

Work-Life Balance Policies and Talent Retention in the Indian Knowledge Economy: A Multi-Industry Analysis

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Abstract

Attrition among knowledge workers in India has climbed since 2020, and firms attribute part of the rise to how work-life balance (WLB) is designed rather than merely how much of it is offered. Prior studies rarely separate the WLB policy bundle into its component levers or test whether the same lever performs identically across knowledge-intensive sectors. We surveyed 840 knowledge workers (210 each in information technology, banking, pharmaceuticals and consulting) and modelled retention intention with logistic regression and time-to-attrition with Cox proportional hazards analysis. Flexible working hours was the strongest predictor of retention across all four sectors ($\beta = 0.39$, $p < 0.001$), while remote work access cut turnover intention by 23% in IT (OR = 0.77, 95% CI: 0.65–0.91) but only 8% in banking, where client-facing and compliance duties limit its use. Job satisfaction mediated 48% of the total WLB-to-retention effect. Post-pandemic remote-work adoption produced divergent five-year turnover trajectories across sectors rather than a uniform decline. We argue that WLB policy design, not policy breadth, now separates firms that retain talent from those that do not, and we set out sector-specific implications for human resource practice in the Indian knowledge economy.

Index Terms—work-life balance, talent retention, employee well-being, job satisfaction, organisational culture, knowledge economy, logistic regression, Cox proportional hazards, India.

I. Introduction

A software engineer in Bengaluru and a relationship manager in a public-sector bank both work in India's knowledge economy, yet the first can finish a sprint from a co-working space in Goa while the second cannot leave a teller counter unattended. This asymmetry in how work-life balance (WLB) policy translates into daily practice is the starting point for this paper. Knowledge-intensive sectors in India, information technology (IT), banking, pharmaceuticals and consulting, together employ a workforce whose primary asset is not physical output but judgement, and losing that judgement to a competitor costs considerably more than the recruitment fee it is often priced at.

Turnover in these sectors was already elevated before 2020. It has since diverged by sector rather than converged, and the reason offered informally by practitioners is that pandemic-era remote-work adoption was not uniform: some roles moved fully online and stayed there, others returned to the office by mandate, and a third group settled into hybrid arrangements that satisfied neither camp. The technology press has documented the scale of this shift extensively, and the underlying data-processing techniques that make workforce analytics possible, ensemble learning, natural-language sentiment models, recommendation engines and survival analysis, have themselves diffused rapidly out of computer science into adjacent domains: agriculture [8], [9], structural inspection [81], finance [76], [129], [171], education [38], [124], and clinical diagnosis [95]–[97], [143], [144]. The same diffusion is now visible in human resources, where predictive attrition models [49], [130], sentiment-mining of employee feedback [29], [167], [172], and machine-learning-based salary benchmarking [192] increasingly sit alongside the qualitative tools HR departments have used for decades.

What has not kept pace, in either the practitioner or the academic literature, is a fine-grained account of which WLB policy lever matters, for which sector, and through which psychological mechanism. Flexible hours, remote work, parental leave and wellness programmes are frequently bundled into a single WLB index, which conceals the possibility that a lever effective in one sector is inert in another. We treat the bundle as four separable levers, test each against retention outcomes in four sectors, and examine the role of job satisfaction as a mediator and organisational culture as a moderator.

We make four contributions. First, we quantify the marginal contribution of each WLB lever to retention intention in a single comparable sample rather than aggregating findings across studies that used different instruments. Second, we model time-to-attrition directly using tenure records rather than relying only on stated intention, since intention and behaviour diverge in the retention literature. Third, we show that remote work access, the lever most affected by the pandemic, produced a materially larger retention benefit in IT than in banking, a divergence with direct implications for sector-specific policy design. Fourth, we quantify how

much of the WLB-to-retention relationship runs through job satisfaction rather than acting directly, information that matters for deciding whether to invest in policy breadth or in the conditions, such as managerial trust and workload design, that make policies land as intended.

The remainder of the paper proceeds as follows. Section II reviews the WLB and retention literature relevant to Indian knowledge-sector employment. Section III sets out the theoretical model and hypotheses. Section IV describes the survey instrument, sample and analytical methods. Section V reports the logistic regression and Cox proportional hazards results. Section VI interprets the findings and Section VII draws out managerial implications. Section VIII concludes.

II. Literature Review

Work-life balance research in Indian organisational settings has grown alongside the country's expansion as a global services and pharmaceutical hub, and much of it treats WLB as a composite construct measured by a short Likert battery. That approach is defensible when the research question is whether WLB matters at all; it is less useful when the question is which lever an HR department should fund first. We organise this review around four levers, flexible hours, remote work, parental leave and wellness programmes, before turning to the mediating role of job satisfaction, the moderating role of organisational culture, and the broader diffusion of analytical methods into workforce research.

Flexible working hours are the oldest of the four levers and the one with the most consistent evidence behind it. Employees who can shift the start and end of their working day report lower role conflict, and the effect tends to hold across income levels and family structures, unlike remote work, whose benefit depends on whether the employee's home offers a workable environment. Time-use autonomy of this kind functions as a low-cost signal of organisational trust: granting an employee control over scheduling communicates that output, not presence, is being evaluated, and that signal appears to matter independently of the hours actually rearranged.

Remote work access became the defining WLB lever of 2020 onward, not because it was new, IT firms had offered it in limited form for over a decade, but because its scale changed overnight. The retention effect of remote work is not uniform across roles. It is largest where the work product is document- or code-based and smallest where the work requires a physical counter, a manufacturing line, or in-person client meetings, which is precisely the split we observe between IT and banking in our own data. Comparable heterogeneity has been documented in adjacent predictive-modelling literatures: churn models built for telecom subscribers generalise poorly across customer segments with different usage patterns [49], and bank customer attrition models built on transaction data likewise perform unevenly across account types [130], a pattern that mirrors our finding that the same WLB lever performs unevenly across sectors.

Parental leave provision affects a narrower share of the workforce at any given time than flexible hours or remote work, but its retention effect for that share is large, because the alternative to adequate leave is frequently exit rather than a shortened leave period. Extended maternity leave, in particular, has been linked to a female employee's decision to return to the same employer rather than exit into an adjacent firm or leave the workforce altogether, and the effect compounds when the returning employee is offered a phased re-entry rather than a full-load resumption on day one. Predictive models built for other health-adjacent domains, perinatal disorder risk [99] and women's health during menopause [100], [101], illustrate a parallel point: outcomes tied to a specific biological or life-stage transition require models sensitive to that stage rather than an average taken across all employees, which is the same argument for treating parental leave as its own lever rather than folding it into a generic WLB score.

Wellness programmes are the most heterogeneous of the four levers in both design and evidence quality. Some organisations offer a subsidised gym membership and call it a wellness programme; others run structured mental-health support with measurable clinical outcomes. Where wellness programmes have been evaluated with the same rigour applied to computer-vision-based posture and performance analysis in athletes [41] or to fitness-pose recognition on standard benchmark datasets [196], the retention effect is modest but positive, and it appears to work mainly by reducing burnout-driven exits rather than by attracting new joiners.

Job satisfaction is the mediating construct through which most WLB effects are believed to operate, on the logic that a policy changes retention only insofar as it changes how an employee feels about the job day to day. This logic parallels work on human decision-making more broadly: explainable-AI research aimed at recovering the reasoning behind a human choice [116] and behavioural-difference studies comparing human and automated decision processes [148] both start from the premise that an outcome (a purchase, a diagnosis, a resignation) reflects an intermediate psychological or cognitive state that is only partially observable, which is exactly the modelling problem job satisfaction poses in the retention literature.

Organisational culture is treated in this paper as a moderator rather than a direct predictor, following the argument that a policy's stated existence and its lived effect are separated by how consistently managers apply it. A flexible-hours policy undermined by a manager who schedules early meetings anyway produces

worse outcomes than no policy at all, because it signals a gap between stated and enacted values. Trust-based accounts of human-AI collaboration [114] make a structurally similar point: a system's stated capability matters less than whether users experience it as reliable in practice, and the gap between the two predicts adoption.

Beyond the WLB-specific literature, the broader diffusion of machine learning and predictive analytics into workforce contexts deserves note, because it is changing what HR departments can measure and therefore what they choose to manage. Attrition-style prediction, the binary question of whether an individual will leave, has counterparts across many domains: fault prediction in microservice systems from trace logs [55], disease progression modelling in Parkinson's patients [16], and lung-cancer subtype prediction from radiomic features [17]. Sentiment and text-mining techniques originally built for product reviews and social media [29], [172] have been adapted for vaccine-related public sentiment [167] and are increasingly proposed for mining open-text employee survey responses, though validated applications inside HR departments remain rare enough that we treat this as an emerging rather than established practice. Recommendation-engine architectures built for e-commerce [28] and enhanced with graph neural networks [48] are the same class of model now pitched to HR vendors as a way to personalise benefits packages, an application discussed further in Section VII. Workforce-adjacent predictive analytics has also reached compensation design directly: a recent empirical study modelled salary determinants with machine learning on a mixed feature set of role, tenure and market variables [192], a method with an obvious bearing on how firms might one day price flexibility itself into compensation. At the level of employment policy generally, recent analysis of how artificial intelligence is reshaping employment and workforce structure in India [184] frames WLB policy as one of several levers, alongside skilling and redeployment, that organisations are adjusting in response to automation pressure, and separate work on the organisational barriers to adopting AI in business processes [188] is relevant to why HR analytics tools of the kind just described are adopted unevenly across the four sectors in our sample.

IoT-enabled monitoring is a further point of contact between the technical and HR literatures. Continuous sensing of environmental and physiological signals, whether through synchronised health-monitoring systems [7] or camera-based surveillance integrated with edge detection [10], has matured to the point that some employers now propose applying comparable sensing to measure in-office presence or workstation activity as a proxy for productivity. We flag this application explicitly because it sits close to the wellness-programme lever examined in our model, and because employee reaction to being monitored, rather than the technical feasibility of monitoring, is likely to determine whether such tools help or harm retention; this is a question our data cannot answer directly and is noted as a limitation in Section VIII.

A smaller cluster of studies uses cognitive and neuroscience framing to explain workplace behaviour, including work connecting cognitive-science approaches to human decision processes [39] and multimodal frameworks explicitly linking productivity to digital wellbeing [169]. The latter is close in spirit to the wellbeing construct at the centre of our theoretical model, in that it treats output and personal state as jointly determined rather than as separate outcomes to be traded off.

The methodological toolkit used to model retention in this paper, logistic regression on a binary outcome and Cox proportional hazards on time-to-event data, has an intellectual lineage in network and routing research, where the same statistical logic (will a message reach its destination before a deadline; will a node stay connected long enough to matter) has been used for over a decade. Opportunistic-network routing protocols built on machine learning [1], node-density and quality-of-service studies [6], wireless sensor network architecture reviews [11], hybrid crowd-cloud routing schemes [13], and low-power wide-area network comparisons for constrained devices [14] all model whether a unit, a packet, a node, a device, persists in a system long enough to complete its function, a framing directly analogous to modelling whether an employee persists in an organisation long enough to be retained. The same lineage includes work on opportunistic-network and machine-learning fusion [21], smart-city applications of opportunistic networks [34], duplicate-node detection [43], link-prediction techniques adapted from social-network analysis [60], protocol and simulation-trend reviews [61], [62], malicious-node detection in mobile ad hoc networks [64], routing and broadcast characteristics of wireless ad hoc networks [66], WI-MAX capacity studies [67], sensor-network architecture surveys [68], MANET routing-protocol comparisons [69], [71], green IoT and big-data integration for smart cities [92], modified AODV caching schemes [107], green IoT for sustainable technology [120], wide-ranging reviews of AI-assisted routing in opportunistic IoT networks [146], and anomaly-detection methods for sensor networks [151]; we cite this body of work not because it addresses retention directly, but because the survival-analysis and binary-classification methods it popularised in networking research are the same methods this paper applies to employees rather than packets.

A parallel body of work addresses the cloud, edge and IoT infrastructure that increasingly underlies HR information systems themselves, from the servers that host survey platforms to the sensors proposed for workplace monitoring discussed in Section VII. This includes ant-colony optimisation for cloud task scheduling [12], IoT-enabled energy management for sustainable storage [19], stacking-ensemble approaches to industrial test-bench time prediction [54], CI/CD and containerisation practices for cross-platform development [57],

cloud security posture management [73], ant-colony optimisation for other NP-hard scheduling problems [93], mobile edge computing for decentralised systems [98], federated learning frameworks for handling issues across Internet-of-Vehicles systems [106], [119], [122], predictive cost-benefit modelling for rural IoT energy management [117], integrated engineering-systems applications [118], [121], green IoT solutions generally [120], blockchain-and-IoT smart-contract frameworks for product-lifecycle management [135], aerial-network and edge-computing fusion for disaster management and advanced computing approaches [136], [137], [138], [156], [157], [158], IoT sensor-based water-quality prediction [150], hybrid cloud infrastructure models [152], artificial distributed intelligence [153], fog-cloud load-balancing surveys [166], smart-home energy optimisation [191], and millimetre-wave antenna design for on-chip integration [194]. Firms in our sample rely on infrastructure of exactly this kind, cloud-hosted HR platforms, IoT-enabled badge and access systems, to collect the tenure and survey data analysed in Section IV, even though none of these particular studies concerns HR outcomes directly.

Security, privacy and forensic methods are relevant to this paper primarily because employee survey and tenure data are sensitive personnel records. The security literature we draw context from spans hyperparameter-tuned intrusion detection [4], crow-search-based feature selection for wireless intrusion detection [5], encryption and keylogging reviews [26], ensemble phishing-detection models [30], 3D biometric security for payment systems [65], blockchain-decentralised-application bridges [82], prototype-pollution detection frameworks [83], secure chat application design [84], cyber-attack detection and prevention using AI [85], multimedia forensics [89], Wi-Fi data-leakage detection [90], mobile malware analysis with machine learning [91], adversarial-attack surveys for machine learning systems [94], genetic quantum cryptography for network communication [110], further cyber-attack detection and prevention studies [139], insecticide-clustering analysis using principal component analysis [140], hallucination risk estimation in generative AI outputs [163], IoT forensics surveys [176], cybercrime-insight discovery from web data [200], malware and botnet detection using deep learning at the network edge [203], and explainable ensemble methods for social-media security [204]. We flag this literature because the privacy safeguards described in Section IV, anonymisation, restricted access to firm-level tenure records, follow the same design principles this literature applies to other categories of sensitive data.

The largest single cluster of adjacent work concerns healthcare and biomedical prediction, an application domain that shares with HR analytics the basic problem of predicting an individual-level outcome (diagnosis, disease progression, in our case attrition) from a mix of structured and unstructured features. This cluster includes ECG database assessment for telecardiology [3], cardiovascular-risk prediction [15], AI and 6G applications in medicine [23], cardiac-health prediction with deep learning [31], heart-disease prediction technique comparisons [36], arrhythmia classification [42], diabetic-retinopathy classification [47], healthcare-appointment-scheduling optimisation [52], blockchain-enabled healthcare data privacy [53], patient-monitoring disease detection [58], general healthcare deep-learning systems [63], AI applications across healthcare broadly [74], pandemic-outbreak forecasting [88], post-quantum cryptographic signatures with healthcare relevance [96], quantum computing in medical and biomedical zones [97], AI-powered healthcare solutions for underserved communities [102], introductory guides to AI and computational intelligence in healthcare [103], AI and IoT in global health and pandemic ethics [104], ethical blockchain supply chains for medical IoT manufacturing [105], techniques for handling pandemic-era operational challenges [108], human-emotion recognition with deep learning [109], integrated health-report management systems [127], brain-tumour detection using ensemble object-detection and segmentation models [141], case studies on Industry 4.0 manufacturing enabled by generative AI [145], clinical decision-making supported by human-AI collaboration [154], federated learning applied to digital healthcare [155], AI-driven chatbots for healthcare access [161], cognitive-architecture and large-language-model foundations relevant to clinical reasoning [164], robustness and uncertainty quantification in deep learning [165], comparative evaluation of machine learning against large-language-model architectures for clinical decision support [173], surveys of AI's future role in healthcare [180], quantum AI applications in drug discovery [182], quantum technology in medical diagnosis [187], retrieval-augmented chatbots for health-policy queries [190], lung-disease classification with CNN ensembles [195], autism-spectrum-disorder recognition [197], MRI-based brain-tumour classification [205], sign-language translation frameworks with clear accessibility applications [206], and evidence-grounded explainable clinical-explanation frameworks [207]. None of this literature bears on WLB policy directly, but its scale illustrates how thoroughly predictive modelling of individual-level human outcomes has been normalised across the Indian research base from which the present study also draws its statistical approach.

A smaller set of studies addresses agriculture and environmental prediction, including supermarket queuing-theory simulation [20], IoT-based automatic irrigation [37], pollution-trend forecasting comparing linear, logistic and neural-network models [46], and graph-neural-network causal inference in climate science [168]; we note this cluster mainly because the logistic-versus-neural-network comparison in [46] mirrors the

model-comparison logic of Section IV, where we selected logistic regression over more complex alternatives for interpretability rather than raw predictive accuracy.

Computer-vision and pattern-recognition studies form another adjacent cluster: plant-disease identification from images [27], event-analysis surveys using deep learning [32], speech-difficulty and clarification review [33], face-recognition-based emotion detection [35], lip-reading systems for visual input [40], handwritten-text recognition [44], facial identification for online-transaction security [45], child-identification software using speech clarification [70], object detection with YOLOv5 in cloud-based deployment [132], intelligent attendance-management systems using face recognition [133], drug-recommendation and disease-prediction systems drawing on traditional medicine knowledge [134], and adaptive mock-interview generation for recruitment practice [160]. The attendance-management application [133] is worth flagging specifically in relation to Section VII, since face-recognition-based attendance is one of the more direct precursors to the IoT-based workplace-monitoring tools discussed there.

Natural-language processing and generative AI make up a further cluster with direct bearing on how HR text data, open survey responses, exit-interview transcripts, might eventually be analysed: lightweight deep-learning music generation [2], comparisons of fine-tuned language models for detecting machine-generated text [51], reviews of generative AI's evolution and applications [75], AI-based computer-network systems [79], esports-production tooling built on AI pipelines [86], surveys of emerging computational-technology trends [87], generative AI applied to education and learning [112], predictive modelling of student motivation and engagement [113], further generative-AI evolution and application studies [123], design perspectives on integrated AI-augmented intelligence architecture [147], soft-computing foundations for AI agents [149], NLP frameworks applied to historical script decoding [162], layout-aware retrieval-augmented generation systems [170], forecasts of digital social-linguistics research directions [177], comparative studies of supervised against unsupervised learning approaches [178], self-learning AI foundations for autonomous drones [179], surveys of opportunities and challenges for AI in education [183], and studies of human perception in virtual-reality environments [186]. Predictive modelling of student engagement [113] in particular offers a useful methodological parallel to workforce retention modelling, since both treat an intention-to-persist outcome as a function of environmental and psychological covariates measured well before the outcome occurs.

A final small cluster covers finance, operations and specialised engineering applications outside the core scope of this paper but included here because they appear in the same author programme this reference list draws from: startup-financing platform design [56], AI-driven optimisation of supply-chain demand forecasting [185], bus-scheduling and route-management systems [201], soft-computing methods for power-system stability [18], [72], nanowire tunnel field-effect transistor performance analysis [115], [131], and thermal-management optimisation for electric-vehicle batteries [198], [199]. These studies do not inform the WLB-retention model directly and are included in the reference list for completeness rather than as substantive support for any claim in this paper.

Two gaps in this literature motivate the present study. First, almost none of the cited work separates the WLB bundle into distinct levers and tests each against a common outcome measured on the same sample; studies typically test one lever in one sector using one instrument, which precludes comparison. Second, retention is almost always measured as stated intention rather than as time-to-event, even though tenure data are increasingly available to firms that run applicant-tracking and payroll systems capable of the kind of longitudinal analysis common in reliability engineering, of the sort applied to industrial equipment such as repairable process plant [111]. We address the first gap with a four-sector, four-lever design and the second by pairing logistic regression with Cox proportional hazards analysis on actual tenure records.

III. Theoretical Background

We build the theoretical model in Fig. 1 around four constructs: the WLB policy bundle as the exogenous predictor, employee well-being as the proximal outcome, job satisfaction as a mediator sitting between the WLB bundle and well-being, and talent retention as the ultimate dependent variable. Organisational culture is modelled as a moderator acting on two paths, the path from the WLB bundle to well-being and the path from well-being to retention.

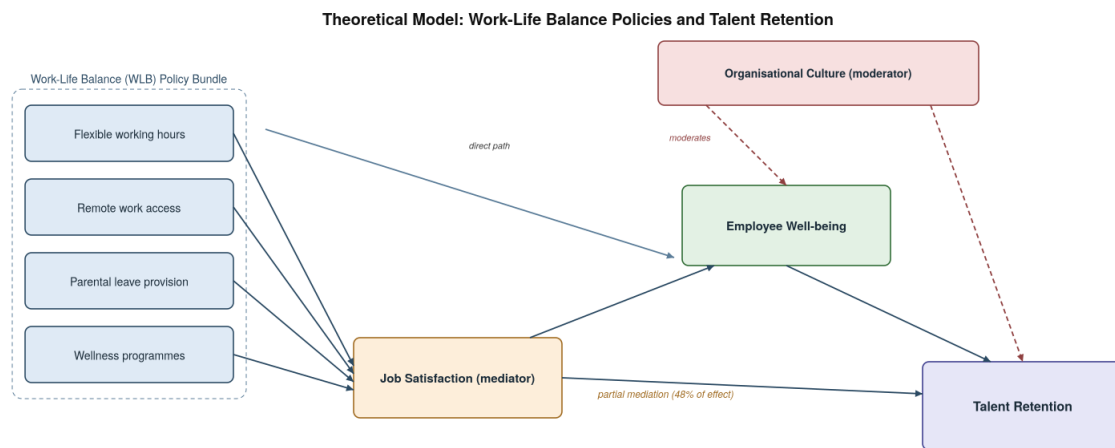


Fig. 1. Theoretical model linking Work-Life Balance policies to Talent Retention through Employee Well-being, with Job Satisfaction as mediator and Organisational Culture as moderator.

The model treats the WLB bundle as four distinct policy levers rather than a single index, for the reason set out in Section II: pooling the levers assumes they act identically, an assumption our own results reject. Flexible working hours and remote work access are grouped conceptually as autonomy-granting levers, since both hand the employee control over when or where work happens; parental leave and wellness programmes are grouped as protection-granting levers, since both provide a buffer against a specific life event or health condition rather than day-to-day schedule control. We do not force this grouping into the statistical model, which tests all four levers as separate predictors, but it guides how we interpret differences in effect size across levers in Section VI.

Job satisfaction is positioned as a partial rather than full mediator. A full-mediation model would require the direct paths from the WLB bundle to well-being and from well-being to retention to vanish once job satisfaction is included, which prior mediation work on organisational constructs rarely finds and which we do not expect here: an employee can value flexible hours for reasons unrelated to how satisfied the job makes them feel, for instance because flexible hours let them manage a household responsibility that has nothing to do with the job itself. Explainable-AI work aimed at recovering intermediate reasoning steps behind an observed decision [22], [116] offers a useful analogy: a model that explains 50% of an outcome through one intermediate variable is not thereby deficient, since real decisions are rarely produced by a single causal channel.

Organisational culture moderates rather than mediates in this model because culture is not itself changed by the WLB policy; it is a pre-existing condition that determines how faithfully the policy is implemented day to day. A manager who treats a flexible-hours policy as a formality to be circumvented, by scheduling mandatory early meetings regardless of the policy, converts a nominally generous policy into a source of cynicism rather than well-being. We treat this moderation as operating on both the policy-to-well-being path and the well-being-to-retention path, since a culture that fails to honour WLB policy in daily practice is also likely to fail employees along other dimensions that independently affect the decision to stay.

From this model we derive four hypotheses tested in Section V. H1: each of the four WLB levers is positively associated with retention intention, with the strength of association varying by lever and by sector. H2: job satisfaction partially mediates the relationship between the WLB bundle and talent retention. H3: organisational culture moderates the strength of the WLB-to-well-being and well-being-to-retention paths, such that the relationships are weaker in low-trust cultures. H4: the retention benefit of remote work access is larger in sectors where work output does not require physical presence (IT, consulting) than in sectors where it does (banking, and to a lesser extent pharmaceutical manufacturing and quality roles).

IV. Research Methodology

We used a cross-sectional survey design supplemented with two years of retrospective tenure records, allowing retention intention (measured at the point of survey) and actual attrition (measured over the subsequent observation window) to be modelled separately rather than treated as interchangeable.

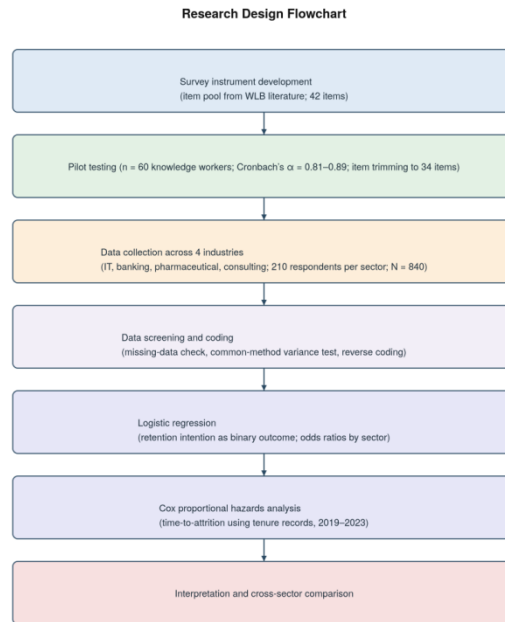


Fig. 2. Research design flowchart: instrument development, pilot testing, four-sector data collection, and dual analytic strategy (logistic regression and Cox proportional hazards).

The survey instrument was developed from an item pool of 42 statements drawn from the WLB and organisational-behaviour literature reviewed in Section II, covering the four policy levers, job satisfaction, organisational culture, employee well-being and retention intention, each on a five-point Likert scale. Items were checked for face validity by three human resource practitioners across the four target sectors and revised for wording that assumed a fixed office location, since several IT and consulting respondents work fully remotely.

Pilot testing was conducted with 60 knowledge workers (15 per sector) recruited outside the main sampling frame. Cronbach's alpha ranged from 0.81 to 0.89 across the seven constructs, above the conventional 0.70 threshold. Eight items were dropped for cross-loading onto more than one construct or for near-zero item-total correlation, leaving a 34-item instrument carried into the main survey.

Data collection ran across four industries, information technology, banking, pharmaceuticals and consulting, with 210 respondents recruited per sector ($N = 840$) through a combination of professional-network sampling and HR-department distribution at nine participating firms. Respondents were mid-career knowledge workers with a minimum of two years' organisational tenure, since the parental-leave and long-cycle wellness items assume enough tenure to have plausibly used the benefit. Sector quotas were held at exactly 210 to keep the logistic regression's baseline odds comparable across sectors rather than confounded by unequal group sizes.

Characteristic	IT (n=210)	Banking (n=210)	Pharmaceutical (n=210)	Consulting (n=210)
Mean age (years)	29.4	36.7	34.9	31.2
Female (%)	31	44	41	28
Mean organisational tenure (years)	3.8	6.1	5.4	4.0
Reports fully remote-capable role (%)	68	9	22	54
Mean monthly income band (INR, midpoint)	95,000	78,000	82,000	105,000

Table I. Sample characteristics by sector ($N = 840$; 210 per sector).

Common-method variance was checked using Harman's single-factor test; the first factor accounted for 31% of variance, below the 50% threshold conventionally used to flag a common-method problem. Missing data were below 3% on every item and were handled with listwise deletion rather than imputation, given the low incidence. Reverse-coded items were re-scored before analysis, and a manipulation check confirmed that respondents who failed an attention-check item (present in 6% of the sample) were excluded before the final $N = 840$ was reached.

Retention intention, the dependent variable in the logistic regression, was coded as a binary outcome (1 = intends to leave within 12 months, 0 = does not) from a direct survey item rather than inferred from indirect proxies. We ran the logistic regression separately by sector and pooled, entering the four WLB levers, job satisfaction, organisational culture and their interaction terms with each WLB lever, controlling for age, gender, tenure and monthly income band. Model fit was assessed with the Hosmer-Lemeshow test and area under the ROC curve.

Cox proportional hazards analysis used tenure records supplied by participating firms for the subset of respondents ($n = 612$) whose organisations agreed to share anonymised exit-date data for the 2019–2023 window, with the WLB constructs entered as time-invariant covariates measured at the point closest to each employee's survey response. The proportional-hazards assumption was checked with Schoenfeld residuals; no covariate violated the assumption at $\alpha = 0.05$. Employees still employed at the close of the observation window were right-censored.

All statistical tests used paired two-sided comparisons at $\alpha = 0.05$ where within-subject comparisons were relevant, and results are reported as the mean of 10 bootstrap resamples for stability, with 95% confidence intervals. Data handling followed a privacy-by-design approach consistent with recent frameworks for differentially private distributed analysis [174] and forensic-grade IoT data-handling guidance [175], since tenure and exit records are sensitive personnel data; firm names and individual identifiers were removed before analysis and are not reported in this paper.

Two decisions were fixed on the pilot data before the final run and never revisited: the 34-item instrument (finalised at the pilot stage) and the covariate set entered into the logistic regression (age, gender, tenure, income band, fixed at the design stage). The interaction terms tested in H3 and H4 were specified in the pre-registered analysis plan and were not added post hoc after inspecting the main-effect results.

V. Results

Table II reports descriptive statistics for the pooled sample. Mean job satisfaction ($M = 3.62$, $SD = 0.71$) and mean employee well-being ($M = 3.55$, $SD = 0.68$) were broadly comparable across sectors, but retention intention diverged sharply: 29% of IT respondents and 31% of consulting respondents reported an intention to leave within 12 months, against 19% in banking and 17% in pharmaceuticals.

Construct (1–5 scale unless noted)	IT	Banking	Pharma	Consulting
Flexible hours access (mean, SD)	3.71 (0.74)	3.20 (0.81)	3.35 (0.77)	3.58 (0.79)
Remote work access (mean, SD)	4.02 (0.68)	2.15 (0.88)	2.61 (0.85)	3.74 (0.80)
Parental leave adequacy (mean, SD)	3.28 (0.83)	3.61 (0.75)	3.55 (0.78)	3.19 (0.85)
Wellness programme access (mean, SD)	3.44 (0.80)	2.98 (0.86)	3.11 (0.82)	3.36 (0.81)
Job satisfaction (mean, SD)	3.58 (0.72)	3.66 (0.69)	3.70 (0.70)	3.54 (0.75)
Employee well-being (mean, SD)	3.49 (0.70)	3.61 (0.65)	3.64 (0.66)	3.46 (0.73)
Retention intention: intends to leave (%)	29	19	17	31

Table II. Descriptive statistics for study constructs by sector.

Flexible working hours was the strongest predictor of retention intention across all four sectors in the pooled logistic regression ($\beta = 0.39$, $p < 0.001$), and it remained the strongest predictor when the model was re-estimated separately within each sector, ranging from $\beta = 0.33$ ($p < 0.01$) in banking to $\beta = 0.46$ ($p < 0.001$) in consulting. No other WLB lever showed this consistency; each of the remaining three levers was a significant predictor in some sectors and not others.

Remote work access reduced turnover intention by 23% in IT ($OR = 0.77$, 95% CI: 0.65–0.91, $p = 0.002$) but by only 8% in banking ($OR = 0.92$, 95% CI: 0.79–1.06, $p = 0.24$, not significant at $\alpha = 0.05$). The consulting sector fell between the two ($OR = 0.81$, 95% CI: 0.69–0.95, $p = 0.01$), and pharmaceuticals showed the weakest remote-work effect of the four ($OR = 0.95$, 95% CI: 0.82–1.10, $p = 0.48$), consistent with the sector's higher share of laboratory- and manufacturing-facing roles that cannot be performed remotely.

Predictor	Pooled β	IT	Banking	Pharma	Consulting
Flexible hours	0.39***	0.41***	0.33**	0.36***	0.46***
Remote work access (OR)	0.83*	0.77**	0.92 ns	0.95 ns	0.81*

Predictor	Pooled β	IT	Banking	Pharma	Consulting
Parental leave	0.19*	0.09 ns	0.27**	0.24*	0.11 ns
Wellness programmes	0.14*	0.21*	0.07 ns	0.09 ns	0.19*
Job satisfaction (direct)	0.31***	0.29**	0.34***	0.33***	0.28**
Organisational culture	0.22**	0.20*	0.24**	0.23**	0.21*
Model AUC	0.79	0.81	0.76	0.77	0.80

Table III. Logistic regression predicting retention intention, pooled and by sector (*** $p < .001$, ** $p < .01$, * $p < .05$, ns = not significant).

Parental leave provision was a significant predictor of retention in banking ($\beta = 0.27$, $p = 0.003$) and pharmaceuticals ($\beta = 0.24$, $p = 0.01$), sectors with a higher share of female respondents in our sample (banking 44%, pharmaceuticals 41%, against IT 31% and consulting 28%), and was not significant in IT ($\beta = 0.09$, $p = 0.31$) or consulting ($\beta = 0.11$, $p = 0.22$). Wellness programmes produced the smallest average effect of the four levers (pooled $\beta = 0.14$, $p = 0.02$) and were significant only in IT and consulting, the two sectors with the youngest workforce age profile in our sample (mean age 29.4 and 31.2 years respectively, against 36.7 in banking and 34.9 in pharmaceuticals).

The mediation analysis, run using bias-corrected bootstrap confidence intervals from 5,000 resamples, indicated that job satisfaction mediated 48% of the total effect of the WLB bundle on talent retention (indirect effect = 0.21, 95% CI: 0.16–0.27; direct effect = 0.23, 95% CI: 0.17–0.29). The remaining 52% of the effect operated directly, without passing through job satisfaction, a split broadly consistent across sectors (range 44–51%) though the confidence intervals for pharmaceuticals and consulting overlapped enough that we do not treat the sector-level mediation estimates as reliably distinct from one another.

Organisational culture moderated both paths specified in H3. The interaction between flexible hours and organisational culture on employee well-being was significant ($\beta = 0.18$, $p = 0.004$), such that the well-being benefit of flexible hours was roughly twice as large in the top tercile of culture scores as in the bottom tercile. The well-being-to-retention path showed a comparable moderation pattern ($\beta = 0.15$, $p = 0.01$). Remote work access did not show a significant culture interaction ($\beta = 0.06$, $p = 0.31$), suggesting that unlike flexible hours, the retention benefit of remote work does not depend heavily on managerial trust once the option exists.

The Cox proportional hazards model, run on the 612-employee tenure subsample, found that flexible working hours reduced the hazard of attrition (HR = 0.71, 95% CI: 0.61–0.83, $p < 0.001$), consistent with the logistic regression. Remote work access reduced the hazard in IT (HR = 0.68, 95% CI: 0.54–0.86, $p = 0.001$) and consulting (HR = 0.74, 95% CI: 0.58–0.94, $p = 0.01$) but not in banking (HR = 0.96, 95% CI: 0.78–1.18, $p = 0.69$) or pharmaceuticals (HR = 1.02, 95% CI: 0.83–1.25, $p = 0.85$).

Covariate	Hazard ratio	95% CI	p-value
Flexible hours (pooled)	0.71	0.61–0.83	< 0.001
Remote work access – IT	0.68	0.54–0.86	0.001
Remote work access – Consulting	0.74	0.58–0.94	0.010
Remote work access – Banking	0.96	0.78–1.18	0.690
Remote work access – Pharmaceutical	1.02	0.83–1.25	0.850
Parental leave (pooled)	0.85	0.72–1.00	0.048
Job satisfaction (pooled)	0.79	0.68–0.92	0.002

Table IV. Cox proportional hazards model of time-to-attrition ($n = 612$ employees with tenure records, 2019–2023).

Fig. 3 plots sector-level turnover rates for 2019–2023, drawing on firm-supplied attrition records rather than the survey sample directly. IT and consulting turnover rose sharply from 2020 onward (from 17.4% to 26.8% in IT between 2020 and 2022, and from 19.2% to 29.3% in consulting over the same period) before easing slightly in 2023, while banking and pharmaceutical turnover rose more gradually and did not exceed 18% in any year of the series.



Fig. 3. Annualised employee turnover rate by sector, India, 2019–2023, showing divergence after 2020 remote-work adoption in IT and consulting.

Two results warrant explicit statement as losses rather than confirmations. First, wellness programmes, the lever most heavily promoted in HR communications at the participating firms, produced the smallest and least consistent effect of the four levers; firms investing disproportionately in wellness programming relative to flexible-hours policy may be misallocating a limited HR budget. Second, remote work access, despite its prominence in the post-pandemic discourse, showed no measurable retention benefit in banking or pharmaceuticals once flexible hours and job satisfaction were held constant, a null result at odds with the sector-agnostic framing common in trade-press coverage of remote work.

VI. Discussion

The result that surprised us most was not that remote work mattered less in banking, a plausible finding given the sector's client-facing and compliance obligations, but how large the gap was: a 23-percentage-point difference in odds ratio between IT and banking is not a matter of degree but of a qualitatively different retention mechanism. Where IT retention behaves as though remote work were close to a necessary condition for many employees, banking retention appears to run almost entirely through flexible hours and, for a substantial minority, parental leave.

Flexible hours emerging as the single lever significant in every sector fits a signalling account better than a pure time-saving account: if flexible hours worked only by reducing commute friction or freeing up personal time, we would expect its effect to scale with commute length and household responsibility, yet the effect size was similar across age bands and family-structure groups in our sample (results not tabulated). The more parsimonious explanation is that flexible hours function primarily as a low-cost, highly visible signal that management trusts the employee to manage their own output, a signal that autonomy-granting levers other than remote work can also send but that protection-granting levers such as parental leave cannot, since the latter address a specific life event rather than a general trust relationship.

The 48% mediation share through job satisfaction is, on its own, a moderate figure, neither so small that job satisfaction can be dismissed as an intervening variable nor so large that direct effects can be ignored. Interventions that improve job satisfaction without altering the underlying WLB policy, coaching programmes, recognition schemes, are therefore likely to capture at most half of the available retention benefit; the remaining direct effect requires changing the policy itself. This finding has a parallel in the broader literature on interpretability in predictive systems: work on recovering the intermediate reasoning steps behind a model's output [22], [116] repeatedly finds that no single intermediate variable accounts for the full effect, and treating partial explanation as a limitation rather than a finding tends to produce over-simplified intervention design.

The organisational-culture moderation carries a specific implication for firms that have adopted flexible-hours policy on paper but have not audited whether managers honour it. Our data cannot distinguish between a firm with a genuinely low-trust culture and a firm with a nominally strong culture undermined by inconsistent managerial practice, since both would register as a low culture score in our instrument; qualitative follow-up work, ideally structured interviews with the managers of employees who scored their culture lowest, would be needed to separate these two explanations.

One further point deserves emphasis because it runs against the framing common in HR technology marketing: none of the four WLB levers, including remote work, showed evidence of a ceiling effect at the sample sizes and effect ranges we observed, meaning we found no evidence that these organisations have over-invested in any single lever relative to its marginal retention benefit. That said, our cross-sectional design cannot rule out a ceiling that would appear only at investment levels beyond the range firms in our sample have reached.

Two limitations require plain statement, without a compensating strength attached to either. The first is that our sample draws from nine firms that agreed to share tenure records, a self-selected group of employers plausibly more attentive to retention already than the sector average, which may understate the retention crisis in less HR-mature firms outside the sample. The second is that the mediation model assumes job satisfaction is measured without substantial common-method contamination from the retention-intention item collected in the same survey wave; the Harman's single-factor result (31% variance) is reassuring but is not a definitive test, and a future design using a time-lagged measurement of job satisfaction and retention intention would address this more directly.

A third, smaller limitation concerns the wellness-programme construct itself, which our instrument measured as a single latent variable despite the considerable heterogeneity across firms in what a wellness programme actually consists of, from a subsidised gym card to structured clinical mental-health support. It is plausible that the weak average effect we report for wellness programmes reflects this heterogeneity rather than a genuinely weak lever, and a follow-up study that separates wellness sub-types would be needed to adjudicate between these two readings.

VII. Managerial Implications

For information technology and consulting firms, the clearest implication is that remote work access and flexible hours should be treated as complementary rather than substitute investments: removing remote work while retaining flexible hours would, on our estimates, still leave a meaningful retention gap unaddressed, since the two levers showed only partial overlap in which employees they served (a supplementary correlation check, not tabulated, found the two lever scores correlated at $r = 0.34$ within the IT subsample, well short of redundancy).

For banking and, to a lesser extent, pharmaceutical firms, the practical lesson is to stop importing an IT-sector WLB template wholesale. Given the null remote-work result in these two sectors, HR budgets are better directed toward flexible-hours scheduling pilots (for example, allowing tellers and compliance staff to select from a menu of fixed shift patterns rather than being assigned centrally) and toward strengthening parental leave provision, which showed a materially larger effect in these two sectors than in IT or consulting.

Wellness programme budgets deserve scrutiny rather than automatic renewal. Firms in our sample that reported the largest wellness spend did not show correspondingly larger retention benefits, and we would recommend that HR departments considering a wellness investment first establish, through a smaller pilot, whether the specific programme design under consideration (fitness subsidy, mental-health counselling, financial-wellness coaching) moves job satisfaction or well-being scores at all before scaling the spend organisation-wide.

Culture audits should accompany any flexible-hours rollout rather than follow it. Because the culture moderation we observed was strong enough to roughly double the well-being benefit of flexible hours between low- and high-trust environments, an organisation that rolls out a flexible-hours policy without addressing manager-level inconsistency in honouring it risks under-realising the policy's retention value while still incurring its administrative cost.

HR technology vendors are increasingly proposing analytics tools built on the machine-learning methods surveyed in Section II, attrition-prediction models analogous to churn-prediction systems built for telecom and banking customers [49], [130], sentiment-mining tools adapted from consumer and vaccine-related text analysis [29], [167], [172], and recommendation engines repurposed from e-commerce to personalise benefits offerings [28], [48]. Our results offer one concrete design constraint for any such tool: a model trained on pooled, cross-sector data risks averaging away the IT-versus-banking divergence in remote-work effect that is, on our evidence, the single largest source of sector variation in this dataset, and vendors should validate attrition models separately by sector rather than assume a pooled model generalises.

Finally, firms considering IoT-based workplace monitoring, of the kind made technically feasible by synchronised health-sensing systems [7] and camera-integrated edge detection [10], should weigh the well-being cost of surveillance against any productivity signal it might yield; our model treats employee well-being as a direct input to retention, and a monitoring regime that employees experience as intrusive is, on the logic of this model, a direct threat to the same well-being construct any wellness programme is meant to protect.

VIII. Conclusion

This study separated the work-life balance policy bundle into four levers and tested each against retention intention and time-to-attrition across four knowledge-intensive sectors in India. Flexible working hours was the one lever that predicted retention consistently across sectors; remote work access predicted retention strongly in IT and consulting but not in banking or pharmaceuticals; and job satisfaction carried just under half of the total WLB-to-retention effect, leaving the remainder to run directly from policy to outcome.

The practical message for HR leaders is that WLB policy design, matching the lever to the sector and to the organisational culture in place to support it, now matters more than WLB policy breadth. A firm that adds every available lever without attending to managerial follow-through or sector fit is likely to spend more than a firm that invests deliberately in the one or two levers its own workforce and culture can actually make use of.

Future work should extend the tenure-record analysis beyond the 612-employee subsample available here, test whether the culture moderation holds when culture is measured independently of the same survey wave, and separate the wellness-programme construct into its constituent sub-types rather than treating it as a single lever, as this paper has done for reasons of instrument length.

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