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THE ROLE OF ANALYTICS AND ARTIFICIAL INTELLIGENCE AT THE WORKPLACE IN ENHANCING EMPLOYEE ENGAGEMENT MEDIATED BY EMPLOYEE TRUST AND AGE

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Abstract
Objective: This article aims to develop a multifaceted model that incorporates artificial intelligence into human resource procedures and organizations, to analyse its impact on employee engagement leading to organization performance mediated by employee trust in artificial intelligence technology, moderated by age.
Methodology: A sample of 238 working professionals and human resource experts across India participated in the study. The paradigms of the model embrace several sides of artificial intelligence incorporation within the elements and activities at the organization, these include, organizational culture, leadership, and the reduction of employee workloads. The modelling and data analysis were conducted using the partial least squares structural equation modelling (PLS-SEM)/fuzzy-set qualitative comparative analysis (fsQCA) technique.
Findings: The verdicts demonstrate that AI-supported in maintaining organizational culture, leadership, and reducing staff workloads all had a positive outcome on employee engagement leading to a substantial impact on organizational performance and employees trust in technology plays a significant impact.
Originality/Value: This study first tackles significant issues about the application of AI and analytics in the workplace and how it affects employee engagement. Second, by adding employee age and trust in AI as novel drivers of employee engagement that lead to organizational motivation and performance, study adds to the body of literature already in existence while offering novel and innovative insights. Finally, by combining linear (PLS) and nonlinear (fsQCA) procedures, the study makes a significant methodological addition.
Keywords: Artificial Intelligence, Employee Engagement, Employee Trust, Organization Performance, FSQCA.

INTRODUCTION

Current advancements in technologies have revolutionized businesses by implanting AI technologies, which have enhanced efficiency, reduced operational costs and improved overall performance (Mazzetti & Schaufeli, 2022). According to the study of Khan et al. (2023), AI has brought multiple advantages to the organisations, for instance, automation of routine tasks, improvement in customer services, and better decision-making. Despite getting all these advantages, reports by Deloitte (2024) have revealed that employees are still very much sceptical about adopting AI, as it is accompanied by fears of job loss and changes in workplace dynamics. This reluctance of employees to adhere to the application of AI is primarily because of their perceived risk, which acts as a boundary to which AI can be implemented in the workplace.
In result of all the concerns related to AI adoption in the workplace, some studies have tried to explore the connection between AI and different characteristics of employee behavior (Gursoy et al., 2019; Fidyah & Setiawati, 2020; Kim et al., 2022; He et al., 2024). One of the aspects of employee behavior is employee engagement, which can be characterised as the emotional and active participation in work-related activities (Sun & Bunchapattanasakda, 2019). Similarly, workplace motivation, encompassing individual drives and incentives, acts as an important aspect of the behaviour of employees and their performance outcomes (Mahmoud et al., 2021).

Along with Artificial Intelligence, the adoption of HR analytics is also gaining significant attention in recent years. HR analytics is a systematic gathering, scrutiny, and interpretation of data associated with human capital within an organisation (Marler & Boudreau, 2017). HR professionals can advance deeper insights into employee behaviours, preferences, and performance drivers. Many studies have highlighted the possible benefits of incorporating HR analytics and AI in HR practices (Huang et al., 2023; Sharma et al., 2025; Xiao et al., 2025).
Both AI technologies and adaptation of HR analytics have the potential to impact multiple industries, including finance, healthcare, human resources, manufacturing supply chain, as well as the public sector (Paschen et al., 2019; Cavanagh et al., 2023). Such technologies have the power to revolutionise the pattern of working, which can impact the overall organisational procedures. As a result, the company needs to integrate artificial intelligence systems into its current procedures and train staff members appropriately to prevent conflict and feelings of self-preservation. The studies of Fernandez & Gallardo-Gallardo (2020) and Ganatra & Pandya (2023) stated that the way businesses handle their human resources could be completely changed by incorporating AI into HR procedures. For decision-making processes to be fair, organizations need to actively identify and reduce biases in AI systems. Prioritizing data privacy and protection, getting informed consent, and putting in place reliable data handling procedures should all be part of their plan.
Despite these promising outcomes, the employment of HR analytics and AI in HR management is not without challenges. Apprehensions related to data privacy, algorithm biases, and ethical considerations necessitate careful planning and governance frameworks. Moreover, the human element remains critical, as technology should complement human decision-making rather than swap it entirely. The current study objects to delve deeper into the influence of HR analytics and AI on employee engagement and workplace motivation. By examining current practices, challenges, and outcomes, this study seeks to provide critical understandings for HR practitioners, organisational leaders, and researchers involved in leveraging data-driven approaches to enhance employee engagement.

LITERATURE REVIEW

Today's swiftly evolving technological landscape, HRM is witnessing a critical transformation in the workplace with the integration of analytics and AI technologies. This technological integration has enhanced employee engagement and workplace motivation in the organisations (Kasinathan & Rajee, 2024). This literature review explores the existing knowledge and empirical evidence regarding the impression of HR analytics and AI on these crucial aspects of organisational behaviour.
There are research outlining the implications of the integration of HR analytics and AI technologies impacting employee engagement and workplace motivation. AI-driven solutions in HR functions provide real-time monitoring of performance and natural language processing, improving employee engagement. The integration of AI and analytics has proven significant by offering insights that are not feasible with traditional methods. Such technologies are now providing a full work climate that encourages clarity, skill development, recognition, and wellbeing, ultimately leading to greater efficiency, enhanced communication, and a collaborative work environment. The use of AI and analytics in HR practices helps organizations acclimate to evolving changes and deliver better results in the hybrid working model. According to Wijayati et al. (2022), AI enhances employee engagement and work performance as workers can save over a third of the time, they would else spend on simple, repetitive tasks with its help. Because of advancements in machine learning techniques, many corporate organisations and academicians are taking an interest in AI and analytics. Although the use of such technology has its own advantages in solving potential problems, it still comes with some practical challenges and a lack of expertise regarding how to apply AI strategically to produce value.
The literature of the current study provides insights into the application of AI and analytics in the context of employee engagement, emphasising technological transformation as well as its related obstacles. Research by Al-Alawi & Albinali (2024) highlighted the significance of harmonising human assessment with data-driven understanding to maximise involvement and retention of employees and ignoring personal information in favour of data-driven approaches in order to contextualise data and algorithms. The incorporation of artificial intelligence into employee engagement represents a change towards more collaborative motivator strategies, which will ultimately produce more effective and captivating outcomes for businesses looking to gain a competitive advantage.
Even with these advantageous results, there are still restrictions and gaps to take into account. Employee trust and emotional autonomy in the workplace may be impacted by worries about job losses, unemployment rates, and privacy issues relating to emotional data incursion by AI techniques (Seppänen et al., 2007). Employee trust is positively correlated with the use of AI and HR analytics in the workplace, underscoring the importance of employee confidence in technology (Braganza et al., 2021).
Many studies support the direct connection between employee engagement and organisational performance. Nonetheless, the study has gaps and restrictions. Research such as (Sibanda et al., 2014) underscores how employee engagement acts as a mediator in improving organisational performance through psychological antecedents and employee loyalty, whereas (Markos & Sridevi, 2010) presents an alternative viewpoint. It implies that employee loyalty and company reputation act as a mediating influence between employee engagement and business performance rather than having a direct correlation. This disparity highlights the need for more research to elucidate the relationship and investigate additional mediating factors with the aim of providing a more

thorough understanding of how employee engagement influences organisational performance. It also points to a gap in our understanding of the direct impact of employee engagement on organisational performance.

Hypothesis Development:

AI and Analytics at the workplace on Employee engagement

According to Mazzetti & Schaufeli (2022), having a strong significant effect on AI and analytics in the workplace, which later has an effect on employee engagement. Studies are providing some empirical hints of the impact of AI-enabled chatbots on employee engagement, particularly through employee voice and climate for trust (Marler & Boudreau, 2017; Mahmoud et al., 2021; Kim et al., 2022; Ali Nawaz Khan et al., 2025; A. N. Khan, 2025). These studies collectively suggest that AI and analytics can play a significant role in improving employee engagement in the workplace. Employee engagement can be defined as an emotional and intellectual obligation towards the organisation or the amount of effort put in by the employees in their job (Anitha, 2014). Additionally, it has been demonstrated that combining AI and analytics in the post-pandemic hybrid workplace can successfully engage talent, particularly in the IT sector, altering HR functions. Additionally, research shows a favourable association between workers' perceptions of AI opportunities and their job satisfaction, with informal learning acting as a mediating factor. All things considered, utilising AI and analytics promotes worker engagement via sentiment analysis, real-time monitoring, and skill development, which raises output and promotes teamwork in the workplace.

H1: AI and Analytics at the workplace has a direct positive relationship with Employee engagement

AI and Analytics at Workplace on Trust of Employees

The concept of trust in technology informs our knowledge of the degree to which employees trust AI within the organization. We believe that the most sophisticated technological advancement to date is artificial intelligence. According to the definition given in the literature, persons who trust technology are more likely to be open to being affected by it because of its practicality, the predictability of its effects, and the reliability of its traders (Seppänen et al., 2007; Mcknight et al., 2011; Nah et al., 2023), The idea of having faith in technology, and by extension artificial intelligence, is the conviction that the other side of the association that is, technology, and in this case, artificial intelligence will operate in a practical, beneficial, and dependable manner, yielding favourable outcomes (Mcknight et al., 2011). The functionality is a reflection of the belief that the technology can accomplish the intended purpose.

One measure of helpfulness is how well and quickly the technology's built-in assistance feature responds. Regarding technology, reliability is the belief that it will function dependably and uniformly. In the same way, people's level of confidence in an instrument or system's ability to accomplish its intended purpose is determined by their level of trust in it, as stated by (Hardré, 2016). Current research backs up the idea that the concept of interpersonal trust serves as the foundation for technological trust. Perceptions of the positive aspects of a particular technology are often the basis for faith in technology, according to various definitions. According to perceptions of the trustee's reliability, trust research is based on similar principles as interpersonal trust (Mcknight et al., 2011). Scientists have employed these methods mostly because humans tend to anthropomorphize technology and imbue it with human motivations or characteristics (Nowak & Rauh, 2005; Lankton et al., 2015). Workers' trust in the company's technology, and consequently their trust in artificial intelligence, which is the primary focus of our research, does not emerge in a vacuum. Rather, it develops inside a company's complicated surroundings (Lee & See, 2004). As a result, when examining employees' faith in AI within the company, we take into account three contexts: overall technological trust, the features of the organizational support for technological trust (intra-organizational trust), and the context defined by the traits of a specific employee using a particular AI solution (individual competence trust).

H2: Artificial Intelligence and Analytics at the workplace has a direct positive relationship with Employee Trust

The mediating role of Employee Trust in AI

The association among the adoption of AI and employee engagement in the workplace is significantly mediated by employee trust. Research has indicated that several criteria, including domain knowledge, challenge and threat assessments, AI transparency, and challenge appraisals, can affect employees' faith in (Yu et al., 2023). Additionally, how employees view the adoption of AI affects their organizational commitment, psychological contract, and organizational trust, all of which have an impact on employee engagement (Yu & Li, 2022). Moreover, employees' faith in AI is influenced by individual and organizational characteristics such as generation, expertise, skills, ownership type, and business type, which in turn affects their desire to use AI technology at work. Consequently, building employee trust in AI through openness, clear communication, and customized training programs can improve worker engagement and make it easier for AI technology to be successfully integrated into the organization

H3: Employee Trust has a mediating effect on Artificial Intelligence and Analytics at the workplace and Employee Engagement

The moderating role of Employee age in AAIW and Employee Engagement

Age indeed acts as a moderating role in the between AI and employee engagement, as evidenced by research in various contexts (Dutta et al., 2022; Dewasiri et al., 2023; Priya et al., 2024). Additionally, it has been found that AI and analytics in the workplace are enhancing employee engagement in a hybrid workplace (Mer & Srivastava, 2023). Furthermore, the impact of AI on workplace engagement has highlighted the need for its cautious implementation to ensure it fosters trust and commitment rather than control within organizations.

H4: Age positively moderates the relationship between AI and Analytics at the workplace and Employee engagement

Employee Engagement and Organizational Performance

According to the study of Rabuana & Yanuar (2023) and Cavanagh et al. (2023), the success of any organisation and employee engagement are significantly correlated to each other. On the other hand, previous literature supports that employee engagement also impacts employees' job satisfaction and their performance (Tampubolon, 2016; Fidyah & Setiawati, 2020; Riyanto et al., 2021). Furthermore, according to Ganatra & Pandya (2023), employee engagement is positively impacted by employee satisfaction, which in turn influences employee performance. Employee engagement significantly improves organizational performance, and how psycap, commitment, motivation, and employee happiness all contribute to this relationship. It is crucial to prioritize and raise employee engagement levels to achieve overall organizational success. As a result, encouraging employee engagement within an organization can result in higher performance outcomes.

H5: Employee Engagement has a positive relation with organizational performance

RESEARCH METHODOLOGY

Sample size and data collection:

A total of 280 working professionals from different organisations and industries were asked to complete the survey for the current study. These workers, along with HR, were employed full-time by private, public, or semi-government companies. A modified survey was distributed to the staff members in various parts of India. The working professionals were not given any incentives to participate, and purposive sampling was used to obtain data from the cross-sectional survey. The study used a descriptive research approach that was validated on 280 working professionals in India. Descriptive and inferential statistics were employed to analyse the cross-sectional data, which was gathered via a customized questionnaire. We sought 280 respondents in all, and 238 responses, or 85% of the total, were sent our way. 42 of the 280 replies had missing data, which led to them being deemed invalid. Consequently, 238 respondents' full replies in every regard were used for additional analysis. G*Power program was utilized to calculate the right sample size, with a least test power requirement of 0.80 (Faul et al., 2007; Faul et al., 2009). As 159 was the least required sample size at the 5 percent significance level, a sample of 238 was determined to be suitable. In structural equation models, the sample size of 238 was also greater than the threshold sample size, which can ideally vary from 100 to 200 or more (Bollen, 1989; Boomsma, 1982). To authenticate the survey instrument, 42 students participated in a pilot study. Thirty-two statements on the self-administered questionnaire, which included seven constructs, were utilized to collect data. Through the questionnaire, basic demographic data like gender, age, educational background, work type, Employee position, and opinions regarding artificial intelligence in the workplace were also gathered. A descriptive research design was used to empirically test the consequences of using analytics and AI at workplace on employee engagement mediated by employee trust in AI which further leads to indirect and direct impacts on organizational performance. The sample units of the investigation were Indian employees and HR working in different domains. Overall, 280 online questionnaires were distributed, and 42 samples were removed in pilot testing. After data cleaning, 238 samples were used for the final analysis, an accepted sample size for PLS-SEM (Kline, 2023).

Measurements of Items

All the variables tested are assesed using a five-point Likert scale, where 1 denotes strongly disagree and 5 denotes strongly agree.

Data analysis

The Smart PLS tool (Hulland, 1999) was used to verify the validity and reliability of the measurement and structural models. Specifically, the Smart-PLS 4.2 software package, developed by Ringle et al. (2005), was used for final data analysis. A bootstrapping with 10,000 subsamples is done for parameter assessment. To supplement the outcomes of the symmetrical approach, we have additionally employed the fsQCA methodology. (Rihoux and Lobe, 2009).

Descriptive Statistics

The age distribution of the participants was from 238 where 126 were males and 112 were females. The sample was collected from respondents from different job positions, from entry-level to leadership, working in various work types such as work from office, home, and hybrid.

Table 1: Descriptive statistics

Demographic	Frequency	Percentage
Gender		
Male	126	52.9%
Female	112	47.1%
Age		
18-24 Years	36	15%
25-35 Years	138	58.3%
36-45 Years	38	15.8%
45-55 Years	16	6.7%
Above 55	10	4.2%

Job Position		
Leadership	15	6.3%
Top Management	13	5.4%
Manager	61	25.4%
Individual Contributor	106	45%
Entry Level	43	17.9%
Work Type		
Work From Home	47	19.6%
Work From Office	90	37.8%
Hybrid	101	42.9%

RESULTS AND DISCUSSION

Measurement Model Assessment

The Consistent partial least squares (PLSc) algorithm was applied for the estimation of structural equation models with reflective measurement models to avoid the pivotal problem of type I and type II errors (Wong, 2013; Dijkstra & Henseler, 2015).

All the hypotheses of the study have been evaluated using SmartPLS 4.0 using nonparametric structural modeling as mentioned by (Kline, 2023). The analysis has been performed using structural equational modeling using bias-corrected sampling through 10,000 bootstrapping iterations. The statistical results of the two-tailed analysis were supposed to be reliable (Hair et al., 2014). The whole analysis phase went down through various stages to compute the reliability and validity.

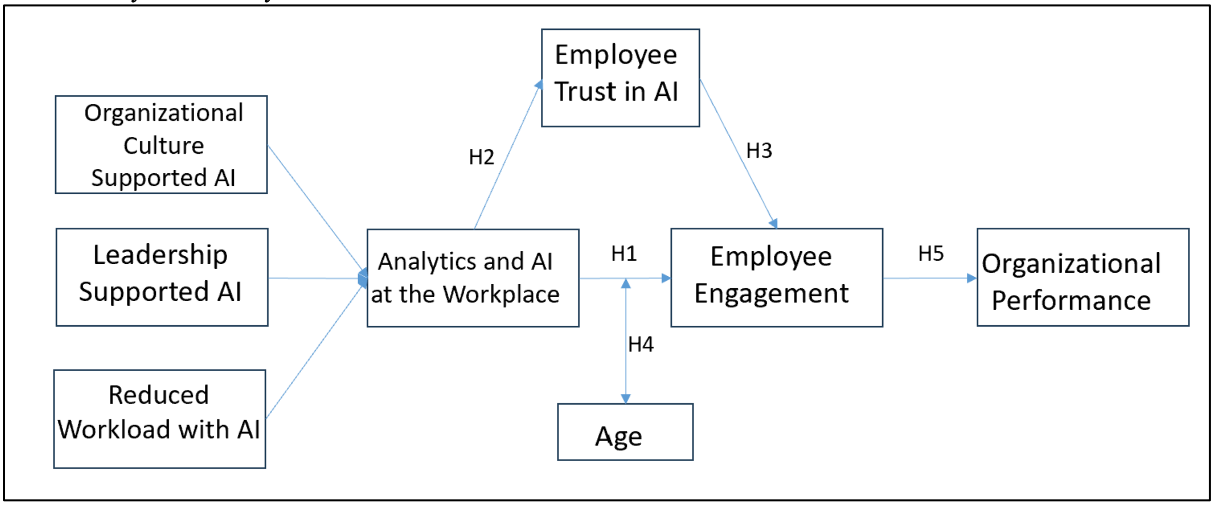

Fig 1: Conceptual Framework

To determine the extent of homogeneity the values of Cronbach alpha have been considered for each subsequent component. Table 2 signifies the reliability of all the constructs by assessing inner consistency by measuring Henseler's rho A and composite reliability along with convergent validity by measuring average variance extracted. Discriminant validity was investigated by applying the HTMT ratio and Fornell & Larcker ratios of correlations which were found to be over the threshold value of 0.85 (Fornell & Larcker, 1981; Henseler et al., 2015; Hamid et al., 2017) and AVE were above 0.50 (Shrestha, 2021; Hair et al., 2022). The indicator loadings of all the constructs were over the threshold value of 0.70 (Shevlin & Miles, 1998; Sarstedt et al., 2017).

Table 2: Reliability and Convergent Validity

	Items	**Loadings**	**Cronbach's alpha**	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
Employee Trust in AI	AT1	0.191	0.721	0.758	0.820	0.457
	AT2	0.774				
	AT3	0.798				
	AT4	0.777				
	AT5	0.676				
	AT6	0.641				
Leadership	L1	0.873	0.909	0.909	0.936	0.785
	L2	0.901				
	L3	0.899				

	L4	0.871				
Organisational culture	OC1	0.817	0.842	0.848	0.895	0.868
	OC2	0.870				
	OC3	0.833				
	OC4	0.724				
Organisational Performance	PR1	0.923	0.900	0.909	0.937	0.832
	PR2	0.895				
	PR3	0.918				
Reduced Workload	RW1	0.891	0.915	0.915	0.940	0.796
	RW2	0.900	0.854			
	RW3	0.901				
	RW4	0.876				

Table 3: HTMT Criterion

	AAIW	AIT	Age	EE	L	OC	PR	RW	Age x AAIW
AAIW									
AIT	0.456								
Age	0.056	0.166							
EE	0.472	0.573	0.052						
L	1.013	0.424	0.031	0.419					
OC	0.983	0.514	0.087	0.534	0.847				
PR	0.898	0.370	0.046	0.399	0.843	0.763			
RW	0.984	0.357	0.044	0.386	0.896	0.766	0.916		
Age x AAIW	0.086	0.167	0.033	0.222	0.047	0.111	0.021	0.089	

Table 4: Fronell-Larcker Criterion

	AAIW	AT	Age	EE	L	OC	PR	RW
AAIW	0.792							
AT	0.389	0.676						
Age	0.051	0.144	1.000					
EE	0.442	0.469	0.029	0.759				
L	0.941	0.360	0.022	0.387	0.886			
OC	0.873	0.411	0.078	0.469	0.740	0.826		
PR	0.830	0.299	0.043	0.373	0.764	0.663	0.912	
RW	0.916	0.296	0.042	0.359	0.817	0.672	0.832	0.892

Second Order Formative Model Assessment

In the current study, analytics and AI at the workplace were evaluated in a reflective-formative constructs (Sarstedt et al., 2019). The latent variable score of the lower-order constructs was assessed to measure the second-order construct scores of analytics and AI at the workplace. To reduce the possibility of multicollinearity, VIF values were assessed which were underneath the limit of 3 (Hair et al., 2019). Also, to confirm the importance of formative indicators bootstrapping method was used on 10,000 sub-samples with a significance level of 5%, which helped in investigating outer weights of formative indicators of second-order construct i.e., analytics and AI at the workplace (Hair et al., 2022).

Table 5: VIF Values

	AAIW	AIT	Age	EE	L	OC	PR	RW	Age x AAIW
AAIW		1.000		1.202					
AIT				1.243					
Age				1.024					
EE							1.000		
L	3.756								
OC	2.277								
PR									
RW	3.104								
Age x AAIW				1.042					

Structural Model Assessment

The procedure Hair et al. (2019, 2022) has been applied to examine the findings for hypothesis testing. The size of the model and relevance of path coefficients were tabulated as per the instruction of Saari et al. (2021) and Ghasemy et al. (2020). Along with low f-square values for employee engagement, all path coefficient values were statistically significant ($p<0.05$). The established link between the independent, dependent, mediating, and moderating variables examined in the study is shown in Fig. 2. The significant predictors of employee engagement were initiated to be ($\beta = 0.334$, t= 4.82, $p< 0.05$, supporting H1), leading to considerably impacting organizational performance positively ($\beta = 0.373$, t= 5.27, $p< 0.05$, supporting H5). However, employee trust in AI was found to be a significant mediator amid analytics and AI at the workplace and employee engagement by respondents in the investigation ($\beta = 0.389$, t= 5.66, $p< 0.05$, supporting H2) and ($\beta= 0.317$, t= 4.24, $p< 0.05$, supporting H3). The research also investigated the moderation consequence of the age of the employees on the relationship between analytics and AI at the workplace and employee engagement which was found to be positive as per the statistics of the samples (t= 3.40, $p< 0.05$, supporting H4).

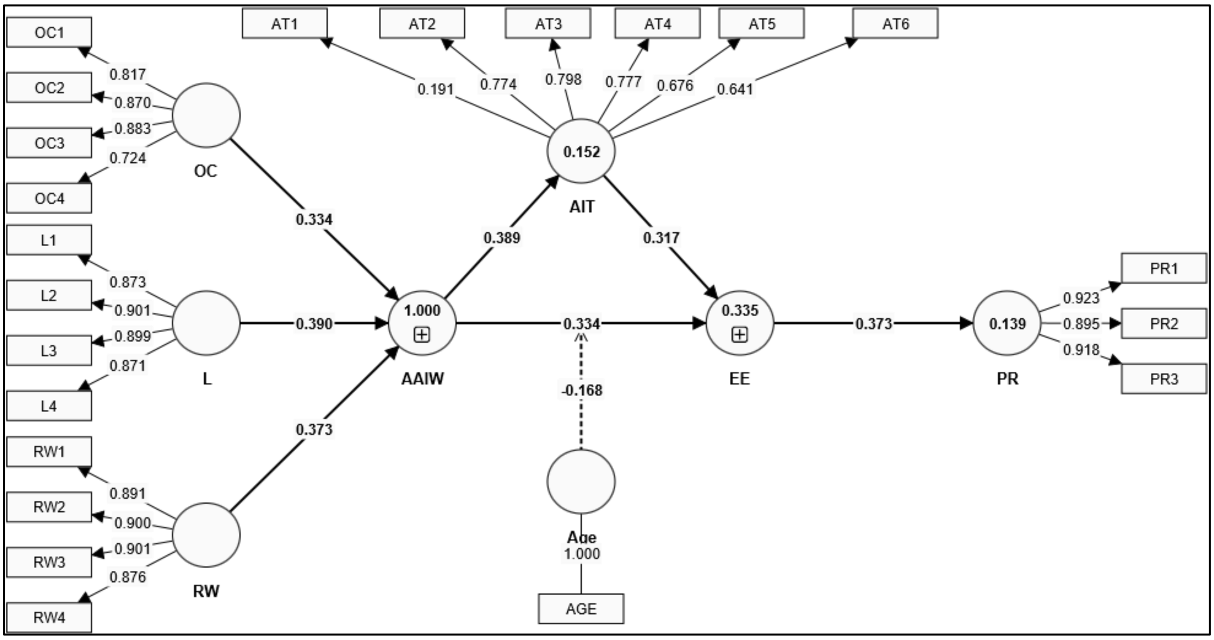

Fig 2: Structural Equational Model

Table 6: Hypothesis Testing of Direct Relationships

Hypothesis	Relationship	Std. Beta	Std. Error	t-Value	P-Value	Decision
H1	Analytics and AI at Workplace → Employee Engagement	0.334	0.069	4.84	0.00	Supported
H2	Analytics and AI at Workplace → Employee Trust in AI	0.389	0.069	5.663	0.00	Supported
H3	Employee Trust in AI → Employee Engagement	0.317	0.075	4.24	0.00	Supported
H4	Age* Analytics and AI at Workplace → Employee Engagement	-0.168	0.049	3.409	0.001	Supported
H5	Employee Engagement → Organisational Performance	0.373	0.071	5.277	0.00	Supported

Table 7: Indirect Effect

Relationships	P- Values
Analytics and AI at the Workplace -> Employee Engagement	0.003
Analytics and AI at the Workplace -> Organisational Performance	0.002
Employee Trust in AI -> Organisational Performance	0.000
Age -> Organisational Performance	0.632
Leadership -> Employee Trust in AI	0.000
Leadership -> Employee Engagement	0.000
Leadership -> Organisational Performance	0.001
Organizational Culture -> Employee Trust in AI	0.000
Organizational Culture -> Employee Engagement	0.000

Organizational Culture -> Organisational Performance	0.002
Reduced Workload -> Employee Trust in AI	0.000
Reduced Workload -> Employee Engagement	0.000
Reduced Workload -> Organisational Performance	0.001
Age x Analytics and AI at the Workplace -> Organisational Performance	0.008

Table 8: Hypothesis Decision

Hypothesis	P-Value	Decision
H1: AI and Analytics at the workplace has a direct positive relationship with Employee engagement	0.00	Supported
H2: AI and Analytics at the workplace has a direct positive relationship with Employee Trust	0.00	Supported
H3: Employee Trust has a mediating effect on Artificial Intelligence and Analytics at the workplace and Employee Engagement	0.00	Supported
H4: Age positively moderates the relationship between AI and Analytics at the workplace and Employee engagement	0.001	Supported
H5: Employee Engagement has a direct positive relationship with organizational performance	0.00	Supported

FsQCA: Fussy Set Qualitative Comparative Analysis

The interdependence of analytics and AI at the workplace, leadership's support for AI, organizational culture, and employees' trust in AI on employee engagement were all explored in this study using fsQCA. The true complexity of human behavior is not addressed by identifying only the effect of every independent variable (Rihoux et al., 2021). This disadvantage can be avoided by developing asymmetric techniques like fsQCA, which provide combinations of variables not included in isolated models (Fernandez-Esquinas et al., 2021). As a result, our work acknowledges the idea that various antecedent combinations might lead to the same solution by employing this multi-method analysis (Rippa et al., 2020).

The fsQCA method compares examples to analyse the intricate causalities of the result using set theory and Boolean algebra. The interaction effects between three or more antecedents are not well-represented by traditional statistical approaches (Ragin, 2012). Alternatively, fsQCA can be used to investigate potential combinations of the 550 elements that influence a result and identify similar routes that lead to the same result (Ragin, 2012). fsQCA is predicated on conjunction, equifinality, and asymmetry. Firstly, rather of concentrating on the overall impact of a single element, fsQCA considers a combination of conditions that lead to a certain result (Rihoux and Ragin, 2008). Second, according to Woodside (2014), fsQCA makes the assumption that several arrangements of equally appropriate components can result in the same outcome. Third, fsQCA considers both causal and conditional asymmetry.

The goal of the fsQCA approach is to use inferential logics to identify the sets of conditions which suggest the outcome. Thus, in order to determine which feasible combinations can result in Employee Engagement, we begin by taking into account, for this methodology, all the components given, with the mediating aspect of employee faith in technology. Thus, two models are taken into account. According to Ragin (2012), the models are expressed as functions where the dependent variable is produced by combining the analysed antecedents.

The functions would be expressed as follows in light of the aforementioned:

Model: EE1 = f (AAIW1, AT1, BEE1, BI1, CEE1, EEE1, HM1, L1, OC1, RW1)

We emphasise descriptions grounded on many case studies (Ragin, 2006) rather than just the net effects of each element in order to emphasise the cumulative effects as distinct paths that can lead to the same outcome (Employee Engagement). Recognising this equifinality is crucial since there are probably several activity-based routes that lead to a particular consumer behaviour (Rippa et al., 2020).

The data needs to be transformed for fsQCA to begin the calibration procedure:

In order to convert the data, the following steps had to be taken: (1) based on the factor loadings and responses of the analysed companies, determine the mean of each construct; and (2) select the suitable percentiles to standardize the results based on the mean score of the corresponding constructs (Ragin et al., 2008). This statistic suggests that the cut-off points should be chosen appropriately to accurately calculate the membership levels. The goals of the study and the unique qualities of the sample or research should be taken into consideration when choosing the cut-off points (Ragin, 2012). The 10th, 50th, and 90th percentiles based on the most important studies in the field. (Beynon et al., 2016; Dul, 2016; Kusa et al., 2022) which, in comparable investigations, suggest these cut-off points. The descriptive statistics of the outcome are displayed in Table 9, in accordance with the recommendations of Pappas and Woodside (2021).

Next, we examine the prerequisites for the Impact on Employee Engagement (EE) in Table 9. Schneider (2018) suggests examining the essential conditions established by the QCA analysis from the perspectives of conceptual significance, empirical relevance, and empirical consistency. If the consistency is more than 0.90, a casual condition is deemed necessary (Ragin, 2012).

Table 9: Descriptive statistics

Variable	Mean	Std.Dev.	Minimum	Maximum	N	Missing
AAIW	-1.68E-05	0.99994	-2.933	1.981	238	0
AT	-8.40E-06	0.999999	-3.457	2.464	238	0
BEE	-2.52E-05	1.000055	-3.164	1.44	238	0
BI	-8.82E-05	1.000009	-2.893	1.618	238	0
CEE	-7.98E-05	1.00003	-3.324	2.259	238	0
EE	3.36E-05	0.999996	-3.595	1.677	238	0
EEE	6.72E-05	0.999945	-3.131	1.502	238	0
HM	-0.00015	1.000079	-2.982	1.753	238	0
L	0.000168	1.000037	-2.527	1.797	238	0
OC	-0.00013	1.000024	-3.062	1.914	238	0
RW	-0.00013	0.99994	-2.476	1.715	238	0

Graph 1: EE1 = f(AAIW1, AT1, BEE1, BI1, CEE1, EEE1, HM1, L1, OC1, RW1)

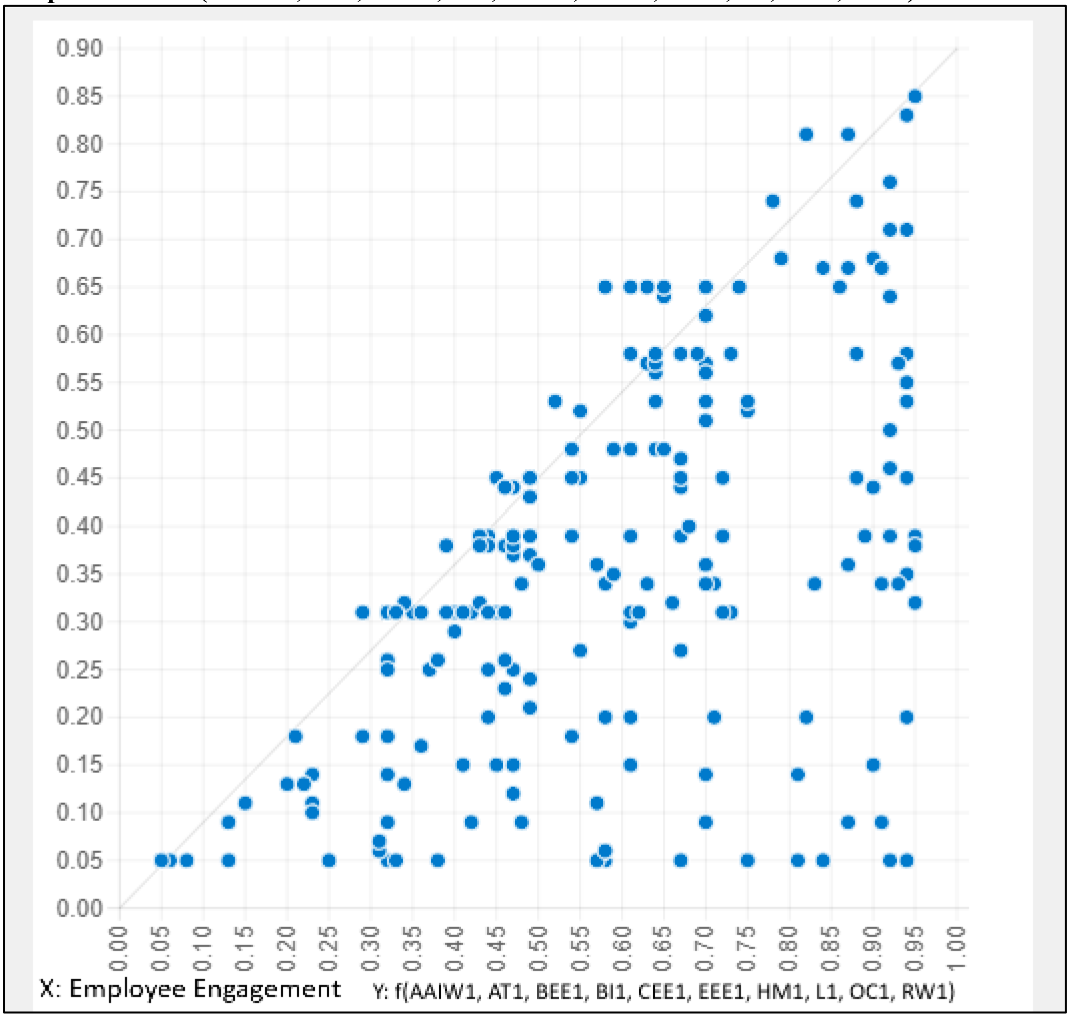

Table 10: Truth Table Analysis

Outcome Variable: Employee Engagement			
Variable	**Condition Tested**	**consistency**	**coverage**
AAIW1	Analytics and AI at the Workplace	0.842048	0.816677
BEE1	Behavioural Employee Engagement	0.92174	0.929371
EEE1	Emotional Employee Engagement	0.946215	0.952565
CEE1	Cognitive Employee Engagement	0.903793	0.858294

BI1	Behavioral Intention	0.842794	0.836068
AT1	Employee Trust in AI	0.860321	0.804818
HM1	Hedonic Motivation	0.838756	0.826745
OC1	Organizational Culture	0.845594	0.823016
RW1	Reducing Workload Supported By AI	0.820497	0.795346
L1	Leadership Supported AI	0.826641	0.79378

A truth table is then used to construct the various combinations of outcomes and circumstances (Table 10) We ascertain the parameters that dictate the intended outcome (Employee Engagement) by analysing them. The consistency and frequency criteria that we have established will decide whether or not the various antecedents are present. According to our investigation, the frequency limitations are determined by the guidelines provided by Greckhamer et al. (2013), whereas consistency limits are determined in accordance with the suggestions provided by Ragin (2006). Eventually, there are as few options as possible (Fiss, 2011). Both the overall solution and the values for each solution above the minimum consistency criterion of 0.75 (Rihoux & Ragin, 2008). The four solutions account for 85.82% of the cases in the presence (employee engagement) category, which is more than the 80% required threshold. The process takes into account the existence of a condition as well as its opposite (negation). The absence of a condition is referred to as the negation of a condition in the literature. In research, the terms absence and negativity have been used interchangeably (Pappas & Woodside, 2021).

Table 11: Table of Truth (Combinations)

	Variable	**Combination 1**	**Combination 2**	**Combination 3**	**Combination 4**
AAIW 1	Analytics and AI at the Workplace	Yes	Yes	Yes	Yes
BEE1	Behavioural Employee Engagement	Yes	Yes	No	Yes
EEE1	Emotional Employee Engagement	Yes	Yes	Yes	Yes
CEE1	Cognitive Employee Engagement	No	Yes	Yes	Yes
BI1	Behavioral Intention	Yes	Yes	Yes	No
AT1	Employee Trust in AI	No	Yes	Yes	Yes
HM1	Hedonic Motivation	No	No	Yes	Yes
OC1	Organizational Culture	Yes	Yes	Yes	No
RW1	Reducing Workload Supported By AI	Yes	No	Yes	Yes
L1	Leadership Supported AI	Yes	Yes	No	Yes
Consistency		0.997843	1	0.979078	1
Raw Coverage		0.621122	0.571599	0.568914	0.560412
Unique Coverage		0.0239407	0.00492245	0.00440019	0.00663781

The presence and negation table 11, is provided by the fsQCA analysis, however we usually start with the analysis of the former since it supplies the majority of data pertaining to the dependent variable (Pappas & Woodside, 2021). Ten antecedent remedies are considered in our case's Impact on Employee Engagement table11, and they all lead to the same outcome. While BEE (Behavioural Employee Engagement), CEE (Cognitive Employee Engagement), RW (Reducing Workload By AI), and L1 (Leadership Supporting AI) are present in three solutions each, AAIW (Analytics and AI at the workplace) and EEE (Emotional Employee Engagement) are present in all four solutions (1-2-3-4). According to Kusa et al. (2022) criterion, unique coverage is the measure that demonstrates the solutions' existence in the various sample data sets.
For this value, Solution 1(Raw Coverage 0.6211), Consistency (0.997), (unique coverage 0.0239) has the maximum level. Since these are key components for employee engagement at the organization, this solution includes AAIW (Analytics and AI at the Workplace), EEE (Emotional Employee Engagement), BEE (Behavioural Employee Engagement), BI (Behavioural Intention), OC (Organisational Culture), RW (Reducing Workload By AI), and L1 (Leadership Supporting AI) as common factors.

DISCUSSION

Our research aims to determine how much employee faith in technology can influence the relationship of analytics and AI-enabled workplaces and employee engagement, as well as how much analytics and AI-enabled workplaces

can be used to promote employee engagement. Additionally, it looks at how employee age affects the relationship between workplaces that are AI- and analytics-enabled and employee engagement.
The first hypothesis, which suggests a favourable correlation between employee engagement and AI-enabled workplaces through analytics, is validated. The results support the idea that workplaces enabled by AI and analytics act as a unswerving voice mechanism in companies by providing staff members some individual attention that focuses on behavioural, cognitive, and emotional engagement traits, as well as opportunities to voice concerns and opinions, which increases engagement.
Furthermore, our study highlights the significance of workers' faith in AI. Particularly when it comes to employee engagement, technology acts as a mediator in the formation of work attitudes. The conclusion that workplaces with AI and analytics enable increased employee trust in AI technology is in line with the findings of Holland et al. (2012) and Holland et al. (2017), who contend that employees continuously assess organizational actions and that giving them a direct voice to voice their concerns is the foundation of trust. We also discovered that an AI-enabled workplace can anticipate employee engagement at any given level of employee faith in technology, bridging the age gap among employees. When we take into account the organisational setting, these findings become much more important.
We also intended to use a non-symmetric methodology to supplement this study in order to properly analyse the elements influencing employee engagement. After examining the suggested remedies, we found that they consist of a number of factors that are related to the adoption of technology; in other words, from a behavioural perspective, each one of the factors alone is sufficient to promote employee engagement. Based on the methods applied, this fact addresses the discrepancy between a construct's combinatorial capacity and relevance. The instances examined in accordance with the model presented determine the dependent construct, but the solutions can be altered by adding new variables, increasing their combinatorial and explanatory strength. Additionally, we see a balance in the significance of each antecedent,
Following on from the above, Employee Engagement, Trust in AI, Leadership, Organization culture could be seen as an essential variable for the Employee engagement. Certainly, solutions 2 shows the absence of Hedonic motivation, which could be considered a more rational behaviour in the engaging employee and solution 3 indicates that Behavioural Employee Engagement and Leadership supporting AI are less relevant initially for employee engagement.

CONCLUSION

Our research adds a value to the body of facts on the AI-HRM interface, particularly as it narrates the effects of AI-enabled workplaces on employee engagement. Although the use of technology in HR operations is on the rise, there is a dearth of an empirical study on how technology is changing employees' attitudes and behaviors. Our research advances this field by utilizing pre-existing theories and frameworks. Workplaces with AI capabilities and employees' faith in technology may effectively and effortlessly deliver a personalized employee experience, something that would otherwise take a lot of time, effort, and money. We look at the connection between AI-enabled workplaces and employee engagement, but we also show how this approach improves employee attitudes by increasing employee trust and engagement, which in turn boosts performance.

Limitations and Future Scope

The study also comes with some boundaries as well. At first, the data of both dependent and independent variables were gathered at the same time, which affected the actual expectedness of the results. The future researches can undertake the longitudinal study to solve the limitations. Additionally, the study was only conducted in India, which limited the population having similar demographic and geographic background. The results can be verified by doing comparable studies in various places. The change in sampling approach may impact the generalisability of the outcome of the of the population studied. Studies utilizing some new sample approach in future studies can address this restriction. Finally, classifying the sample according to how employees interact with AI and AI-powered solutions within the company could improve the research findings. Such limitations may be examined in future research to improve the study's validity.

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