

Investigating Emotional Intelligence and Employees' Well-Being in an AI-Enhanced Workplace



Amandeep Gill, Ashish Mathur, Shailendra Singh Bhadouria

Abstract: This study focuses on the connections between employee well-being in AI-enhanced workplaces, integration of artificial intelligence (AI), and emotional intelligence (EI). Data were collected and analyzed from workers in various industries using quantitative methodologies. Positive connections between emotional intelligence (EI) and artificial intelligence (AI) are evident in the results, suggesting a possible alignment in AI-driven contexts. The slight negative correlations between AI and well-being indicate intricate connections. While component analysis identifies distinctive EI and AI factors, cluster analysis reveals distinct employee profiles based on EI, AI, and well-being scores. One of the implications is the importance of integrating emotional intelligence (EI) and artificial intelligence (AI) to enhance employee well-being. Future studies may examine these constraints and investigate intervention strategies for more healthful workplaces in the AI era. This research provides valuable insights into the complex dynamics of EI, AI, and wellbeing, offering guidance for organisational practices and future research endeavours.

Keywords: Artificial Intelligence, Emotional Intelligence, Workplace, Employees' Well-Being, Employees' Health.

I. INTRODUCTION

In recent years, an increasing body of literature has delved into the intricate relationships between emotional intelligence (EI) and artificial Intelligence (AI) and its impacts on employee performance and retention across various industries, notably within the hospitality sector [1]. while AI significantly modifies employee performance, emotional intelligence significantly affects employee retention, which has been studied extensively. Four components of employee emotional intelligence are management, social awareness, relationship selfawareness, and self-management [2].

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Suggests a strong correlation between these components and workplace effectiveness [3]. Highlight the positive correlation between emotional intelligence and organisational commitment, as well as its role in enhancing productivity. Additionally, [4] suggests that emotional intelligence tests can serve as effective selection strategies due to their predictive ability for job performance.

Integrating AI into human resource management (HRM) practices has become imperative, especially in response to the challenges posed by the COVID-19 pandemic [5]. outline how AI-driven solutions, utilizing data mining, predictive analytics, and machine learning, have streamlined HRM functions, improving employee well-being and cost savings. As highlighted by [6], implementing AI presents challenges, particularly in ensuring clarity in defining "worker well-being" and addressing technical constraints [7]. emphasize the importance of developing worker-centered, data-driven wellbeing technologies while considering social implications and organizational culture. The literature highlights the complex interplay between emotional intelligence, artificial intelligence, and employee outcomes, underscoring the need for a nuanced understanding to enhance organisational effectiveness and wellbeing. These insights are crucial for informing HRM strategies and fostering a supportive work environment ([8], [9], [10], [11], [12], [13], [14], [15], [16]).

II. OBJECTIVES

Explore the relationships between artificial intelligence 1 (AI), emotional intelligence (EI), and the well-being of employees.

Hypothesis

1. (H0): Emotional intelligence (EI) and AI integration (AI) do not significantly correlate.

(H1): Emotional intelligence (EI) and AI integration (AI) correlate.

2. (H0): Well-being (W) and AI integration (AI) do not significantly correlate.

3. (H1): Well-being (W) and AI integration (AI) are significantly correlated.

III. RESEARCH METHODOLOGY

This study employs a quantitative research approach to gain a deeper understanding of the relationships between employee well-being in AI-enhanced workplaces, emotional intelligence (EI), and the integration of AI. The design enables the

systematic collection and analysis of numerical data to determine correlations between variables.

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The study's participants are workers from various organisational environments and industries where AI integration is a standard practice. A purposeful sample strategy was employed to select individuals who had experience working with AI technologies. Surveys and questionnaires are used to collect data from participants on their emotional intelligence scores, opinions about the integration of AI in the workplace, and self-reported wellbeing metrics. For this study, 157 repossessions were collected from working employees. To ensure ethical and informed voluntary participation and maintain participant confidentiality, informed consent must be obtained from participants prior to data collection. The confidentiality and privacy of participants in data collection are safeguarded by adhering to ethical rules concerning data storage, processing, and analysis. Variables and Measurements: Emotional intelligence (EI) is measured using established scales that evaluate several facets of emotional perception, understanding, and management, such as the Trait Emotional Intelligence Questionnaire (TEIQue) or the Emotional Intelligence Appraisal (EIA). Integration of Artificial Intelligence (AI): Measured by asking participants how they feel about AI-driven procedures, automation tools, and machine learning applications used in their workplaces.

Well-being is assessed using multidimensional tools that consider the social, mental, and physical aspects of well-being, such as the WHO-5 Well-being Index. Analysing Data: Reliability analysis: Uses Cronbach's alpha, standardized alpha, and Guttman's lambda to evaluate the internal consistency of measuring scales for well-being, EI, and AI. Correlation Analysis: Depending on the distribution of variables, Pearson's correlation coefficient or Spearman's rank correlation coefficient is used to investigate the correlations between Emotional Intelligence (EI), Artificial Intelligence (AI), and wellbeing. Data. In EI and AI, factor analysis was utilized to Determine underlying constructs. Techniques such as principal component analysis and maximum likelihood estimation were employed to extract components and evaluate model fit. Cluster analysis is used to classify individuals based on their well-being, AI, and emotional intelligence (EI) scores. It employs methods such as kmeans clustering to identify unique employee profiles or clusters.

IV. RESULTS

(Table 1) Reliability	Analysis
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Measu	Ra w Al ph a	Stand ardize d Alpha	Gutt man' s Lam bda 6 (SM C)	Averag e Inter- item Correla tion (averag e r)	Signa 1-to- Noise Ratio (S/N)	Alph a Stan dard Erro r (AS E)	Me	Standa rd Deviat ion (SD)	Median R
Interna 1 Consis tency	0.7 5	0.82	0.87	0.18	4.5	0.03 2	10	0.52	0.15

^{95%} confidence boundaries

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Feldt 0.68 0.75 0.82

Duhachek: 0.69, 0.75, and 0.82

The scale demonstrates strong internal consistency, as indicated by the overall reliability analysis. With values of 0.75, 0.82, and 0.87, respectively, Cronbach's alpha, standardized alpha, and Guttman's Lambda 6 scores indicate strong dependability. Dependability is indicated by the average interitem correlation of 0.18 and the signal-to-noise ratio of 4.5. These results imply that the scale has a generally acceptable level of reliability.

(Table 2)	Charac	teristics (of Do	emogr	aphy
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Demographic Variable	Measures	Frequency	Percentage %	
Age	20 - 25	23	14.6 %	
	26 - 30	29	18.4 %	
	31 - 35	37	23.5 %	
	36 - 40	30	19 %	
	above 40	38	24.5 %	
Years of Experience in the Workplace	Less than one year	58	37 %	
	1 - 5 years	23	14.6 %	
	6 -10 years	33	21 %	
	Above ten years	43	27.4 %	
Marital Status	Un- married	45	28 %	
	Married	113	72 %	

The demographic features of age and years of work experience, along with the corresponding frequencies and percentages, are displayed in Table 2. Age distribution:

Age distribution

Most people fall within the age range of 31 to 40, with 19.5% and 23.5% of the population residing in the 36–40 age range. 14.6% are in the 20–25 age range, and 18.4% are in the 26–30 age range. Twenty-five percent (24.5%) of the population is over forty.

Years of Work Experience:

A sizable fraction of people (37%) have worked for less than a year. 21% of respondents have six to ten years of experience, while 27.4% have more than ten years. 1 to 5 years of experience make up 14.6%. In conclusion, most people fall within the age range of 31 to 40, and there is a broad range of experience levels, with a sizable fraction of individuals. Some have less than one year of experience, and others have more than ten years. Marital status:

Table 2 presents demographic information on marital status, specifically regarding the number of unmarried and married individuals, along with their respective frequencies and percentages. Unmarried: There are 45 unmarried individuals, making up 28% of the total population. Married: There are 113 married individuals, accounting for 72% of the Population. Most (72%) of the population is married, while the remaining 28% are unmarried.

In summary, most individuals fall within the age range of 31 to 40, with varying levels of experience.

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Some have less than one year of work experience, while others have more than ten years. Additionally, 72% of the population is married, with the remaining 28% unmarried. (H1): Emotional intelligence (EI) and AI integration (AI) have a Strong Positive Correlation

> print (correlation EI AI)

[1] 0.3310914

There is a positive correlation between emotional intelligence (EI) and AI integration (AI), with a value of 0.3310914. This means that there is a tendency for workplaces with higher AI integration to also have employees with more robust emotional intelligence

(H1): Well-being (W) and AI Integration (AI) are Significantly Correlated Negatively

> print (correlation AI W)

[1] -0.02239911

There is a very weak negative correlation between AI integration (AI) and well-being (W), with a value of -0.02239911.

Factor analysis of Emotional Intelligence (EI) and AI Integration

> print (ei factor)

Factor Analysis using method = miners

Call: fa (r = ei items, factors = 1, rotate = "varimax")

Standardized loadings (pattern matrix) based upon the correlation matrix

MR1 h2 u2 com

EI1 0.32 0.100 0.900 1

EI2 0.53 0.286 0.714 1

EI3 0.30 0.089 0.911 1

- EI4 0.97 0.943 0.057 1
- EI5 0.34 0.114 0.886 1

MR1

SS loadings 1.53

Proportion Var 0.31

Mean item complexity = 1

Test of the hypothesis that 1 factor is sufficient.

Df null model = 10 with the objective function = 0.74 with Chi-Square = 71.05

The degree of the model is 5, and the objective function was 0.12.

- The root mean square of the residuals (RMSR) is 0.08.
- The df corrected root mean square of the residuals is 0.12. The harmonic n.obs is 99, and the empirical chi-square is 13.68 with prob < 0.018

The total n.obs was 99, with a likelihood chi-square of 10.91 and with prob < 0.053

Tucker Lewis Index of factoring reliability = 0.805

RMSEA index is 0.109, and the 90 % confidence intervals are 0 and 0.2 $\,$

BIC = -12.06

Fit based upon off-diagonal values = 0.91

Measures of factor score Adequacy

MR1

Correlation of (regression) scores with factors 0.98 Multiple R-squares of scores with factors 0.95 Minimum correlation of possible factor scores is 0.90 Factor analysis on a set of items labelled EI1 through EI5. Here is the interpretation of the results: 1. Factor Loadings:

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- Factor loadings represent the correlation between each item and the underlying factor extracted by the analysis. There is only one factor extracted, labelled MR1.
- The loadings show the strength and direction of the relationship between each item and the factor.
- For example, E11 has a loading of 0.32 on MR1, indicating a moderately positive correlation.
- EI4 has the highest loading of 0.97, indicating a strong positive correlation.

2. Variance Explained:

• The total variance explained by the factor model is 31%, which means the extracted factor accounts for 31% of the variance in the data.

3. Factor Reliability:

- The Tucker-Lewis Index (TLI) of factoring reliability is 0.805, indicating good reliability.
- The Root Mean Square Error of Approximation (RMSEA) is 0.109, which is somewhat high but acceptable.

4. Model Fit:

- The fit indices indicate that the model fits reasonably well. The off-diagonal fit is 0.91, suggesting a good fit.
- 5. Factor Score Adequacy:
- The correlation of regression scores with factors is 0.98, indicating a high correlation between observed and factor scores.
- The multiple R-squares of scores with factors are 0.95, indicating that the factor model accounts for 95% of the variance in observed scores.
- The minimum correlation of possible factor scores is 0.90, suggesting good adequacy.

Overall, the factor analysis suggests that the one-factor model fits the data reasonably well and provides a meaningful interpretation of the underlying factor, MR1, as well as the commonality among the items EI1 through EI5.

> print(ai_factor)

Factor Analysis using method = minres

Call: fa(r = ai_items, nfactors = 1, rotate = "varimax")

Standardized loadings (pattern matrix) based upon the correlation matrix

- MR1 h2 u2 com
- AI1 0.47 0.21723 0.78 1
- AI2 0.76 0.57875 0.42 1
- AI3 0.73 0.52648 0.47 1
- AI4 0.66 0.43199 0.57 1

AI5 0.02 0.00028 1.00 1

MR1

SS loadings 1.75

Proportion Var 0.35

Mean item complexity = 1

Test of the hypothesis that 1 factor is sufficient.

df null model = 10 with the objective function = 0.94 with Chi-Square = 89.6

The degree of the model is 5, and the objective function was 0.03.

The root mean square of the residuals (RMSR) is 0.03.

The df corrected root mean square of the residuals is 0.05.

The harmonic n.obs is 99 with the empirical chi-square 2.01 with a prob < 0.85

The total n.obs was 99 with a likelihood chi-square of 2.74 and a prob < 0.74

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Tucker Lewis Index of factoring reliability = 1.057

RMSEA index = 0, and the 90 % confidence intervals are 0.0.1

BIC = -20.23

Fit based upon off-diagonal values = 0.99 Measures of factor score Adequacy

Juacy MR1

Correlation of (regression) scores with factors = 0.88Multiple R-squared of scores with factors 0.78Minimum correlation of possible factor scores is 0.56

Factor analyses are separately conducted for two sets of items: EI (emotional intelligence) and AI (artificial intelligence). The output provides information about the factor loadings, communalities, fit statistics, and measures of factor score adequacy for each factor extracted. For the EI factor analysis:

The standardized loadings (pattern matrix) in the factor analysis of emotional intelligence (EI) show the relationship between each EI item and the extracted component (MR1).

EI1: 0.32; EI2: 0.53

EI4: 0.97 EI3: 0.30

EI5: 0.34

The commonalities (h2) indicate that the amount of each item's variance is explained by the factor, ranging from 0.089 to 0.943. Model fit is evaluated Using fit statistics like Bayesian Information Criterion (BIC) and Root Mean Square of Residuals (RMSR). Measures of factor score adequacy, such as multiple R-squares of scores with factors and correlation of regression scores with factors, indicate the validity and reliability of the factor scores.

Factor Loadings represent the correlations between the observed variables (EI items) and the extracted factor (MR1). Higher loadings indicate stronger relationships between the variables and the factor.

Communalities (h2): These represent the proportion of variance in each observed variable that is accounted for by the extracted factor. Higher commonalities suggest that the factor explains more variance in the variable.

Fit Statistics: These include measures such as the root mean square of residuals (RMSR), Tucker Lewis Index, RMSEA index, and BIC (Bayesian Information Criterion). These statistics evaluate how well the model aligns with the observed data.

Measures of Factor Score Adequacy: These assess the reliability and validity of the factor scores derived from the factor analysis. This includes the correlation of regression scores with factors, the multiple R-squared of scores with factors, and the minimum correlation of possible factor scores.

For the AI factor analysis, similar information is provided.

Standardized loadings in the factor analysis of artificial intelligence (AI) demonstrate the relationship between the extracted factor (MR1) and the AI components.

AI1: 0.47, AI2: 0.76 AI3: 0.73

AI4: 0.66

AI5: 0.02.

Model fit is assessed using fit statistics like RMSR and BIC, while the validity and reliability of the factor scores are evaluated using metrics of factor score adequacy.

Both factor analyses indicate a relatively good fit to the data, with items that are in excellent alignment with the corresponding factors. Overall, both factor analyses had a reasonably good fit to the data, as indicated by fit statistics and measures of factor score adequacy. The factor loadings suggest the items are well-aligned with their respective factors.

V. CLUSTERING

The cluster between artificial intelligence (AI), emotional intelligence (EI), and the well-being of employees.

> cluster_model

K-means clustering with three sizes: 41, 7, and 51 clusters. Cluster means

EI_avg AI_avg and W_avg 1 3.292683 3.551220 3.121951 2 3.971429 2.657143 2.678571 3 4.101961 4.149020 2.909314 Within cluster sum of squares by cluster: [1] 16.060488 1.119464 14.117206 (between SS / total SS = 52.7 %)



The k-means clustering has grouped the data into three clusters based on the average values of EI (emotional intelligence), AI (artificial intelligence), and W (well-being). An interpretation of the clusters:

Cluster 1 (Blue):

Members of this cluster tend to have moderate levels of emotional intelligence (EI) and assertiveness (AI), but relatively lower levels of overall well-being. They might possess some emotional and artificial intelligence skills, but their well-being scores are comparatively lower. Possible characteristics: Individuals proficient in understanding emotions and using AI techniques may experience challenges maintaining overall wellbeing.

Cluster 2 (Red):

This cluster represents individuals with higher levels of emotional intelligence (EI) but lower levels of analytical intelligence (AI) and overall well-being. They demonstrate strong emotional intelligence skills but may need more expertise in artificial intelligence and experience lower overall wellbeing. Possible characteristics: Empathetic and socially adept individuals may need to be more technologically savvy to overcome challenges in maintaining their well-being. Cluster 3 (green):

Members of this cluster exhibit higher levels of emotional

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intelligence (EI) and achievement motivation (AM), as well as relatively higher well-being scores. They possess a balance of emotional and artificial intelligence skills, resulting in better overall well-being.

Possible characteristics: individuals who excel in understanding emotions, leveraging AI, and maintaining their well-being, indicating a Well-rounded and balanced profile. These interpretations are based on the average EI, AI, and W values for each cluster. However, individual characteristics exist within each cluster.

Mean Squared Error (MSE)



(Figure 2)

Interpreting the results of the random forest model involves understanding how well the predicted values align with the actual values. The plot and the mean squared error (MSE) were calculated.

Mean Squared Error (MSE):

The MSE measures the average squared difference between the predicted and actual values in the test set. A lower MSE indicates better predictive performance. Plot:

The plot shows the predicted W avg values (x-axis) against the actual W avg values (y-axis). Each point represents a data point from the test set.

The red line represents the line where predicted values equal actual values. Points closer to this line indicate more accurate predictions.

Interpretation: If the points in the plot are clustered closely around the red line, it suggests that the model's predictions are close to the actual values. The model's predictions are less accurate if the points are scattered far from the red line. By analyzing the MSE and the plot, the random forest model performs well in predicting the W avg values based on the EI avg and AI avg features. An MSE of approximately 0.0832 indicates that, on average, the squared difference between the predicted W avg values and the actual W avg values in the test set is 0.0832. This value measures the model's prediction error, where lower values indicate better predictive performance.

VI. DISCUSSION

1. Hypothesis for the Positive Correlation between Emotional Intelligence (EI) and AI Integration (AI): Workplace Adaptation: Employees in workplaces with higher AI integration may be required to adapt to technological changes and Complex work environments. This adaptation process might encourage the development of emotional intelligence as individuals navigate interpersonal relationships and communication in these dynamic settings. Training and Development Programs: Organisations that invest in AI integration prioritise training programs to enhance employee emotional intelligence. These programs can foster empathy, self-awareness, and effective communication, which are valuable in human-AI and general workplace interactions.

2. Hypothesis for the Weak Negative Correlation between AI Integration (AI) and Well-Being (W): Technostress: Despite the correlation being very weak, individuals working in environments with higher AI integration may experience technostress, which refers to the stress or anxiety arising from the use of new technologies. This stress could occur due to concerns about job security, fear of automation replacing human roles, or difficulties adapting to rapidly changing technological landscapes. Work-Life Balance: The increased integration of AI may blur the boundaries between work and personal life, potentially leading to negative impacts on well-being, such as burnout or difficulty disengaging from work-related tasks. This is particularly relevant in industries where AI-driven processes require continuous monitoring or constant connectivity.

VII. CONCLUSION

An emotional intelligence (EI) and artificial intelligence (AI) correlation analysis is conducted to explore the relationships between EI, AI, and employee well-being (W). Positive correlations are observed between emotional intelligence (EI) and artificial intelligence (AI), suggesting a tendency for workplaces with higher AI integration to have employees with stronger emotional intelligence. However, negative correlations are found between AI and W. Factor analysis is then employed to identify the underlying constructs of EI and AI. The study reveals distinct factors representing Emotional and artificial intelligence skills, with a good model fit and adequate factor scores. These findings contribute to understanding the structure of EI and AI in the study context, as cluster analysis groups employees based on their scores for EI, AI, and W. Three clusters are identified, each representing distinct profiles of emotional intelligence (EI), analytical intelligence (AI), and well-being among employees. Interpretations of these clusters offer insights into how EI, AI, and W interact within various workplace groups.

Limitations that may impede correlation determination include sample assumptions, measurement issues, or the crosssectional nature of the study design. Future research subjects could consist of intervention strategies, qualitative approaches, or longitudinal studies to address the limitations mentioned and gain a deeper understanding of the complex dynamics between emotional intelligence (EI), artificial intelligence (AI), and workplace well-being. By employing a rigorous research methodology encompassing data gathering, analysis, and interpretation, this study offers significant new insights into how well-being, emotional intelligence, and artificial intelligence impact employees' experiences in AI-enhanced work environments.

The data analysis section aligns with the study objectives of investigating the impact of emotional intelligence and artificial intelligence on employee well-being in AI-enhanced workplaces. The findings contribute to a deeper understanding of the relationships between these

variables and offer implications for

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promoting employee well-being in contemporary work environments.

In conclusion, the study sheds light on the intricate dynamics between emotional intelligence (EI), artificial intelligence (AI), and employee well-being in workplaces enhanced by AI.

Through rigorous data analysis, several key findings have emerged. Implications for Workplace Practices: The findings underscore the importance of fostering emotional intelligence skills among employees, particularly in the context of AI integration. To create supportive and conducive work environments, strategies that promote employee well-being should consider the interplay between emotional intelligence (EI), artificial intelligence (AI), and other workplace factors. The study offers valuable insights into the complex interrelationships between emotional intelligence (EI), artificial intelligence (AI), and employee well-being, providing implications for organisational practices and informing future research directions. By understanding and leveraging these dynamics, organisations can strive to create healthier and more productive work environments in the era of AI.

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Ethical Approval and Consent to Participate	No, the article does not require ethical approval or consent to participate, as it presents evidence that is not subject to interpretation.
Availability of Data and Materials	Not relevant.
Authors Contributions	Each author has made an independent contribution to the article. The individual contributions of each author are presented below for clarity and transparency. Amandeep contributed to the conceptualisation, methodology, and writing of the original draft. Prof. Ashish Mathur contributed to data curation, analysis, manuscript review, and editing. Prof. Shailendra Singh Bhadouria contributed to the supervision. All authors have read and approved the final version of the manuscript.

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