Employee and Management Attitudes Towards HR Analytics Adoption: A Mixed-Methods Investigation Using the Technology Acceptance Model

Smitha S[1*] and Anushree Singh[2]
[1,2] School of Management, CMR University, Bengaluru, India
smitha_s@cmr.edu.in

Abstract. The research looks at employee and management perceptions of how HR analytics are being adopted in the workplace. Using the Technology Acceptance Model (TAM) as the framework for this research project, this study used a sequential explanatory mixed-methods approach to gather quantitative data through surveys of 350 employees and qualitative data through semi-structured interviews with 15 managers. Using Structural Equation Modelling (SEM), perceived usefulness (PU) and management support (MS) positively predict the intention to adopt HR analytics, while there is significantly negative impact from privacy risk (PR). Data literacy (DL) positively impacts the adoption of HR analytics moderated by the organisation's culture (OC); and the relationship between privacy risk and the intent to adopt HR analytics is fully mediated by employee trust. . By highlighting clear leadership commitment, ethical data governance, and open communication as crucial organizational elements that will support the implementation of HR analytics, qualitative interviews supplement and contextualize the quantitative findings. Analysis of control variables found that prior experience in analytics and HR role will also substantially impact an employee's readiness to adopt HR analytics. The conclusion of this research indicates that the long-term and continued successful adoption of HR analytics is dependent not only on the technological capacity of an organisation but also on a unified and integrated strategy that includes leadership, ethical considerations of data, and trust of the employee.
Keywords: HR analytics, technology adoption, employee attitudes, management support, organisational culture, data literacy, structural equation modelling

1. Introduction

HR analytics, also known as people analytics, has become more well-known in recent years as a strategically important capability for organizations to apply data-oriented methods to talent management, empower retention improvements, and guarantee that workforce strategies are in line with larger business objectives. With consistent evidence from the industry indicating that HR analytics would elevate the strategic power of HR functions, even so, the level of uptake and effective utilisation of such

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systems is thus far found to vary across industries or size organisations (Coolen et al., 2023; Wirges et al., 2022).

Since employee and manager attitudes mediate behaviour intentions and actual adoption outcomes, understanding these scenic dimensions of both groups is highly imperative. This study thus explores the intricate interplay between individual-level attitudes, organisational enablers such as leadership support and data-driven culture, and structural constraints such as data quality limitations, privacy concerns, and analytical capability limitations governing HR analytics adoption (Anthun et al., 2024; Sattar, 2024).

While one can point to an increasing literature in HR analytics over the past twelve years, most prior studies focus either on managerial angles or employee angles. Perhaps more seriously, these approaches tend to apply generalized technology adoption frameworks to evaluate attitude alignment within organizations and ethical considerations for people analytics without adequate calibration to sector-specific and organizational dimensions. This study addresses such a gap by working within an extended TAM framework.

2. Literature Review

2.1 The definition and benefits of HR analytics

HR analytics is a comprehensive method of analysing employee data (HR Analytics) that combines descriptive, diagnostic, predictive and prescriptive analyses to assist management in making decisions about all areas affecting the overall success of an organisation, including workforce planning, recruitment, talent management, performance management and retention. Both previous and present research and documented studies show that when proper HR analytics are used by employers, the result is an improvement in the overall quality of the decisions being made by employers, an increase in the overall strategic credibility of the HR function and ultimately, improved financial results (McCartney 2022; Society of Human Resource Management [SHRM] 2021).

2.2 The gap in adoption of HR analytics and their Institutionalisation

Despite the rapid proliferation of literature and vendors related to HR analytics, many organisations have hardly begun to implement HR analytics. Research conducted using systematic review has demonstrated that 40 has continuously had a number of organisational characteristics (i.e., top management support, analytical capabilities, quality of data, strategic alignment, and organisational culture) are indicators of enabling HR analytics to be instituted within an organisation. Typically, a more reliable method of achieving institutionalisation is to integrate analytics into the existing HR processes rather than create standalone analytics projects (Coolen et al. 2023; Ekka and Singh 2022).

2.3 Employee Acceptance and Attitudes towards HR analytics

Many factors impact an employee’s acceptance of the HR analytics applied in organisations, including perceptions of usefulness, data literacy (which is similar to perceived ease of use according to the Technology Acceptance Model [TAM]), trust in the data, privacy concerns regarding data obtained about them and perceptions of how the HR analytics affect their professional futurePositive employee attitudes, according to research, encourage participation in HR procedures that depend on the use of analytics, while mistrust and worries about employee analytics and the possibility of algorithms tracking employee behavior are major obstacles to their use (Jasni et al. 2023; Sattar 2024).

2.4 Management Attitude and the Role of Leadership

The attitudes of senior leadership and HR management are the primary factors that influence an organisation’s inclination and capability to hold HR analytics.

2.5 Research Gap and Contribution

Although there have been many studies regarding the HR analytics and its implementation in organizations, there are a lot of gaps in the current body of knowledge. Firstly, the most of HR analytics research focuses on managerial perspective, that is their view toward the HR analytics and its impacts on their organizations. Due to this factor, there are only very limited numbers of study regarding employees' view of HR analytics and whether they think the HR process is fair and ethical or not (see Jasni et al., 2023; Sattar, 2024). Secondly, there is very few empirical research conducted for employees' views of ethical, transparent, fairness and privacy application of data in the HR analytics environment. Secondly, most of HR analytics research has concentrated on the individual level constructs (e.g. Data literacy or privacy) and their direct influences on individual's adoption, without taking into consideration interaction effects between these individual factors and contextual factors (e.g. Organization culture, management support, and interpersonal trust) within an organization. Because both technical and individual factors may influence individual's adoption decision on HR analytics, a more general, integrated perspectives of HR analytics adoption would benefit researchers in the HR field as well as practitioner (see Coolen et al., 2023; Ramakrishna et al., 2024). Lastly, although TAM and UTAUT is widely adopted in information system research, these frameworks are not heavily employed in HR analytics research. The moderating effects of the organization culture and management support toward the relation of employee's views of HR analytics and the mediator role of employee's trust have not been investigated. It is recommended for HR analytics research to study the following aspects to build up a body of knowledge toward HR analytics adoption and to develop appropriate implementation strategy for business to have HR analytics adopted by employees in a beneficial way.

2.6 **Theoretical Framework and Hypotheses**

This research is based on the technology acceptance model (Davis, 1989) and enhanced with the elements focusing on the organizational context and the dynamics of trust and privacy of HR analytics adoption environment. This research will propose and examine the following six constructs:
1. Perceived Usefulness (PU) is the extent to which an individual believes that using HR analytics can improve both the organizational performance and the quality of HR decision making.
2. Data Literacy/Perceived Ease of Use (DL) refers to the individual's ability and the degree in which he or she thinks that he or she is able to understand the information generated by analytics.
3. Privacy Risk (PR)refers to the individual's level of concern that HR analytics technology can be used to monitor, investigate and/or discriminate the individual employees.
4. Management Support (MS)refers to the commitment and resource provisions from the higher-level management regarding HR analytics adoption initiatives, evident from employees' perspective.
5. Organizational Culture (OC)refers to the individual's beliefs about how far the evidence based and data-driven approach to decision making is entrenched in the organization's culture.
6. Adoption Intention (AI)refers to the individual employee's willingness and readiness to use HR analytics tools and processes in performing work-related tasks.

Following this theoretical framework, the following hypotheses are put forward:
H1: Perceived usefulness (PU) of HR analytics is positively related to the adoption intention (AI) of HR analytics.
H2: Data literacy (DL) is positively related to adoption intention (AI) of HR analytics.
H3: Privacy risk (PR) toward HR analytics is negatively related to adoption intention (AI) of HR analytics.

3. Method

3.1 Research Design

This study uses a sequential explanatory mixed-methods methodology (Creswell & Plano Clark, 2018), with semi-structured qualitative interviews acting as the explanatory strand and a cross-sectional quantitative survey as the primary strand. When statistical data needs to be elaborated upon and contextualized by detailed participant stories, this approach is suitable. The Institutional Research Committee granted ethical approval for the study, and prior to their involvement, each subject gave their informed consent**.**

3.2 Quantitative Strand: Survey

This poll was completed by 350 workers in the manufacturing, IT, healthcare, and services sectors in Europe and India. In order to ensure sufficient representation of the theoretically relevant subgroups, the target population was stratified by sector and employment level (HR professional vs. non-HR employee). Participants were then purposefully chosen from the available and willing participants within each stratum. The final sample was made up of 30% HR professionals and 70% non-HR workers, with 52% of respondents being men and 48% being women. Small to medium-sized enterprises (45%) and large businesses (55%) were roughly equally represented.

3.3 Qualitative Strand: Interviews

A total of 15 managers, including HR Directors, CHROs and senior line managers, were purposively selected to conduct semi-structured interviews based on their direct experience with people analytics projects. each

4. Results

4.1 Exploratory Factor Analysis

EFA was conducted on the full item pool ($N = 350$) prior to CFA. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.914, indicating excellent suitability for factor analysis, and Bartlett's test of sphericity was significant ($\chi^2(253) = 4268.45$, $p < .001$). Six factors were extracted, accounting for 68.3% of total variance. All item loadings exceeded 0.70, with no cross-loadings above 0.30, confirming the adequacy of the proposed factor structure. Full EFA results are presented in Table 1.

Table 1: Exploratory Factor Analysis Results

Construct	Item	Factor loading	Communality
Perceived Usefulness (PU)	PU1	0.812	0.659
	PU2	0.845	0.714
	PU3	0.798	0.637
	PU4	0.826	0.682
Data Literacy (DL)	DL1	0.774	0.599
	DL2	0.811	0.658

	DL3	0.792	0.627
	DL4	0.836	0.699
Privacy Risk (PR)	PR1	0.781	0.610
	PR2	0.828	0.686
	PR3	0.807	0.651
	PR4	0.764	0.584
Management Support (MS)	MS1	0.853	0.728
	MS2	0.841	0.707
	MS3	0.819	0.671
	MS4	0.834	0.696
Organisational Culture (OC)	OC1	0.788	0.621
	OC2	0.821	0.674
	OC3	0.804	0.646
	OC4	0.832	0.692
Adoption Intention (AI)	AI1	0.884	0.781
	AI2	0.865	0.748
	AI3	0.891	0.794

Note. KMO = 0.914; Bartlett's test of sphericity $\chi^2(253) = 4268.45$, $p < .001$. All factor loadings > 0.70; no cross-loadings > 0.30.

4.2 Confirmatory Factor Analysis and Measurement Model

CFA was performed using maximum likelihood estimation. Model fit indices satisfied all recommended thresholds: $\chi^2/df = 2.12$ (< 3.00), GFI = 0.93 (> .90), AGFI = 0.89 (> .80), CFI = 0.95 (≥ .95), TLI = 0.94 (> .90), NFI = 0.92 (> .90), RMSEA = 0.045 (< .08), and SRMR = 0.051 (< .08), collectively indicating acceptable model fit. Full fit statistics are reported in Table 5.

Table 2: Confirmatory Factor Analysis: Standardised Factor Loadings

Construct	Item	Standardised loading	t-value	p-value
PU	PU1	0.81	15.67	< .001
	PU2	0.85	16.83	< .001
	PU3	0.80	15.24	< .001
	PU4	0.83	16.05	< .001
DL	DL1	0.77	14.28	< .001
	DL2	0.81	15.49	< .001
	DL3	0.79	14.97	< .001
	DL4	0.84	16.21	< .001
PR	PR1	0.78	14.63	< .001
	PR2	0.83	15.81	< .001
	PR3	0.81	15.29	< .001
	PR4	0.76	14.01	< .001
MS	MS1	0.85	16.42	< .001
	MS2	0.84	16.10	< .001
	MS3	0.82	15.61	< .001
	MS4	0.83	15.89	< .001
OC	OC1	0.79	14.89	< .001
	OC2	0.82	15.55	< .001
	OC3	0.80	15.14	< .001
	OC4	0.83	15.98	< .001
AI	AI1	0.88	17.61	< .001
	AI2	0.87	17.22	< .001
	AI3	0.89	17.94	< .001

Note. All standardised loadings exceed the recommended threshold of 0.70, confirming adequate indicator reliability.

Table 3: Reliability and Convergent Validity Assessment

Construct	Cronbach's α	Composite reliability (CR)	AVE
PU	0.89	0.91	0.71
DL	0.85	0.88	0.65
PR	0.81	0.86	0.61

MS	0.87	0.90	0.69
OC	0.83	0.87	0.63
AI	0.90	0.93	0.81

Note. Acceptance thresholds: α > .70; CR > .70; AVE > .50. All constructs satisfy convergent validity criteria.

Table 4: Discriminant Validity: Fornell–Larcker Criterion

Construct	PU	DL	PR	MS	OC	AI
PU	**0.843**					
DL	0.521	**0.806**				
PR	−0.398	−0.342	**0.781**			
MS	0.602	0.477	−0.291	**0.831**		
OC	0.587	0.514	−0.256	0.631	**0.794**	
AI	0.672	0.541	−0.473	0.614	0.582	0.900

Note. Diagonal values (bold) are square roots of AVE. Each exceeds off-diagonal correlations in the same row and column, confirming discriminant validity.

Table 5: Structural Model Fit Indices

Fit index	Recommended threshold	Obtained value	Assessment
χ^2/df	< 3.00	2.12	Satisfactory
GFI	> .90	0.93	Satisfactory
AGFI	> .80	0.89	Satisfactory
CFI	≥ .95	0.95	Satisfactory
TLI	> .90	0.94	Satisfactory
NFI	> .90	0.92	Satisfactory
RMSEA	< .08	0.045	Satisfactory
SRMR	< .08	0.051	Satisfactory

Note. GFI = Goodness-of-Fit Index; AGFI = Adjusted GFI; CFI = Comparative Fit Index; TLI = Tucker–Lewis Index; NFI = Normed Fit Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardised Root Mean Square Residual.

4.3 Structural Model and Hypothesis Testing

The structural model was estimated using maximum likelihood SEM following validation of the measurement model. Hypothesised path coefficients, standard errors, *t*-values, and significance levels are reported in Table 6. The model accounts for a substantial proportion of variance in adoption intention ($R^2 = .64$).

Table 6: Structural Model Results and Hypothesis Tests

Hyp.	Relationship	β	SE	t	p	Decision
H1	PU → AI	0.44	0.06	7.33	< .001	Supported
H2	DL → AI	0.21	0.05	4.20	.002	Supported
H3	PR → AI	−0.29	0.06	−4.83	< .001	Supported
H4	PU × MS → AI	0.17	0.05	3.40	.010	Supported
H5	PR → Trust → AI	−0.18a	0.04	−4.50	< .001	Supported
H6a	PU × OC → AI	0.14	0.05	2.80	.030	Supported
H6b	DL × OC → AI	0.13	0.05	2.60	.040	Supported

Note. β = standardised path coefficient; SE = standard error. aIndirect effect via bootstrapping; see Table 7. All hypotheses supported at $p < .05$.

Perceived usefulness emerged as the strongest direct predictor of adoption intention (β = 0.44, $p < .001$), consistent with foundational TAM propositions (Davis, 1989). Data literacy demonstrated a significant though comparatively smaller positive effect (β = 0.21, $p = .002$), indicating that the capacity to engage analytically with HR data meaningfully facilitates adoption readiness. Privacy risk exerted the most substantial negative effect (β = −0.29, $p < .001$), underscoring that concerns about employee surveillance and data misuse represent a primary behavioural barrier. Management support significantly amplified the positive effect of perceived usefulness (β = 0.17, $p = .010$), while data-driven organisational culture moderated the effects of both perceived usefulness (β = 0.14, $p = .030$) and data literacy (β = 0.13, $p = .040$), confirming that contextual organisational factors constitute important boundary conditions for individual-level TAM predictions.

Table 7: Mediation Analysis via Bootstrapping (5,000 Resamples)

Mediated path	Indirect β	Boot LLCI	Boot ULCI	Conclusion
PR → Trust → AI	−0.18	−0.265	−0.092	Mediation supported
PU → Trust → AI	0.12	0.058	0.214	Mediation supported

Note. LLCI = lower-limit confidence interval; ULCI = upper-limit confidence interval. Zero is excluded from both intervals, confirming significant indirect mediation effects.

Table 8: Control Variable Effects on Adoption Intention

Control variable	β	p	Interpretation
Age	−0.06	.213	Not significant
Organisational tenure	0.08	.114	Not significant
HR role (vs. non-HR)	0.17	.011	Significant: HR professionals show stronger adoption intention
Firm size	0.13	.029	Significant: larger firms exhibit higher adoption readiness
Prior analytics experience	0.26	< .001	Significant: strongest control predictor

Note. Age and tenure did not significantly predict adoption intention, indicating that adoption enablers operate consistently across demographic groups. HR role, firm size, and prior analytics experience each exerted significant independent effects.

The non-significance of age and tenure suggests that adoption-focused interventions need not be demographically differentiated; rather, organisations can channel resources into targeted training and capability-building programmes accessible to all employee groups. The significance of prior analytics experience (β = 0.26, $p < .001$) aligns with the qualitative theme of capability development as a prerequisite: managers in the interview strand described how short experiential workshops—focused on interpreting real analytics outputs rather than abstract data concepts—substantially accelerated employee readiness.

5. Discussion

According to the research's findings, adopting HR analytics necessitates a comprehensive grasp of interconnected organizational, relational, and human aspects. Perceived utility was found to be the main predictor of HR analytics adoption intention, which is consistent with Davis' (1989) original TAM and later implementations in organizational IS. The current findings, however, go beyond the TAM by showing that, when mediated by management support and data-driven culture, perceived usefulness has a significant amount of variance rather than a predictable amount, suggesting that the organizational environment will have a significant impact on individual usefulness. The study's most practically significant finding is that perceived privacy risk has a large negative effect on HR analytics adoption (β = -0.29).Employee worries around surveillance, algorithmic bias, and ethically employing personal information will make it difficult for organisations to adopt Human Resource Analytics (HR Analytics) successfully. These results carry a clear implication demonstrating that HR Analytics works is necessary but not sufficient to secure organisational buy in .The mediation analysis is instructive here. Employee trust accounted for the path running from perceived privacy risk to adoption intention ,when staff doubt that their organisation will handle analytics data ethically and openly, their willingness to engage drops sharply .The reverse holds just as strongly. Where trust has been established through visible governance, candid communication and leaders who behave consistently over time, employees prove far more receptive to analytics driven HR practices.

6. Conclusion

The evidence collected here points towards a single conclusion: whether an organisation adopts HR analytics turns on a blend of individual disposition, organisational conditions, and the relational quality of trust, rather than on technology alone. Working from an extended Technology Acceptance Model (TAM) adapted to a sequential explanatory mixed-methods design, and drawing on 350 employees and 15 senior managers across several sectors, the study found that six factors such as perceived usefulness, data literacy, privacy risk, management support, organisational culture, and trust together explained 64% of the variance in adoption intention.

Three contributions follow from this as follows. The first is theoretical reach by folding privacy risk and trust into the standard TAM constructs, the model extends acceptance the model extends acceptance theory into the specific terrain of HR analytics. The second is contextual evidence management support and organisational culture operate as genuine moderators, which strengthens the case for situating technology-adoption models within their organisational setting rather than treating adoption as a purely individual decision. The third concerns mechanism: by showing that trust carries the effect of ethical governance through to actual adoption behaviour, the study connects two literatures that rarely meet research on organisational ethics and research on technology acceptance

The practical message is more direct. Organisations that want to move HR Analytics from pilot to practice need to work on four fronts at once rather than betting on any single lever. They should make the employee level payoff of analytics explicit, not only the organisational one, replace abstract data literacy training with hands on sessions built around real analytics output, pot managerial backing on a policy footing instead of leaving it to individual enthusiasm and actively diagnose where trust breaks down listening to managers and frontline staff rather than assuming where the concern lies.

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