The object of the study focuses on the process of AI adoption in HRM systems in technology-driven organizations of Indian IT sector. Despite a growing investment in AI-enabled HR systems, there is relatively scarce empirical evidence on how organizational and environmental determinants together affect AI adoption and how this translates into actionable workforce effectiveness.

The study addresses this problem by proposing and testing an integrated structural model that investigates organizational preparedness, technological readiness, competitive pressure, and security/privacy concerns in influencing AI adoption and subsequent impact on effective HRM.

To address this problem, an integrated structural model was developed which has been empirically tested through data collected from 378 professionals working in the Indian IT sector and analyzed using partial least squares structural equation modeling. Specifically, the findings indicate that technological readiness ($\beta = 0.464$, $p = 0.003$), competitive pressure ($\beta = 0.308$, $p = 0.018$) and security/privacy concerns ($\beta = 0.303$, $p < 0.001$) are significant predictors of AI adoption, whereas organizational preparedness is not statistically significant in this model. AI adoption has a significant positive effect on effective HRM ($\beta = 0.799$, $p < 0.001$) and explains 63.8% of its variance.

The results show that technology infrastructure and governance assurance, in contrast to mere or formal readiness, explain successful deployment of AI. These outcomes are contingent upon the interaction between technological capability and competitive dynamics and governance mechanisms that permit successful adoption. This study contributes by modelling AI adoption as a strategic mechanism that connects contextual enablers to HRM outcomes instead of adoption intention. The findings are relevant in technologically driven markets that are digitally mature, competitive and sensitive to governance

Keywords: AI adoption in HRM, security/privacy, competitive pressure, Indian IT sector

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IDENTIFICATION OF ARTIFICIAL INTELLIGENCE ADOPTION DETERMINANTS AFFECTING HUMAN RESOURCE MANAGEMENT EFFECTIVENESS IN THE INDIAN INFORMATION TECHNOLOGY SECTOR

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1. Introduction

With a digital competitiveness never seen before, companies are under significant pressure to capitalize on cutting edge technologies to ensure efficient operations, effective workforce and strategic agility [1]. Among the technologies, artificial intelligence (AI) has been gaining some attention as a key driver that shapes how organizations manage information and automate tasks they perform, human resources management (HRM) practices. However, the AI adoption is not an option but a strategic must-have for competitive and effective organizations [2], especially within knowledge-intensive sectors such as information technology (IT).

Using AI embedded in HRM functions enhances the accuracy of decision-making. Moreover, analytics in HR improves talent management and boosts workforce productivity via data-driven insights along with intelligent automation [3]. But the adoption of AI is not a simple-matter and depends on a variety of organizational and environmental factors. However, although AI is progressively integrated with HRM practices, organizations still face difficulties in terms of its effective implementation outcomes. These challenges stem from the interplay among technological capabilities, organizational conditions, and external environmental pressure across the adoption process. In technology-centric domains like the Indian IT industry, this need for agile, data-oriented and scalable HR systems experience a multipliable effect making the tracking of these influencing factors increasingly critical [4].

Moreover, data security/privacy issues, as well as the ethical application of AI, have also been identified as critical factors influencing organizational trust and adoption [5]. These issues are particularly relevant in digitally intensive environments that process vast amounts of employee data across AI-enabled platforms. Consequently, organizations need to strike a balance between innovation and governance for responsible and effective AI usage in HRM.

From a practical point of view, recognizing the main determinants behind AI adoption is critical for organizations aiming to improve HRM efficiency with intelligent technologies. Insight into how these various factors interact can help to inform HR managers as well as decision-makers

in the design of HR systems that are sound, secure and performance-oriented. Moreover, these insights are extremely useful to the Indian IT sector which is one marked by rapid technological evolution, high competitiveness and growing adoption of AI-powered workforce management solutions [6].

The current study makes both theoretical and practical contributions by investigating how organizational, technological, and environmental factors together shape AI adoption processes, leading to successful HRM. These findings are anticipated to offer practical insights for organizations, which strive to utilize AI in sustainable workforce management and strategic performance enhancement [7].

Thus, it is pivotal to research the determinants of AI adoption and its effectiveness on productive HRM in IT-based organizations. In particular, the following are the study questions:

– RQ1: what are organizational, technological and environmental factors affecting AI adoption in HRM systems;

– RQ2: what is the impact of AI adoption on HRM effectiveness;

– RQ3: how much do these determinants altogether explain AI-driven HRM outcomes in technology-driven companies.

2. Literature review and problem statement

AI has proven itself a disruptive digital technology with the potential to transform organizational processes and HRM practices in every industry. Previous study states that recruitment and selection, workforce analytics, employee performance monitoring, and strategic decision making are among the HR functions that AI in organizations streamlines. For instance, a previous work has highlighted that AI technologies have helped improve talent acquisition processes through comprehensive automation of various predefined tasks within HR functions, optimize workforce planning, and enable the organizations to provide predictive analytics for efficient strategic management of workforce [3, 8]. Furthermore, study has shown that technology readiness and maturity of the digital infrastructure are key to enabling organizations in implementing AI systems [9, 10].

Moreover, external environmental forces have been recognized as significant factors affecting the adoption of advanced digital technologies. Competitive pressure, institutional dynamics, and technology diffusion within industries that motivate organizations to move to AI-enabled HR practices for strategic competitiveness at the operational level [11, 12]. Consistent with this, recent study emphasized the role of security/privacy governance mechanisms in shaping organizational trust towards AI systems containing sensitive employee data [6].

Conversely, despite these advances in the literature, there are still several important questions that have not been addressed regarding the integrated drivers of AI adoption in HRM contexts. Most studies investigate organizational readiness, technological capability or environmental pressures in isolation, offering fragmented theoretical explanations for AI adoption outcomes. Subsequently, scant empirical evidence explains the ways that various organizational and environmental predictors interact to promote AI adoption and how such adoption translates into measurable HRM effectiveness.

This limitation can be caused by the nature of implementation of AI in organizational regimes. The successful implementation of AI systems requires the alignment of technological infrastructure, governance systems, managerial capabilities and environmental responsiveness. Such multivariate conditions create a set of objective challenges for empirical studies, particularly in some emerging economies where the levels of technological maturity and organizational capabilities differ widely between organizations.

A possible solution to address these challenges is to establish an integrated comprehensive analytical framework that considers simultaneously the key organizational and environmental determinants of AI adoption, and evaluates their effects on HRM outcomes. Understanding AI adoption as a strategic organizational device, connecting contextual enablers with actual HR performance, provides researchers with elements to better explain the ways through which digital transformation underpins workforce management effectiveness.

While some recent researches were aimed to identify specific determinants of AI adoption in HRM contexts [6, 13], these studies tend to either concentrate on individual factors or purely conceptual arguments, rather than conducting empirical analyses of integrative structural models linking the determinants of adoption and HRM effectiveness. Thus, the pathways by which AI adoption translates into organizational capabilities lack insight in practice for measurement.

The above all indicates that it is necessary to conduct an in-depth empirical investigation examining the combination of factors that drive AI adoption and its effect on effective HRM. Thus, the effect of AI adoption on HRM effectiveness through organizational preparedness, technological readiness, competitive pressure and security/privacy concerns is an important and relevant research area specifically in tech-intensive sectors like Indian IT industry.

One of the important factors affecting technology adoption is organizational preparedness. It refers to the extent of alignment between organizational structure, leadership support, knowledge and resource available with AI implementation requirements [9]. Firms with strategic readiness, digital vision and human resources in abundance are more likely to be able to test and scale AI applications for these HR areas. Poor HR performance and scattered adoption initiatives are the result of an unpreparedness.

Another factor plays crucial role for AI implementation and that is the technological readiness. This affect the accessibility, applicability power and the readiness of IT infrastructure and data quality/analytical capabilities used to effectively implement AI applications [10]. In addition, AI systems depend on solid data architectures and the ability to integrate with current HR information systems to be successful. The results revealed that readiness had positive and significant factors associated with perceived usefulness, perceived ease of use which meant that organizations may value AI as well as perceive it to be usable therefore will onboard it into HRM processes. Based on the above, the following hypotheses are developed:

– organizational preparedness has a positive impact on AI adoption;

– technological readiness has a positive impact on AI adoption.

Besides those internal forces, external environmental pressure is driving decisions on AI adoption. The competitive pressure forces the organizations to deploy innovative-technologies in order to have efficiency and also, to attract in-house talent against competition [11]. In a knowledge-intensive, high-tech competitive environment successful com-

petitors strategic own practice application of AI-based HR acts as gravity for organizations to put similar practices into place in order to avoid being strategically disadvantaged. Thus, competitive pressure is expected to drive AI adoption more and more: competitive pressure positively affects AI adoption.

Even though AI security/privacy applications have potential positives, these technologies raise major issues in terms of security/privacy and are some of the primary barriers to adoption, particularly in HRM environments where sensitive employee information is a daily concern. Security/privacy factors affect trust of organizations in AI systems as well as employees' acceptance toward algorithmic acceptance [13, 14] Institutions that see a higher risk in data breach, algorithmic bias or non-compliance with regulations may be slower and more constrained in adopting AI. Thus, security/privacy concerns will likely play a major role in AI adoption decisions: security/privacy positively influences AI adoption.

And the use of AI is emerging as a fundamental driver to effective HRM. AI-powered HR practices allow evidence-based decision-making, reduce administrative workload, augment workforce analytics and align with HR strategies and organizational objectives [8]. That is, AI frees HRM professionals from routine and repetitive work to focus on strategic and value-enhancing activities, thereby enhancing the effectiveness of HRM. Thus, the last hypothesis is suggested: AI adoption positively influences effective HRM.

Previous study suggests that organizational readiness, technological competence, competitive pressure and security/privacy concerns are central factors shaping the adoption of AI in organizations [4, 7]. This is particularly true in IT organizations, which are subject to rapid technological shifts, high employee skill set demands and aggressive market competition that requires agile and reliable digital infrastructures.

Although there is an increased academic focus on AI adoption and digital transformation, there has been limited empirical research that explicates how these organizational and environmental factors have a combined influence on AI adoption outcomes in the context of HRM, especially in emerging economies such as India [5]. With a large, diverse and high on innovation IT practice in India is one of the fastest growing technology hubs globally making it worthwhile to examine context embedded AI powered HRM systems closely. Additionally, these security and employee privacy concerns have developed into serious basic issues in regards to trust and acceptance of utilization of AI based applications in HR [6].

Drawing on a technology adoption and organizational capability perspective, this study conceptualizes AI adoption as one potential mode of strategic vehicle through which the antecedents at both the organizational as well as technological levels become realized to drive the processes leading to effective HRM outcomes. AI-aided efficient HRM can help in performance appraisals, employee career growth and workforce planning thus leading in enhancing effectiveness of the organization as well as sustainability [15]. The study address an important gap in the AI and HRM research by combining organizational preparedness, technological readiness within a comprehensive framework competitive pressure and security/privacy concerns.

Thus, the present study is an empirical examination of AI adoption in an Indian IT context aimed to contribute theoretically as well as practically by uncovering what drives AI adoption and how does it affect effective HRM. The results are expected to offer valuable insights for scholars, HR leaders and policy makers who seek to leverage the AI tools in building strong, effective, and future-ready HR systems in tech-driven organizations [16].

Nevertheless, the existing studies only give a limited view on AI adoption in HRM. Much of the extant research looked at determinants like technological readiness, organizational preparedness or environmental pressure in isolation, leading to piecemeal theoretical explanations. In addition to this, much of the literature is concerned with adoption intention rather than empirically validated organizational outcomes which further hinders the practical relevance of these findings.

There are several reasons why existing studies fall short in addressing this problem. The implementation of AI is inherently multidimensional, requiring the synchronous alignment of the technological capability, organizational preparedness and governance mechanisms. Nonetheless, most studies use overly simplified models that do not account for the combined and interactive influences of these determinants. Moreover, empirical studies usually fail to combine drivers of AI adoption with performance outcomes and thus cannot clarify the process behind how adopting AI leads to measurable effectiveness in HRM.

While previous studies have identified various important determinants like organizational preparedness, technological readiness, competitive pressure, security/privacy concerns, few of them have investigated these factors in a common empirical framework. As a result, the ways in which these contextual enablers work together in stimulating AI adoption and subsequently effective HRM still need to be explored within technology-intensive organizations.

Thus, an integrated empirical framework is needed to simultaneously explore the organizational, technological and environmental determinants of AI adoption and measure their impact on HRM effectiveness. Filling this gap provides a more nuanced view of how contextual elements interact to shape measurable organizational outputs and offers both academic and practical implications for organizations operating in digitally progressive contexts like Indian IT sector.

Even though previous studies have addressed the concepts of AI adoption and digital transformation separately, little is known regarding the systematic integration of organizational, technological, and environmental determinants by which AI adoption could facilitate effective HRM outcomes in general but especially within developing economies characterized as technology-intensive. Smart systems have strategic significance in every aspect of the economy these days when it comes to how organizations manage their workforce performance, governance practices and competitive positioning.

3. The aim and objectives of the study

The aim of the study is to explore the impact of AI adoption in enhancing workforce performances through effective HRM within technology driven organizations, with a prime focus on Indian IT sector. It will enable enterprises to know what strategic and technological conditions are required on the ground for successful AI embedding in an all-encompassing manner, helping them create HR systems that are evidence-based, secure, performance-ensured shifting in decision quality, operational efficiency and workforce effectiveness-oriented over the short and long-term period.

In order to achieve this goal, the following objectives are carried out:

– to analyze the profile and characteristics of respondents who participated in the survey, to validate that the data is fit for purpose as well as representative enough for further analysis;

– to assess the reliability and validity of the measurement model through indicator loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), discriminant validity criteria and multicollinearity;

– to determine the explanatory power of the structural model and to assess overall fit of the models using coefficient of determination (R^2), standardized root mean square residual (SRMR) and normed fit index (NFI);

– to analyze the structural links in the model such as organizational and environmental constructs on AI adoption, as well as the impact of AI adoption on HRM effectiveness.

4. Materials and methods

The object of the study focuses on the process of AI adoption in HRM systems in technology-driven organizations of Indian IT sector. The study examines the effect of AI- enabled HR practices which is measuring the workforce effectiveness in terms of improved decision quality, operational efficiency and strategic HR outcomes.

Specifically, the study is predicated on a hypothesis that AI adoption serves as a strategic mechanism through which organizational and environmental predictors translate into effective HRM. More specifically, it hypothesizes that organizational readiness, technological readiness, competitive pressure and security/privacy concerns affect AI adoption and AI adoption in turn has a positive impact on effective HRM as depicted in Fig. 1 showing the proposed conceptual model.

This study assumes that IT organizations in Tamil Nadu operate digitally advanced environments suitable for AI-enabled HR systems. It further presumes that respondents have adequate knowledge regarding AI practices in their organizations, and that the level of adoption mentioned by those respondents accurately depicts adoption levels, which would correlate with HRM effectiveness.

It examines four antecedents of AI adoption and one outcome variable, effective HRM, but does not examine other possible organizational and behavioral factors.

This study assumes that IT employees differ in their perceptions of technological experience, organizational settings and environmental pressures that can all shape their attitude towards AI-enabled HRM. These perceptions are assumed to reflect how the respondents have experienced AI enabled HR systems in their organizations.

IT professionals from Tamil Nadu in India were chosen as the participants so that there will be alignment and analytical capabilities over context selection. IT industry was selected due to its high degree of digitization, early adopters of AI-based HR solutions and dynamic workforce demand. Focusing on this segment allows the study to monitor a setting where the adoption of AI is both strategically pertinent and operationally evidential. This implies that only HRM practices within the IT sector context and not in other industry or function areas, are included.

A cross-sectional quantitative research design contributed in empirically testing the proposed model. The data were obtained from a formal online survey instrument through purposive sampling, distributed to IT professionals with direct or indirect exposure to AI-enabled HR practices. In sum, 378 valid responses were received which is a sufficiently large sample size for PLS-SEM analysis. Using an online format for the survey allowed for more inclusive participation, and resulted in consistent, efficient data collection.

A reliable and evidence-based instrument was developed by modifying reliable scales which were already used in other studies for a similar purpose. Organizational preparedness was assessed by means of items borrowed and modified from the previous literature on AI implementation process in relation to managerial support, resource availability, and organizational preparedness at large. Technology readiness statements measured the sufficiency of IT, system fit, and technical skill. Competitive pressure was assessed through items based on perceptions towards industry competition and peer adoption characteristics, whereas security/privacy concerns referred to the perception of data protection, ethical use and system trust. AI adoption was tested by examining the degree of the integration of AI with HR processes, and effective HRM was represented by efficiency, decision quality, and strategic HR outcomes applied from previous studies.

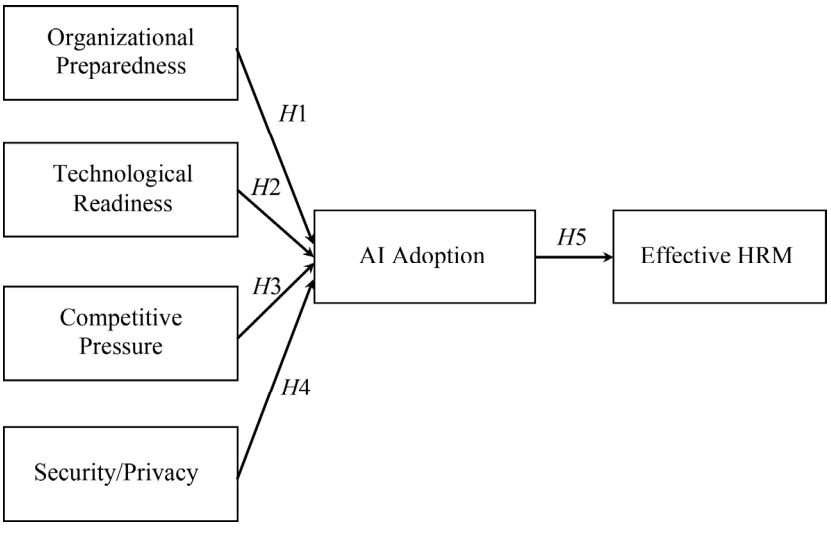

Fig. 1. Conceptual framework

The questionnaire contained sections of interest pertaining to demographic characteristics (first) and construct measure (second), utilizing a five-point Likert scale from "strongly disagree" (1) to "strongly agree" (5). The measurement scales included four items for organizational preparedness, five for technological readiness, three for competitive pressure, five for security/privacy concerns, four for AI adoption and five focused on effective HRM [12, 13]. The instrument was subjected to peer review by experts for items clarity, content-related validity and contextual appropriateness before fully implementing it.

The method used in this study shows to follow an established procedures of partial least squares structural equation modelling (PLS-SEM). The measurement scales and analytical techniques are largely adapted from previous validated

studies, with slight contextual changes. The measurement scales and analytical techniques are adapted from prior validated studies, with minor contextual modifications. Therefore, the methods represent a structured application of standard and widely accepted analytical procedures rather than newly developed techniques.

Data analysis was conducted using SmartPLS software. Prior to analysis, the dataset was screened for completeness and consistency, and responses with missing or invalid values were excluded. The analysis followed a two-stage approach. In the first stage, measurement model was tested to assess indicator reliability, internal consistency reliability, convergent and discriminant validity of the scales research model. Indicator loadings, CR, AVE, and discriminant validity were investigated based on the established PLS-SEM criteria [17]. In the second stage, path coefficients in addition to R^2 and effect sizes (f^2) also were examined for the structural model.

With a relatively high number of resampling trials, bootstrapping was used to assess significance of the indirect and direct relationships, which produces less biased estimates and enables the calculation of confidence intervals for path coefficients [17]. Variance inflation factors (VIF) [18] values were calculated to assess multicollinearity among predictor constructs. The use of PLS-SEM is justified due to its suitability for analyzing complex models with multiple constructs and its ability to handle non-normal data distributions. The method is particularly appropriate for predictive research in emerging domains such as AI adoption. However, the approach is limited by its reliance on cross-sectional data and self-reported measures, which may restrict causal interpretation and generalizability.

5. Results of artificial intelligence adoption determinants and their impact on human resource management

5. 1. Profile of respondents and sample characteristics

The demographic details of the 378 respondents from Indian IT industry of Tamil Nadu is summarized in Table 1. The sample is mostly male 61.4% and female 38.6% which mirrors the gender distribution in the IT workforce roles of respondents that are male, but only one out of every three respondents were females. The sample primarily consists of early to mid-career professionals, among whom 74.1% of the participants are aged 21–40 years for this reason, it is a relatively early- and middle-career profession. It is an educated sample, on which more than half of the sample have a master degree (52.4%).

On an experience scale, most have worked in the HR function for between 5 and 10 years (38.1%) and those with less than five years were next highest (25.4%), which indicates a healthy mix of career history within HR. The middle management staffs are in the majority (47.1%), and most of them work in medium- to large-scale enterprises (79.4%). Very importantly, a significant number of participants in this sample report moderate to high exposure to AI-enabled HR practices (78.3%) suggesting that this sample is very appropriate for inquiring into the adoption of AI and effectiveness of HRM.

Table 1

Respondents demographic profile

Demographic variables	Categories	Frequency (n)	Percentage (%)
Gender	Male	232	61.4
	Female	146	38.6
Age (years)	21–30	124	32.8
	31–40	156	41.3
	41–50	74	19.6
	Above 51	24	6.3
Educational qualification	Bachelor's degree	138	36.5
	Master's degree	198	52.4
	Doctorate / Others	42	11.1
Work experience (years)	Less than 5	96	25.4
	5–10	144	38.1
	11–15	86	22.8
	Above 15	52	13.7
Job level	Entry-level	104	27.5
	Middle-level	178	47.1
	Senior-level	96	25.4
Organization size	Small (< 250 employees)	78	20.6
	Medium (250–500 employees)	132	34.9
	Large (> 500 employees)	168	44.5
Exposure to AI- enabled HR practices	Low	82	21.7
	Moderate	176	46.6
	High	120	31.7

5. 2. Measurement model evaluation: reliability, convergent validity, discriminant validity assessment and multicollinearity

Table 2 presents the measurement model findings, where the reliability and convergent validity for all constructs were acceptable. All indicators have high factor loadings above the 0.70 threshold and demonstrate sufficient indicator reliability Fig. 2. The averages suggest in general affirmative attitudes on all constructs with acceptable response variation.

The internal consistency is well established as the Cronbach's alpha and composite reliability values are all above 0.70 for every construct, representing high measurement reliability [19]. Convergent validity is further vindicated by AVE values that range from 0.734 to 0.867 which surpasses the minimum cut-off threshold of 0.50 [20]. In general, the results indicate that the measurement model is adequate and acceptable for further structural model examination.

Discriminant validity measurement is measured by Fornell-Larcker criterion, which states that the square root of AVE for each construct should be more than its correlation with other constructs [21]. As indicated in Table 3, the diagonal figures for AI adoption (0.856), competitive pressure (0.921), effective HRM (0.892), organizational preparedness (0.860), security/privacy (0.931) and technological readiness (92.3) are stronger than their between-construct correlations alone.

These results suggest that each construct has more shared variance with its own indicators than with other constructs, thus demonstrating acceptable discriminant validity and defending the measurement model used in further structural tests.

All VIF values shown in Table 4 are between 1.676 to 4.559, which is much lower than the critical value of 5.0 [19]. This confirms that there is no multicollinearity between the measurement items and the predictor constructs are statistically independent.

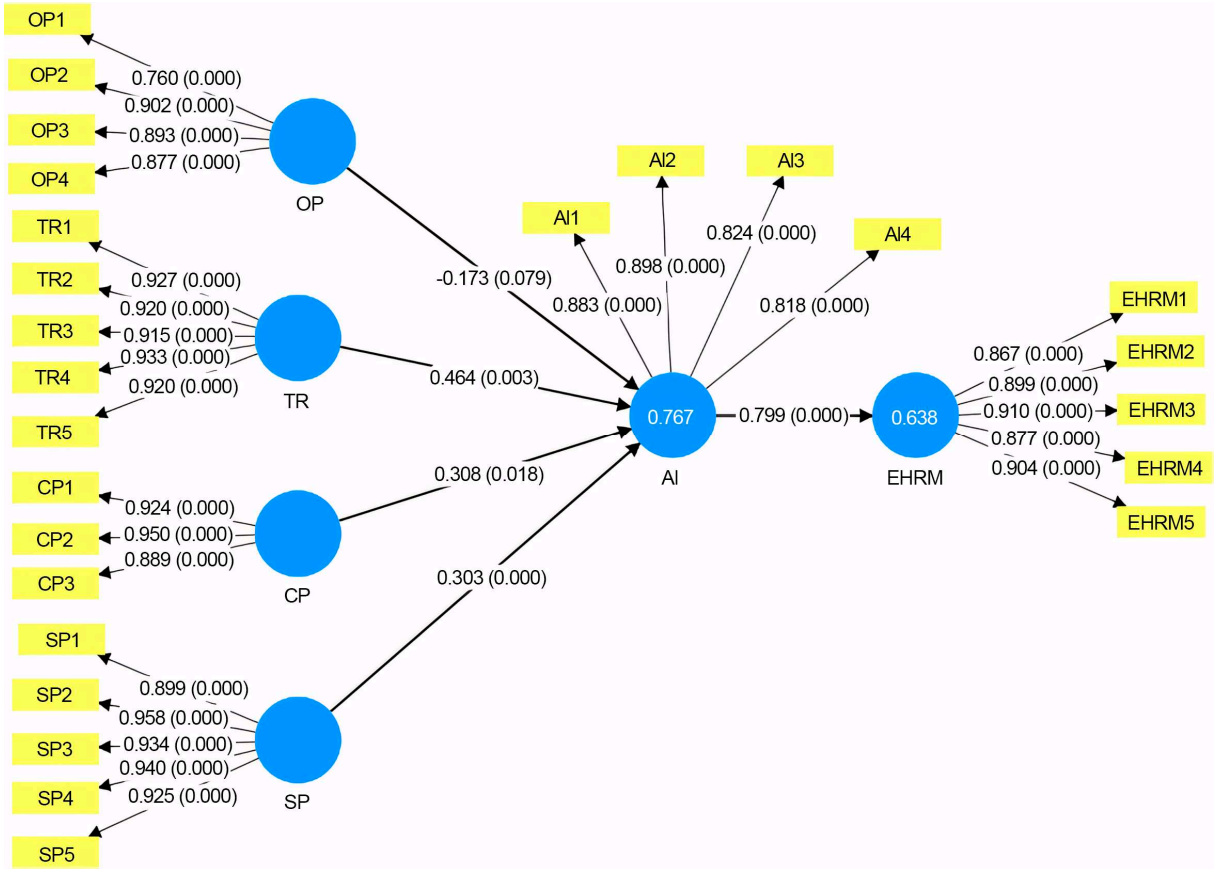

Fig. 2. Consolidated bootstrapping and partial least squares structural equation modeling algorithm results

Table 2

Factor loading, measurement of scale, and validity

Constructs	Items	Mean	Factor loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Organizational preparedness (OP)	OP1	4.173	0.760	0.881	0.919	0.740
	OP2	4.245	0.902			
	OP3	4.245	0.893			
	OP4	4.286	0.927			
Technological readiness (TR)	TR1	4.163	0.920	0.956	0.966	0.852
	TR2	4.194	0.915			
	TR3	4.133	0.933			
	TR4	4.102	0.920			
	TR5	4.122	0.927			
Competitive pressure (CP)	CP1	4.214	0.924	0.910	0.944	0.848
	CP2	4.194	0.950			
	CP3	4.173	0.889			
Security/privacy (SP)	SP1	4.184	0.899	0.962	0.970	0.867
	SP2	4.245	0.958			
	SP3	4.224	0.934			
	SP4	4.112	0.940			
	SP5	4.296	0.925			
AI adoption (AI)	AI1	4.102	0.883	0.879	0.917	0.734
	AI2	3.704	0.898			
	AI3	3.755	0.824			
	AI4	3.398	0.818			
Effective HRM (EHRM)	EHRM1	3.918	0.867	0.936	0.951	0.795
	EHRM2	4.143	0.899			
	EHRM3	4.122	0.910			
	EHRM4	4.245	0.877			
	EHRM5	4.235	0.904			

Table 3

Fornell-Larcker criterion

Constructs	AI	CP	EHRM	OP	SP	TR
AI	0.856	–	–	–	–	–
CP	0.828	0.921	–	–	–	–
EHRM	0.799	0.771	0.892	–	–	–
OP	0.673	0.799	0.653	0.860	–	–
SP	0.782	0.754	0.867	0.683	0.931	–
TR	0.742	0.916	0.798	0.845	0.786	0.923

Table 4

VIF

Factor	VIF
OP1	1.676
OP2	3.318
OP3	3.352
OP4	2.488
TR1	3.087
TR2	2.610
TR3	3.466
TR4	2.719
TR5	2.730
CP1	3.181
CP2	2.090
CP3	2.346
SP1	2.791
SP2	3.168
SP3	3.204
SP4	2.918
SP5	3.713
AI1	2.313
AI2	3.078
AI3	1.991
AI4	2.274
EHRM1	2.764
EHRM2	4.559
EHRM3	3.652
EHRM4	3.614
EHRM5	4.107

Relatively low VIF values for all indicators of organizational preparedness, technological readiness, competitive pressure, security/privacy, AI adoption and effective HRM indicate that each construct adds distinctiveness to the model. In summary, these results indicate that the model was well specified and help control for inflation of the regression coefficient estimates and also helped make the structural relationships more reliable and interpretable.

5. 3. Structural model fit and predictive accuracy assessment

Model fit indices of the saturated and estimated models are presented in Table 5. Standardized root mean square residual (SRMR) value for saturated model is 0.071, represents a good fit and SRMR (0.097) of the estimated model remains acceptable as per literature on PLS-SEM [22].

Chi-square values should be interpreted with caution as they are sensitive to model complexity and sample size. The acceptable fit indices (0.724 and 0.711) of normed fit index (NFI) values confirm the model adequately for structural analysis as a whole [23].

Table 5

Model fit

Indices	Saturated model	Estimated model
SRMR	0.071	0.097
Chi-square	1036.060	10833.283
NFI	0.724	0.711

The R^2 and adjusted R^2 values for endogenous construct in the model is presented in Table 6, explaining a high level of variance by the proposed model. The R^2 for AI adoption is 0.767, which means that organizational preparedness, technology readiness, competitive pressure and security/privacy collectively explain 76.7 percent variance in adopting of AI.

Table 6

R^2 and Adjusted R^2

Constructs	R^2	R^2 Adjusted
AI	0.767	0.757
EHRM	0.638	0.634

The R^2 of effective HRM is 0.638, which means AI adoption explains 63.8% of the variance in effectiveness of HRM. Both are greater than the recommended threshold of 0.50 indicating moderate to high predictive accuracy of the model [24] (Fig. 2). The adjusted R^2 for the model (0.757 and 0.634 for AI adoption and effective HRM respectively), provide further evidence of stability and robustness to the model. Taken together, these findings suggest that the proposed model is theoretically valid and robust in predicting AI adoption and its contribution to HRM effectiveness in Indian IT.

5. 4. Direct impact and strategic role of artificial intelligence adoption in enhancing effective human resource management

The results of the structural model are shown in Table 7 present a varied support for the hypotheses. The effect of organizational preparedness on AI adoption (H1) was negative and not significant ($\beta = -0.173$, $t = 1.757$, $p = 0.079$, $f^2 = 0.036$), implying that factors contributing to organizational preparedness is not enough to lead organizations toward adopting AI in the Indian IT industry. This implies that preparedness must be coupled with specific technological and strategic enablers to translate into actual adoption outcomes.

Table 7

Hypothetical relationships

Hypothesis	Beta (β)	t-value	p-value	f-square	Decision
H1 (OP → AI)	–0.173	1.757	0.079	0.036	Insignificant
H2 (TR → AI)	0.464	3.007	0.003	0.095	Significant
H3 (CP → AI)	0.308	2.360	0.018	0.057	Significant
H4 (SP → AI)	0.303	3.826	0.000	0.149	Significant
H5 (AI → EHRM)	0.799	23.224	0.000	1.761	Significant

On the contrary, technological readiness had a positive and statistically significant impact on AI adoption (H2: $\beta = 0.464$, $t = 3.007$, p-value $= 0.003$ $f^2 = 0.095$), indicating that a strong IT network infrastructure, and data issues (availability) and system compatibility were critical in supporting

AI implementation. Competitive pressure also exerted a significant effect on the adoption of AI (H3: $\beta = 0.308$, $t = 2.360$, $p = 0.018$, $f^2 = 0.057$), implying that firms are incited to adopt HR practices enabled by AI as a result of that they need to respond to industry competition and the need to maintain strategic parity. Security / privacy concerns also had a significant and positive impact on AI adoption (H4: $\beta = 0.303$, $t = 3.826$, $p < 0.001$, $f^2 = 0.149$), reinforcing the importance of protection against data loss as well as trust and legal compliance as factors in organizational decisions regarding the deployment of AI technologies.

More specifically, AI adoption had a strong and large effect on effective HRM (H5: $\beta = 0.799$, $t = 23.224$, $p < 0.000$, $f^2 = 1.761$), thus providing confirmatory proof that AI adoption is an important driving force behind the effectiveness of HRM. This result endorses other earlier studies which claims that AI-driven HR systems optimize efficiency and decision quality as well as strategic HR outcomes through data- driven insights and automation [19]. Overall, the results provide partial evidence supporting the hypothesized framework and validate the role of technological and environmental determinants in predicting AI adoption and HRM effectiveness.

6. Discussion of empirical findings on artificial intelligence adoption and effective human resource management in the Indian information technology sector

The findings of this study explain how organizational, technological, and environmental determinants translate into effective HRM through AI adoption in technology-driven organizations. As demonstrated in Table 7 and Fig. 2, technological readiness, competitive pressure, and security/privacy concerns significantly influenced AI adoption, whereas organizational preparedness did not exhibit a direct significant effect. Likewise, AI adoption had a strong positive effect on effective HRM and accounted for significant variance in its explanation. These findings show that AI adoption acts as a strategy in which contextual enablers convert into measurable HR outcomes.

As shown in Table 7, technological readiness exhibits a significant positive influence on AI adoption ($\beta = 0.464$, $p = 0.003$). In addition, Fig. 2, exemplifies the strength of relationship in the structural model, accentuating the importance of system compatibility, infrastructure capability and technical expertise as enablers in AI-driven HR practices. This result is in harmony with previous study that highlights technological maturity as a criterion to digital transformation [9, 10] but drives more by establishing a comparatively stronger effect in HRM contexts. In contrary, earlier studies which treat technological readiness as an enabling condition, the current study considers it as an emerging operational impetus for AI-based HR shifting, especially in technology-intensive settings.

The results in Table 7 shows that competitive pressure is positively associated with AI adoption ($\beta = 0.308$, $p = 0.018$), which is consistent with theoretical perspectives on institutional and competitive dynamics recommending that industry-driven forces contour technological diffusion [11]. However, the current findings build on previous study by showing that competitive pressure serves not just as an external force but it actively drives AI adoption in HRM systems indicating that organizations are not only reacting to market imperatives, but also proactively utilizing AI in order to maintain competitive edge.

The results in Table 7 also reveal that security and privacy concerns can significantly drive AI adoption ($\beta = 0.303$, $p < 0.001$), contributing a significant change to extant literature. Although previous studies usually refer to these issues as barriers for adoption [3], the recent findings show an inverse effect. Such divergence can be linked to the maturity of regulatory compliance mechanisms and governance frameworks present in technology-based organizations, especially within the Indian IT segment. In these contexts, strong data protection mechanisms build trust in organizations and help to initiate AI deployment, rather than hinder it.

In contrary to the results indicated in Table 7, organizational preparedness does not exert a statistically significant influence on AI adoption ($\beta = -0.173$, $p = 0.079$), contrasting with previous studies that regard readiness as a primary driver of the technology adoption process [9]. This shows that just strategic intent and perception of preparedness is not enough to ensure the implementation of AI without necessary tech capability and impulsion from environment. The findings also advance existing readiness-based models for implementation by differentiating perceived organizational preparedness from adoptive capacity, which provides greater precision in understanding mechanisms of adoption.

As shown in Table 7, AI adoption has a strong and significant positive effect on HRM effectiveness ($\beta = 0.799$, $p < 0.001$). This relationship is further supported by the R^2 values reported in Table 6, where the AI adoption explains a substantial proportion of variance in HRM effectiveness. This finding aligns with prior studies on digital transformation in HRM [12, 13], while extending them by empirically validating AI adoption as a performance-enabling mechanism rather than merely an adoption outcome. The results thus shift the focus from intention-based adoption models toward outcome-oriented frameworks that emphasize realized organizational value.

The findings in Table 6 represents the outcomes for the structural model with an R^2 of 0.767 and 0.638 corresponding to AI and EHRM suggesting a substantial predictive capability for the model. These results affirm the strength of the proposed framework and underscore the necessity of combining various drivers when adapting for AI adoption behavior.

These findings of the study are predominantly applicable to technology-dominated organizations functioning in competitive and digitally mature circumstances, such as the Indian IT industry. The findings apply most directly in contexts where the digital infrastructure is developed, data governance frameworks are established and competitive pressure is high. The explanatory power of the model may diverge in contexts with low-digital or public-sector characteristics, where technological maturity and environmental pressure varies. The current study offers a broader explanation than alternative models including the technology organization environment (TOE) framework and technology acceptance model (TAM) as it establishes relations among adoption determinants to observable HRM outputs positively driven by AI adoption.

This study contributes to the existing theoretical perspectives by showing that the drivers of effective AI adoption go beyond organizational preparedness or external pressure rather, they emerge from multi-dimensional contextual elements, with technological capability being pivotal. The findings from this study contribute to link organizational performance outcomes and technology adoption research by modeling AI adoption as a mediating mechanism that strategically connecting contextual determinants to measurable HR effectiveness. The results establish that AI adoption is a strategic conduit by which competitive dynamics, technological capability and governance mechanisms coalesce

to produce effective HRM outcomes. The study enhances the knowledge of the AI-driven workforce transformation process in emerging economies with an integrated empirical framework consisting of organizational, technological and environmental dimensions.

Certain limitations should be recognized. The cross-sectional nature of the study limits causal inference, and also, as the respondents were from IT firms located in Tamil Nadu, it may not be generalizable across corporates in other industries and geographies. The study also focuses more on organizational-level factors as opposed to employee-level psychological variables like AI trust and perceived algorithmic fairness.

Along with these contextual limitations, methodological disadvantages are also apparent. First, Self-report perceptual measures may lead to common method bias, and objective performance indicators of HR effectiveness were not examined. Second, the dynamics of AI adoption may change with rapid technological evolution over time, making it difficult for the results to be temporally stable. Future studies may use longitudinal designs to assess the dynamics of AI adoption and HRM effectiveness while applying multi-level modeling methods to account for employee insights and they can also rely on objective HR analytics data that provides validity beyond self-reports. Strengthening external validity requires extending the model across sectors and national contexts. On the other hand, such extensions may run into methodological challenges in terms of defining measures that can be standardized and accessed with organizational AI performance data, as well as the ethics of accessing employee data.

7. Conclusion

1. The respondent profile analysis and sample characteristics confirm that the dataset is appropriate and relevant for examining AI adoption and HRM environments contextually. The sample comprise largely of early to mid-career professionals constituting 74.1% amongst the age 21–40 years having a strong educational background where 52.4% hold master's degree. There exist a substantial exposure to AI-enabled HR practices with 78.3% reporting moderate to high exposure. These characteristics indicate that the respondents possess both technical familiarity and experiential insight that is required to meaningfully evaluate AI-driven HR systems. Strengthening the credibility of findings, this ensures that the result reflect on realistic organizational conditions in technology-intensive settings.

2. Evaluation of the measurement model demonstrate a high level of reliability and validity across all the constructs. Composite reliability values are consistently above 0.90 exceeding the recommended threshold value of 0.70 and AVE values range from 0.734 to 0.867 confirming the strong convergent validity. Fornell-Larcker criterion have been established for discriminant validity and VIF values remain below 5, indicating the absence of multicollinearity. These results highlight robustness of the measurement framework ensuring that the constructs are distinct empirically and sound statistically. This integrated validation strengthens the precision and consistency of empirical model when compared to fragmented approaches in prior studies.

3. Structural model assessment shows substantial explanatory and predictive power of the proposed framework. The model elucidates 76.7% of variance in AI adoption with R^2 value of 0.767 and 63.8% in HRM effectiveness with R^2 value of 0.638, indicating high level of predictive accuracy. Model fit indices that includes SRMR value ranging from 0.071 to 0.097 and NFI values ranging 0.711 and 0.724 also fall within the acceptable threshold, confirming the model adequacy. The findings exhibit that the integrated framework effectively encapsulates the complex relationship between organizational, environmental and technological determinants. In contrast to traditional models which operate on separate factors, the present study offers a more integrative mechanical explanation by jointly modelling multiple determinants within a common framework.

4. The analysis of structural relationships confirms that technological readiness ($\beta = 0.464$; $p = 0.003$), competitive pressure ($\beta = 0.308$; $p = 0.018$), and security/privacy concerns ($\beta = 0.303$; $p < 0.001$) significantly impact AI adoption while organizational preparedness is not statistically significant in predicting AI adoption ($\beta = -0.173$; $p = 0.079$). Moreover, the effect of AI adoption is also significantly positive on HRM effectiveness ($\beta = 0.799$; $p < 0.001$), thus confirming its potential as a major performance-enabling mechanism. Findings indicate that operational technological capability and external environmental forces are more important to drive the adoption of AI than formal organizational readiness. This differs from earlier studies because of the widely competitive environment with higher technology existing in Indian IT sector, hence infrastructure capability and system integration and governance mechanism gets more pivotal than general preparedness. The findings further reveal that AI adoption serves as a strategic conduit that converts contextual factors into an increment in desired HRM outcomes, such as improved decision quality and efficiency, and alignment with organizational strategy.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors have used artificial intelligence technologies within acceptable limits to provide their own verified data, which is described in the study methodology section.

Authors' contributions

Kevin Durai A: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization; **Anbu A**: Supervision, Validation, Writing – Review & Editing, Project administration.

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