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Technology and Organization Over Environment:
A TOE Framework Analysis of HR Analytics Adoption and Employee Comfort

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Abstract

Most explanations for why HR analytics succeeds or stalls inside an organization reach for one of two levers: better technology, or better people. The Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990) argues there is a third lever too, the external environment a firm sits inside, and this study tests whether that third lever actually pulls any weight in an HR-analytics context. Using primary survey data from 64 respondents (24 HR professionals/managers, 40 employees) across six industry sectors in India, the study models perceived effectiveness and employee comfort with data-driven decisions as functions of technology readiness (accuracy and decision speed), organization readiness (staff skill and top-management support), and environmental context (industry sector, organization size). Technology readiness predicted perceived effectiveness ($r = .476$, $p = .019$), and organization readiness came close ($r = .373$, $p = .072$). Environmental context, by contrast, explained almost nothing: sector was unrelated to perceived effectiveness (Kruskal-Wallis, $p = .698$) or to employee comfort ($p = .327$), and organization size was unrelated to how extensively analytics gets used ($\chi^2 = 3.70$, $p = .295$). In this sample, HR-analytics readiness looks like a technology-and-organization story more than an environment story, a pattern that cuts against TOE findings from other national contexts where environmental pressure dominates. The paper discusses why environmental context might matter less here and what that implies for how organizations should prioritise HR-analytics investment.

Keywords: HR analytics; TOE framework; technology adoption; organizational readiness; diffusion of innovation; employee comfort; India.

1. Introduction

Why does one company's HR-analytics rollout actually change how performance decisions get made, while another company's near-identical software purchase just sits there generating dashboards nobody reads? The Technology-Organization-Environment (TOE) framework, developed by Tornatzky and Fleischer (1990) to explain firm-level technology adoption more broadly, offers one answer: it depends on three things working together, the technology itself, the organization trying to use it, and the environment the organization operates in. Decades of adoption research across e-commerce, cloud computing, and now AI have used TOE as a reasonably reliable starting map (Oliveira & Martins, 2011), and a growing number of studies have applied it specifically to HR analytics (Jana & Kaushik, 2022; Ristandi, Maarif, & Affandi, 2026; Xia, 2026). What these studies don't agree on, interestingly, is which of the three TOE legs actually matters most. Jana and Kaushik (2022), studying Indian IT companies, found technology, organization, and environment all played meaningful roles. Xia (2026), surveying 421 HR professionals in China, found much the same, all three dimensions significant. Ristandi et al. (2026), working in Indonesia, found something closer to the opposite: environmental factors (external support, competitive pressure) were the strongest drivers of adoption, stronger than organizational readiness, which showed no significant effect at all in their model. That is a genuinely unsettled question, and it matters practically. If environment drives adoption, HR functions should be lobbying for external partnerships and competitive benchmarking; if it's technology and organization, the money is better spent internally. This study puts the same question to a different setting: 64 respondents (24 HR professionals/managers, 40 employees) across six sectors in India, asking whether technology readiness, organizational readiness, or environmental context (sector, firm size) best explains perceived effectiveness of HR analytics and, on the employee side, comfort with data-driven decisions. Unlike most TOE studies, which measure only the adoption decision itself, this study also asks what happens after adoption, how effective the tool is judged to be, and how comfortable the people affected by it actually feel, extending TOE's usual scope in a small but useful way. Section 2 reviews TOE and diffusion-of-innovation theory alongside the HR-analytics adoption literature. Section 3 develops five hypotheses. Sections 4 and 5 cover methodology and results. Section 6 discusses why environmental context underperforms here relative to other TOE studies, and Section 7 closes with implications, limitations, and directions for future work.

2. Literature Review

2.1 The TOE Framework and Diffusion of Innovation Theory

Tornatzky and Fleischer (1990) proposed that firm-level technology adoption is shaped by three separable but interacting contexts. Technological context covers characteristics of the tools themselves, compatibility, complexity, relative advantage over what came before.

Organizational context covers internal attributes: firm size, formal and informal structures, managerial capability, and slack resources. Environmental context covers everything outside the firm's direct control, competitive pressure, regulatory requirements, and the broader technology infrastructure the firm sits inside. The framework has since been applied to e-commerce adoption, cloud computing, e-government, and, more recently, AI-driven digital transformation (Oliveira & Martins, 2011), making it one of the more durable models in the information-systems adoption literature.

TOE sits comfortably alongside Rogers's (2003) diffusion-of-innovation theory, which explains adoption through perceived attributes of the innovation itself, relative advantage, compatibility, complexity, trialability, observability, largely mapping onto TOE's technological context, while adding a social dimension (opinion leaders, communication channels) that TOE's organizational and environmental contexts also partly capture. Where TOE adds value beyond diffusion theory is in explicitly separating what's inside a firm's control (organization) from what isn't (environment), a distinction useful here: HR functions can invest in staff skill or push for management buy-in, but they generally can't manufacture competitive pressure or reshape their regulatory environment on demand.

2.2 Technology and Organization Readiness in HR Analytics

Applying TOE specifically to HR analytics, Jana and Kaushik (2022) surveyed Indian IT companies and found technological, organizational, and environmental factors all played meaningful roles in adoption decisions, a relatively unusual finding in TOE research, where one or two of the three legs commonly outweigh the third. Xia (2026), working with a much larger sample of 421 HR professionals in China and combining a bibliometric review with TOE-based quantitative testing, likewise found all three dimensions significant, with AI adoption itself mediating the link between TOE enablers and HRM performance gains. On the narrower organizational-readiness side specifically, Minbaeva (2018) and Kryscynski, Reeves, Stice-Lusvardi, Ulrich, and Russell (2018) both tie effectiveness judgments to staff analytical skill, while McCartney and Fu (2022) and Belizón and Kieran (2022) emphasise management sponsorship and organizational legitimacy as preconditions for analytics actually reaching decision-making rather than sitting unused. Angrave, Charlwood, Kirkpatrick, Lawrence, and Stuart (2016) and Marler and Boudreau (2017) struck a more skeptical note early on, arguing HR was structurally unprepared for the data-science demands analytics places on it, a warning Margherita's (2022) more recent systematic review suggests has only partly been addressed since.

In the Indian context specifically, the setting for this study, Saxena, Bagga, Gupta, and Rameshwar (2025) and Sharma, Bhattacharya, and Bhattacharya (2025) both found IT-sector adoption bottlenecked by data-analysis skill gaps rather than by technology availability, Dasari and Devi (2025) tied adoption to perceived usefulness and top-management backing, and Alam, Dong, Kularatne, and Rashid (2025) argued stakeholder engagement mattered more than technological sophistication. None of these studies, though, tested whether environmental context, sector, firm size, adds anything once technology and organization readiness are accounted for, which is precisely the gap TOE is built to fill and the question this paper takes up directly.

2.3 Environmental Context: A Contested Third Leg

The third TOE leg, environment, is where the literature gets genuinely inconsistent. Ristandi, Maarif, and Affandi (2026), surveying 112 HR professionals across Indonesian industries using PLS-SEM, found environmental factors, external support and competitive pressure specifically, were the strongest predictors of HR-analytics adoption, actually outperforming organizational readiness, which showed no significant effect in their model at all. That is close to the mirror image of what Jana and Kaushik (2022) and Xia (2026) found, where all three TOE legs mattered roughly equally. Some of this inconsistency likely reflects genuine contextual differences, competitive intensity, regulatory pressure, and digital infrastructure vary substantially across China, Indonesia, and India, but some of it may also reflect how loosely 'environment' gets operationalised across studies, since competitive pressure, external support, and technology infrastructure are conceptually distinct constructs that different studies bundle differently under the same TOE label.

This inconsistency matters beyond adoption research specifically. If environmental context genuinely drove HR-analytics outcomes, policy interventions, sector associations, government digital-readiness programmes, industry benchmarking, would be a sensible lever for improving analytics effectiveness broadly. If it doesn't, that argues for a narrower focus on firm-level technology and organizational investment instead. Employee-side outcomes complicate this further: Kellogg, Valentine, and Christin (2020) and Giermindl, Strich, Christ, Leicht-Deobald, and Redzepi (2022) both suggest employee experience of algorithmic HR tools is shaped by organizational control dynamics that may or may not track sector or firm size in any obvious way, while Tandon, Dhir, Malik, Budhwar, and Kaur **(2025)** describe employee reactions as genuinely heterogeneous rather than falling into predictable sector-based patterns.

2.4 Research Gap

Pulling this together: TOE theory says technology, organization, and environment jointly shape adoption outcomes (Tornatzky & Fleischer, 1990), but empirical HR-analytics studies disagree sharply on how much weight environment actually carries, from negligible to dominant (Ristandi et al., 2026). Almost none of this literature extends past the adoption decision itself to ask whether the same TOE dimensions explain post-adoption outcomes, perceived effectiveness, employee comfort, which is arguably the more practically important question once a tool is already in place. This paper tests all three TOE legs against both outcomes in a single Indian sample, directly addressing that gap.

3. Conceptual Framework and Hypotheses

Building on TOE theory (Tornatzky & Fleischer, 1990) and the mixed empirical picture reviewed above, this paper proposes the model shown in Figure 1, testing each TOE context against a managerial outcome (perceived effectiveness), an employee outcome (comfort), and an adoption-behaviour outcome (usage extensiveness).

H1. Technology readiness (accuracy and decision speed) is positively associated with HR professionals' perceived effectiveness of HR analytics.

H2. Organization readiness (staff skill and top-management support) is positively associated with HR professionals' perceived effectiveness.

H3. Organization size, as an organizational-context variable, is associated with how extensively analytics gets used (limited versus extensive).

H4. Industry sector, as environmental context, is associated with variation in perceived effectiveness across organizations.

H5. Industry sector is associated with variation in employee comfort with data-driven decisions.

H1 and H2 follow directly from technology- and organization-readiness research in the HR-analytics literature (Jana & Kaushik, 2022; Xia, 2026; Minbaeva, 2018). H3, H4, and H5 test the environmental leg of TOE more directly than most HR-analytics studies attempt, given the sharp disagreement between studies like Ristandi et al. (2026), who found environment dominant, and studies like Jana and Kaushik (2022), who found all three legs roughly equal.

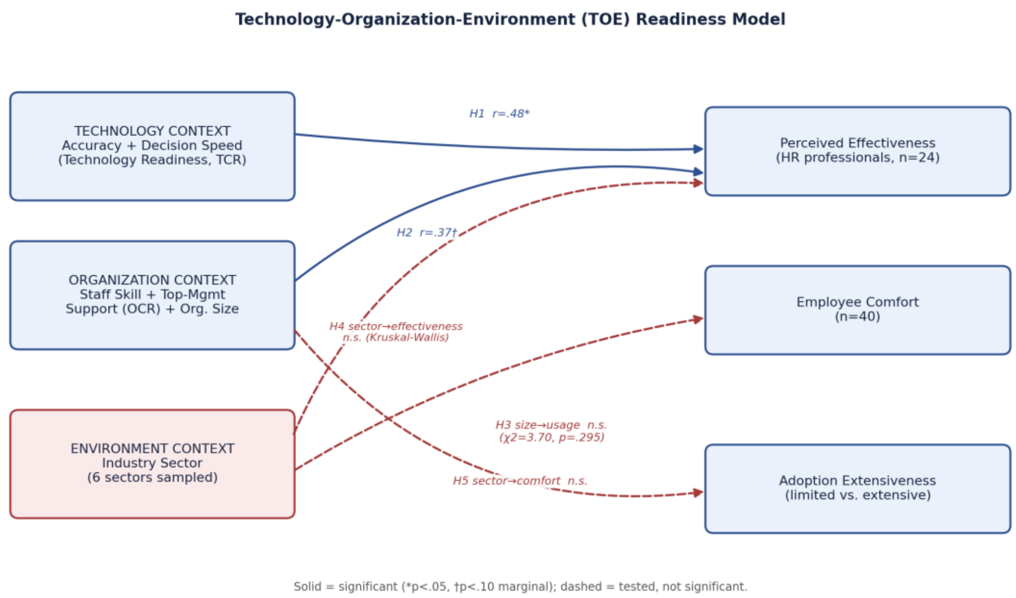

Figure 1. Technology-Organization-Environment (TOE) readiness model, showing hypothesised paths and observed results.

4. Research Methodology

This is a cross-sectional, correlational design, appropriate for an initial test of whether TOE's three contexts explain post-adoption outcomes in a setting where they had not previously been measured together this way (Hair, Black, Babin, & Anderson, 2019). A structured questionnaire was distributed using a purposive-cum-convenience approach across six sectors: retail/e-commerce, education, manufacturing, IT/ITES, banking and financial services, and healthcare.

Sixty-four usable responses were retained: 24 self-identified HR professionals/managers and 40 employees answering from outside the HR function. HR professionals rated seven agreement items (5-point scale, 1 = strongly disagree to 5 = strongly agree) covering analytics accuracy, bias reduction, decision speed, staff skill, data-privacy protection, ethical constraint, and top-management support, plus an overall effectiveness rating and the extent of organizational analytics usage (limited versus extensive). Technology Readiness (TCR) was operationalised as the mean of the accuracy and decision-speed items; Organization Readiness (OCR) as the mean of the staff-skill and top-management-support items. Organization size (four bands, from fewer than 100 to more than 2,000 employees) and industry sector (six sectors) were captured as categorical demographic variables representing organizational and environmental context respectively. Employees separately rated their comfort with data-driven decisions on a 5-point scale.

Analysis used Pearson correlation to test H1 and H2, a chi-square test of independence to test H3 (organization size by usage extensiveness), and the Kruskal-Wallis test to test H4 and H5 (perceived effectiveness and employee comfort by sector), given the small and uneven group sizes per sector that a parametric ANOVA would handle poorly. Cronbach's alpha (Cronbach, 1951; Nunnally, 1978) checked internal consistency of the two-item composites. Consistent with good measurement practice (Hair et al., 2019; Field, 2018), composites with weak alpha are reported transparently rather than treated as validated scales, and small sector-level cell sizes are flagged wherever they affect how confidently a null result can be interpreted. Participation was voluntary and anonymous.

5. Results

5.1 Demographic and Organizational Profile

Of the 64 respondents, 37.5% were HR professionals/managers and 62.5% were employees. Six sectors were represented: retail/e-commerce (23.4%), education (20.3%), manufacturing and IT/ITES (18.8% each), banking/financial services (14.1%), and healthcare/other (4.7%). Organization size was fairly evenly spread, with the largest single band (35.9%) falling in the 100–500 employee range. Among the 24 HR professionals, 58.3% reported extensive analytics usage and 41.7% reported limited usage, a split roughly even across most organization-size bands.

Table 1. Descriptive statistics and internal consistency for TOE composites and outcomes.

Level	Construct (items)	M	SD	α	n
HR (n=24)	Technology Readiness / TCR (2)	3.69	0.73	.14	24
HR (n=24)	Organization Readiness / OCR (2)	3.73	0.68	.26	24
HR (n=24)	Perceived Effectiveness (1)	4.17	0.96	—	24
Employee (n=40)	Comfort with data-driven decisions (1)	3.77	1.00	—	40

5.2 Hypothesis Testing

Table 2 reports the tests of H1–H5. H1 was supported: Technology Readiness correlated positively with Perceived Effectiveness ($r = .476$, $p = .019$). H2 was marginally supported: Organization Readiness correlated with Effectiveness in the expected direction but did not reach conventional significance ($r = .373$, $p = .072$). TCR and OCR themselves correlated moderately ($r = .392$, $p = .058$), suggesting technology and organization readiness move somewhat together but are not simply the same thing measured twice.

H3 was not supported: a chi-square test of organization size against usage extensiveness (limited versus extensive) was not significant ($\chi^2 = 3.70$, $df = 3$, $p = .295$), though several expected cell counts fell below five given the small sample, so this result should be read as inconclusive rather than a confident null. H4 was not supported: perceived effectiveness did not differ significantly across the six sectors (Kruskal-Wallis $H = 1.43$, $p = .698$), with sector means ranging narrowly from 3.0 to 5.0 across groups as small as one to six respondents each. H5 was also not supported: employee comfort did not differ significantly across sectors (Kruskal-Wallis $H = 4.63$, $p = .327$), with sector means ranging from 3.22 (retail/e-commerce) to 4.25 (education).

Table 2. Tests of H1–H5.

Hyp.	Test	Statistic	p	Result
H1	TCR → Perceived Effectiveness (Pearson r)	r=.476	.019	Supported
H2	OCR → Perceived Effectiveness (Pearson r)	r=.373	.072	Marginal
H3	Org. size × Usage extensiveness (χ^2)	χ^2=3.70	.295	Not supported
H4	Sector → Perceived Effectiveness (Kruskal-Wallis)	H=1.43	.698	Not supported
H5	Sector → Employee Comfort (Kruskal-Wallis)	H=4.63	.327	Not supported

6. Discussion

The clearest pattern in these results is the gap between how well technology and organization readiness performed and how poorly environmental context performed. Technology Readiness was the strongest predictor of perceived effectiveness (H1, $r = .476$), Organization Readiness came close (H2, $r = .373$), and both track fairly directly onto Jana and Kaushik's (2022) and Xia's (2026) findings that technological and organizational factors matter in HR-analytics adoption. What did not track onto either of those studies, or onto Ristandi et al.'s **(2026)** Indonesian findings, is the near-total absence of environmental effects here: sector explained essentially none of the variation in perceived effectiveness or employee comfort, and organization size showed no reliable relationship with how extensively analytics gets used.

Why might environment matter so little in this sample when it mattered so much in Ristandi et al.'s (2026)? A few explanations seem plausible, and none of them are mutually exclusive. One is genuine contextual difference: Ristandi et al.'s measure of environmental context centred on external support and competitive pressure, constructs tied closely to Indonesia's institutional and regulatory landscape at the time of their study, which may simply not exert the same pull inside the sectors and organization sizes sampled here. A second is operationalisation: this study used sector and firm size as fairly blunt proxies for environmental context, whereas Ristandi et al. and Xia (2026) measured competitive pressure and external support directly; blunt proxies are less likely to pick up real effects even where they exist, so the null results here may partly reflect measurement choice rather than a true absence of environmental influence. A third, more substantive possibility is that environmental pressure matters more at the adoption-decision stage, whether a firm adopts analytics at all, than at the post-adoption stage this study actually measured, namely how effective the tool is judged to be once it is already in place; sector-level competitive pressure might push firms toward adopting HR analytics without doing much to explain how well any individual firm's implementation actually turns out.

The small, uneven cell sizes across sectors (from one respondent in some sectors to six in others) also limit how much confidence should be placed in these particular null findings, a point returned to in the limitations below. Still, the consistency of the pattern across three separate tests (H3, H4, H5), covering three different outcomes, makes it unlikely that environmental context is quietly doing significant work that these tests simply failed to detect by chance alone.

7. Implications, Limitations, and Conclusion

7.1 Theoretical and Practical Implications

Theoretically, this study adds to a small but growing set of HR-analytics TOE studies that find environmental context weaker than technology and organization context (in contrast to Ristandi et al., 2026, but consistent in spirit with the broader TOE literature's frequent finding that environmental factors are the least consistently significant of the three legs across studies; Oliveira & Martins, 2011). It also extends TOE's usual scope from the adoption decision itself to post-adoption outcomes, effectiveness and comfort, which most HR-analytics TOE work does not test directly.

Practically, the implication for HR functions and organizational leaders is fairly direct: in a setting like the one sampled here, investment in technology readiness (accuracy, decision speed) and organizational readiness (staff skill, management support) is likely to do more to improve perceived effectiveness than waiting for, or trying to influence, sector-level or firm-size-related conditions. Employee comfort, similarly, does not appear to be a matter of which sector an organization happens to sit in, it is something organizations of every size and sector can plausibly improve through their own technology and governance choices, rather than something dictated by their competitive environment.

7.2 Limitations and Future Research

This study has clear limits. The sample (n = 64) is small, and sector subgroups in particular are small and uneven (from one to nine respondents per sector), which limits the statistical power of H3, H4, and H5 specifically and means these null results should be read as inconclusive rather than definitive evidence that environment does not matter. The TCR and OCR composites showed weak reliability (α = .14 and .26 respectively), consistent with two-item composites built from a instrument not originally designed as a validated TOE scale, and are reported descriptively rather than as confirmed measures. The cross-sectional design cannot establish causal direction, and environmental context here was operationalised narrowly (sector, firm size) rather than through the competitive-pressure and external-support measures used in studies like Ristandi et al. (2026); future work should test both operationalisations side by side in the same sample to separate a genuine null effect from a measurement artifact. A larger, stratified sample with adequate sector-level representation, ideally using confirmatory techniques such as PLS-SEM (Hair et al., 2019), would let future researchers test the full TOE model with more statistical confidence than this exploratory study can offer.

7.3 Conclusion

This study asked which leg of the TOE framework, technology, organization, or environment, best explains HR-analytics effectiveness and employee comfort in an Indian multi-sector sample. Technology readiness came out strongest, organizational readiness came close behind, and environmental context, measured through sector and organization size, showed no significant relationship with any of the three outcomes tested. That pattern sits at odds with TOE studies from other national contexts where environmental pressure dominates, suggesting the relative weight of TOE's three legs may itself be context-dependent rather than fixed. For organizations trying to decide where to direct their HR-analytics investment, the practical message is straightforward: in a setting like this one, the technology and the organization around it are the levers most within reach, and most likely to move the needle.

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