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Performance Appraisal Fairness, Perceived Organisational Support, Employee Engagement and Human Resource Analytics: A Human-Centred Decision-Support Framework

Nusrat Khan*

Department of Business Administration, College of Administrative and Financial Sciences, Saudi Electronic University, 23442 Jeddah, Saudi Arabia

* Correspondence: Nusrat Khan (n.khan@seu.edu.sa)

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Abstract: This study develops a human-centred human resource (HR) decision-support framework integrating performance appraisal fairness, perceived organisational support (POS), employee engagement and workforce analytics. Drawing on the Social Exchange Theory, the conceptual component proposes that appraisal fairness and POS are positively associated with employee engagement and that POS may strengthen the positive relationship between appraisal fairness and engagement. These relationships are proposed rather than empirically tested because the secondary dataset does not contain validated measures of appraisal fairness or POS. However, an "Engagement Score" is available; its measurement provenance is undocumented. Accordingly, the analytics case is used to examine the sufficiency and governance limitations of administrative HR records rather than to test the proposed conceptual relationships. The illustrative analytics component uses the publicly available HR Analytics Dataset. The raw file contained 3,150 records and 39 variables; removal of 150 exact duplicate records resulted in a final analytical dataset of 3,000 observations. A target-leakage audit identified ExitDate, EmployeeStatus, TerminationType, TerminationDescription and exit-dependent tenure measures as inappropriate prospective predictors. Following their exclusion, a leakage-controlled Random Forest (RF) model showed essentially chance-level discrimination, with an area under the receiver operating characteristic curve (ROC-AUC) of 0.507 and an area under the precision–recall curve (PR-AUC) of 0.528. Logistic regression produced similarly weak performance (ROC-AUC = 0.475). These findings demonstrate the importance of data provenance, temporal validity, leakage control, fairness assessment and human oversight when developing HR analytics systems. The study therefore contributes a theoretically grounded and systems-oriented framework for responsible workforce decision support while identifying direct empirical testing of the proposed moderation relationship as an important direction for future research.

Keywords: Performance appraisal fairness; Perceived organisational support; Employee engagement; Human-centred decision support; Human resource analytics; Target leakage; Data governance; Workforce management

1 Introduction

Due to the changes in society and the workforce, organisations have begun to rely heavily on the use of data-driven insights and advanced analytics to retain their competitive edge and to develop a resilient, skilled workforce of human capital systems [1]. As workplace environments evolve into more dynamic, transparent, and technologically enabled organisations, it is becoming increasingly important to use fair and credible methods to evaluate performance [2]. Organisations are continuing to utilise performance management systems to acquire sophisticated performance-related data in order to identify factors affecting engagement and develop strategies to improve engagement [3]. However, many organisations still struggle to achieve significant improvements in employee engagement, as employees do not view the appraisal process as fair due to the disconnect between the formal appraisal process and the employee's perception [4].

When organisations demonstrate through the formal appraisal process that they value their employees and their contributions, this will create a greater positive response to the appraisal process from the employee [5]. This reflects

the idea of supporting employees through perceived organisational support (POS) in an organisation. POS serves as a psychological and social mechanism through which the employee interprets the evaluation outcomes [6]. Therefore, POS will greatly influence the employee's interpretation of their performance appraisal. When POS is high, the employee is likely to view the appraisal process as supportive and credible, leading to increased engagement and reciprocal organisational commitment [7].

Changes in digital human resource (HR) systems, continuous feedback systems, as well as artificial intelligence (AI) technologies used to determine an employee's performance and/or value as an employee, have impacted how employees relate to performance management [8]. However, these advancements have also led to the need for organisations to create environments in which employees are treated fairly and to help eliminate the fear/uncertainty caused by constant change within the organisation [8]. It is essential for the continued development of sustainable HR practices that create long-term organisational health to understand how employee perceptions regarding the support provided by organisations' POS impact the connections between different motivation and engagement levels and the fairness of performance appraisals [9].

This research examines the connection between performance appraisal fairness and employee motivation/engagement and the role of POS in that relationship, with the aim of informing a framework for sustainable HR practices [10]. The main objective of this study is to develop a human-centred HR decision-support framework that integrates employees' perceptual responses to performance management with operational workforce analytics. The central research problem addressed in this study is how an HR decision-support system can combine theoretically relevant employee perceptions with administrative workforce data, and what limitations arise when decision support relies predominantly on administrative records. Administrative HR data can describe workforce characteristics and outcomes, but they do not necessarily capture the psychological mechanisms through which employees interpret organisational practices. Conversely, perceptual constructs such as appraisal fairness, POS and engagement provide theoretically meaningful information but require validated measurement before they can be incorporated responsibly into analytical systems. The present study therefore treats the conceptual framework as an information-requirements layer and the analytics case as a methodological demonstration of the limitations of administrative data when those perceptual measures are unavailable.

At the perceptual level, the framework proposes that performance appraisal fairness and POS contribute to employee engagement, with POS operating as a boundary condition that may strengthen the fairness–engagement relationship. At the operational level, the illustrative HR analytics case demonstrates how administrative workforce data can support workforce analysis while also revealing the methodological risks associated with temporal ambiguity and target leakage. Importantly, employee turnover is not treated as a proxy for engagement, and the secondary-data analysis does not constitute an empirical test of the proposed moderation relationship. Accordingly, the study addresses three research questions (RQs):

RQ1: How does existing theory explain the relationship between performance appraisal fairness and employee engagement?

RQ2: Why can POS theoretically operate as a boundary condition on the appraisal fairness–employee engagement relationship?

RQ3: What does the administrative-data case reveal about the information and governance requirements of a human-centred HR decision-support system?

The contribution of the study is therefore twofold. First, it develops a theoretically grounded framework distinguishing the direct effects of appraisal fairness and POS on engagement from the proposed interaction between them. Second, it uses an illustrative public HR dataset to demonstrate why responsible workforce analytics requires explicit attention to data provenance, prediction timing, target leakage, fairness auditing and human review. The analytics case complements the conceptual model by representing the operational-data layer of an HR decision-support system; it does not provide empirical validation of the psychological relationships proposed in the conceptual framework.

2 Literature Review

The existing body of literature on performance appraisal fairness, POS, and employee engagement is both broad and well-established, drawing from multiple disciplines including organisational behaviour, HR management, and social psychology. The review presented below is organised thematically and examines each of these constructs in turn, before addressing the theoretical relationship between them. The primary objective of this review is to establish the conceptual and empirical foundation for the proposed moderated model in which POS is hypothesised to moderate the relationship between appraisal fairness and employee engagement. The review draws upon peer-reviewed journal articles, meta-analyses, and conceptual frameworks published predominantly within the last decade, reflecting the growing interest in sustainable and data-informed HR practice.

2.1 Performance Appraisal Fairness: Concept, Dimensions, and Importance

Performance appraisal fairness refers to employees' perceptions of the fairness of the criteria, procedures, interpersonal treatment and outcomes associated with evaluating their performance [11, 12]. Appraisal fairness encompasses procedural fairness, which concerns the consistency and neutrality of evaluation procedures; distributive fairness, which concerns the perceived fairness of appraisal outcomes; and interactional fairness, which concerns employees' treatment during the appraisal process [12, 13]. Research suggests that employees who perceive performance appraisals as fair are more likely to accept appraisal outcomes and demonstrate positive work attitudes and behaviours [14]. Furthermore, relational justice during appraisal interactions is associated with stronger supervisor–employee relationships and greater acceptance of performance feedback [15]. In today's work environment, fairness is a vital component of employee engagement and has a strong impact on sustaining a high level of HR practice [16].

2.2 Perceived Organisational Support: Theoretical Foundations

POS refers to a person's belief about their employer's support for the employee's value and well-being [17]. This perception comes from how an organisation interacts with and provides services to an employee. Employees will determine their relationship with the organisation based on POS [18]. POS is based on a number of activities that demonstrate appreciation toward employees: recognition practices (How/when do you acknowledge employees' efforts?); fairness (How fairly do you make decisions?); development opportunities (What type of training opportunities are available?); and supportive leadership (How supportive is the supervisor?) [19]. Employees who feel valued, respected or appreciated will develop a stronger emotional bond to the organisation, thereby enhancing their motivation and willingness to participate [20]. As a key building block of organisational behaviour, POS has been studied for its impact on various workplace outcomes such as job satisfaction, employee commitment, and employee engagement [21].

Social Exchange Theory is the basis for POS [22]. It is based on the premise that human interaction and relationships are based on a system of social exchange [23]. In the organisation/employee relationship, POS is considered to be the basis of the organisation/employee relationship [24]. When a person perceives that he/she is being provided the benefits of POS, they feel a reciprocal obligation to give back to the organisation, and this will result in the employee providing positive contributions to the organisation (e.g., greater productivity, increased satisfaction with their job, and less employee turnover) [25].

As work environments evolve through a mixture of remote and in-person work formats, faster digital development and changes in how employees expect to work [26], POS performs a vital role in providing stability for workers adjusting to working via a home office, using technology or both, while adjusting to different levels of interpersonal contact [27]. Workers face uncertainty, a fractionalisation of their workload and decreased levels of contact with others who do similar jobs [28]. If employees have a high level of POS, they will have a foundation for support in these areas [29]. Additionally, POS has an impact on how employees view their HR practices (such as performance evaluations) [30]. Employees who believe there is a high level of support will be more inclined to perceive performance evaluations as fair, credible and developmental [31]. Therefore, POS improves the overall well-being of the individual as well as supporting sustainable HR practices by developing trust and fairness and maintaining employee engagement over a period of time [32].

2.3 Relationship Between Performance Appraisal Fairness and Employee Engagement

The connection between fairness in performance appraisal and the level of involvement that employees have with their jobs has been the subject of many studies in the field of organisational behaviour [5]. Most of the research findings support fairness being a very important factor that drives people's emotional and psychological attachment to their job in the workplace [33]. The more that employees perceive that the performance appraisal system is fair, open and uses objective criteria, the more they are likely to trust the organisation/management and feel that their contribution is truly acknowledged [34]. A fair appraisal provides employees with a greater understanding of their expected performance, enhances the value of their work, and validates their contribution to the success of the organisation, all of which are key ingredients of employee engagement [35]. The aspect of fairness is also a motivation for employees to commit their time, effort and energy in performing their duties [36].

The theme of fairness in an employee's performance evaluation also helps build on how an employee perceives their employer as being fair and honest, which in turn creates a greater degree of engagement [37]. The reason for this is that fair performance evaluations reflect the fair process, which ensures there is a fair and consistent process used to evaluate employees, as well as fair distribution [25]. In addition, fair distribution helps to create a match between how well an employee has performed and the rating or reward received by that employee for the performance [38]. Finally, fair interaction is an important component of the fair system, since it illustrates how employees would be treated during the feedback process and fosters a strong bond between an employee and their supervisor [39]. Therefore, when all of these dimensions of the fair system are in place, the employee feels they are

being treated fairly; they have a sense of psychological discovery and therefore have a higher probability of positively contributing to their employer/organisation [40]. In contrast, when the evaluation process is not fair, the level of trust in the performance evaluation system decreases, the employee's morale decreases, and the employee becomes less engaged [41].

An employee who approaches their job with a continuous learning perspective tends to be more enthusiastic and take ownership of their work [42]. Additionally, when employees receive fair performance evaluations, they are likely to see more chances for advancement and growth in responsibility in an organisation, which in turn deepens the emotional attachment that employees feel toward their organisations and reduces the chance that the employee will leave the organisation [43]. In addition to assisting with objective assessments of employee growth and development, fair performance evaluations help employees connect more closely with their organisation's goals and demonstrate increased levels of discretionary effort to help the organisation achieve its goals [44].

As the digital environment of the workplace continues to evolve and grow at an exponential rate, a growing number of employees are either working as part of a hybrid workforce or utilising technology in their jobs; managers and supervisors have a critical need to ensure that they are treating their employees fairly by evaluating employees based on measurable performance indicators and how employees are treated in terms of engagement [45]. There are fewer opportunities to interact on a daily basis with coworkers and supervisors; thus, the lack of daily visibility and the rapid evolution of the workplace result in increased rates of turnover, which has occurred due to concerns about possible bias and lack of transparency in the digital world [46]. Employees will feel a sense of trust and belonging to the organisation if they know that they have been treated fairly [47]. Fairness is also used as a strategic tool to improve employee engagement and to create a sustainable HR system for the long-term growth of the organisation [48].

2.4 Theoretical Model and Hypothesis Development

Performance appraisal fairness and POS represent related but conceptually distinct employee perceptions. Appraisal fairness concerns employees' evaluation of the procedures, outcomes and interpersonal treatment associated specifically with the performance appraisal process. In contrast, POS reflects a broader belief that the organisation values employees' contributions and cares about their well-being. Prior research has linked appraisal justice with employee engagement and retention-related outcomes, while POS has independently been associated with engagement and other positive work attitudes. However, these direct relationships should be distinguished from the proposition that POS changes the strength of the relationship between appraisal fairness and engagement.

H1: Perceived performance appraisal fairness is positively associated with employee engagement.

H2: POS is positively associated with employee engagement.

H3: POS positively moderates the relationship between performance appraisal fairness and employee engagement, such that the positive relationship between appraisal fairness and employee engagement is stronger when POS is high.

The proposed moderating role of POS should also be distinguished from mediation and antecedent explanations. A mediation model would imply that fair appraisal practices increase POS, which subsequently increases engagement. An antecedent model would instead position POS as a factor shaping employees' perceptions of appraisal fairness. Both are theoretically plausible alternatives. The present framework conceptualises POS as a broader organisational perception that exists alongside appraisal-specific fairness perceptions. Drawing on the Social Exchange Theory, employees who perceive high organisational support may attach greater relational meaning and credibility to fair appraisal treatment and consequently reciprocate more strongly through engagement. POS is therefore proposed as a boundary condition affecting the strength of the fairness–engagement association rather than as the mechanism through which fairness produces engagement. Future primary-data research should compare these alternative specifications empirically.

2.5 Responsible Human Resource Analytics and Human-Centred Decision Support

The use of analytics in employment decisions introduces requirements that extend beyond predictive accuracy. Tambe et al. [49] identify fundamental challenges in applying data science to HR, including the complexity of HR phenomena, limitations of organisational datasets, accountability and fairness concerns, and possible adverse employee responses to algorithmic decision-making. Köchling and Wehner [50] similarly show that algorithmic decision-making in HR recruitment and development may reproduce discrimination and perceived unfairness when data, model design or organisational processes are inadequate. Human oversight is particularly important because algorithm-based HR decisions can affect employee autonomy, dignity and personal integrity. Leicht-Deobald et al. [51] argue that efficiency and consistency gains from algorithmic HR systems must therefore be balanced against risks to employee integrity and responsible organisational judgement. Evidence from algorithmic hiring further demonstrates that claims of bias mitigation or predictive effectiveness require rigorous empirical validation rather than reliance on technical or vendor claims alone [52]. These studies suggest that responsible HR analytics should be treated as a governed decision-support system rather than merely as a predictive modelling exercise. Data

provenance, temporal validity, leakage control, out-of-sample validation, fairness assessment, decision authority and ongoing monitoring are therefore incorporated as explicit components of the human-centred architecture proposed in this study.

Table 1 demonstrates that the closest prior studies address important but incomplete portions of the proposed framework. Nair and Salleh [2] conceptually connect appraisal justice with engagement but examine trust rather than POS as the relevant boundary condition. Uraon and Kumarasamy [3] provide empirical evidence connecting appraisal justice and job engagement, although their model emphasises mediation and downstream job outcomes rather than POS moderation. Micacchi et al. [40] directly connect performance appraisal justice with work engagement in a public-sector setting but do not examine organisational support as a boundary condition. Lai et al. [31], conversely, demonstrate that POS can operate as a moderator in an employee-outcome relationship, but their model concerns job stress and turnover intention rather than appraisal fairness and engagement. Collectively, these studies support the individual theoretical links underlying the present framework while leaving the proposed fairness × POS interaction in relation to employee engagement directly untested. The present study therefore treats this interaction as a theoretical proposition rather than an empirically established relationship.

Table 1. Closest prior studies and the remaining research gap

Study	Constructs/Context	Sample/Method	Main Relevance	Remaining Gap
Nair and Salleh [2]	Performance appraisal justice, trust, employee engagement	Conceptual study	Proposed appraisal justice–engagement relationships and a moderating role for trust	No empirical examination of POS as a moderator
Uraon and Kumarasamy [3]	Appraisal justice, job engagement, job satisfaction, intention to stay	503 employees from 50 IT companies; PLS-SEM	Appraisal justice was positively related to job engagement; engagement mediated downstream outcomes	POS not examined as a boundary condition
Micacchi et al. [40]	Performance appraisal justice and work engagement	Public-sector employees; survey sample of 1,483, with a discrete-choice subsample	Directly connects appraisal justice with work engagement	Does not test POS × appraisal fairness
Lai et al. [31]	POS, job stress, turnover intention	720 SME employees in China	Demonstrates the theoretical use of POS as a moderator of an employee-outcome relationship	Does not examine performance appraisal fairness or engagement
Present study	Appraisal fairness, POS and employee engagement	Conceptual framework and illustrative HR analytics case	Proposes POS as a boundary condition and embeds the framework within human-centred HR decision support	Direct moderation requires future validated primary-data testing

Note: HR = human resource; IT = information technology; PLS-SEM = partial least squares structural equation modelling; POS = perceived organisational support; SME = small and medium-sized enterprise.

3 Administrative Human Resource Data and Turnover Classification: An Illustrative Sensitivity Analysis

The analytics component serves as an illustrative test of the information available to an HR decision-support system when it relies on administrative workforce records without validated measures of the employee perceptions identified in the conceptual framework. Its purpose is therefore not to demonstrate successful employee-level turnover prediction. Instead, the case examines whether the available administrative variables provide useful discrimination after post-outcome and temporally ambiguous information is removed, and uses the resulting evidence to identify data, validation and governance requirements for responsible HR decision support. In this sense, the conceptual model specifies information that a theoretically informed system should seek to capture, while the administrative-data case demonstrates the limitations of the information presently available.

3.1 Human-Centred Human Resource Decision-Support Architecture

The conceptual framework can be embedded within a human-centred HR decision-support system in which perceptual and administrative information perform complementary functions. The proposed architecture contains eight interconnected stages. First, the data-input layer integrates validated perceptual measures, such as appraisal fairness, POS and employee engagement, with appropriately time-stamped administrative HR records. Second, the data-governance and preprocessing layer addresses missingness, coding consistency, duplicate observations, temporal alignment, redundant variables and target leakage. Third, the analytical layer supports descriptive, diagnostic and, where temporal validity permits, predictive analysis. Fourth, the validation and fairness layer assesses out-of-sample performance, subgroup disparities, calibration and the consequences of false-positive and false-negative classifications. Fifth, the decision-support layer translates validated results into workforce-level

information rather than automatic personnel actions. Finally, the human-review and feedback layer requires professional HR judgement before any intervention and enables subsequent monitoring, auditing and model updating as workforce conditions or data distributions change. The system is therefore intended to augment rather than replace managerial judgement. Model outputs should be treated as one source of evidence within a broader decision process, particularly where employee data involve demographic or other sensitive attributes. Decisions affecting recruitment, appraisal, development, promotion or retention should remain subject to contextual assessment, fairness review and accountable human oversight. Figure 1 presents the proposed conceptual framework. Table 2 provides the operational specification for different constructs used in the study.

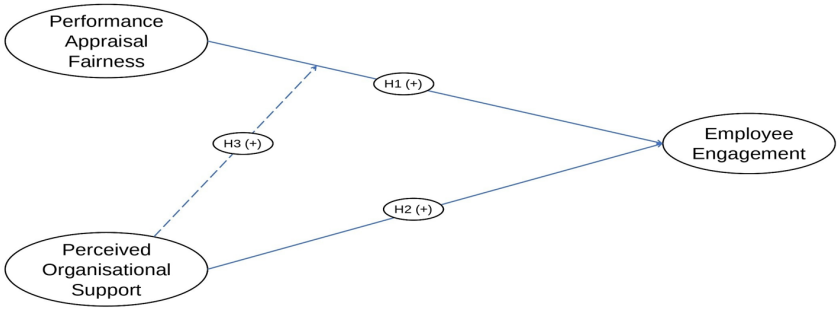


Figure 1. Proposed conceptual framework linking performance appraisal fairness, perceived organisational support and employee engagement

Note: H1–H3 = hypotheses 1–3.

Table 2. Operational specification of the human-centred human resource decision-support system

Stage	Data/Input	Processing Task	Responsible Actor	Output	Validation Requirement	Decision Rule
1. Problem definition	Workforce-management question; intended decision; observation point	Define outcome, unit of analysis and decision date	Human resources (HR) decision owner and analytics lead	Approved analysis specification	Decision purpose and observation point must be explicit	If a defensible observation point cannot be defined, analysis is restricted to methodological/ diagnostic use
2. Data intake	Perceptual measures; administrative records; protected attributes stored separately for auditing	Establish provenance, measurement validity and temporal availability	Data steward and HR analytics team	Governed input dataset	Source, timing and measurement status documented	Undocumented or post-outcome fields cannot be used as predictive inputs
3. Data quality and leakage screening	Governed input dataset	Missingness checks, duplicate removal, coding checks, temporal alignment and leakage detection	Data analyst and data steward	Analysis-ready dataset	No direct or indirect post-outcome information in predictors	Leakage or unresolved temporal ambiguity triggers exclusion of affected variables; pervasive problems stop predictive modelling
4. Model development	Training data containing permitted predictors	Fit baseline and candidate models using training data only	Data scientist/analyst	Candidate model(s)	Preprocessing and model estimation confined to training data	No model output proceeds directly to a personnel decision
5. Performance validation	Held-out test data and cross-validation results	Evaluate discrimination, calibration and error patterns	Independent analyst/model validator	Validation report	Model must demonstrate stable out-of-sample performance and meaningful improvement over non-informative and baseline performance	Failure to demonstrate useful discrimination results in rejection for predictive decision use
6. Fairness review	Model outputs and protected attributes used only for auditing	Assess subgroup performance and potentially unequal error patterns	HR governance/ethics reviewer	Fairness assessment	No material unexplained disparity that renders use unacceptable	Failed fairness review suspends deployment and requires model/data revision

7. Human decision review	Validated outputs, uncertainty information and organisational context	Interpret evidence against policy and contextual information	Authorised HR manager	Decision-support recommendation	Managerial review and documented rationale required	Model output cannot autonomously trigger recruitment, appraisal, retention or disciplinary action
8. Monitoring and updating	New observations, outcomes, performance and fairness metrics	Monitor drift, validity and changing workforce conditions	Model owner and HR governance team	Monitoring report	Performance, data quality and fairness remain within approved limits	Material deterioration triggers suspension; retraining requires new temporally valid data and full revalidation

Three governance states follow from this architecture. Model rejection occurs when data leakage, inadequate temporal definition or insufficient out-of-sample discrimination prevents responsible predictive use. Model suspension occurs when a previously validated system subsequently fails data-quality, performance or fairness monitoring. Model retraining may occur only when sufficiently new and appropriately governed data become available, after which the complete validation and fairness-review process must be repeated. More complex modelling cannot substitute for failure at an earlier governance stage.

3.2 Illustrative Operational Scenario

To demonstrate how the architecture operates, consider a workforce-management request to assess whether available data can support turnover-related planning at the departmental level. The scenario begins at a predefined observation point T_0, at which the dataset is frozen, and only information demonstrably available on or before T_0 is eligible for modelling. Variables generated by or after an employee's departure cannot enter the predictive feature set. Protected demographic attributes are separated from the predictive inputs and retained only where appropriate for fairness auditing.

Table 3. Illustrative decision-support scenario

Step	Operational Question/Action	Present-Case Outcome
Decision request	Can available workforce data support turnover-related planning?	Permissible as an analytical question
Observation point	Freeze all information available at T_0	A defensible common prospective T_0 cannot be reconstructed
Leakage screening	Exclude ExitDate, EmployeeStatus, TerminationType, TerminationDescription and exit-dependent tenure	Excluded
Temporal screening	Exclude variables whose timing relative to departure cannot be established	Survey/training variables excluded
Model development	Compare candidate model with simpler baseline	RF compared with LR
Performance gate	Require useful and stable discrimination beyond non-informative/baseline performance	Failed: RF ROC-AUC = 0.507; LR ROC-AUC = 0.475
Decision-support output	Determine what information may be passed to HR	Diagnostic finding: available fields are insufficient for reliable employee-level turnover discrimination
Human review	Review data limitations, errors and fairness implications	Required
Final decision boundary	Determine whether employee-level action is permissible	No employee-level intervention permitted
Next action	Improve data architecture and repeat validation with appropriately time-stamped data	Future research/system development

Note: HR = human resource; LR = logistic regression; RF = random forest; ROC-AUC = area under the receiver operating characteristic curve; T_0 = predefined observation point.

The present public dataset cannot reconstruct a defensible common prospective observation point for all variables. Consequently, the empirical analysis in this study represents a methodological sensitivity analysis rather than an operational prospective prediction experiment. Nevertheless, applying the proposed system rules demonstrates what the decision outcome would be: once post-outcome and temporally ambiguous information is removed, the available models perform approximately at chance level and therefore fail the performance-validation gate. The system would consequently withhold employee-level risk classifications or retention recommendations and report that the available evidence is insufficient for predictive decision use. Table 3 presents the illustrative decision-support scenario, outlining the key operational steps, governance requirements and corresponding outcomes based on the available dataset.

4 Research Methodology

4.1 Data Source and Reproducibility

The illustrative analytics case uses the publicly available HR Analytics Dataset hosted on Kaggle, specifically the file Messy_HR_Dataset_Detailed.csv. The dataset was accessed on 16 July 2026. The raw file contained 3,150 observations and 39 variables. After removing 150 exact duplicate rows, 3,000 unique observations remained for analysis. The source repository does not document an identifiable organisation, industry or geographical population and does not provide sufficient provenance information to establish conclusively whether the records represent real or simulated employees. Accordingly, the present study treats the file strictly as an illustrative public HR dataset and does not generalise its results to a specific organisation, industry or country. The dataset contains a variable labelled "Engagement Score"; however, no item wording, scale-development procedure or psychometric validation information is supplied in the source documentation. It is therefore used only descriptively and is not treated as a validated measure of the employee-engagement construct proposed in the conceptual model. The dataset contains no direct measures of performance appraisal fairness or POS and consequently cannot test H1–H3. Table A1 in the Appendix reports all 39 variables contained in the source file, including their definitions, data type, missingness, preprocessing treatment and role in the revised analysis.

4.2 Analytical Framework

The study adopts a two-part integrative design comprising a conceptual component and an illustrative analytics component. The conceptual component develops theoretically grounded propositions linking performance appraisal fairness, POS and employee engagement. These relationships are not empirically tested using the secondary dataset. The analytics component instead examines the methodological use and limitations of administrative HR data for turnover classification. Following duplicate removal and target-leakage screening, a leakage-controlled Random Forest (RF) classifier was estimated and compared with logistic regression (LR) as a baseline model. Model performance was evaluated using an independent stratified test sample and five-fold stratified cross-validation. The analytics component therefore serves as an illustration of the operational-data layer of the proposed human-centred HR decision-support architecture rather than as empirical validation of H1–H3. Figure 2 illustrates the proposed human-centred HR decision-support architecture, integrating the analytical components with the governance mechanisms necessary for responsible workforce decision-making.

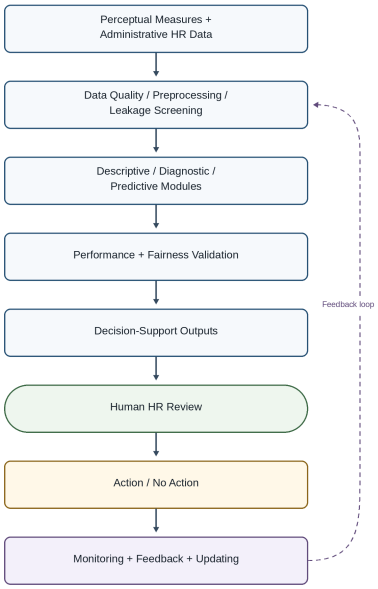


Figure 2. Human-centred human resource decision-support architecture

Note: HR = human resource.

5 Data Analysis and Findings

5.1 Data Preprocessing and Leakage Control

Data preprocessing was conducted in two stages. First, exact duplicate records were identified across all fields and removed, reducing the dataset from 3,150 to 3,000 unique observations. Variables containing direct personal

identifiers or high-cardinality quasi-identifiers were removed from the analytical feature set. Categorical predictors retained in the sensitivity analysis were transformed using ordinal encoding, while the Current Employee Rating variable was retained numerically.

Second, a target-leakage audit was performed before model estimation. Retrospective exit status was defined as 1 when ExitDate was present and 0 when no exit date was recorded. ExitDate, EmployeeStatus, TerminationType and TerminationDescription were excluded from all predictor sets because they either directly encode or become available only at or after departure. Tenure calculated using an employee's exit date was also excluded because it incorporates information that is not available prospectively. Survey- and training-related variables were excluded from the predictive sensitivity analysis because their timing relative to employee departure cannot be established consistently from the dataset. Consequently, the revised analysis does not claim that the dataset provides a validated prospective employee-turnover forecasting system. The final leakage-controlled sensitivity model included only Title, BusinessUnit, EmployeeType, PayZone, EmployeeClassificationType, DepartmentType, Division, State, JobFunctionDescription, Performance Score, and Current Employee Rating. Demographic attributes including gender, race and marital status were excluded from the predictive feature set and retained only for descriptive or fairness-audit purposes.

Following the removal of 150 exact duplicate records, the final analytical dataset comprised 3,000 unique observations. No observations were excluded on the basis of outlier detection. All 3,000 observations were retained for the subsequent leakage-controlled methodological sensitivity analysis, which was not intended to constitute a validated prospective turnover-prediction exercise.

5.2 Model Development and Evaluation

The 3,000 observations were divided using a stratified 75:25 train–test split with a random seed of 42. The training sample contained 2,250 observations (1,100 non-exit and 1,150 exit cases), while the independent test sample contained 750 observations (367 non-exit and 383 exit cases). No over- or undersampling was applied because the classes were approximately balanced. The RF classifier was estimated using the following parameters: n_estimators = 500, min_samples_leaf = 2, random_state = 42, criterion = "gini", max_depth = 8, min_samples_split = 2, max_features = "sqrt", bootstrap = True, and class_weight = "balanced". In logistic regression, C represents the inverse of regularisation strength. LR was estimated using solver = "lbfgs", penalty = "l2", C = 1.0, max_iter = 1,000, and class_weight = "balanced". Binary classifications were generated using a probability threshold of 0.50. Categorical variables were processed using scikit-learn's OrdinalEncoder with default settings, assigning integer codes to categorical levels. Infrequent categories were not pooled, and no minimum-frequency threshold was applied. In the reported implementation, categorical encoding was fitted to the complete analytical dataset before the train–test split. Consequently, categories appearing in the held-out test sample were already represented in the fitted encoder. However, this procedure did not restrict preprocessing to the training sample and therefore introduces a limitation concerning the independence of model evaluation.

Five-fold stratified cross-validation with shuffling and a random seed of 42 was additionally conducted on the training data. Because the source dataset does not permit reconstruction of a defensible common prospective prediction date, the modelling exercise is interpreted as a methodological sensitivity analysis rather than a validated prospective turnover-prediction experiment. Its purpose is to assess the discriminatory performance of the retained administrative variables after excluding outcome-derived and temporally ambiguous information.

5.3 Leakage-Controlled Classification Results

Removal of post-departure and temporally ambiguous information substantially changed the interpretation of the analytics case. On the independent test sample, the leakage-controlled RF achieved an accuracy of 0.507, an area under the receiver operating characteristic curve (ROC-AUC) of 0.507 and an area under the precision–recall curve (PR-AUC) of 0.528. Precision, recall and F1-score for the exit class were 0.516, 0.561 and 0.538, respectively. The corresponding confusion matrix contained 165 true negatives, 202 false positives, 168 false negatives and 215 true positives. LR produced similarly weak results, with an accuracy of 0.481, ROC-AUC of 0.475 and PR-AUC of 0.501. Precision, recall and F1-score for the exit class were 0.492, 0.501 and 0.497, respectively. Its confusion matrix contained 169 true negatives, 198 false positives, 191 false negatives and 192 true positives. Five-fold stratified cross-validation confirmed the absence of stable discriminatory performance. Mean RF ROC-AUC was 0.481 (standard deviation [SD] = 0.013), while mean PR-AUC was 0.511 (SD = 0.006). LR produced a mean ROC-AUC of 0.454 (SD = 0.016) and a mean PR-AUC of 0.487 (SD = 0.011). These results indicate that, once outcome leakage is controlled, the retained administrative fields do not support reliable prospective turnover discrimination. Table 4 summarises the performance of the leakage-controlled RF and LR models on the independent test sample across accuracy, precision, recall, F1-score, ROC-AUC and PR-AUC.

Table 4. Leakage-controlled model performance on the independent test sample

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	PR-AUC
RF	0.507	0.516	0.561	0.538	0.507	0.528
LR	0.481	0.492	0.501	0.497	0.475	0.501

Note: PR-AUC = area under the precision–recall curve; ROC-AUC = area under the receiver operating characteristic curve; RF = random forest; LR = logistic regression; Precision, recall and F1-score refer to the exit class (1).

5.4 Descriptive Comparison by Exit Status

Because several continuous and ordinal variables were not assumed to satisfy normality, group comparisons were conducted using Mann–Whitney U tests, where U denotes the test statistic. Categorical performance ratings were compared using a chi-square (χ^2) test. Statistical significance was assessed using p-values. Retrospective observed tenure was calculated using ExitDate for employees with a recorded departure and to 6 August 2023, the latest date represented in the dataset, for observations without an exit date. This measure is reported descriptively only and was not included as a predictor because it incorporates outcome-dependent information for departed employees.

Age did not differ meaningfully between observations with and without recorded exits. Median age was 51.95 years (interquartile range [IQR]: 35.80–67.06) among non-exit observations and 51.48 years (IQR: 36.03–67.17) among exit observations (U = 1,119,874, p = 0.847). Current employee ratings were also virtually identical (median = 3, IQR: 2–3 in both groups; U = 1,116,350.5, p = 0.712). Performance-score distributions did not differ significantly across exit status (χ^2 = 0.199, p = 0.978, Cramér's V = 0.008). Similarly, the available Engagement Score had a median of 3 (IQR: 2–4) in both groups (U = 1,125,186.5, p = 0.975).

Retrospective observed tenure was lower among exit observations (median = 1.07 years, IQR: 0.42–2.03) than among non-exit observations (median = 2.46 years, IQR: 1.18–3.73; U = 1,634,028.5, $p < 0.001$). This difference should not be interpreted as evidence that tenure causally reduces turnover because the tenure measure for departed employees is mechanically bounded by the exit date. It therefore illustrates why outcome-dependent tenure should not be used as a prospective turnover predictor. Accordingly, no feature-importance ranking or employee-level risk interpretation is derived from the leakage-controlled model.

6 Results and Discussion

6.1 Discussion

The principal analytical finding of the illustrative case is narrow but important. After post-outcome and temporally ambiguous variables were removed, the retained fields did not meaningfully discriminate between exit and non-exit observations in this dataset. The leakage-controlled RF produced a ROC-AUC of 0.507, while LR produced a ROC-AUC of 0.475. The analysis therefore does not establish a usable employee-level turnover model. At least three non-mutually-exclusive explanations may account for this result. First, the retained administrative variables may contain limited prospective information about subsequent departure. Variables describing job classification and current ratings may be insufficient to distinguish employees who later exit from those who remain. Second, the public dataset lacks a sufficiently reliable temporal structure to establish a common prospective observation point for all potentially relevant variables. This limits the ability to distinguish genuinely antecedent information from contemporaneous or retrospective records. Third, theoretically relevant employee perceptions may be missing or inadequately measured. In particular, the dataset does not contain validated measures of appraisal fairness or POS, while the provenance and psychometric properties of the available Engagement Score are undocumented. These explanations cannot be separated empirically with the present data. The chance-level performance therefore does not demonstrate that appraisal fairness, POS or engagement explain turnover, nor does it validate H1–H3. Those relationships remain theoretical propositions requiring independent primary-data testing. Equally, the findings do not establish that administrative HR variables are generally incapable of supporting turnover prediction; they show only that the leakage-controlled fields retained in this particular dataset failed to provide useful discrimination.

The result nevertheless has an important decision-support implication. An operational HR analytics system requires a mechanism for recognising when the available information is inadequate and withholding predictive recommendations accordingly. In the proposed architecture, the present models would fail the performance-validation gate and would therefore be rejected for employee-level decision use. The appropriate output would be a diagnostic assessment identifying data and measurement deficiencies rather than a set of employee risk scores. This finding also clarifies the relationship between the conceptual and analytical components. The conceptual framework identifies theoretically meaningful perceptual information that an integrated HR information system should consider collecting, whereas the analytics case illustrates the limits of relying on administrative records alone. The two components therefore contribute to a common information-design problem without treating the analytics case as empirical validation of the conceptual model.

6.2 Implications for Organisational Decision Making

The principal practical implication of the illustrative case is not that the current models can identify employees who are likely to leave, but that HR decision-support systems require stronger data and validation before employee-level predictions can be considered. After post-outcome and temporally ambiguous variables were excluded, neither the RF nor logistic-regression model demonstrated useful out-of-sample discrimination. The present analysis therefore does not support individual risk scoring, targeted retention intervention or automated personnel decisions. At its current level of evidence, the analytics component can support only diagnostic learning about data adequacy and modelling limitations. HR managers may use such analyses to identify weaknesses in data collection, determine which theoretically relevant constructs are absent, and specify requirements for future workforce analytics. Any employee-level predictive application would require appropriately time-stamped longitudinal data, a clearly defined prediction point, external validation, probability calibration, stable out-of-sample performance, subgroup fairness assessment and explicit human oversight. The decision-support framework therefore treats model output as conditional evidence rather than as a personnel decision. When minimum data-quality, performance or fairness requirements are not satisfied, the appropriate system response is to withhold employee-level recommendations and return the analysis for data improvement, model revision or further validation.

6.3 Ethical and Regulatory Implications

Before implementing data-driven models for employee turnover prediction, organisations must consider the ethical and regulatory implications of using such systems in employment-related decisions [41]. The inclusion of demographic characteristics, such as age, gender and race, may introduce risks of algorithmic bias and discriminatory outcomes, particularly when predictive models reproduce patterns embedded in historical employment data. Organisations should therefore evaluate model fairness, examine prediction errors across relevant demographic groups, and establish appropriate safeguards against discriminatory decision-making [41, 53]. Transparency concerning employee-data collection, processing and interpretation is essential for responsible HR analytics. Organisations should communicate the purpose and limitations of predictive systems and establish governance procedures that promote accountability, fairness and human oversight [53, 54]. Where applicable, the European Union's General Data Protection Regulation (GDPR) requires organisations to establish an appropriate lawful basis for processing personal data, observe principles of purpose limitation and data minimisation, implement appropriate security measures, and comply with relevant safeguards governing automated decision-making [55].

Accordingly, predictive analytics should support rather than replace human judgement in employment-related decisions. Organisations should avoid relying exclusively on algorithmic outputs when making decisions that could adversely affect employees, particularly when predictive models demonstrate limited discriminative performance [54]. Within the proposed framework, ethical governance, transparent data practices and human oversight are therefore essential components of responsible HR decision support. The practical contribution of this framework lies in guiding the development of accountable HR analytics systems rather than identifying employees for automatic retention or disciplinary interventions.

In applied settings, HR analytics should be used to identify aggregate patterns, generate questions for further investigation and support professional judgement. Any employee-level predictive application would require clearly defined prediction timing, external validation, probability calibration, subgroup fairness assessment, analysis of false-positive and false-negative consequences, and continuous monitoring for changes in data quality or model performance. Where sensitive demographic attributes are available, they should be subject to explicit governance and fairness review rather than being used uncritically as decision variables.

7 Future Directions

Future research should prioritise stronger research design and data quality before introducing more complex predictive algorithms. Longitudinal studies should establish a clearly defined observation point at which all predictor information is demonstrably available before the subsequent employee outcome. Such datasets should combine administrative workforce records with validated measures of theoretically relevant employee perceptions, including performance appraisal fairness, POS and employee engagement. Future studies should also directly test the proposed conceptual relationships using validated psychometric measures and compare the moderating specification of POS with plausible mediation and antecedent models. For the analytics component, prospective models should be evaluated against simple baselines using independent validation samples, calibration analysis and subgroup fairness assessments. Individual-level risk scoring or a personalised retention intervention should be considered only if future models demonstrate stable and practically meaningful out-of-sample performance, satisfy predefined fairness and governance requirements, and undergo accountable human review. More complex machine-learning methods should therefore be introduced only when justified by the quality, temporal structure and predictive information contained in the data.

8 Limitations

Several limitations should be recognised. First, the conceptual relationships among appraisal fairness, POS and employee engagement are not empirically tested in the present study because the secondary dataset does not contain validated measures of appraisal fairness or POS. Although the dataset includes a variable labelled Engagement Score, its underlying items and psychometric properties are not documented, and it is therefore not treated as a validated engagement construct. Second, the source dataset does not document a specific organisational, industrial or geographical population, limiting substantive generalisation. Third, the absence of a clearly defined longitudinal prediction point restricts the use of several administrative, survey and training variables for prospective turnover prediction. Fourth, the leakage-controlled models demonstrated essentially chance-level discrimination, indicating that the available administrative variables are insufficient for reliable employee-level forecasting. Finally, the illustrative case does not provide external validation, calibration analysis or longitudinal monitoring.

Future research should collect primary data using validated scales for performance appraisal fairness, POS and employee engagement and directly test the proposed moderation model. Longitudinal designs should align perceptual measures and administrative variables at clearly defined prediction points and evaluate alternative theoretical specifications, including moderation, mediation and antecedent models. Future HR analytics research should additionally incorporate external validation, fairness auditing, calibration and continuous model monitoring before decision-support systems are considered for organisational deployment.

9 Conclusion

This study develops a human-centred HR decision-support framework linking performance appraisal fairness, POS and employee engagement with responsible workforce analytics. The theoretical component proposes that appraisal fairness and POS are positively associated with engagement and that POS may strengthen the fairness–engagement relationship. These propositions remain to be tested using validated primary measures.

The illustrative analytics case provides an important systems-level insight into the limitations of administrative HR data for employee turnover classification. Following the exclusion of post-outcome and temporally ambiguous variables, the leakage-controlled models demonstrated approximately chance-level discriminatory performance, with ROC-AUC values of 0.507 for RF and 0.475 for LR. These findings indicate that the retained administrative variables did not provide sufficient discriminatory information for reliable employee-level turnover classification in the present dataset.

Ethical Approval

The empirical illustration uses a publicly available HR dataset and does not involve direct interaction with human participants by the authors. However, the source file contains employee-level demographic and employment attributes, including age-related information, gender, race and marital status, which would constitute sensitive or legally protected information in many real-world employment contexts. The provenance documentation available with the public dataset is insufficient to establish whether the records represent real or simulated employees; consequently, the data are used strictly for methodological illustration and no claims are made regarding identifiable individuals or a specific organisation. Real-world implementation of comparable HR analytics would require appropriate privacy protection, data minimisation, employee transparency or notification where required, assessment of demographic bias, meaningful human review, and safeguards against discriminatory or punitive decisions based solely on algorithmic outputs.

Data Availability

The dataset used in the illustrative analytics case is publicly available through Kaggle as the HR Analytics Dataset (file: Messy_HR_Dataset_Detailed.csv). The dataset was accessed on 16 July 2026. The source URL is: https://www.kaggle.com/datasets/hopesb/hr-analytics-dataset?select=Messy_HR_Dataset_Detailed.csv.

Conflicts of Interest

The author declares no conflicts of interest.

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Appendix

Table A1. Dataset variables, definitions, missingness, and treatment in the revised analysis

Variable	Definition/Type	Missing	Revised Treatment/Role
Unnamed: 0	Row index; integer	0%	Removed
FirstName	Employee first name; text	0%	Identifier; removed
LastName	Employee surname; text	0%	Identifier; removed
StartDate	Employment start date	0%	Parsed as date; descriptive only
ExitDate	Employment exit date	48.9%	Used to define retrospective exit status; never a predictor
Title	Job title; categorical	0%	One-hot encoded in sensitivity model

Supervisor	Supervisor name; text	0%	High-cardinality identifier; removed
ADEmail	Employee email; text	0%	Identifier; removed
BusinessUnit	Business unit; categorical	0%	One-hot encoded
EmployeeStatus	Current/termination status; categorical	0%	Post-outcome information; excluded
EmployeeType	Contract/full-time/part-time	0%	One-hot encoded
PayZone	Compensation zone	0%	One-hot encoded
EmployeeClassificationType	Employment classification	0%	One-hot encoded
TerminationType	Type of termination	0%*	Post-outcome; excluded
TerminationDescription	Narrative termination reason	48.9%	Post-outcome; excluded
DepartmentType	Department category	0%	One-hot encoded
Division	Organisational division	0%	One-hot encoded
DOB	Date of birth	0%	Used only for descriptive age calculation; not a predictor
State	State/location category	0%	One-hot encoded
JobFunctionDescription	Job-function category	0%	One-hot encoded
GenderCode	Gender category	0%	Sensitive attribute; descriptive/fairness audit only
LocationCode	Numeric location identifier	0%	High-cardinality quasi-identifier; excluded
RaceDesc	Race category	0%	Sensitive attribute; descriptive/fairness audit only
MaritalDesc	Marital-status category	0%	Sensitive attribute; descriptive/fairness audit only
Performance Score	Categorical appraisal rating	0%	One-hot encoded in sensitivity model
Current Employee Rating	Current rating, 1–5	0%	Ordinal/numeric predictor in sensitivity model
Employee ID	Employee identifier	0%	Identifier; removed
Survey Date	Survey-record date	0%	Temporally ambiguous; excluded from model
Engagement Score	Engagement score, 1–5	0%	Descriptive only; validation undocumented
Satisfaction Score	Satisfaction score, 1–5	0%	Descriptive only
Work-Life Balance Score	Work-life balance score, 1–5	0%	Descriptive only
Training Date	Training-record date	0%	Temporally ambiguous; excluded
Training Program Name	Training programme category	0%	Excluded from prospective model
Training Type	Training type	0%	Excluded from prospective model
Training Outcome	Training outcome	0%	Excluded from prospective model
Location	Free-text location	0%	High-cardinality field; excluded
Trainer	Trainer identifier/name	0%	High-cardinality field; excluded
Training Duration (Days)	Training duration	0%	Excluded owing to temporal ambiguity
Training Cost	Training expenditure	0%	Excluded owing to temporal ambiguity

Note: DOB = date of birth; ID = identifier; Unk = unknown. *Although TerminationType contains no conventional missing values, 1,467 of the 3,000 unique observations (48.9%) are coded as "Unk"; the variable is nevertheless excluded because termination information is post-outcome.