



Enhancing Workplace Decision-Making through EQ-Based Artificial Intelligence: A Human-Centric Approach

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Abstract. AI has brought about enormous changes in the decision-making process at the workplace since it allows data-driven insights and predictive analytics. Nevertheless, typical AI systems do not have emotional intelligence (EQ), which restricts their efficacy in multi-faceted human-centered situations. This paper discusses the application of EQ in AI systems to facilitate workplace decision-making, especially in Human Resource Management (HRM). The research, based on a mixed-method design that involves survey results from HR professionals and an EQ-enabled AI prototype model, reveals that EQ-based AI systems can positively influence decision accuracy, employee engagement, and organisational performance. The results emphasize that AI based on EQ not only improves rational decision-making but also incorporates empathy, ethical factors, and understanding of contexts. The paper adds to the developing sphere of human-centric AI and offers practical suggestions to organisations aiming to streamline workplace decision-making.

Keywords: Emotional Intelligence, Artificial Intelligence, Decision-Making, HRM, Human-Centric AI, Workplace Analytics

1. Introduction

The paper contributes in three main ways: (1) EQ-AI Framework for HRM: a new prototype that integrates Natural Language Processing (NLP) sentiment analysis with Random Forest decision trees, making it possible to predict the signals of emotional intelligence (EQ) in unstructured text-based data, and generate actionable EQ scores for HRM; (2) Empirical Validation: conducted a validation study using a mixed-methods approach (150 survey participants, 20 semi-structured interviews, and AI model benchmarking), demonstrating statistically significant improvements in decision making, employee engagement, and retention rates compared to traditional approaches to AI; and (3) A Human-centric AI Design Paradigm: practical design guidelines and empirical evidence were provided to help incorporate affective and ethical considerations into algorithmic decision making that bridge the gap between affective computing theory and HRM practice.

In the modern dynamic organisational environment, strategic goals and competitive advantage are important and effective decision-making is essential. Artificial Intelligence (AI) has become a potent technology that can be used to improve the decision-making process at the workplace, utilizing large data sets, predictive modelling, and automation. Companies are turning more and more to AI to make hiring decisions, conduct performance appraisals, and plan their workforce [1].

Although these developments have been made, the traditional AI systems remain largely logic based and not able to comprehend the emotional and social contexts [2]. The decision-making processes in the workplace are not rational but are affected by human emotions, interpersonal relations and organisational culture [3]. People do not

always make efficient, but effective and ethical decisions as AI systems lack emotional intelligence [4].

The capacity to sense, comprehend and control emotions is called Emotional Intelligence (EQ), which is critical in making decisions in human beings [5]. An alternative approach, known as EQ-based AI, can be used to address the issue of the lack of emotional sensitivity in AI by integrating EQ into the systems, thereby enabling them to be more analytical and predictive.

This study aims to:

- Test the efficacy of EQ-based AI in decision-making in the workplace.
- Compare EQ-based AI and conventional AI systems.
- Determine its effects on HRM performance including recruitment, engagement and retention.

2. Literature Review

2.1 Artificial Intelligence in Workplace Decision-Making

AI has become a vital facilitator of data-driven decision-making in contemporary organisations. Increased speed, accuracy, and scalability of decision-making: AI systems can process extensive datasets and detect complex patterns [6]. HRM predictive analytics and automation are some of the applications of AI that have changed the process of recruitment and workforce planning [7]. Despite these developments, researchers note that there is an efficiency-empathy trade-off, as these decisions made by AI do not always consider emotions and human context [8]. Such a restriction may result in less trust between employees and dehumanisation of the processes in the workplace [9]. As a result, the necessity to include emotional intelligence in AI systems to improve the quality of decisions is growing.

2.2 Emotional Intelligence in Organisational Contexts

Emotional Intelligence (EI) as proposed by Goleman is the skill to detect, comprehend, and manage feelings in self and others [10]. According to Mayer and Salovey, EI is a cognitive-emotional skill that affects decision-making and relations between individuals [11]. Empirical studies show that EI has a strong influence on the effectiveness of leadership, job satisfaction, and organisational performance [12, 13]. Emotionally intelligent decision-making enhances HRM outcomes in the areas of recruitment, conflict resolution, and employee engagement [12]. Therefore, the introduction of EI in technological systems can be potentially instrumental in improving the workplace decision-making processes.

2.3 Human-Centric and Ethical AI

Human-centric AI focuses on the alignment of AI systems based on human values like fairness, transparency, and accountability [14]. Ethical AI models emphasize the need to avoid bias, be explainable, and maintain the trust the user has in the decisions made by the algorithm [15]. AI systems used in HRM have to strike an equilibrium between efficiency and relational and ethical factors. It is found that employees tend to believe in AI systems more when they believe it to be fair, transparent, and aligned to human values [16]. Thus, the inclusion of emotional intelligence in AI technologies is a logical continuation of human-centred AI principles.

2.4 EQ-Based AI and Affective Computing

The EQ-based AI incorporates the emotional intelligence in machine systems based on the technologies of affective computing, sentiment analysis, and Natural Language Processing (NLP)[17]. These systems are able to recognize emotional signals in text, speech and behaviour, and thus make decisions based on context [18]. Studies show that AI with emotional intelligence enhances the teamwork and effectiveness of decisions, especially in virtual and hybrid workplaces [19]. Moreover, the sentiment-sensitive AI solutions have been demonstrated to improve HR analytics by collecting the emotion and behavioural tendencies of the employees [18]. These developments underscore the need to incorporate emotional intelligence into AI-powered decision-making processes.

2.5 AI, Emotion, and Decision-Making in HRM

Recruitment, performance assessment and employee engagement are some of the current applications of AI-based HR systems [28], [29][20]. Although these systems enhance efficiency, they do not appear to be emotionally sensitive and thus tend to make impersonal decisions and lower employee satisfaction [9]. Research has indicated that workers feel that AI-made decisions are less compassionate than human decisions, although they may be objective [21]. Also, algorithmic bias and the absence of the contextual comprehension are also major issues of AI-based HRM [22]. The inclusion of EQ into AI systems can help to overcome these problems by making AI systems more emotionally aware, fairer, and more accepting of the AI-made decisions.

2.6 Research Gap

Despite the plethora of research on AI in HRM and emotional intelligence as a single entity, little evidence has been found on their combination [36], [37][23]. The majority of the existing models are efficiency- and predictive-accuracy based, which overlooks the emotional and social aspects of decision-making [4]. New studies in the area of human-AI collaboration indicate that, when human emotional intelligence is combined with machine intelligence, the outcomes of decisions can be greatly enhanced [24]. Nevertheless, the empirical confirmation of AI systems based on EQ in the workplace settings is still lacking [25]. This paper fills this gap by developing and analyzing an EQ-based AI system to improve decision-making in the workplace, which will become part of the AI and HRM literature.

3. Methodology

3.1 Research Design

To the extent that quantitative measures and qualitative data were sought to obtain, a mixed-method research design was adopted. The methodology allowed triangulated analysis of EQ-based AI systems, which guaranteed statistical results were supplemented with contextual, human insights of HR practitioners in different organisational contexts.

Justification for Mixed-Method Design: A quantitative-only design would have allowed us to report model performance data but not the qualitative factors (contextual and experiential) that HR professionals consider when making AI-supported decisions; these factors are important to understand trust, resistance and fairness. In contrast, interviews alone cannot offer the statistical validity required to

assess an AI prototype. The mixed method approach allows the quantitative survey and AI model findings to triangulate each other, while the qualitative interviews explain the why: the survey statistics show what is occurring at population level, while the interview findings provide the why (Creswell & Plano Clark, 2017). The AI model results also triangulate primary data by providing objective evidence at the level of the algorithm to support (or discredit) self-reported perceptions.

Sample Size Justification: The 150 HR professionals surveyed are above the minimum required for regression analysis ($N = 50 + 8m$, where m = number of predictors) as recommended by Tabachnick and Fidell (2013) [26], and greater than the $N \geq 100$ often cited for acceptable factor analysis [27].

Measures to Reduce Bias: We took several measures to reduce potential bias. The online survey was delivered anonymously through an external platform, making it impossible for survey participants to be identified by their employers; this minimizes social desirability bias and increases the likelihood of honest responses. The respondents were assured of the confidentiality of their responses and the same were utilized only for research purpose - voluntary participation. The survey questions were pre-tested by 5 HR practitioners to remove any leading questions and to make it more clear. All interviewees were assured of confidentiality and the transcripts were anonymised prior to analysis and stored on a secure institutional server (as approved by institutional ethics committees). Researchers used reflexivity notes in the process of qualitative coding to reduce confirmation bias.

Table 1. Summarises the key components of the research design.

Component	Details	Purpose
Research Design	Mixed-Method (Quantitative + Qualitative)	Capture breadth and depth of decision-making behaviour
Survey	150 HR professionals across industries	Statistical generalisability across sectors
Interviews	20 senior HR managers (semi-structured)	Contextual and experiential insights
Secondary Data	Organisational reports; AI performance logs	Validation and triangulation of primary data
AI Model	NLP + Sentiment Analysis + Random Forest	EQ-based emotional tone classification
Analysis Tool	SPSS + Accuracy/Precision/Recall metrics	Statistical validation and model evaluation

3.2 Data Collection

Three sources of data were combined: a structured survey of 150 HR professionals, semi-structured in-depth interviews with 20 top HR professionals and secondary data

(organisational performance reports and AI performance logs). The multi-source approach ensured statistical breadth and contextual depth.

3.3 Model Development

The prototype of the AI based on the EQ has been developed with the help of Natural Language Processing (NLP), sentiment analysis and a machine learning based random forest algorithm. The model was used to process the unstructured language data in candidate interviews, employee feedback and internal communications and transformed into actionable emotional intelligence indicators.

EQ Feature Engineering and Scoring: We derived EQ scores from text-based inputs in a multi-step process. First, we pre-processed candidate interview transcripts, employee pulse survey unstructured fields, and HR communication logs with Natural Language Processing (NLP) techniques (tokenization, stop-word removal, lemmatisation). Next, a lexicon-based sentiment analyser (VADER for brief texts; a fine-tuned BERT model for long-form texts) allocated three EQ scores to each segment: positive affect intensity (PAI, 0-1), negative affect intensity (NAI, 0-1), and emotional neutrality index (ENI, 0-1). Third, the following four higher-order EQ dimensions were computed from these signals: (i) Self-Awareness Score (SAS) - extent of first-person emotional expressions; (ii) Empathy Score (ES) - frequency of other-focused and perspective-taking expressions; (iii) Emotional Regulation Index (ERI) - proportion of neutral and positive to negative affect within a time window; and (iv) Social Sensitivity Score (SSS) - interpersonal awareness based on pronoun and relational-verb cues. The four scores constituted the feature vector for the classification model. Two organisational psychologists classified data into three classes (High EQ / Moderate EQ / Low EQ) by consensus coding on 20% holdout set, with agreement (Cohen's κ) was 0.81.

System Architecture / Workflow: The EQ-AI pipeline is a five-stage process: (Stage 1) Raw Input - unstructured text from interviews, feedback and employee communications is ingested. (Stage 2) NLP Pre-processing - text is tokenized, stop words removed, and lemmatized; (Stage 3) Sentiment and Affect Scoring - VADER/BERT assigns PAI, NAI and ENI to each text segment. (Stage 4) EQ Feature Extraction - SAS, ES, ERI and SSS are calculated and combined into a feature vector. (Stage 5) Random Forest Classification - the feature vector is classified into High/Moderate/Low EQ categories, which are then presented to HR decision makers as intelligence signals, alongside traditional performance indicators. An optional human-in-the-loop (HITL) review and override step enables HR to validate and, if needed, manually override model predictions and ensuring human oversight.

Justification for Random Forest over Alternative Models: Random Forest (RF) was chosen as the classification model after benchmarking against Support Vector Machines (SVM), Logistic Regression, K-Nearest Neighbours and a shallow Multi-Layer Perceptron (MLP). RF achieved better performance in terms of accuracy (87%), precision (84%) and recall (82%) on the validation set. The selection was based on three criteria: (i) Interpretability - RF offers feature importance rankings which help HR professionals understand which EQ dimensions were used most to predict an outcome (a requirement for explainable AI[28]); (ii) Small sample robustness - RF can handle moderate sample sizes ($n \approx 150$ -200) and mixed-scale features without overfitting[29] (deep Neural Networks typically require larger labelled samples for generalisation[30]); (iii) Interaction handling - RF captures non-linear interactions between EQ dimensions (e.g., high ES and low ERI) automatically[31], whereas

SVM with a linear kernel cannot capture non-linear interactions and requires a non-linear kernel to do so[32]. SVM with an RBF kernel had comparable accuracy (84%) but produced a black-box result unsuitable for HRM transparency requirements, and was sensitive to the regularisation parameter C. Neural networks were not chosen due to the lack of sufficiently large data, and the considerable computational effort required for relatively small improvements in accuracy.

3.4 Variables

Table 2. Presents the operationalised independent and dependent variables.

Variable Type	Variable Name	Measurement	Scale
Independent	Type of AI System	Traditional AI vs. EQ-Based AI	Nominal (Binary)
Dependent	Decision Quality	Accuracy score (%)	Continuous (0–100%)
Dependent	Employee Engagement	Likert-based engagement score	Ordinal (1–5)
Dependent	Staff Retention	Turnover rate (%); Prediction metrics	Continuous / Ratio

3.5 Data Analysis

Data from quantitative surveys have been analysed statistically using SPSS software and descriptive and inferential analyses have been provided. The performance of the AI model was evaluated using accuracy, precision, and recall measures to prove reliability and generalizability of results in the context of organizations.

3.6 Ethics Statement

This study was carried out in strict compliance with a range of prerequisite ethical standards set by the Institutional Review Board (IRB) of Quantum School of Business. The written and well-informed consent was obtained from the participants before their due participation. There was no compulsion for participation or anonymity, and the respondents were told that the information they provided would only be used for research purposes and that they had the right to withdraw at any time without giving any reason. Survey data was gathered via an external platform (which was secure and anonymous) and was not identifiable by the employers. Interview transcripts were anonymised prior to analysis, and stored on a password protected institutional server, as per institutional data governance policy. The research did not involve vulnerable populations, sensitive personal health data, or deceptive procedures. All procedures have due conformity with the principles of the Declaration of Helsinki and the guidelines of the Committee on Publication Ethics (COPE).

4. Results

The following sections present quantitative and qualitative findings from both the survey analysis and EQ-based AI model evaluation. Results are supported by comparative tables.

4.1 Decision-Making Accuracy

The EQ-based AI system had an overall accuracy of 25% in decision-making compared to traditional AI. The improvement was most evident in screening recruits and performance appraisals where emotional and contextual clues were decisive.

Table 3. shows the comparative accuracy results in major decision areas.

Decision Domain	Traditional AI (%)	EQ-Based AI (%)	Improvement (%)
Recruitment Screening	62	85	▲ 23
Performance Evaluation	65	88	▲ 23
Conflict Resolution	58	79	▲ 21
Workforce Planning	70	89	▲ 19
Overall (Average)	64	85	▲ 25

Accuracy Gain Explanation: The 25% average performance gain over traditional AI methods can be explained by three factors. First, the traditional AI baseline in the tested domains (62-70% accuracy) was deliberately established by reference to rule-based and logistic-regression baselines rather than the latest deep-learning models, as the aim of the study is to assess the contribution of emotional intelligence features specifically, rather than general ML advancement. Second, the EQ feature vector introduces dimensions that are not captured by traditional AI systems' numeric and categorical features (e.g., traditional HRM data does not capture affective tone, empathy, or emotional regulation cues, so their inclusion greatly increases the discriminative capacity of the classifier). Third, candidate screening and employee performance evaluation are text-intensive applications where emotional and contextual cues in language are highly predictive (e.g., cultural fit, conflict potential), but traditional AI systems that only access the structured HR metrics (i.e., non-linguistic features) cannot make use of these cues, thus establishing an upper bound on accuracy. These gains are admittedly specific to text-intensive HRM; in decision-making tasks with structured, numerical features, the gain would be less pronounced.

4.2 Employee Engagement

Table 4. gives a dimension-by-dimension analysis of pre- and post-deployment scores.

Engagement Dimension	Pre-Deployment	Post-Deployment	% Change
Overall Engagement Score	55	85	▲ 54.5%
Job Satisfaction Rating	52	82	▲ 57.7%

Trust in Management/AI	48	76	▲ 58.3%
Feedback Responsiveness	50	79	▲ 58.0%
AI Acceptance Rate	40	72	▲ 80.0%
Early Dissatisfaction Detection Accuracy	41%	78%	▲ 90.2%

4.3 Retention Outcomes

The predictive retention model showed a high level of performance across all validation metrics and demonstrated significant improvement over the traditional AI benchmarks. Turnover dropped to 8.5% after four quarters down from 16.8%.

Table 5. shows the performance and retention pattern of the model.

Metric	Traditional (%)	AI EQ-Based (%)	AI Δ Gain
Accuracy	69	87	▲ 18
Precision	66	84	▲ 18
Recall	63	82	▲ 19
F1-Score	64	83	▲ 19
Turnover Rate (Post-Deployment)	16.8%	8.5%	▼ 49.4%

Explaining Turnover Reduction: The 50% turnover reduction (from 16.8% to 8.5%) in the four post-deployment quarters requires explanation. This is the overall attrition rate at the organizational level in the pilot group over the evaluation period, compared to the same departments prior to deployment. A number of potential causal mechanisms may explain the scale of this improvement: (i) the EQ-AI system drew attention to signals of emotional dissatisfaction from pulse surveys and communication logs, allowing human resources (HR) to engage in retention conversations prior to decision-making to leave an organization ; (ii) the model also improved hiring decisions by weighing cultural and emotional fit; and (iii) generally higher perceptions of fairness and transparency in AI-enabled HR decisions (Table 6 shows trust scores improve from 2.8 to 4.5) may have independently reduced disengagement-based quitting behavior. However, as mentioned below, these findings are from a prototype deployment in a single organisational environment, and should be replicated for generalisations.

Correlation vs. Causation Caveat: The findings on the associations between EQ-AI deployment and improved engagement and retention should be interpreted cautiously. The design of the study is not a randomized controlled trial; pre-post changes in a single group are vulnerable to the influence of other changes in the organization (e.g., personnel management issues, salary changes, or economic factors during the study period). Thus, the improvement outcomes should be interpreted as strong

correlational evidence of co-occurrence, but not definitive evidence for causal relationships. To demonstrate a causal link, a quasi-experimental design with time-matched controls, or ideally a longitudinal multi-site RCT, would need to be used[33]. The current evidence is consistent with EQ-AI being the cause of the improvements described, and the plausibility of the mechanisms outlined above enhances the inference; but future studies should apply causal inference methods to disentangle the impact of EQ-AI from other factors.

4.4 Qualitative Findings

The quantitative data were supported by the interview responses from the HR managers, which had a consistent set of themes. The ratings of EQ-based AI were significantly higher in all perceptual dimensions than traditional AI systems. The summary of the major qualitative themes and the rating (n = 20 HR managers) is presented in Table 6.

Table 6. HR Manager Ratings-Qualitative Perception Themes (Likert Scale 1–5)

Qualitative Theme	Trad. AI (1–5)	EQ-AI (1–5)	Key Manager Insight
Fairness in Decisions	3.1	4.4	EQ-AI reduced perceived bias in hiring
Trust in AI System	2.8	4.5	Emotional context increased system credibility
Cultural Alignment	3.0	4.3	Decisions better reflected company values
Transparency Perceived	2.6	4.1	HR felt more informed about AI rationale
Ease of AI Adoption	3.3	4.2	EQ interface improved user acceptance

5. Discussion

The findings confirm that EQ-based AI provides a substantially richer approach to decision-making in the workplace than conventional AI. The system does not focus exclusively on data-driven models but also emotionally and contextually intelligent. In addition to the ability to achieve efficiency, EQ-based AI makes more accurate, empathetic and ethical decisions, essential in human-centric organizational contexts.

How Survey and AI Model Findings Complement and Conform: The study was designed to ensure that the survey and AI model findings complement, and not just corroborate, each other. Table 6 shows HR professionals' perception of EQ-AI (e.g., fairness, trust, cultural fit), whereas Table 5 shows objective, algorithmically-derived metrics of the performance of the AI model (e.g. accuracy, precision, recall). The level of consistency between the two sources of the evidence (the correlation between high HR-perceived fairness (Table 6, 4.4/5) and enhanced objective decision-making accuracy (Table 3, 85% vs. 64%) is triangulation. As both streams meet, throughout this study, our confidence in the results is greatly increased. Finally, the qualitative interview themes (e.g., "emotional context increased system credibility") offer

explanatory insights that the AI model cannot provide, and the AI model provides objective performance metrics that ensure qualitative perceptions are based on actual system performance, rather than just expectations.

Evidence Base for Trust and Decision-Quality Claims: The study provides multifaceted evidence to the claims that EQ-AI boosts trust and the quality of decisions. On trust: HR managers' average rating on "Trust in AI System" increased from 2.8 to 4.5 on a 5-point Likert scale (Table 6), paralleled by existing research that shows perceived transparency of algorithms and perceived fairness are the main predictors of trust of an AI system [34]. AI Acceptance Rate from 40% to 72% (Table 4) operationalises trust via behavioural acceptance, not just self-rated trust. On decision quality: the 25% increase in accuracy in Table 3 is a model-level metric benchmarked against expert-coded ground truth (not a self-reported metric) and is complemented by F1-scores of 0.83 on the retention prediction task (Table 5), which indicates that precision and recall are balanced. These confirmatory quantitative measures offer better evidence than single measures.

Model Failure Modes and Limitations of the EQ-AI System: AI models are not optimal across all use cases, so it is critical to understand the limitations of the EQ-AI system. We identified three patterns of failure. First, the model was sensitive to irony and culturally loaded emotional cues: text with irony or implicitly expressed cultural affect cues (found in high-context cultures) was reliably misclassified, as existing lexicon-based sentiment analysis software was trained mainly on Western, English corpora [35]. Second, model performance diminished when the length of input text was extremely short (fewer than 20 tokens), because EQ feature extraction relies on text context; the model produced uncertain ERI and SSS values for single-sentence feedback forms. Third, the model was slightly exhibited a slight positive bias on tasks that required performance evaluation: employees who wrote longer, more elaborated feedback was given higher scores on empathy features, introducing a potential proxy for educational attainment that could lead to adverse impact if not adjusted through bias-auditing methods. These findings highlight the need for human involvement in model practices, especially in critical decision-making (e.g., promotion or termination).

Scalability Considerations: The current prototype has been tested in a mid-sized pilot deployment (200-1,500 employee organisations). When the system is deployed in large organisations (10,000+ employees), there are different considerations. High employee communications volumes require either GPU-accelerated inference servers for real-time NLP processing or batch processing for asynchronous inference [36, 37], increasing deployment costs. Architecturally, the linguistically varied text from large organizations across departments, locations and channels (email, chat, HR software) requires domain-specific language models which must be retrained as organizational language changes [38]. Governance too is more complex: privacy regulation (e.g., GDPR Article 22 safeguards for automated decision-making) [39],[40], and explainability requirements grow for decisions affecting large populations [41, 42]. Future research should evaluate the system in a staged roll-out for large organizations, starting with low-stakes applications (e.g., analysis of anonymous pulse surveys), and then moving to high-stakes decision support.

Practical Challenges and Real-World Deployment: Practical Considerations in Deploying EQ-AI: There are a number of practical issues to consider in the transition from prototype to production deployment. Communication Cost: the deployment of EQ-AI to workforce members requires clear communication of data collected, EQ

score calculation, and decision-making impact. If not, employees might regard the system as a surveillance tool, suppressing open communication and so reducing the quality of the data used to train the model. This study has shown that while pre-implementation information sessions and AI transparency statements are required, ongoing communication and feedback loops are critical. Integration and Deployment: existing HRM systems are often legacy systems with low API extendibility, making integration with NLP-based pipelines more difficult; customised middleware solutions add 3-6 months to the deployment process. Organisational differences in data quality (e.g. survey response rates, retention of communication logs, and HR information system architecture) can significantly impact the model's accuracy unless data quality audits are conducted before deployment. Employee Opposition: HR practitioners used to rely on intuition may initially resist, or over-rely upon, the AI-based EQ scores; training in human-in-the-loop decision-making and role clarity regarding the use of model predictions and human judgement is required.

5.1 Theoretical Implications

The present research has significant contributions to the existing theory in three areas which are interrelated. First, it generalises Emotional Intelligence theory (Goleman [10]; Mayer and Salovey [11]) outside the human mind into artificial intelligence, showing that EQ concepts can be computerised. Second, it promotes human-oriented AI systems, aligning with the principles of human-centered AI [14], it moves the decision-making models in HRM forward by illustrating the importance of considering the affective dimensions of the algorithmic process, which has traditionally been dominated by logic and statistical modelling [7].

5.2 Practical Implications

The potential practical usefulness of EQ-based AI to organisations is enormous. Implementation of EQ-based AI systems can help organisations better hire employees by adding contextual and emotional cues to the process of assessing candidates; boost employee satisfaction and trust in AI-based practices; and decrease turnover rates by retaining employees more efficiently through more accurate and empathetic retention modelling.

5.3 Ethical Considerations

Although AI based on EQ has some significant advantages, the implementation of AI also has some significant ethical implications that companies should take responsibility in addressing. The aggregation and processing of the emotional manifestations of employees pose a serious privacy threat [43, 44]; organisations need to have powerful data governance policies to safeguard the personal sensitive information. Without strict ethical supervision, emotional data may be used to spy on the person or discriminatory profile [43, 44]. The employees are entitled to know how the AI systems assess their emotional reaction; the explainability mechanisms and accountability framework should thus be made clear to preserve trust and adherence to ethical AI practices [45].

Conclusion

This research confirms that the AI based on EQ is highly effective in boosting workplace decision-making as it combines analytical intelligence with emotional sense. The empirical results indicate that EQ-based AI can be a useful tool in the contemporary organisation as it has proven to increase decision quality, employee

engagement, and retention results in a measurable way. The incorporation of the concepts of affective computing, NLP, and the use of the Random Forest classification as a single EQ-AI tool is a significant move towards human-centric AI in HRM.

Limitations

Like a range of advantages, the study also has a few limitations. The sample used (150 survey respondents and 20 interviewees) limits the generalisability of results. The test was performed with a prototype model instead of a commercial deployment. The study was narrowed down to a specific number of industries; cross-sector generalisability still needs to be explored.

Research Validity Enhancing: To enhance the study's internal and external validity, some design decisions were made and are noted here. Internal validity was strengthened by data triangulation (three separate sources of data: survey, interviews and AI performance metrics) and the use of objective (not self-reported) algorithm-level performance measures. The inter-rater agreement on EQ class labels (Cohen's $\kappa = 0.81$) suggests construct operationalisation was strong. Some external validity is limited by the purposive sampling and English language, single country data set. The instrument validity of the survey was enhanced through the face validity tests with a panel of five HR experts before it was used, and by ensuring that Cronbach's alpha for multi-item engagement scales met the criterion of $\alpha \geq 0.70$. However, the system prototype and the pilot scope limit the results to being indicative. The research should be considered as proof-of-concept evidence to inform larger-scale experimental trials, not as an evaluation of a product ready for deployment.

Future Research

Future directions of research involve: (i) extensive empirical research in different organisational and cultural settings; (ii) cross-cultural examination of EQ-based AI acceptance and performance; and (iii) the combination of the framework proposed with advanced generative AI models to further develop emotion reasoning abilities.

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Competing Interests

The authors herewith declare that they have no competing interests in the study. Neither author has received funding, employment, consultancy, stock ownership, honoraria, patents, or other financial interests of any kind that could have impacted the design, conduct, reporting, or publication of this research.

Data Availability Statement

Because of the confidentiality agreements made by the survey and interview participants when the data were gathered, it is not possible to make the data publicly

available. Anonymized and aggregated quantitative information from the survey (n = 150) will be made available by the corresponding author, should this be requested and reasonable on the basis of institutional ethics. The relevant author will be able to share the logs of the AI model performance for benchmarking if reasonably requested.

Author Contributions

Lokesh Kumar: Conceptualisation, Methodology, Data Collection, Formal Analysis, Writing – Original Draft. Manish Srivastava: Literature Review, Validation, Writing – Review and Editing, Supervision. Both authors have read and approved the final version of the manuscript.

References

1. Matin, A.: Embedding Artificial Intelligence in Next Generation Human Resource Development Implementations. *International Journal of Advanced engineering Management and Science*. 11, 140–148 (2025). <https://doi.org/10.22161/ijaems.114.17>
2. Gonier, D., Adduci, A., LoCasio, C.: Cross Fertilizing Empathy from Brain to Machine as a Value Alignment Strategy. *arXiv (Cornell University)*. (2023). <https://doi.org/10.48550/arxiv.2312.07579>
3. Ibneatheer, M. ur R., Rostan, P., Rostan, A.: Internal processes in decision-making (mental, emotional, cultural, ethical and spiritual) of Afghan business leaders. *PSU Research Review*. 7, 33–50 (2021). <https://doi.org/10.1108/prr-10-2020-0037>
4. Shukla, A., Algnihotri, A., Singh, B.: Analyzing How AI And Emotional Intelligence Affect Indian IT Professional's Decision-Making. *EAI Endorsed Transactions on Pervasive Health and Technology*. 9, (2023). <https://doi.org/10.4108/eetpht.9.4654>
5. Sharma, R., Dhanta, R., Solomon, D.D.: The Role of Emotional Intelligence in Effective Leadership and Decision-Making in Business Management. In: *Advances in logistics, operations, and management science book series*. pp. 98–112. Routledge (2023)
6. Russell, S., Norvig, P.: *Artificial Intelligence: A Modern Approach*. Pearson (2021)
7. Tambe, P., Cappelli, P., Yakubovich, V.: Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. *California Management Review*. 61, 15–42 (2019). <https://doi.org/10.1177/0008125619867910>
8. Lee, M.K.: Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society*. 5, (2018). <https://doi.org/10.1177/2053951718756684>
9. Sadeghi, S.: Employee Well-being in the Age of AI: Perceptions, Concerns, Behaviors, and Outcomes. *arXiv (Cornell University)*. (2024). <https://doi.org/10.48550/arxiv.2412.04796>
10. Goleman, D.: *Emotional Intelligence: Why It Can Matter More Than IQ*. (1995)

11. Mayer, J.D., Salovey, P.: What is emotional intelligence? In: Emotional development and emotional intelligence. pp. 3–31. Basic Books (1997)
12. Vrba, J.: Emotional Intelligence: Catalyst for enhanced human resource management performance. *World Journal of Advanced Research and Reviews*. 22, 1815–1819 (2024). <https://doi.org/10.30574/wjarr.2024.22.1.1282>
13. Lopes, P.N., Brackett, M.A., Nezlek, J.B., Schütz, A., Sellin, I., Salovey, P.: Emotional Intelligence and Social Interaction. *Personality and Social Psychology Bulletin*. 30, 1018–1034 (2004). <https://doi.org/10.1177/0146167204264762>
14. Shneiderman, B.: Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human–Computer Interaction*. 36, 495–504 (2020). <https://doi.org/10.1080/10447318.2020.1741118>
15. Doshi-Velez, F., Kim, B.: Towards A Rigorous Science of Interpretable Machine Learning. *arXiv (Cornell University)*. (2017). <https://doi.org/10.48550/arxiv.1702.08608>
16. Binns, R., Kleek, M.V., Veale, M., Lyngs, U., Zhao, J., Shadbolt, N.: “It’s Reducing a Human Being to a Percentage.” 1–14 (2018). <https://doi.org/10.1145/3173574.3173951>
17. Thirunagalingam, A., Whig, P.: Emotional AI Integrating Human Feelings in Machine Learning. In: *Advances in computational intelligence and robotics book series*. pp. 19–32. IGI Global (2024)
18. Gelbard, R., Ramon-Gonen, R., Carmeli, A., Bittmann, R.M., Talyansky, R.: Sentiment analysis in organizational work: Towards an ontology of people analytics. *Expert Systems*. 35, (2018). <https://doi.org/10.1111/exsy.12289>
19. Huzooree, G., Yadav, M., Dewasiri, N.J.: AI and Emotional Intelligence in Project Management. In: *Advances in computational intelligence and robotics book series*. pp. 111–130. IGI Global (2025)
20. Leinweber, D.: Stupid Data Miner Tricks: Overfitting the S&P 500. *The Journal of Investing*. 16, 15–22 (2007)
21. Woodruff, A., Anderson, Y.A., Armstrong, K.J., Gkiza, M., Jennings, J., Moessner, C., Viégas, F., Wattenberg, M., Webb, L., Wrede, F., Kelley, P.G.: “A cold, technical decision-maker”: Can AI provide explainability, negotiability, and humanity? *arXiv (Cornell University)*. (2020). <https://doi.org/10.48550/arxiv.2012.00874>
22. Friedler, S.A., Scheidegger, C., Venkatasubramanian, S., Choudhary, S., Hamilton, E.P., Roth, D.: A comparative study of fairness-enhancing interventions in machine learning. 329–338 (2019). <https://doi.org/10.1145/3287560.3287589>
23. Affective Computing Group, MIT Media Lab: Overview of affective computing research. MIT (2020)
24. Kolomaznik, M., Petrik, V., Slama, M.E., Juřík, V.: The role of socio-emotional attributes in enhancing human-AI collaboration. *Frontiers in*

- Psychology. 15, 1369957–1369957 (2024).
<https://doi.org/10.3389/fpsyg.2024.1369957>
25. Ojha, M., Archana, Mishra, A.K., Jyoti, K., Kandpal, V.: Role Of Artificial Intelligence in Working with Emotional Intelligence in Leadership: A Bibliometric Analysis. *E3S Web of Conferences*. 556, 1035–1035 (2024).
<https://doi.org/10.1051/e3sconf/202455601035>
 26. Bujang, M.A., Sa'at, N., Sidik, T.M.I.T.A.B.: Determination of Minimum Sample Size Requirement for Multiple Linear Regression and Analysis of Covariance Based on Experimental and Non-experimental Studies. *Epidemiology Biostatistics and Public Health*. 14, (2022).
<https://doi.org/10.2427/12117>
 27. Zygmunt, C.S., Smith, M.: Robust factor analysis in the presence of normality violations, missing data, and outliers: Empirical questions and possible solutions. *The Quantitative Methods for Psychology*. 10, 40–55 (2014). <https://doi.org/10.20982/tqmp.10.1.p040>
 28. Phillips, P.J., Hahn, C.A., Fontana, P., Yates, A.N., Greene, K., Broniatowski, D., Przybocki, M.A.: Four principles of explainable artificial intelligence. (2021)
 29. Erişkin, L., Köksal, G.: Interactive and nonparametric modeling of preferences on an ordinal scale using small data. *Expert Systems with Applications*. 65, 345–360 (2016).
<https://doi.org/10.1016/j.eswa.2016.08.063>
 30. Aggarwal, U.: Active and Incremental Deep learning with class imbalanced data. *HAL (Le Centre pour la Communication Scientifique Directe)*. (2022)
 31. Strobl, C., Malley, J.D., Tutz, G.: An introduction to recursive partitioning: Rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological Methods*. 14, 323–348 (2009). <https://doi.org/10.1037/a0016973>
 32. Kundu, K., Costa, F., Huber, M., Reth, M., Backofen, R.: Semi-Supervised Prediction of SH2-Peptide Interactions from Imbalanced High-Throughput Data. *PLoS ONE*. 8, (2013). <https://doi.org/10.1371/journal.pone.0062732>
 33. Shadish, W.R., Cook, T.D., Campbell, D.T.: *Experimental and Quasi-Experimental Designs for Generalized Causal Inference*. Houghton Mifflin, Boston (2002).
 34. Shin, D.: User Perceptions of Algorithmic Decisions in the Personalized AI System: Perceptual Evaluation of Fairness, Accountability, Transparency, and Explainability. *Journal of Broadcasting & Electronic Media*. 64, 541–565 (2020). <https://doi.org/10.1080/08838151.2020.1843357>
 35. Sun, J., Ahn, H., Park, C.Y., Tsvetkov, Y., Mortensen, D.R.: Cross-Cultural Similarity Features for Cross-Lingual Transfer Learning of Pragmatically Motivated Tasks. *arXiv (Cornell University)*. (2020).
<https://doi.org/10.48550/arxiv.2006.09336>

36. Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing: Industry Track. (2023). <https://doi.org/10.18653/v1/2023.emnlp-industry>
37. Quan, D., Wang, R., Lian, Z., Wang, N.: Optimizing Large Language Model Scaling with Micro Batch Pipeline and Inference Parallelism. Research Square (Research Square). (2024). <https://doi.org/10.21203/rs.3.rs-4575587/v1>
38. Mathav Raj, J., Kushala, V.M., Warriar, H., Gupta, Y.K.: Fine Tuning LLM for Enterprise: Practical Guidelines and Recommendations. arXiv (Cornell University). (2024). <https://doi.org/10.48550/arxiv.2404.10779>
39. Netter, E.: The human and machine part in “automated” decisions. Proposals for a rewriting of article 22 of the GDPR. HAL (Le Centre pour la Communication Scientifique Directe). (2022)
40. Fabiano, N.: Affective Computing and Emotional Data: Challenges and Implications in Privacy Regulations, The AI Act, and Ethics in Large Language Models. arXiv (Cornell University). (2025). <https://doi.org/10.48550/arxiv.2509.20153>
41. Usmani, U.A., Happonen, A., Watada, J.: Enhancing Artificial Intelligence Control Mechanisms: Current Practices, Real Life Applications and Future Views. In: Lecture notes in networks and systems. pp. 287–306. Springer International Publishing (2022)
42. Haque, A.B., Islam, A.K.M.N., Mikalef, P.: Explainable Artificial Intelligence (XAI) from a user perspective: A synthesis of prior literature and problematizing avenues for future research. Technological Forecasting and Social Change. 186, 122120–122120 (2022). <https://doi.org/10.1016/j.techfore.2022.122120>
43. Mantello, P., Ho, T.M.: Why we need to be weary of emotional AI. AI & Society. 39, 1447–1449 (2022). <https://doi.org/10.1007/s00146-022-01576>
44. Mantello, P., Ho, T.M.: Emotional AI and the future of wellbeing in the post-pandemic workplace. AI & Society. 39, 1883–1889 (2023). <https://doi.org/10.1007/s00146-023-01639-8>
45. Kumar, J.R.R., Kalnawat, A., Pawar, A.M., Jadhav, V.D., Srilatha, P., Khetani, V.: Transparency in Algorithmic Decision-making: Interpretable Models for Ethical Accountability. E3S Web of Conferences. 491, 2041–2041 (2024). <https://doi.org/10.1051/e3sconf/202449102041>

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