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Integrating Technological, Organizational, and User factors in Predicting Implementation Success of Human Resource Information System: An Empirical Study in Indian Universities

Ali Albouti, K.D Balaji

Faculty of Management, SRM Institute of Science and Technology Kattankulathur Campus, Tamil Nadu-603203, India

aa2301@srmist.edu.in

Abstract. Human Resource Information System (HRIS) is becoming crucial for improving administrative efficiency and workforce management in higher education. However, universities in developing contexts such as India still face challenges related to weak technological infrastructure, limited organizational readiness, and low user competency. This study proposes an integrated Predictive HRIS implementation framework by combining the Technology-Organization-Environment (TOE) model, TAM/UTAUT, and the Resource-Based View (RBV). Data from 187 HR and administrative professionals were analyzed using PLS-SEM, supported by Importance-Performance Map Analysis (IPMA) and PLSpredict for predictive validation. Results show that technological infrastructure ($\beta = 0.41$, $p < 0.001$), organizational readiness ($\beta = 0.36$, $p < 0.001$), and user competency ($\beta = 0.33$, $p < 0.01$) significantly boost HRIS effective implementation, while environmental pressure ($\beta = 0.09$, $p > 0.05$) remains non-significant. Mediation analysis further indicates that user competency partially mediates the relationship between technological infrastructure and HRIS implementation (indirect $\beta = 0.132$, direct $\beta = 0.28$, $p < 0.01$). The model explains 62% of the variance ($R^2 = 0.62$) and emphasizes strong predictive relevance ($Q^2 = 0.027$-0.223). The findings advance HRIS and digital transformation research by moving from descriptive to predictive, capability-based modeling and highlight the necessity to strengthen digital infrastructure, organizational readiness, and user competency to achieve sustainable digital transformation in universities.

Keywords: Human Resource Information System (HRIS), Predictive Modeling, Higher education institutions, Digital transformation

1. Introduction

Digital transformation has emerged as a strategic imperative in higher education, positioning the Human Resource Information System (HRIS) as a central mechanism for achieving operational efficiency, process automation, and data-driven decision-making in academic administration.

Recent global analyses highlight that higher education institutions face persistent challenges related to governance complexity, digital readiness gaps, and uneven resource allocation, particularly in developing contexts (McCarthy et al., 2023). Similarly, international assessments emphasize that higher-education systems worldwide must evolve toward more integrated, capability-driven digital ecosystems to ensure sustainable transformation (OECD, 2023).

Despite policy emphasis on digital transformation, universities in emerging economies continue to encounter structural and behavioral barriers including inadequate digital infrastructure, disparate technological proficiency, bureaucratic rigidity, and institutional resistance to change that constrain the effective implementation of HRIS (Rana & Kaur, 2024). Reports from UNESCO and the World Bank further highlight that while digitalization is increasingly prioritized, readiness and capability gaps persist, particularly in governance capacity, infrastructure maturity, and human capital development. Thus, HRIS adoption within Indian universities should be viewed not merely as a technological initiative, but as a multidimensional institutional capability challenge shaped by organizational readiness and user competency (Pandit & Paul, 2023).

Previous HRIS research has predominantly relied on single-theory explanatory frameworks such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), or the Technology-Organization-Environment (TOE) framework. This theoretical fragmentation has yielded limited insight into the cross-level interactions among technological, organizational, and human dimensions, and has offered little predictive capacity for understanding implementation success. Moreover, predictive analytics an essential component of contemporary information systems research remains underutilized in HRIS studies, particularly within the higher-education context (Shmueli & Koppius, 2011).

To address these gaps, the present study proposes a Predictive HRIS Implementation Framework that integrates the TOE model, the Resource-Based View (RBV), and TAM/UTAUT to construct a comprehensive socio-technical model of HRIS adoption. Drawing on survey data from 187 HR and administrative professionals in Indian universities, the study examines how technological infrastructure, organizational readiness, user competency, and environmental pressures collectively shape HRIS implementation outcomes. By adopting a predictive explanatory orientation through PLS-SEM and PLSpredict, this research advances HRIS scholarship from descriptive assessment toward predictive understanding, offering theoretically grounded and practically actionable insights for policymakers and university leaders aiming to foster digitally capable, service-oriented institutions.

2. Literature Review

Higher education institutions consistently utilize Human Resource Information System (HRIS) to enhance personnel management, optimize administrative processes, and promote digital transformation initiatives. However, the outcomes of HRIS adoption vary substantially among institutions, highlighting the necessity to recognize the various factors influencing its effective implementation.The existing literature can be categorized into four primary thematic domains: technological determinants, organizational and human resource capabilities, user-centered behavioral factors, and combined theoretical frameworks, each providing partial insights into the predictors of HRIS success in higher education. The following synthesis provides a conceptual framework for the formulation of a comprehensive predictive model.

1. Technological determinants:

HRIS has evolved from basic administrative record-keeping system to advanced, data-driven platforms that facilitate workforce analytics and strategic decision-making in higher education. Empirical research consistently identifies technological capability encompassing system integration, reliability, scalability, and data quality as a fundamental facilitator of HRIS performance (Igbaria et al., 1997; DeLone & McLean, 2003; Henderson & Venkatraman, 1999; Panayotopoulou et al., 2010).

Integrated technology-adoption frameworks affirmed that technological readiness, perceived utility, and organizational fit collectively impact the acceptance and effectiveness of digital HR platforms, particularly in cloud-based environments (Gangwar et al., 2015; Low et al., 2011). Recent evaluations conducted after the pandemic highlight the growing significance of cloud HR systems, cybersecurity protocols, and data governance in ensuring operational continuity and service excellence in universities (Kane, 2019, 2022; Odeh et al., 2017). These studies collectively underscore that a robust technological infrastructure is imperative for institutional digital transformation.

2. Organizational and Human Resource Capabilities:

The efficient of HRIS implementation is essentially dependent upon organizational readiness, specifically the institution's internal capacity to secure leadership commitment, distribute resources, and develop robust governance processes. This perspective, rooted in the Resource-Based View (RBV), asserts that strategic resources and managerial agility are crucial for converting technology potential into enduring organizational value (Barney, 1991; Rahman et al., 2016).

Previous empirical research from developing contexts demonstrates that bureaucratic inflexibility, restricted autonomy, and inadequate finance frequently hinder digital transformation in universities (Kapur & Mehta, 2004; Khan et al., 2015; Quaosar, 2018). Recent literature highlights that governance maturity, institutional agility, and ongoing competence development are critical for the effective implementation of HRIS (Dahal & Khadka, 2025; Altarawneh et al., 2024) Hence, institutional transformation depends as much on leadership and structural alignment as on technological investment.

3. User-centric factors:

Prior work emphasis that user competency is a critical determinant of HRIS efficacy, as the system's success relies on users' digital literacy, confidence, and perceived ease of use, which are essential components of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Davis, 1989; Venkatesh et al., 2003).

Also, many previous research affirms that Insufficient digital competence, lack of structured training, and resistance to adaptation remain to constitute substantial obstacles in higher education (Kananu et al., 2016; Paul et al., 2024). Recent studies on educational digitalization highlight that the enduring integration of technology requires continuous professional development, supportive digital learning environments, and alignment between user competencies and institutional strategy (Alsakka, 2023). Consequently, augmenting user competency is both a technical necessity and a socio-behavioral imperative for the effective utilization of HRIS.

4. Integrated frameworks and research gaps:

Despite extensive research on HRIS adoption, the majority utilize singular theoretical frameworks such as TAM, UTAUT, or TOE, which yield valuable yet fragmented insights, thus constraining forecast precision. Multi-theoretical integration has been proposed to encapsulate the intricate interactions across technological, organizational, and behavioral dimensions (Oliveira & Martins, 2011).

Institutional theory enhances understanding by acknowledging that coercive, normative, and mimetic influences affect digital adoption (Teo et al., 2003). However, research from higher education is inconclusive, indicating that governance frameworks and regulatory contexts may influence these outcomes differently compared to corporate settings. Recent expansions of the UTAUT and e-HRM frameworks indicate that digital HR systems serve as strategic facilitators, modulating the connection between HR practices and corporate performance (Obeidat, 2017; Kwarteng et al., 2024).

Service-informatics research emphasizes the need for comprehensive, predictive models that concurrently account for institutional preparation, user dynamics, and digital maturity (Luo et al., 2024). Addressing this need, the present study integrates the TOE, TAM/UTAUT, and RBV frameworks into a unified predictive structure for HRIS implementation in universities, bridging prior theoretical fragmentation with a service-oriented, data-driven perspective.

3. Hypothesis Development

This study integrates the Technology-Organization-Environment (TOE) framework, the Resource-Based View (RBV), and the Technology Acceptance Model/Unified Theory of Acceptance and Use of Technology (TAM/UTAUT) to construct a comprehensive and predictive socio-technical model for understanding HRIS implementation in higher education institutions. The integration of these perspectives enables a multilevel explanation of how technological infrastructure, organizational readiness, user competency, and contextual pressures collectively determine HRIS effectiveness.

From the TOE framework, technological infrastructure represents the quality, integration, and reliability of an institution's IT systems that support HRIS operations (Tornatzky & Fleischer, 1990). A strong digital infrastructure ensures system interoperability, data accuracy, and workflow efficiency, thereby enhancing perceived usefulness and ease of use (Davis, 1989; DeLone & McLean, 2003). Hence, institutions with mature technological foundations are more likely to achieve effective HRIS implementation.

Grounded in the RBV, organizational readiness reflects an institution's internal strategic capabilities such as leadership commitment, resource availability, and governance maturity that transform technology adoption into sustainable organizational value (Barney, 1991; Rahman et al., 2016).

Well-prepared institutions can align HRIS initiatives with strategic goals and foster long-term digital transformation.

The TAM/UTAUT perspective highlights user competency as a critical behavioral enabler that translates institutional resources into realized system performance (Venkatesh et al., 2003). Skilled and digitally confident users are better equipped to engage effectively with HRIS applications, thereby reducing resistance and enhancing utilization outcomes. Consistent with the socio-technical perspective, technological infrastructure not only supports system functionality but also strengthens user competency by improving accessibility, usability, and confidence in digital environments (Chen et al., 2024).

As users gain proficiency through enhanced infrastructure, their competency can, in turn, amplify HRIS implementation outcomes.

Drawing on institutional theory, environmental pressure including regulatory, normative, and competitive forces represents contextual constraints that may influence HRIS adoption (DiMaggio & Powell, 1983). However, in India's highly regulated and low-competition higher-education sector, such pressures are expected to have a limited direct impact compared to internal capability factors.

Based on this theoretical rationale, the following hypotheses are proposed:

H1: Technological infrastructure has a positive and significant effect on HRIS effective implementation.

H2: Organizational readiness has a positive and significant effect on HRIS effective implementation.

H3: User competency has a positive and significant effect on HRIS effective implementation.

H4: Environmental pressure has a positive but non-significant effect on HRIS effective implementation.

H5: User competency partially mediates the relationship between technological infrastructure and HRIS effective implementation.

This study integrates the TOE, RBV, and TAM/UTAUT frameworks to propose a Predictive HRIS implementation model conceptualizing HRIS as a digital service system. As shown in Figure 1, technological infrastructure, organizational readiness, and user competency are expected to enhance HRIS implementation, while environmental pressure has a limited contextual role. User competency also mediates the link between technological infrastructure and HRIS outcomes. This framework advances HRIS research by moving from descriptive to predictive, capability-based modeling, positioning HRIS as a key enabler of sustainable digital transformation in higher education.

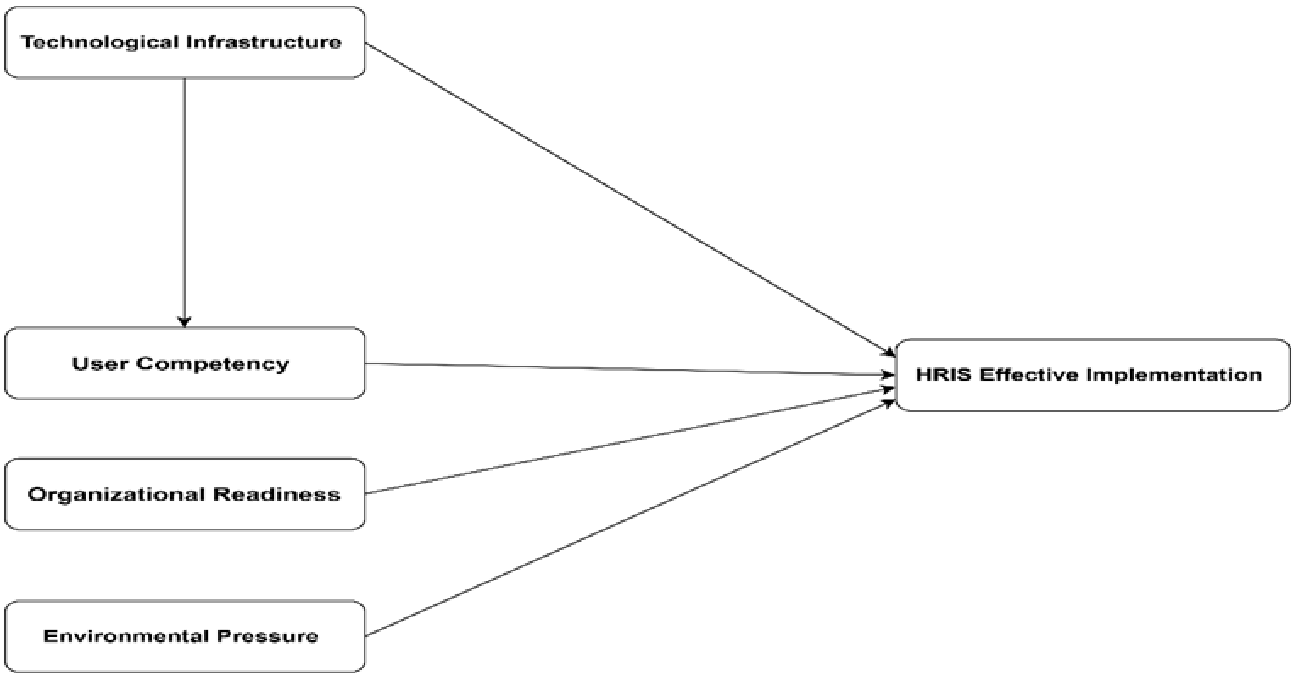

Fig. 1: Predictive HRIS implementation framework

4. Materials and Methods

This study employed a quantitative, cross-sectional survey design to examine the determinants of effective Human Resource Information System (HRIS) implementation in Indian higher-education institutions. The research adopts an explanatory predictive orientation, making Partial Least Squares Structural Equation Modeling (PLS-SEM) suitable due to its strength in complex models, prediction emphasis, and non-normal data handling compared to covariance-based SEM (Hair et al., 2019; Shmueli et al., 2019).

4.1. Sampling and data collection

The target group consisted of HR professionals and administrative personnel involved in HRIS processes at public and private institutions in Tamil Nadu distribution of respondents as presented in Table 1.0 A purposive sample strategy was utilized to choose respondents with at least six months of HRIS experience, ensuring informed responses. Tamil Nadu was chosen as the study context because it represents one of India’s most digitally progressive higher-education hubs, with a diverse mix of public and private universities actively implementing HRIS and e-governance initiatives, making it a suitable setting for examining digital transformation readiness. We received 187 valid replies from an online survey disseminated via official university communication channels.

A non-response bias analysis, contrasting early and late responders, revealed no significant differences ($p > 0.10$). Participation was optional and anonymous, ensuring the study's ethical integrity and alleviating respondents' concerns regarding evaluation. Prior to data collection, both institutional authorization and participant permission were secured.

Table 1. Distribution of respondents

University	HR& Administrative staff	Sample size (%)
Public	61	33.15
Private	126	66.85

4.2. Power analysis and sample adequacy:

To ensure sufficient statistical power for the structural model, an a priori power analysis was conducted using GPower 3.1. Assuming a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$, and a desired statistical power of 0.80, the minimum required sample size was estimated to be N = 134. Considering the model's complexity and the potential inclusion of interaction or mediation effects, the upper bound sample requirement was approximated at $N \approx 160$.

The final dataset, comprising 187 valid responses, therefore, exceeds both theoretical and statistical thresholds, confirming that the sample is adequate to detect meaningful structural relationships with high reliability and precision. Additionally, the 10-times rule proposed by Hair et al. (2019) was applied as a supplementary validation criterion. Since the most complex construct in the model has five incoming structural paths ($10 \times 5 = 50$ minimum cases), the achieved sample size of 187 far surpasses this requirement, reinforcing the methodological robustness and representativeness of the data.

Hence, the sample size is considered statistically powerful and methodologically appropriate for predictive SEM analysis.

4.3. Instrument development and validation

The survey instrument was adapted from established HRIS and technology-adoption scales and refined through expert feedback and a pilot test (n = 30) to ensure clarity and face validity. All constructs were measured reflectively using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Indicators with loadings < 0.70 were removed unless CR and AVE thresholds were satisfied (Hair et al., 2019). Reliability and validity benchmarks were achieved across all constructs.

4.4. Mitigating common method bias (CMB):

Both procedural and statistical remedies were applied to address potential common method bias. Procedurally, respondent anonymity, randomized item ordering, and section separation were used to reduce evaluation apprehension. Statistically, Harman's single-factor test showed that the first factor accounted for only 32.8% of the variance, below the 50% threshold. Additionally, full collinearity VIFs (all < 3.3) confirmed the absence of both vertical and lateral collinearity (Kock, 2015). These results collectively indicate that common method bias was not a significant concern in this study.

4.5. Data cleaning and normality

Before conducting the PLS-SEM analysis, data screening was performed to ensure accuracy and analytical suitability. Responses with more than 10% missing values were excluded, while minimal missing data (<1%) were treated using mean imputation, consistent with PLS-SEM guidelines. Sampling adequacy was supported by the Kaiser-Meyer-Olkin measure (KMO = 0.887) and Bartlett's Test of Sphericity ($\chi^2 = 3852.02$, df = 187, $p < 0.001$). Normality checks (skewness, kurtosis, Kolmogorov-Smirnov) indicated non-normal data distribution, further justifying the use of PLS-SEM. All VIF values were below 5.0, confirming no multicollinearity issues. Overall, these steps ensured that the dataset was reliable and appropriate for structural equation modeling.

4.6. Data analysis and PLS-SEM justification:

Partial Least Squares Structural Equation Modeling (PLS-SEM) was conducted using SmartPLS to assess both measurement and structural models. This method was chosen for its suitability in predictive and exploratory research, its ability to handle complex models with mediation or moderation, and its robustness to non-normal data (Hair et al., 2019; Shmueli et al., 2019).

A two-step analytical approach was applied: first, evaluating the measurement model for reliability and validity (using loadings, α, CR, AVE, and HTMT), and second, testing the structural model through path coefficients, t-values, effect sizes (f^2), predictive relevance (Q^2), and explained variance (R^2).

Out-of-sample predictive validity was assessed using PLSpredict with 10-fold cross-validation, confirming positive Q^2 values and superior RMSE performance compared to the linear regression benchmark. The Importance-Performance Map Analysis (IPMA) was also performed to derive managerial insights and prioritize improvement areas.

Overall, the analytical strategy combines explanatory rigor with predictive precision, strengthening both the theoretical and practical value of the proposed Predictive HRIS Implementation Framework.

5. Results

5.1. Demographic characteristics:

Table 2 summarizes the demographic characteristics of the respondents. The sample comprised 57.2% male and 42.8% female participants. The majority (36.9%) were aged between 36 and 43 years, while 50.8% held a master's degree. Regarding professional experience, 40.6% had 5-10 years, 30% had more than 10 years, and 29.4% had less than 5 years. This profile reflects a mature, experienced respondent base suitable for evaluating HRIS practices in higher education.

Table 2. Demographic profile of respondents.

Characteristic	Category	Frequency	Percentage
Gender	Male	107	57.20
	Female	80	42.80
Age group	Below 36 years	64	34.20
	36 - 43	69	36.90
	Above 43	54	28.90
Educational qualification	Bachelors' degree	82	43.90
	Master's degree	95	50.80
	Doctorate	10	5.30
Work experience	Less than 5 years	55	29.40
	5-10 years	76	40.60
	More than 10 years	56	30

5.2. Measurement model evaluation:

The measurement model demonstrated strong reliability and validity. As shown in Table 3, all Cronbach's alpha (α) and Composite Reliability (CR) values exceeded the 0.70 benchmark (Nunnally, 1978), confirming internal consistency. The Average Variance Extracted (AVE) for each construct was above 0.50, indicating satisfactory convergent validity. Discriminant validity was verified using both the Fornell-Larcker criterion (Fornell & Larcker, 1981) and the HTMT ratio (Henseler et al., 2015). The square roots of AVE (diagonal values) exceeded inter-construct correlations, and all HTMT ratios were below 0.85, establishing that the constructs were empirically distinct.

Table3: Measurement reliability, Convergent & discriminant validity results

Construct	α	CR	AVE	√AVE	TI	OR	UC	EP	HRIS
TI	0.84	0.88	0.60	**0.774**	—	0.612	0.588	0.402	0.672
OR	0.82	0.87	0.58	**0.761**	0.780	—	0.571	0.416	0.641
UC	0.80	0.85	0.57	**0.755**	0.750	0.740	—	0.395	0.618
EP	0.78	0.83	0.55	**0.741**	0.550	0.560	0.530	—	0.355
HRIS	0.86	0.89	0.62	**0.780**	0.840	0.820	0.800	0.480	—

Notes: √AVE; off-diagonal values represent inter-construct correlations. All HTMT ratios < 0.85 confirm discriminant validity. TI = Technological Infrastructure, OR = Organizational Readiness, UC = User Competency, EP = Environmental Pressure, HRIS = Human Resource Information System Implementation

5.3. Structural model assessment:

The structural model results, presented in Table 4: Structural Model Assessment Results, reveal that Technological Infrastructure (TI), Organizational Readiness (OR), and User Competency (UC) have significant positive effects on HRIS implementation, while Environmental Pressure (EP) remains non-significant. Specifically, TI ($\beta = 0.28$, $p < 0.01$), OR ($\beta = 0.36$, $p < 0.001$), and UC ($\beta = 0.33$, $p < 0.01$) directly enhance HRIS effectiveness, whereas EP ($\beta = 0.09$, $p > 0.05$) shows no meaningful influence.

Bootstrapping results (5,000 subsamples) further confirm a partial mediation effect, where UC mediates the relationship between TI and HRIS implementation (indirect $\beta = 0.132$, 95% CI [0.060, 0.210], $p < 0.01$), while the direct effect remains significant ($\beta = 0.28$, $p < 0.01$). This implies that robust technological infrastructure improves HRIS outcomes both directly and indirectly through enhanced user competency.

Effect sizes ($f^2 = 0.10$-0.18) indicate small-to-medium practical relevance, and confidence intervals for significant paths did not cross zero, confirming model robustness. The extended model explains 62% of the variance in HRIS implementation ($R^2 = 0.62$) and 16% in user competency ($R^2 = 0.16$), demonstrating strong explanatory and predictive power.

Table 4. Structural model assessment results

Path	β	t-value	p-value	f²	95% CI	Sig.	Hypothesis Support
TI → UC	0.40	4.75	<0.01	0.15	[0.22, 0.56]	**	Supported
UC → HRIS	0.33	3.98	<0.01	0.11	[0.16, 0.45]	**	Supported
TI → HRIS (direct)	0.28	3.61	<0.01	0.10	[0.12, 0.42]	**	Supported
OR → HRIS	0.36	4.27	<0.001	0.14	[0.19, 0.49]	***	Supported
EP → HRIS	0.09	1.21	>0.05	0.02	[−0.03, 0.26]	ns	Not Supported
TI → HRIS (indirect via UC)	0.132	—	<0.01	—	[0.060, 0.210]	**	Supported

Notes: *** $p < 0.001$; ** $p < 0.01$; f^2 and t-values are not reported for the indirect path, as these metrics apply only to direct effects

These findings reaffirm that internal technological and organizational capabilities, together with user competency, serve as the principal enablers of effective HRIS implementation in Indian higher education institutions. The non-significant influence of environmental pressure further underscores that, within India's centralized and low-competition educational environment, internal readiness and capability factors outweigh external pressures in determining digital transformation success. Figure 2 illustrates the structural model results of the predictive HRIS implementation framework. The path coefficients and explained variances (R^2) depict the relative strength and significance of the hypothesized relationships, including both direct and indirect effects through the mediating role of user competency.

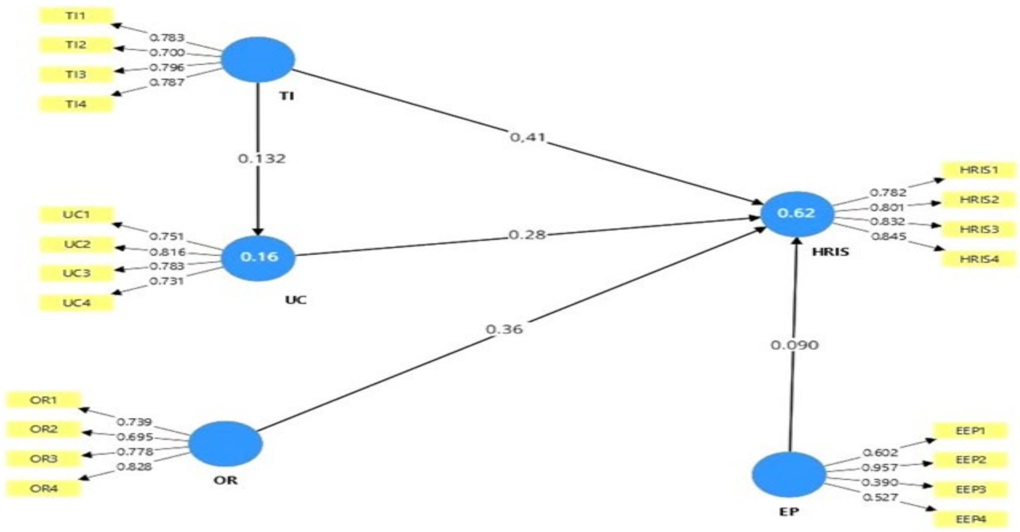

Fig 2. Structural model results of the Predictive HRIS Implementation Framework

5.4. Importance Performance Map Analysis (IPMA)

To generate actionable managerial insights, the Importance-Performance Map Analysis (IPMA) was conducted to rank the latent constructs based on their total effects (importance) and rescaled performance scores (0–100). As presented in Table 5, Technological Infrastructure (importance = 0.42) and Organizational Readiness (0.40) emerged as the most influential enablers of HRIS implementation, both exhibiting strong performance levels. User Competency (importance = 0.33), which also mediates the effect of technological infrastructure on HRIS outcomes, recorded the lowest performance score (60), identifying it as the most critical area for managerial improvement. In contrast, Environmental Pressure (importance = 0.10) demonstrated limited strategic influence and should be monitored periodically rather than prioritized for immediate intervention.

Table5. IPMA summary of result:

Construct	Importance (Total effect)	Performance (0–100)	Managerial implication
Technological Infrastructure (TI)	0.42	70	Sustain/optimize (core enabler)
Organizational Readiness (OR)	0.40	68	Strengthen governance and resource support
User Competency (UC)	0.33	60	Primary improvement priority (training, coaching, job aids)
Environmental Pressure (EP)	0.10	76	Low priority; monitor regulatory changes only

For managerial guidance universities should continue investing in technological infrastructure and organizational readiness to maintain HRIS efficiency and resilience, while giving priority to enhancing user competency, which now serves as both a key predictor and a mediating capability. Environmental pressure remains a low-priority contextual factor.

5.5. Out-of-sample predictive assessment (PLSpredict):

To assess the model's predictive validity beyond its explanatory capacity, PLSpredict with 10-fold cross-validation was applied. All Q^2 values were positive (0.027-0.223), confirming predictive relevance (Stone, 1974; Geisser, 1974).

The PLS-based RMSE values were lower than those of the linear regression (LM) benchmark in three out of four indicators, indicating superior predictive accuracy.

The inclusion of User Competency as a mediating construct slightly enhanced overall prediction precision by reinforcing the indirect link between technological infrastructure and HRIS implementation.

Table 6 presents a concise summary of the predictive validity outcomes.

Table 6: Summary of PLSpredict Predictive validity results

Metric	Range / Result	Interpretation
Q^2	0.027 - 0.223	Positive predictive relevance
RMSE (PLS vs. LM)	PLS < LM in 3/4 indicators	Strong predictive accuracy

Overall, the findings affirm that the proposed Predictive HRIS Implementation Framework possesses strong out-of-sample validity and practical value for forecasting HRIS success in higher education.

6. Discussion

The findings reveal that effective HRIS implementation in Indian higher education is primarily driven by internal institutional capabilities technological infrastructure, organizational readiness, and user competency while environmental pressure remains insignificant. This reinforces the view of HRIS as a socio-technical service system, where technological, organizational, and human resources jointly enable digital transformation (Maglio & Spohrer, 2008; Al Hiali et al., 2023).

Technological infrastructure emerged as the strongest determinant, ensuring data reliability, system integration, and workflow automation. It also indirectly influences HRIS implementation through user competency, confirming a partial mediation effect. This aligns with socio-technical theory (Bednar & Welch, 2020), which suggests that digital infrastructure enhances usability and confidence, thereby improving user proficiency and system performance.

Organizational readiness indicated a significant positive impact, highlighting the role of leadership, governance, and institutional culture in enabling transformation. This supports the RBV (Barney, 1991) and TOE (Tornatzky & Fleischer, 1990) perspectives, emphasizing that strategic alignment and managerial commitment are vital for sustainable HRIS success (Altarawneh et al., 2024; Dahal & Khadka, 2025).

User competency acted as both a direct and indirect driver, reflecting its central role in translating institutional resources into effective HRIS outcomes. Consistent with TAM and UTAUT (Venkatesh et al., 2003), higher perceived usefulness and ease of use result from enhanced digital skills. The IPMA results identified user competency as a high-priority improvement area, underscoring the need for targeted training and digital upskilling initiatives.

Environmental pressure had no significant effect in this study, diverging from many findings in private-sector contexts. The findings reflect India's highly centralized and regulation-driven higher-education governance system, where limited institutional autonomy and market competition reduce the influence of external normative or coercive forces. Instead, HRIS adoption is primarily driven by internal institutional capabilities such as technological infrastructure, governance maturity, and human-resource readiness (Bennich, 2024; Lu & Wang, 2023).

7. Implications

This study contributes to HRIS and service-informatics research by clearly demonstrating that internal institutional capabilities rather than external environmental pressures are the primary determinants of HRIS success in higher education. Through the integration of the TOE, RBV, and TAM/UTAUT frameworks within a unified socio-technical and service-oriented lens, the study introduces the Predictive HRIS Implementation Framework, positioning HRIS as a digital service system enabled by infrastructure robustness, governance maturity, and user competency. This aligns with the service science paradigm, advancing HRIS scholarship from descriptive analysis toward predictive and value co-creation perspectives (Maglio & Spohrer, 2008).

Practically, the findings suggest three key implications. First, institutional efforts should focus on strengthening internal digital readiness including secure, interoperable infrastructure and sustained governance mechanisms. Second, predictive modeling tools such as PLSpredict can enhance both theoretical insight and managerial foresight by identifying critical success levers. Third, universities should embed HR analytics and structured training programs to build digital competencies and ensure long-term organizational resilience. Collectively, these insights provide a focused roadmap for cultivating future-ready HR digital ecosystems in higher education.

8. Limitations and Future Research Direction

This study has several limitations. The cross-sectional design restricts causal inference, and the sample limited to universities in Tamil Nadu may constrain the generalizability of findings across diverse governance and institutional contexts. Although multiple procedural and statistical remedies were employed, the reliance on self-reported data may still introduce perceptual bias. Furthermore, environmental pressure was measured perceptually rather than through objective policy or competitiveness indicators.

Although the dataset included both public and private universities, multi-group analysis (MGA) was not conducted, as the study aimed to develop a unified predictive framework applicable across the higher education sector. Future research could extend this framework by comparing sectoral variations (public vs. private institutions) to examine how governance structures and funding mechanisms moderate HRIS adoption outcomes.

Additionally, future studies should employ longitudinal and multi-regional designs, integrate institutional performance datasets, and explore hybrid predictive approaches (e.g., combining SEM with machine learning) to enhance both explanatory and predictive capabilities of HRIS models in higher education.

9. Conclusion

This study establishes that the effective implementation of HRIS in higher education is predominantly shaped by internal institutional capabilities specifically technological infrastructure, organizational readiness, and user competency while external environmental pressures exert minimal influence in the Indian higher-education context. By advancing from descriptive assessment to predictive modeling through the Predictive HRIS Implementation Framework, the study contributes to both theory and practice by integrating technological, organizational, and behavioral dimensions into a unified socio-technical perspective. The findings highlight that strengthening institutional digital capacity, governance structures, and workforce digital competence represents the most viable pathway toward achieving sustainable, data-driven human resource systems. Collectively, these insights provide actionable guidance for universities aiming to accelerate digital transformation and enhance long-term institutional resilience.

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