governance structure can be extended to Performance Calibration and Internal Mobility.

Table 5: Control Coverage Heatmap Values by Decision Domain

Control Category	*Recruiting*	*Performance Calibration*	*Internal Mobility*	*Main Purpose*
Data Validation	0.94	0.90	0.92	Confirms input data quality before recommendations are used
Fairness Testing	0.91	0.88	0.89	Checks whether outcomes are balanced across evaluated groups
Explanation Capture	0.92	0.87	0.90	Records why the recommendation was generated
Human Review Evidence	0.89	0.91	0.88	Confirms that reviewers actively evaluated the recommendation
Override Documentation	0.90	0.89	0.87	Captures reviewer changes and justification
Audit Log Completeness	0.94	0.90	0.91	Preserves decision history for audit and compliance review

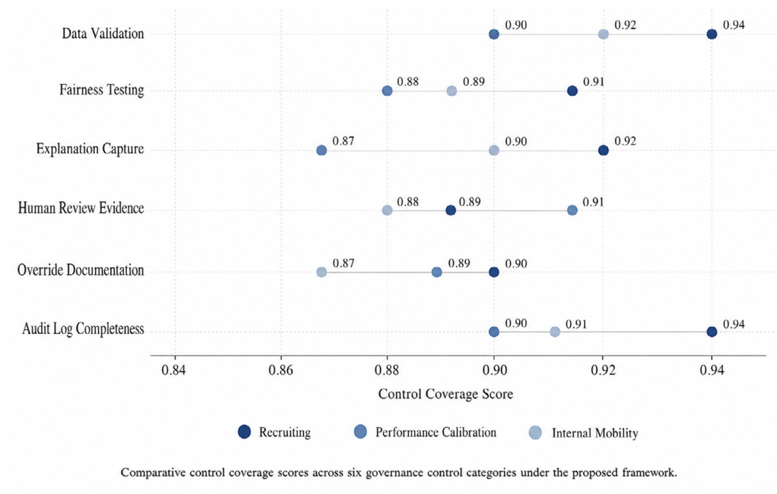

Figure 7: Control Coverage Strength Matrix Across SAP SuccessFactors Governance Controls

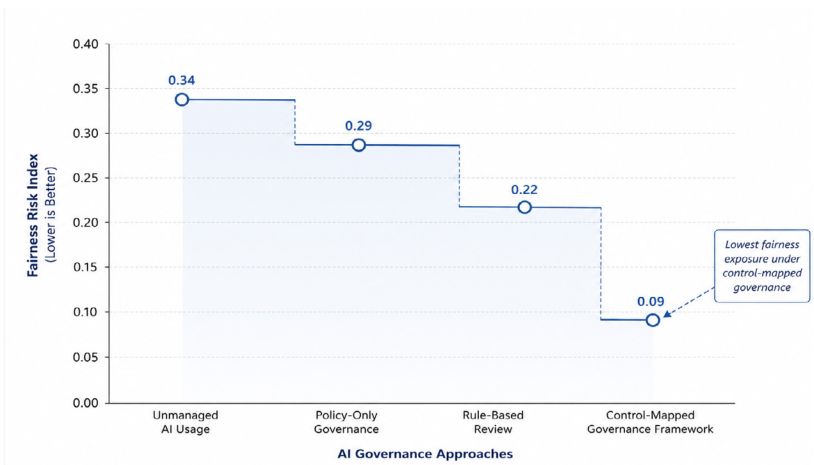

Figure 8: Fairness Risk Reduction Across AI Governance Approaches

This phased approach allows organizations to build governance maturity gradually, validate metric usefulness, improve reviewer behavior, and strengthen audit evidence without disrupting existing HR operations.

Overall, the practical value of the proposed framework is that it gives organizations a repeatable method for converting responsible AI expectations into measurable HR system controls. It supports better accountability, stronger audit preparation, more consistent human review, and improved fairness monitoring. In this way, the framework helps position SAP SuccessFactors not only as a system of record or talent management platform, but as a governed decision-support environment for responsible enterprise HR transformation.

Limitations, Boundary Conditions, and Future Research Directions

Although the proposed framework provides a measurable approach for governing high-risk AI-assisted HR decisions in SAP SuccessFactors, the study has certain limitations that should be recognized. The first limitation is that the evaluation is based on simulated enterprise HR decision scenarios rather than live production data. This design protects employee privacy and allows controlled comparison across governance approaches, but it may not fully capture the complexity of real organizational behavior, country-specific HR practices, local compliance rules, and manager decision patterns.

A second limitation relates to data variability across SAP SuccessFactors implementations. Organizations configure Recruiting, Performance and Goals, Career Development, Succession, Learning, and Employee Central differently based on business structure, geography, job architecture, approval workflows, and reporting maturity. Because of this, the same governance metric may require different thresholds in different environments. For example, an acceptable fairness-risk threshold in candidate shortlisting may not be appropriate for performance calibration or internal mobility recommendations. The framework therefore should be treated as an adaptable model rather than a fixed scoring template.

A third limitation is the measurement of fairness itself. Fairness in HR decisions is complex because outcomes may be influenced by job requirements, experience level, skills, performance history, location, availability, and business need. A numerical fairness score

Figure 9: Phased AI Governance Adoption Roadmap for SAP SuccessFactors

can help identify potential risk, but it cannot fully explain whether a difference in outcomes is unfair, justified, or caused by missing context. For this reason, fairness metrics should be combined with domain review, legal interpretation, and HR judgment before final conclusions are made.

The framework also depends on the quality of human review. Human oversight is included as a measurable control, but the effectiveness of this control depends on reviewer training, accountability, access to explanations, and willingness to challenge system-generated recommendations. If reviewers approve recommendations without meaningful evaluation, the governance process may appear compliant while remaining weak in practice. Future implementations should therefore include reviewer training, escalation rules, periodic review sampling, and quality checks on override documentation.

Another boundary condition is system integration. The framework assumes that decision logs, explanations, reviewer actions, and audit evidence can be captured in a structured manner. In practice, some organizations may rely on external analytics tools, middleware, custom reports, or manual documentation outside SAP SuccessFactors. This can create fragmented evidence trails. Future research should examine how governance records can be integrated across SuccessFactors modules, SAP BTP, reporting tools, workflow systems, and audit repositories.

Future research can extend this study in several directions. First, the proposed metrics should be tested using anonymized real-world HR datasets across multiple industries. Second, longitudinal studies can evaluate whether fairness risk, audit readiness, and recommendation consistency improve over repeated review cycles. Third, future work can develop domain-specific versions of the framework for Recruiting, Performance Calibration, Succession Planning, Compensation, Learning, and Workforce Planning. Fourth, additional research can examine how generative AI explanations influence recruiter, manager, and HR business partner trust in AI-assisted recommendations.

A further extension would be the development of a governance dashboard for SAP SuccessFactors AI decision monitoring. Such a dashboard could display Control Coverage Score, Fairness Risk Index, Human Oversight Effectiveness, Decision Traceability Score, Recommendation Consistency Ratio, and Audit Readiness Index by process, country, business unit, and decision type. This would allow HR, compliance, and audit teams to identify weak control areas before they become serious governance risks.

In summary, the proposed framework provides a strong foundation for measurable AI governance in SAP SuccessFactors, but its practical value will increase through real-world validation, configuration-specific adaptation, continuous monitoring, and stronger integration with enterprise audit processes. These future directions can help move HR AI governance from one-time compliance review toward a continuous assurance model for responsible talent decision-making.

Conclusion

This study presented a control-mapped AI governance framework for managing high-risk HR decisions in SAP SuccessFactors, with specific focus on Recruiting, Performance Calibration, and Internal Mobility. The central problem addressed in the paper is the gap between responsible AI principles and actual governance execution inside enterprise HR workflows. While many organizations define policies around fairness, transparency, accountability, and human oversight, these principles often remain disconnected from measurable controls at the decision level. The proposed framework responds to this gap by treating every AI-assisted HR recommendation as a governed decision object that requires risk classification, control mapping, fairness evaluation, human review validation, and audit evidence.

The framework demonstrates that AI governance becomes stronger when it is measurable and process-specific. Rather than relying on broad compliance statements, the study defines quantitative indicators such as Control Coverage Score, Fairness Risk Index, Human Oversight Effectiveness, Decision Traceability Score, Recommendation Consistency Ratio, and Audit Readiness Index. These metrics allow organizations to evaluate whether AI-assisted recommendations are properly controlled before they influence hiring, performance evaluation, promotion readiness, or internal career movement. This approach shifts governance from a one-time approval activity to a repeatable assurance model.

The comparative evaluation shows that unmanaged AI usage creates significant governance weaknesses because recommendations may be generated without adequate fairness monitoring, reviewer accountability, or traceable evidence. Policy-only governance improves awareness but remains limited because written principles do not automatically produce operational safeguards. Rule-based review strengthens workflow control, but it may still miss fairness drift, passive approvals, and fragmented audit evidence. The proposed control-mapped framework performs better because it connects governance controls directly to HR decision points and produces measurable evidence across the decision lifecycle.

A key contribution of this study is its SAP SuccessFactors-specific focus. The framework is not presented as a generic AI ethics model. It is designed around the structure of enterprise HR processes where recruiting teams, managers, HR business partners, and compliance stakeholders interact with configured workflows, employee data, skill profiles, performance records, and talent recommendations. By aligning governance with actual SuccessFactors decision domains, the framework offers a practical path for organizations that want to use AI-assisted capabilities while maintaining fairness, explainability, accountability, and audit readiness.

The study also highlights that human oversight must be treated as an active control, not a symbolic approval step. AI-supported HR decisions require reviewers who understand the recommendation, examine the explanation, evaluate the risk, and document the reason for acceptance or override. Similarly, decision traceability must be built into the workflow rather than reconstructed after a concern arises. When explanations, reviewer actions, timestamps, recommendation outputs, and final decisions are captured together, organizations are better prepared for internal audit, compliance review, and responsible workforce governance.

Overall, the proposed framework provides a structured method for converting responsible AI expectations into measurable enterprise HR controls. It supports better governance visibility, stronger audit preparation, improved fairness monitoring, and more disciplined human review across SAP SuccessFactors decision workflows. As AI becomes more embedded in talent acquisition, performance management, and internal mobility, organizations will need governance models that are not only ethical in language but verifiable in operation. The control-mapped approach developed in this study offers a foundation for that shift by making high-risk HR AI decisions more transparent, measurable, and accountable.

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