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

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***Abstract:** This study focuses on the connections between employee well-being in AI-enhanced workplaces, the 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 EI and AI are seen in the results, indicating 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 significance of fostering EI and AI integration in enhancing employee well-being. Future studies may examine these constraints and investigate intervention strategies for more healthful workplaces in the AI era. This research offers insightful information about the intricate dynamics of EI, AI, and well-being, offering guidance for organizational practices and future research endeavors.*

***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][17]. while AI significantly modifies employee performance, emotional intelligence significantly affects employee retention, which has been studied extensively. Four components of employee emotional intelligence are relationship management, social awareness, self-awareness, and self-management [2][18].

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Suggests a strong correlation between these components and workplace effectiveness [3]. Highlight the positive correlation between emotional intelligence and organizational commitment and 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 well-being technologies while considering social implications and organizational culture. The literature underscores the intricate interplay between emotional intelligence, artificial intelligence, and employee outcomes, emphasizing the need for a nuanced understanding to enhance organizational effectiveness and well-being. These insights are crucial for informing HRM strategies and fostering a supportive work environment ([8], [9], [10], [11], [12], [13], [14], [15], [16][19]).

II. OBJECTIVES

1. Explore the relationships between artificial intelligence (AI), emotional intelligence (EI), and the well-being of employees [20][21].

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 uses a quantitative research approach to better understand the connections between employee well-being in AI-enhanced workplaces, emotional intelligence (EI), and AI integration. 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 organizational environments and industries where AI integration is standard. A purposeful sample strategy was used to choose people who had worked 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 well-being metrics. For this study, 157 repossessions were collected from working employees. To ensure ethical and confident voluntary participation and answer confidentiality, informed consent from participants should be acquired before 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 or the emotional intelligence appraisal. 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 are used to investigate correlations between EI, AI, and well-being. Data. In EI and AI, factor analysis was utilized to Determine underlying constructs. Techniques like principal component analysis or maximum likelihood estimation were employed to extract components and evaluate model fit. Cluster analysis is used to classify individuals according to their well-being, AI, and EI scores; it uses methods such as k-means clustering to find unique employee profiles or clusters.

IV. RESULTS

(Table 1) Reliability Analysis

Measure	Raw Alpha	Standardized Alpha	Guttman's Lambda 6 (SMC)	Average Inter-item Correlation (average_r)	Signal-to-Noise Ratio (S/N)	Alpha Standard Error (ASE)	Mean	Standard Deviation (SD)	Median R
Internal Consistency	0.75	0.82	0.87	0.18	4.5	0.032	10	0.52	0.15

95% confidence boundaries
lower alpha upper
Feldt 0.68 0.75 0.82
Duhachek: 0.69, 0.75, and 0.82

The scale has strong internal consistency, according to 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 inter-item 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) Characteristics of Demography

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:

Most people are in the age range of 31 to 40, with 19.5% and 23.5% of the population 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 are between the ages of 31 and 40, and there is a broad range of experience levels, with a sizeable fraction. Some have less than one year of experience, and others have more than ten years.

Marital status:

Table 2 provides demographic information on marital status, specifically regarding the number of unmarried and married individuals and 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 are between the ages of 31 and 40, with varying experience levels. Some have less than one year of work experience, while others have more than ten years. Additionally, the % of the population, 72%, is married, with the remaining 28% being unmarried.

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(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 also to 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 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

df 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	0.90

Factor analysis on a set of items labeled EI1 through EI5. Here is the interpretation of the results:

1. Factor Loadings:
   - Factor loadings represent the correlation between each item and the underlying factor extracted by the analysis. There's only one factor extracted, labeled MR1.
   - The loadings show the strength and direction of the relationship between each item and the factor.
   - For example, EI1 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, 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 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

df 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

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
MR1
Correlation of (regression) scores with factors = 0.88
Multiple R square of scores with factors 0.78
Minimum correlation of possible factor scores 0.56

Factor analyses separately 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 assess how well the model fits 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, multiple R square of scores with factors, and 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.

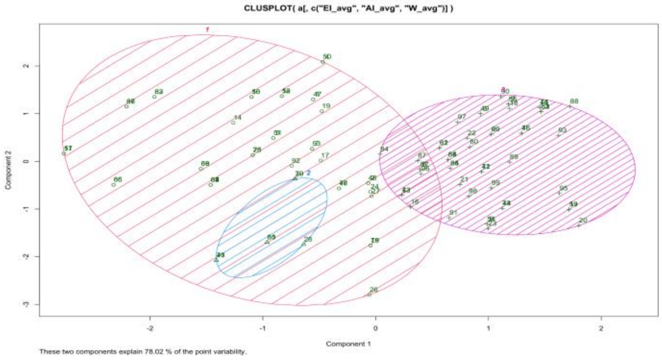
AI1: 0.47, AI2: 0.76
AI3: 0.73
AI4: 0.66
AI5: 0.02.

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 acceptable fit to the data, with items that are in excellent alignment with the factors that correspond to them. 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

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 %)



(Figure 1)

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 EI and AI but relatively lower levels of 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 well-being.

Cluster 2 (Red):

This cluster represents individuals with higher levels of EI but lower levels of AI and well-being. They demonstrate strong emotional intelligence skills but may need more expertise in artificial intelligence and experience lower overall well-being. Possible characteristics: Empathetic and socially adept individuals may need to be more technologically savvy or face challenges in maintaining well-being.

Cluster 3 (green):

Members of this cluster exhibit higher levels of EI and AI and relatively higher well-being scores. They have a balance of emotional and artificial intelligence skills and better overall well-being.

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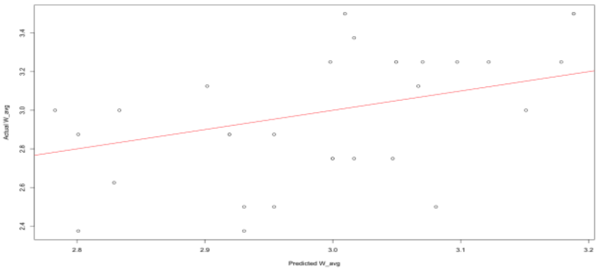
Possible characteristics: individuals who excel in understanding emotions, leveraging AI, and maintaining their well-being, indicating a Well-rounded and balanced profile. These interpretations are based on each cluster's average EI, AI, and W values. However, individual characteristics exist within 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: Organizations investing in AI integration prioritize training programs to enhance employee emotional intelligence. These programs could foster empathy, self-awareness, and effective communication, 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: Increased AI integration might blur the boundaries between work and personal life, leading to potential negative impacts on well-being, such as burnout or difficulty disengaging from work-related tasks. This could be particularly relevant in industries where AI-driven processes require round-the-clock 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 EI and 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 good model fit and factor score adequacy. These findings contribute to understanding the structure of EI and AI in the study context—cluster analysis groups employees based on their EI, AI, and W scores. Three clusters are identified, each representing different profiles of EI, AI, and well-being among employees. Interpretations of these clusters provide insights into how EI, AI, and W interact within various groups in the workplace.

Limitations that may impede correlation determination include sample assumptions, measurement issues, or the cross-sectional nature of the study design. Future research subjects could include intervention strategies, qualitative approaches, or longitudinal studies to get over the restrictions mentioned and learn more about the intricate dynamics of EI, AI, and well-being in the workplace. 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 better understanding of the relationships between these variables and provide implications for promoting employee well-being in modern work environments.

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

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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 promoting employee well-being should consider the interplay between EI, AI, and other workplace factors. The study provides valuable insights into the complex interrelationships between EI, AI, and employee well-being, offering implications for organizational practices and future research directions. By understanding and leveraging these dynamics, organizations can strive towards creating healthier and more productive work environments in the era of AI.

DECALARION STATEMENT

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Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material	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 conceptualizing, methodology, and writing 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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