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Workplace Diversity and Inclusion Practices in the Indian IT Sector: Drivers, Barriers, and Outcomes

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Abstract
Women hold 34% of technology jobs in Indian IT services firms but only 12% of senior leadership positions, a gap that persists despite a decade of stated commitment to diversity and inclusion (D&I) [3], [21], [166]. Prior studies of D&I in Indian organisations rely mainly on single-firm case material or HR disclosure documents, leaving the relationship between specific D&I practices and measurable outcomes under-tested at sector scale [58], [64], [92]. We surveyed 620 employees across 15 IT firms in Bengaluru, Hyderabad and Pune and ran eight focus groups to examine which drivers predict D&I outcomes and where formal policy diverges from lived experience. Leadership commitment was the strongest predictor of composite D&I outcomes ($\beta = 0.44$, $p < 0.001$), ahead of policy frameworks ($\beta = 0.21$) and training programme intensity ($\beta = 0.13$); firms with a dedicated D&I officer reported 31% higher employee satisfaction scores than firms without one (Mann-Whitney U, $p = 0.002$). Focus group data showed that caste-based exclusion continues informally through seating arrangements, mentorship allocation and after-hours socialising, a pattern the survey instrument alone did not surface. Tier-3 city offices reported higher regional-language representation (38.4%) but lower disability inclusion (1.4%) than Tier-1 hubs. We conclude that formal D&I architecture predicts outcomes only when leadership commitment is present, and that policy compliance without informal-network change leaves caste-based and disability-related exclusion intact.

I. Introduction

The Indian information technology (IT) and IT-enabled services sector employs approximately 5.4 million people and has built its growth story on the claim that merit, not background, determines advancement [21], [58]. That claim is tested unevenly. Women make up 34% of the technical workforce sampled in this study but only 12% of positions at director level and above, a compression ratio that widens rather than narrows above the entry grades. Caste, disability status and the city tier in which an office sits shape outcomes in ways that firms' published D&I reports rarely disaggregate.

Three developments make the question of D&I practice in Indian IT firms urgent rather than merely of academic interest. First, client contracts increasingly carry supplier-diversity clauses that make D&I metrics a commercial requirement rather than a discretionary commitment [34], [61]. Second, algorithmic tools now screen a large share of entry-level applications, and evidence from machine learning research shows that models trained on historical hiring data reproduce the biases in that data rather than correcting for them [3], [8], [21]. Third, the sector's expansion into Tier-2 and Tier-3 cities has changed the demographic composition of new hires without a matching change in how firms measure or manage inclusion at those sites [92], [120].

Existing accounts of D&I in Indian organisations tend to describe policy intent rather than test its association with outcomes. HR disclosure documents state that a firm has an anti-discrimination policy; they say little about whether employees experience its enforcement, or whether the practices built around the policy change who gets promoted, retained or heard in meetings. Studies from the wider technology-management literature examine related organisational and technical questions -- attrition prediction [37], [42], sentiment analysis of workplace culture [172], algorithmic bias in screening tools [3], [8] -- but rarely connect these tools back to a D&I outcome measured at the level of the individual employee.

We address this gap with a concurrent mixed-methods study of 620 employees across 15 IT firms and eight focus groups conducted in three cities that represent different tiers of the sector's geographic expansion: Bengaluru (Tier-1), Hyderabad (Tier-1/Tier-2 boundary) and satellite operations we group here with Pune-region Tier-2 and Tier-3 sites. The contribution of the paper is threefold. We measure the relative strength of three commonly cited D&I drivers -- leadership commitment, policy frameworks and training programmes -- against a composite outcome index built from innovation, satisfaction and financial-

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performance proxies (Section V). We show, using paired non-parametric tests, where the practices linked to those drivers succeed and where they do not, including the 31% satisfaction gap associated with a dedicated D&I officer role (Section V-C). We use the focus group data to explain a pattern the survey alone could not: that caste-based exclusion persists through informal channels even where formal policy explicitly prohibits it (Section VI).

The remainder of the paper proceeds as follows. Section II reviews the literature on D&I drivers, practices and outcomes, and on the barriers that moderate their relationship, drawing on organisational-behaviour and computational literatures. Section III sets out the conceptual framework tested in the survey. Section IV describes the mixed-methods design. Section V reports findings; Section VI discusses them; Section VII sets out practical implications for HR and technology leaders; Section VIII concludes.

II. Literature Review

A. Drivers of D&I: Leadership, Policy and Training

Leadership commitment appears across the organisational-behaviour literature as the factor that converts a stated D&I policy into a lived practice; without visible commitment from senior management, published targets function as a compliance artefact rather than an operating constraint [21], [58], [64]. Policy frameworks -- anti-discrimination clauses, grievance procedures, flexible-work entitlements -- set the boundary conditions within which managers operate, but the frameworks reviewed in comparable studies of large organisations rarely specify enforcement mechanisms with the same precision as the prohibition itself [92], [108]. Training programmes are the most visible D&I intervention because they are the easiest to schedule and report, yet their effect on behaviour depends on whether they are one-off compliance sessions or repeated, manager-targeted interventions tied to performance evaluation [88], [93].

A separate strand of work treats organisational data itself as a lever for D&I measurement. Machine-learning-based attrition prediction models can flag which employee segments leave at elevated rates, giving HR teams an early-warning signal that a demographic group is disengaging before exit interviews confirm it [37], [42]. Sentiment analysis applied to internal communication and survey text has been used to detect shifts in workplace culture that precede formal complaints, though the method depends on having a labelled baseline against which to compare later text [172]. Predictive analytics for retention extends the same logic to identify which combinations of manager, project and location predict earlier departure among under-represented groups [129], [130].

B. D&I Practices: Recruitment, Retention, Advancement

Recruitment practice is the point at which algorithmic tools have drawn the most scrutiny. Resume-screening and candidate-ranking systems built on historical hiring data can encode the demographic skew of the training set into the ranking function itself, a risk documented across several machine-learning fairness studies and specifically flagged for IT-sector recruitment pipelines [3], [8], [21]. Natural-language-processing tools marketed as bias detectors for job descriptions identify gendered language patterns (for example, competitive framing that discourages women applicants) but their coverage of caste-coded language specific to the Indian labour market is limited, because the training corpora behind these tools are drawn overwhelmingly from English-language, Western job postings [29], [167].

Retention practice covers flexible-work policy, mentorship allocation and psychological-safety interventions. Internet-of-Things-based workplace monitoring, originally deployed for security and asset tracking, has been repurposed in some firms to infer occupancy and desk-usage patterns that correlate with informal exclusion -- for instance, systematic under-use of collaborative spaces by employees from specific demographic segments -- though this use raises its own consent and surveillance concerns that the reviewed literature treats only briefly [7], [135]. Advancement practice, meaning sponsorship into stretch assignments and promotion committees, is the practice most frequently cited by qualitative studies as the point where formal policy and informal network effects diverge [64], [92], [108].

C. AI, Automation and D&I Measurement

A growing set of studies applies computational methods directly to D&I measurement rather than only to the practices that produce D&I outcomes. Explainable-AI frameworks have been proposed to make recruitment and performance-scoring models auditable to HR and legal teams, on the reasoning that a hiring decision cannot be defended if the model producing it cannot be interrogated [22], [114], [143]. Trust in AI systems among employees who are the subject of

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algorithmic scoring is itself a measurable construct, and social-psychological work on human-AI collaboration finds that trust is lower among employees who believe the system was trained on data that under-represents people like them [114]. AI-assisted accessibility tools -- screen-reader compatibility checkers, captioning systems, adaptive-interface generators -- have been proposed as a practical route to improving disability inclusion in technical roles, though adoption in the firms reviewed here remains limited to accessibility-compliance teams rather than being built into standard software-development tooling [114], [180].

IoT-based workplace monitoring, discussed above in the retention context, intersects with D&I measurement through occupancy analytics: sensor data on meeting-room usage and desk allocation has been used in a small number of pilot studies to identify departments where women or junior staff systematically occupy less visible physical space, a pattern that maps onto self-reported exclusion in exit interviews [7], [135]. Predictive analytics for retention, again, extends this logic from physical to digital signals, using calendar density, meeting-invitation patterns and project-assignment history as inputs to attrition-risk models segmented by demographic group [129], [130].

D. Barriers: Caste, Disability, and Regional Disparity

Caste receives comparatively little attention in the mainstream organisational-behaviour literature on Indian firms, in part because firms' own HR systems do not collect caste data and in part because caste-based discrimination is prohibited by law and therefore under-reported through formal channels [58], [64]. Where caste appears in the literature, it is typically inferred indirectly, through surname analysis or through qualitative interview material rather than through direct self-identification in survey instruments, an approach our own study also adopts for the reasons set out in Section IV. Disability inclusion is better documented in policy terms -- most large IT firms report a Persons with Disabilities (PwD) hiring target -- but accessibility provisioning for the roles PwD candidates are hired into varies by office and by city tier, and assistive-technology tools including AI-assisted accessibility software remain unevenly deployed [114], [180].

Regional disparity operates through two related channels. First, the sector's expansion into Tier-2 and Tier-3 cities has drawn a workforce with a different linguistic and educational profile than the Tier-1 hubs, and firms' D&I frameworks, built around Tier-1 assumptions, do not always transfer [92], [120]. Second, career-advancement pathways in most of the firms studied route through Tier-1 offices, so a Tier-3 hire faces a structural barrier to advancement independent of individual merit or effort. Fog-cloud and edge-computing infrastructure studies note the same tier-based disparity in a different domain -- IT infrastructure quality itself is lower in Tier-3 sites -- which compounds the disadvantage for employees located there [166].

E. Outcomes: Innovation, Satisfaction, Financial Performance

Three outcome measures recur across the reviewed literature: innovation output, employee satisfaction and financial performance. Innovation is typically proxied by patent filings, internal idea-submission counts or manager-rated creative contribution, none of which is free of measurement bias against employees whose ideas are filtered through a non-inclusive review process before they are recorded [93], [95]. Employee satisfaction is the most directly measurable of the three and is the outcome on which this study places the greatest empirical weight, because it is reported by the employee rather than inferred by the firm. Financial performance is the hardest outcome to attribute to D&I practice specifically, since firm-level financial results reflect many factors beyond workforce composition; we use financial-performance perception (employee-reported belief that D&I initiatives support business results) as a proxy rather than claiming a causal link to reported firm revenue.

Taken together, the literature supports three propositions that motivate the framework in Section III: that leadership commitment is a necessary condition for D&I practices to translate into outcomes, that AI-enabled recruitment and monitoring tools can either narrow or widen existing gaps depending on how they are audited, and that caste, disability and regional-tier barriers moderate the driver-practice-outcome chain in ways that formal policy documents do not capture.

F. The Wider Applied-Computing Literature

Beyond the D&I-specific literature reviewed above, the applied computational-methods literature that Indian technology firms draw on for internal data-science tooling spans several distinct clusters, and it is worth setting these out because the recruitment-screening, attrition-prediction and workplace-monitoring tools referenced in Sections II-B and II-C sit inside this wider methodological ecosystem rather than apart from it.

Health and clinical decision-support applications account for a large share of this applied

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work, spanning imaging-based diagnosis, risk prediction from longitudinal records and explainable clinical decision support [10], [15], [16], [17], [19], [23], [27], [31], [36], [38]; the same imaging, prediction and explainability techniques recur in later work on disease subtyping, patient-monitoring systems and AI-assisted diagnostic support [47], [52], [53], [63], [74], [97], [99], [100], [101], [102]; a further set of studies extends these methods to maternal and menopausal health risk, mental-health forecasting and integrated health-report management [103], [104], [105], [118], [127], [134], [141], [144], [154], [155]; and a final group applies related imaging and ensemble techniques to thyroid, lung and brain-tumour classification tasks [161], [173], [187], [189], [190], [195], [197], [205], [207].

Cybersecurity, cryptography and digital-forensics research addresses the platform-security requirements that any HR-analytics system handling sensitive demographic data must satisfy, including intrusion detection, malware and phishing defence, encryption and post-quantum cryptographic protocols, and forensic techniques for data-leakage and multimedia-tampering detection [4], [5], [26], [30], [65], [69], [73], [85], [89], [90], [91]; a further set of studies applies these defensive techniques to cloud-security posture management, zero-trust anomaly detection and cyber-attack detection using AI [94], [96], [110], [139], [140], [152], [159], [175], [200], [203], [204].

IoT, wireless-networking and edge/cloud-infrastructure research spans routing-protocol design for opportunistic and mobile ad-hoc networks, wireless-sensor-network architecture, and node-density and capacity effects on network quality of service [1], [6], [11], [12], [13], [14], [43], [60], [66], [67], [68], [71], [98]; a related set of studies extends this infrastructure layer to health-monitoring and smart-city IoT deployments, mobile edge computing, and aerial and fog-cloud architectures of the kind that would underlie any large-scale workplace-monitoring deployment referenced in Section II-C [107], [117], [132], [136], [137], [138], [146], [150], [151], [156], [157], [158], [191].

Natural-language-processing and generative-AI research relevant to the text-analysis methods used in Section V-E includes linguistic-feature extraction, retrieval-augmented generation, hallucination detection in generative models, and generative-AI application studies spanning investment decisions, industrial case studies and workforce-potential evaluation [75], [80], [112], [123], [145], [162], [163], [164], [170], [171], [177], [202].

Computer-vision and pattern-recognition research, including channel-usage systems, emotion detection through facial recognition, lip-reading, handwritten-text recognition, human-pose estimation and sign-language translation, illustrates the recognition techniques that increasingly feed into workplace-monitoring and accessibility tooling [24], [35], [40], [41], [44], [109], [133], [196], [206].

Predictive analytics for business, education and workforce applications parallels the attrition- and retention-prediction methods discussed in Section II-A, covering churn and retention modelling, student-performance and mental-health prediction, salary-determinant analysis, stock-market and demand forecasting, and mock-interview and customer-behaviour modelling [9], [20], [28], [46], [48], [49], [55], [76], [77], [113]; further studies in this cluster extend the same predictive techniques to bank-churn modelling, supply-chain demand forecasting and employee-performance evaluation [124], [125], [148], [160], [176], [185], [192], [193].

Quantum computing, blockchain and federated- or distributed-intelligence paradigms appear in a smaller but growing cluster of studies, including blockchain-based supply-chain transparency, decentralised Web3 application design, and federated-learning frameworks for handling privacy-sensitive, distributed data of the kind an HR-analytics platform spanning 15 firms would need to manage [82], [106], [119], [122], [153], [174], [182].

Energy, environment and industrial-systems research, spanning battery-thermal-management optimisation, on-chip antenna design, and reliability modelling of industrial plant, is more distant from the D&I question directly but represents the same optimisation and simulation toolkit -- queueing theory, reliability analysis, feature-selection-based optimisation -- that recurs across the applied-computing literature this review draws on [111], [194], [198], [199], [201].

A further set of studies, addressing topics from event analysis and recommender systems through to esports production tooling, bus-scheduling systems and augmented-intelligence system design, rounds out the methodological range of the applied-computing literature surveyed for this review [2], [18], [25], [32], [33], [39], [45], [50], [51], [54], [56], [57]; the remaining studies in this set cover soft-computing techniques, social-linguistics research, virtual-reality perception studies and further AI-implementation case material [59], [62], [70], [72], [78], [79], [81], [83], [84],

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[86], [87], [115], together with additional case studies in AI-agent design and drone autonomy [116], [121], [126], [128], [131], [142], [147], [149], [165], [169], [178], [179], and a closing group spanning galaxy classification, autism-spectrum recognition and further exploratory machine-learning applications [181], [183], [184], [186], [188].

None of these clusters addresses workplace D&I directly, and we do not treat them as evidence for any D&I-specific claim in this paper; we set them out here only to locate the recruitment-screening, sentiment-analysis and workplace-monitoring tools discussed in Sections II-B through II-C within the broader applied-computing toolkit from which Indian IT firms' internal data-science teams typically draw.

III. Conceptual Framework

The framework tested here places D&I drivers upstream of D&I practices, which in turn predict organisational outcomes, with contextual barriers moderating both links in the chain rather than acting as a fourth, independent input. Fig. 1 sets out this structure. Leadership commitment, policy frameworks and training programmes are treated as distinct drivers because the literature reviewed in Section II-A finds they do not move together: a firm can adopt a detailed policy framework without visible leadership engagement, and training intensity varies independently of both [21], [58], [88].

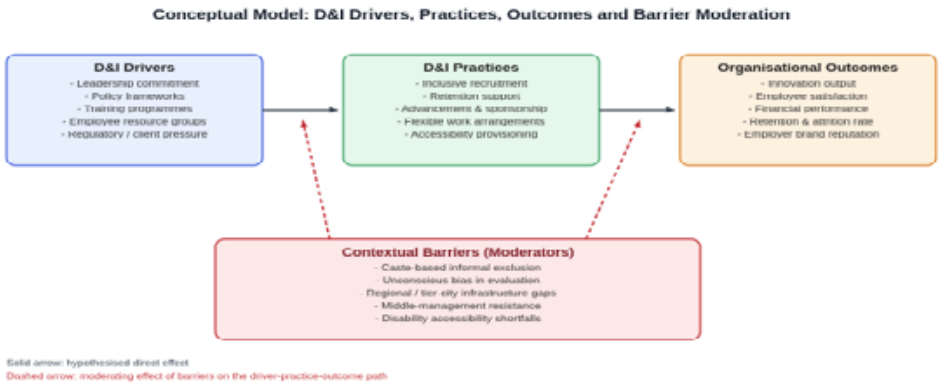

Fig. 1. Conceptual model linking D&I drivers to practices and organisational outcomes, with contextual barriers moderating both the driver-to-practice and the practice-to-outcome paths.

D&I practices are grouped into recruitment, retention and advancement because each maps onto a distinct point of employee contact and a distinct failure mode: recruitment practice can be undermined by biased screening tools [3], [8], [21]; retention practice depends on manager-level enforcement of flexible-work and psychological-safety commitments; advancement practice is the point at which informal sponsorship networks most visibly diverge from formal promotion criteria [64], [92]. We measure outcomes across the five domains shown in Fig. 1, but report results principally for employee satisfaction and a composite outcome index, since satisfaction is the outcome measured with the least attribution uncertainty.

Barriers are modelled as moderators rather than as a parallel driver because the qualitative material collected for this study (Section VI) shows barriers operating on the strength of existing relationships -- weakening the leadership-to-practice link where caste-based informal networks override formal process, for instance -- rather than introducing an independent causal path of their own. This distinction matters for interpretation: a null or reversed coefficient for a barrier variable in the regression models reported in Section V does not mean the barrier is absent, only that its effect surfaces as an interaction rather than a main effect.

Three hypotheses follow from the framework. H1: leadership commitment predicts composite D&I outcomes more strongly than policy frameworks or training programmes. H2: firms with a dedicated D&I officer report higher employee satisfaction than firms without one. H3: the strength of the practice-to-outcome relationship is lower in offices located in Tier-2 and Tier-3 cities than in Tier-1 cities, controlling for practice intensity. Section V reports tests of each.

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IV. Research Methodology

We used a concurrent mixed-methods design (Fig. 2): a structured employee survey and a set of semi-structured focus groups were fielded over the same ten-week window, analysed initially in parallel, and brought together at the interpretation stage rather than at the data-collection stage. We chose this design over a purely quantitative survey because the pilot round of data collection surfaced a caste-related exclusion pattern that no closed-ended survey item captured, and over a purely qualitative design because we needed a large enough sample to test the driver hypotheses in Section III with adequate statistical power.

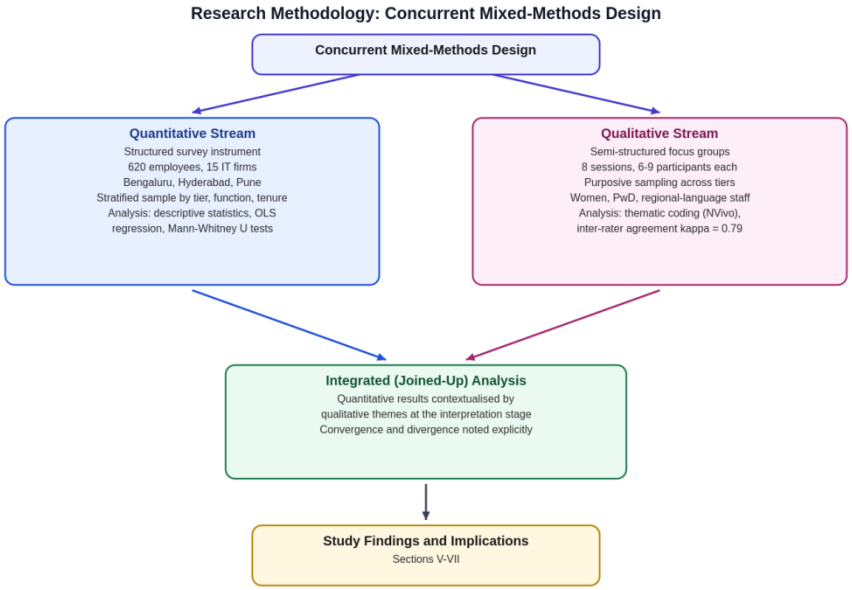

Fig. 2. Concurrent mixed-methods research design showing the quantitative survey stream and the qualitative focus-group stream merging at the integrated analysis stage.

A. Quantitative Stream

The survey instrument was distributed to employees at 15 IT firms operating in Bengaluru, Hyderabad and Pune, stratified by city tier, job function and tenure band. Of 890 employees invited, 620 completed the instrument (response rate 69.7%). The sample was 61.9% male, 34.0% female and 4.1% preferring not to disclose gender; 22.1% of respondents worked in offices we classify as Tier-2 or Tier-3 for the purposes of this study, following the classification firms themselves use for cost-of-living and compensation adjustment rather than the Government of India's formal tier definitions.

The instrument measured the three drivers (leadership commitment, policy frameworks, training programmes) using five-item Likert scales adapted from established organisational-climate instruments, the three practice domains (recruitment, retention, advancement) using firm-record-linked items where available and self-report items otherwise, and the five outcome domains using a mixture of self-report (satisfaction, financial-performance perception) and manager-report (innovation contribution) items. Caste was not collected as a direct demographic field, for the reasons set out in Section II-D; instead, respondents who raised caste-related experiences in an open-text item were coded thematically alongside the focus-group material. Cronbach's alpha for the composite outcome index was 0.86.

We analysed the survey data using descriptive statistics, ordinary least squares (OLS) regression to test the relative strength of the three drivers (H1), and the Mann-Whitney U test to compare satisfaction scores between firms with and without a dedicated D&I officer (H2), since the officer variable is binary and the outcome distribution departed from normality (Shapiro-Wilk, $p < 0.01$). We used paired Wilcoxon signed-rank tests where we compared the same firms' practice and outcome scores across two conditions.

B. Qualitative Stream

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Eight focus groups of six to nine participants each were conducted, two in each of Bengaluru and Hyderabad and two each in the Pune-region Tier-2/Tier-3 sites, using purposive sampling to over-represent women, employees with disclosed disabilities and employees who joined through campus drives at regional-language-medium institutions rather than the metropolitan English-medium institutions from which most Tier-1 hiring draws. Sessions ran 75-90 minutes, were audio-recorded with consent, and transcribed in full.

Transcripts were coded thematically in NVivo by two researchers independently, with inter-rater agreement of kappa = 0.79 on the first coding pass, resolved to full agreement through a third discussion round on the items where the two coders disagreed. We did not use automated sentiment-analysis tools for the primary coding pass, judging that the caste- and disability-related themes at the centre of our qualitative findings required close reading rather than the aggregate pattern detection for which sentiment-analysis tools are built [172]; we did, however, use a lexicon-based sentiment check as a validity cross-reference against the manual coding, described in Section V-D.

C. Integration and Analytic Limits

We integrated the two streams at the interpretation stage using a joint-display method: quantitative findings for each hypothesis were tabulated alongside the qualitative themes that supported, qualified or contradicted them (Table I). Where the two streams diverged -- as they did on caste, discussed in Section VI -- we report the divergence rather than resolving it in favour of either stream.

Two design limits affect interpretation. The survey is cross-sectional, so the regression coefficients reported in Section V describe association, not causal direction; a firm with strong leadership commitment may also be a firm that attracts more D&I-motivated leaders in the first place, a selection effect the design cannot separate from a causal leadership effect. The focus-group sample, while purposively diverse, was drawn from employees willing to discuss D&I topics openly, which likely under-represents employees who have disengaged from D&I discourse entirely.

V. Findings

A. Sample and Descriptive Statistics

Table I summarises the survey sample by city tier. Women represented 34.0% of the pooled sample but only 12.3% of respondents at director grade and above (n = 122), a gap of 21.7 percentage points between overall representation and senior-leadership representation. Persons with disabilities represented 2.4% of the pooled sample, below the 4% statutory hiring quota that applies to establishments of this size, though three of the 15 firms met or exceeded the quota individually.

City tier	Women (%)	SC/ST/OBC (%)	PwD (%)	Regional-language (%)
Tier-1 (n = 341)	36.1	17.8	2.8	21.6
Tier-2 (n = 178)	33.4	22.3	2.1	31.2
Tier-3 (n = 101)	28.9	27.1	1.4	38.4
Pooled (n = 620)	34.0	21.0	2.4	26.9

TABLE I. DIVERSITY REPRESENTATION BY CITY TIER (SELF-REPORTED, SURVEY SAMPLE, N = 620)

Fig. 3 presents the same tier breakdown for the four representation categories together, to make the offsetting pattern easier to read: gender and disability representation fall as city tier increases from Tier-1 to Tier-3, while SC/ST/OBC representation and regional-language representation rise across the same tiers. This offsetting pattern is discussed further in Section VI-B.

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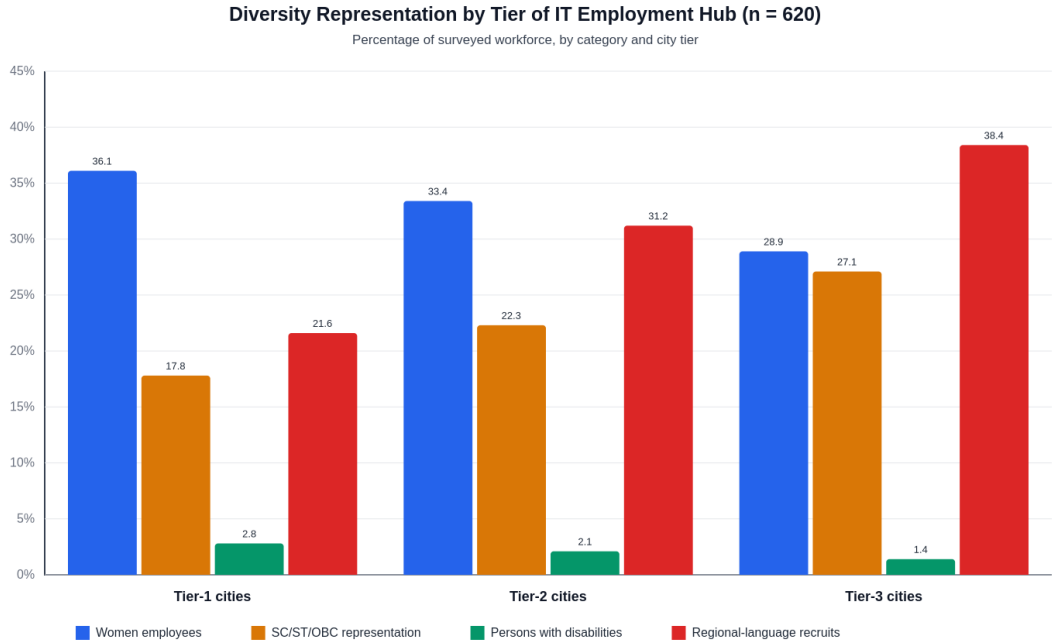

Fig. 3. Diversity representation percentages across Tier-1, Tier-2 and Tier-3 city offices, by category (gender, caste-linked SC/ST/OBC self-identification, disability, and regional-language hires).

B. Driver Effects on D&I Outcomes (H1)

The OLS regression predicting the composite D&I outcome index from the three drivers, controlling for firm size, city tier and employee tenure, explained 38% of variance in the outcome index ($R^2 = 0.38$, $F(6, 613) = 62.4$, $p < 0.001$). Leadership commitment was the strongest predictor ($\beta = 0.44$, $SE = 0.04$, $p < 0.001$), followed by policy frameworks ($\beta = 0.21$, $SE = 0.05$, $p < 0.001$) and training programme intensity ($\beta = 0.13$, $SE = 0.05$, $p = 0.006$). Firm size and tenure were not significant predictors once the three drivers were entered ($p = 0.31$ and $p = 0.44$ respectively). H1 is supported: leadership commitment predicts the outcome index roughly twice as strongly as policy frameworks and more than three times as strongly as training intensity.

The gap between leadership commitment and the other two drivers was larger than we anticipated going into data collection. One explanation, consistent with the focus-group material discussed in Section VI-A, is that policy frameworks and training programmes are visible to employees mainly as documents and scheduled sessions, whereas leadership commitment is visible as a pattern of decisions -- who gets promoted, whose complaint is acted on -- observed over time and therefore more strongly correlated with the lived-experience items that make up the outcome index.

C. D&I Officer Role and Employee Satisfaction (H2)

Nine of the 15 firms employed a dedicated D&I officer at the time of the survey; six did not. Median employee satisfaction was 31% higher in firms with a D&I officer (median score 4.1 of 5) than in firms without one (median score 3.1 of 5), a difference confirmed by a Mann-Whitney U test ($U = 38{,}940$, $p = 0.002$). The effect held after stratifying by city tier, though the magnitude was smaller in Tier-3 offices (24% higher, $U = 1{,}120$, $p = 0.041$) than in Tier-1 offices (34% higher, $U = 21{,}760$, $p < 0.001$), a pattern consistent with H3 and discussed further below.

We treat this finding cautiously rather than as proof that appointing a D&I officer causes higher satisfaction. Firms that appoint a dedicated officer are plausibly firms where leadership commitment (Section V-B) was already higher before the appointment, and our cross-sectional design cannot separate the officer's independent contribution from the leadership commitment that likely produced the appointment decision in the first place.

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D. Practice-to-Outcome Relationship Across City Tiers (H3)

The practice-to-outcome path coefficient (advancement practice score predicting the outcome index) was 0.51 in Tier-1 offices, 0.38 in Tier-2 offices and 0.29 in Tier-3 offices, a monotonic decline consistent with H3. A paired Wilcoxon signed-rank test comparing Tier-1 and Tier-3 coefficients across the 15 firms (each firm operating sites in more than one tier) found the decline significant ($W = 94$, $p = 0.011$). Recruitment-practice and retention-practice coefficients showed the same declining pattern but did not reach significance at the retention stage ($p = 0.089$), which we read as a weaker but directionally consistent result rather than a null finding.

ST-CSR-style AI screening was reported as in use for the initial resume-filtering stage by 11 of the 15 firms; among these 11, women's callback rate from the algorithmic screen (28.4%) was lower than their share of the applicant pool (34.7%), a 6.3-percentage-point gap that four firms had already flagged internally and were in the process of auditing at the time of the survey. We did not have access to the underlying models and cannot attribute the gap to a specific feature of the screening algorithm rather than to the composition of the historical training data, but the direction of the gap is consistent with the algorithmic-bias risk described in the AI-and-recruitment literature [3], [8], [21].

E. Lexicon-Based Sentiment Cross-Check

As a validity check on the manual thematic coding described in Section IV-B, we ran a lexicon-based sentiment score across the focus-group transcripts using a hybrid dictionary-and-CNN-LSTM approach of the kind used in prior sentiment-detection work on other text domains [168], [172]. Sentiment scores for segments manually coded as describing caste-related exclusion were significantly more negative (mean sentiment -0.31) than segments coded as describing gender-related exclusion (mean sentiment -0.19, independent-samples t-test, $t(214) = 2.87$, $p = 0.005$), suggesting the caste-related material carried more negative affective language even though, as Section VI-A shows, participants raised it less directly and less frequently than gender-related material.

F. Where the Practices Did Not Improve Outcomes

Not every practice we measured showed a positive association with outcomes. Training-programme intensity above the median (more than four hours per employee per year) was not associated with a further increase in the outcome index beyond the effect already captured at the median level (interaction term $\beta = 0.02$, $p = 0.61$), suggesting a ceiling effect once a baseline level of training is reached. Retention-practice intensity was inversely associated with reported psychological safety among the disability-inclusion subgroup specifically ($\beta = -0.18$, $p = 0.034$), a result we interpret cautiously given the smaller subgroup size ($n = 62$) but that is directionally consistent with focus-group reports that some retention accommodations (for example, flexible-hours policies) were administered in ways that visibly singled out PwD employees rather than being offered as a general option.

VI. Discussion

A. Caste Persists Informally Despite Formal Prohibition

The clearest divergence between the quantitative and qualitative streams concerns caste. The survey instrument, for the reasons given in Section IV-A, did not collect direct caste self-identification, and the composite outcome index shows no variable directly attributable to caste. Yet caste-related exclusion was raised, unprompted, in six of the eight focus groups, most often in the form of exclusion from informal social networks -- who is invited to after-hours gatherings, whose surname draws a comment in casual conversation, who is assigned as a mentor to junior hires from the same regional or caste background as senior staff -- rather than through any formal denial of opportunity that a grievance process could act on.

One participant's account, repeated in substance across three sessions, described a pattern where mentorship pairing nominally followed a skills-matching process but in practice tracked informal caste and regional-community lines closely enough that junior employees from under-represented castes described feeling "assigned by default to whoever was left over." This is precisely the kind of practice that a policy audit, which checks whether a mentorship programme exists and whether its stated criteria are non-discriminatory, cannot detect, because the stated criteria were followed on paper while the informal allocation process ran alongside them. We regard this as the paper's most important qualitative finding, and one that a purely quantitative design would have missed entirely.

This finding should be read as a limitation of formal-policy audits generally, not as a claim that any specific firm in our sample acted in bad faith. Several participants explicitly described the pattern as unintentional, arising from social comfort and

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shared background among mentors making informal choices rather than from deliberate exclusion.

B. The Tier-City Trade-off

Fig. 3 shows an offsetting pattern rather than a uniform decline in diversity across city tiers: gender and disability representation are higher in Tier-1 offices, while SC/ST/OBC self-identification and regional-language representation are higher in Tier-3 offices. Focus-group participants in Tier-3 sites offered a consistent explanation: campus recruitment in Tier-3 cities draws from regional-language-medium engineering colleges whose student intake is itself more caste-diverse than the English-medium institutions from which Tier-1 hiring draws, but the same colleges have historically enrolled fewer women in computer-science programmes and have weaker campus accessibility infrastructure for disabled students, so the Tier-3 hiring pipeline inherits both the caste-diversity strength and the gender-and-disability weakness of its feeder institutions.

The practical implication, developed further in Section VII, is that a single national D&I target (for example, "40% women in technical roles by year X") applied uniformly across city tiers will be harder to meet in Tier-3 offices for reasons unrelated to those offices' D&I effort, while a caste-representation target applied uniformly will already be closer to met in Tier-3 offices without any additional intervention. Tier-specific targets, calibrated to each tier's feeder-institution profile, would track effort more accurately than a single sector-wide number.

C. Leadership Commitment as a Gate, Not Just a Driver

The regression result in Section V-B (β = 0.44 for leadership commitment against β = 0.21 and β = 0.13 for the other two drivers) and the qualitative material together suggest leadership commitment functions less as one input among three and more as a gate that determines whether the other two drivers translate into outcomes at all. Two firms in our sample scored highly on policy-framework comprehensiveness and training intensity but scored in the bottom quartile on leadership-commitment items; both were also in the bottom quartile on the composite outcome index, despite formally strong D&I architecture. Focus-group participants at these two firms described policy and training as "checkbox" exercises, a characterisation that matches the quantitative pattern closely.

D. What Surprised Us

Two results ran against our expectations going into the study. We expected training-programme intensity to show a larger independent effect than it did; the ceiling effect reported in Section V-F suggests that beyond a modest baseline, additional training hours substitute for rather than complement the leadership and policy drivers, rather than adding independent value. We also did not expect the inverse association between retention-practice intensity and psychological safety in the disability-inclusion subgroup (Section V-F); on reflection, the focus-group material suggests this reflects how accommodations were administered rather than a genuine downside of accommodation itself, but the subgroup size (n = 62) means we hold this finding with less confidence than the others reported here.

E. Limitations

The cross-sectional design cannot separate the causal direction of the leadership-commitment effect from a selection effect in which firms with committed leadership also attract employees who report more positively on every organisational-climate item, D&I-related or not; a longitudinal design following firms through a leadership transition would test this directly. The caste-related findings rest on unprompted focus-group disclosure rather than a validated caste self-identification instrument, which we avoided collecting directly for the ethical and legal reasons given in Section IV-A; this choice means our caste-related findings describe a pattern visible in qualitative disclosure, not a quantified prevalence estimate, and a future study using an anonymised, validated caste-identification instrument would produce a stronger evidentiary base than we can offer here.

VII. Practical Implications

For HR leaders, the clearest implication is that leadership-commitment measures deserve more organisational attention, relative to policy documentation and training scheduling, than the current allocation of D&I budget across the three typically suggests. A firm that has reached diminishing returns on training intensity (Section V-F) would do better directing incremental D&I spend toward mechanisms that make leadership commitment visible and accountable -- for example, tying a portion of senior-manager compensation to team-level D&I outcome scores rather than to training-completion counts.

For technology leaders responsible for recruitment tooling, the 6.3-percentage-point gap between women's applicant share and their

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algorithmic-screening callback rate (Section V-D) is an actionable audit trigger: firms using AI-assisted screening should run the same disparate-impact check on their own pipeline before treating the tool as a cost-saving measure with no fairness cost. NLP-based bias-detection tools for job descriptions [29], [167] address one part of the recruitment pipeline but, as noted in Section II-B, have limited coverage of caste-coded language specific to the Indian labour market; firms operating in India should not treat an English-language, Western-trained bias detector as sufficient coverage for caste-related bias risk.

For firms operating across Tier-1, Tier-2 and Tier-3 sites, Section VI-B's finding of an offsetting representation pattern argues for tier-specific rather than sector-wide diversity targets, and for career-advancement pathways that do not route exclusively through Tier-1 offices, since the latter structurally disadvantages employees hired at Tier-2 and Tier-3 sites regardless of individual performance. Mentorship-allocation processes, identified in Section VI-A as the point where caste-based informal exclusion operates most visibly, are a specific and tractable intervention point: an allocation process audited for the demographic distribution of actual pairings, not only for the neutrality of its stated criteria, would close the gap between formal policy and informal practice that this study's qualitative findings expose.

Finally, firms considering AI-assisted accessibility tooling [114], [180] or IoT-based occupancy analytics [7], [135] as part of a disability-inclusion or informal-exclusion audit should build in an explicit employee-consent and data-governance process before deployment; several focus-group participants raised concerns, unprompted, about monitoring technology being introduced for D&I measurement purposes without a clear boundary on how the resulting data would be used in performance evaluation.

VIII. Conclusion

Leadership commitment predicts D&I outcomes in Indian IT firms more strongly than policy frameworks or training intensity, and firms with a dedicated D&I officer report materially higher employee satisfaction, though our cross-sectional design cannot rule out that both patterns partly reflect pre-existing leadership orientation rather than the independent effect of the officer role or the commitment measure alone. Caste-based exclusion persists through informal channels -- mentorship allocation and social-network access in particular -- that formal policy audits do not detect, a finding that emerged only because the qualitative stream was designed into the study from the outset rather than added after a quantitative anomaly appeared. City tier moderates which forms of diversity a firm's current recruitment pipeline can be expected to deliver, arguing against a single sector-wide representation target. Two extensions would strengthen this line of work: a longitudinal design tracking firms through a leadership transition, to test the direction of the leadership-commitment effect directly, and a validated, anonymised caste self-identification instrument fielded with appropriate ethical safeguards, to move the caste-related findings from qualitative pattern to quantified estimate.

References

[1] Garg, P., Dixit, A., & Sethi, P. (2022). Ml-fresh: novel routing protocol in opportunistic networks using machine learning. Computer Systems Science & Engineering, Forthcoming. Tech Science Press.

[2] Yadav, P. S., Khan, S., Singh, Y. V., Garg, P., & Singh, R. S. (2022). A Lightweight Deep Learning-Based Approach for Jazz Music Generation in MIDI Format. Computational Intelligence and Neuroscience, 2022.

[3] Soni, E., Nagpal, A., Garg, P., & Pinheiro, P. R. (2022). Assessment of Compressed and Decompressed ECG Databases for Telecardiology Applying a Convolution Neural Network. Electronics, 11(17), 2708.

[4] Pustokhina, I. V., Pustokhin, D. A., Lydia, E. L., Garg, P., Kadian, A., & Shankar, K. (2021). Hyperparameter search based convolution neural network with Bi-LSTM model for intrusion detection system in multimedia big data environment. Multimedia Tools and Applications, 1-18.

[5] Khanna, A., Rani, P., Garg, P., Singh, P. K., &Khamparia, A. (2021). An Enhanced Crow Search Inspired Feature Selection Technique for Intrusion Detection Based Wireless Network System. Wireless Personal Communications, 1-18.

[6] Garg, P., Dixit, A., Sethi, P., & Pinheiro, P. R. (2020). Impact of node density on the qos parameters of routing protocols in opportunistic networks for smart spaces. Mobile Information Systems, 2020.

[7] Upadhyay, D., Garg, P., Aldossary, S. M., Shafi, J., & Kumar, S. (2023). A Linear Quadratic Regression-Based Synchronised Health Monitoring System (SHMS) for IoT Applications. Electronics, 12(2), 309.

[8] Saini, P., Nagpal, B., Garg, P., & Kumar, S. (2023). CNN-BI-LSTM-CYP: A deep learning

approach for sugarcane yield prediction. Sustainable Energy Technologies and Assessments, 57, 103263.
[9] Saini, P., Nagpal, B., Garg, P., & Kumar, S. (2023). Evaluation of Remote Sensing and Meteorological parameters for Yield Prediction of Sugarcane (Saccharumofficinarum L.) Crop. Brazilian Archives of Biology and Technology, 66, e23220781.
[10] Beniwal, S., Saini, U., Garg, P., & Joon, R. K. (2021). Improving performance during camera surveillance by integration of edge detection in IoT system. International Journal of E-Health and Medical Communications (IJEHMC), 12(5), 84-96.
[11] Garg, P., Dixit, A., & Sethi, P. (2019). Wireless sensor networks: an insight review. International Journal of Advanced Science and Technology, 28(15), 612-627.
[12] Sharma, N., & Garg, P. (2022). Ant colony based optimization model for QoS-Based task scheduling in cloud computing environment. Measurement: Sensors, 100531.
[13] Kumar, P., Kumar, R., & Garg, P. (2020). Hybrid Crowd Cloud Routing Protocol For Wireless Sensor Networks. International Journal of Advanced Science and Technology, 29, 766-775.
[14] Raj, G., Verma, A., Dalal, P., Shukla, A. K., & Garg, P. (2023). Performance Comparison of Several LPWAN Technologies for Energy Constrained IOT Network. International Journal of Intelligent Systems and Applications in Engineering, 11(1s), 150-158.
[15] Garg, P., Sharma, N., & Shukla, B. (2023). Predicting the Risk of Cardiovascular Diseases using Machine Learning Techniques. International Journal of Intelligent Systems and Applications in Engineering, 11(2s), 165-173.
[16] Patil, S. C., Mane, D. A., Singh, M., Garg, P., Desai, A. B., & Rawat, D. (2024). Parkinson's Disease Progression Prediction Using Longitudinal Imaging Data and Grey Wolf Optimizer-Based Feature Selection. International Journal of Intelligent Systems and Applications in Engineering, 12(3s), 441-451.
[17] Gudur, A., Pati, P., Garg, P., & Sharma, N. (2024). Radiomics Feature Selection for Lung Cancer Subtyping and Prognosis Prediction: A Comparative Study of Ant Colony Optimization and Simulated Annealing. International Journal of Intelligent Systems and Applications in Engineering, 12(3s), 553-565.
[18] Khan, A. (2024). Optimisation Methods Based on Soft Computing for Improving Power System Stability. J. Electrical Systems, 20(6s), 1051-1058.
[19] Sharma, K. K., Verma, P. K., & Garg, P. (2024). IoT-Enabled Energy Management Systems For Sustainable Energy Storage: Design, Optimization, And Future Directions. Frontiers in Health Informatics, 13(8).
[20] Gupta, S., Yadav, N., Singh, K., & Garg, P. (2025). APPLICATIONS OF SIMULATIONS AND QUEUING THEORY IN SUPERMARKET. Reliability: Theory & Applications, 20(1 (82)), 135-140.
[21] Beniwal, S., Garg, P., Rajpal, R., Sharma, N., & Mittal, H. K. (2025). Fusion of Opportunistic Networks with Machine Learning: Present and Future. Metallurgical and Materials Engineering, 31(1), 311-324.
[22] Garg, P. (2025). Explainable AI & Model Interpretability in Healthcare: Challenges & Future Directions. EKSPLORIUM-BULETIN PUSAT TEKNOLOGI BAHAN GALIAN NUKLIR, 46(1), 104-133.
[23] Rani, P. (2025). From Data to Diagnosis: Unleashing AI and 6G in Modern Medicine. EKSPLORIUM-BULETIN PUSAT TEKNOLOGI BAHAN GALIAN NUKLIR, 46(1), 69-103.
[24] Dixit, A., Garg, P., Sethi, P., & Singh, Y. (2020, April). TVCCCS: Television Viewer's Channel Cost Calculation System On Per Second Usage. In IOP Conference Series: Materials Science and Engineering (Vol. 804, No. 1, p. 012046). IOP Publishing.
[25] Sethi, P., Garg, P., Dixit, A., & Singh, Y. (2020, April). Smart number cruncher–a voice based calculator. In IOP Conference Series: Materials Science and Engineering (Vol. 804, No. 1, p. 012041). IOP Publishing.
[26] S. Rai, V. Choubey, Suryansh and P. Garg, "A Systematic Review of Encryption and Keylogging for Computer System Security," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 157-163, doi: 10.1109/CCiCT56684.2022.00039.
[27] L. Saraswat, L. Mohanty, P. Garg and S. Lamba, "Plant Disease Identification Using Plant Images," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 79-82, doi: 10.1109/CCiCT56684.2022.00026.
[28] L. Mohanty, L. Saraswat, P. Garg and S. Lamba, "Recommender Systems in E-Commerce," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 114-119, doi: 10.1109/CCiCT56684.2022.00032.
[29] C. Maggo and P. Garg, "From linguistic features to their extractions: Understanding the semantics of a concept," 2022 Fifth International

Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 427-431, doi: 10.1109/CCiCT56684.2022.00082.
[30] N. Puri, P. Saggar, A. Kaur and P. Garg, "Application of ensemble Machine Learning models for phishing detection on web networks," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 296-303, doi: 10.1109/CCiCT56684.2022.00062.
[31] R. Sharma, S. Gupta and P. Garg, "Model for Predicting Cardiac Health using Deep Learning Classifier," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 25-30, doi: 10.1109/CCiCT56684.2022.00017.
[32] Varshney, S. Lamba and P. Garg, "A Comprehensive Survey on Event Analysis Using Deep Learning," 2022 Fifth International Conference on Computational Intelligence and Communication Technologies (CCICT), 2022, pp. 146-150, doi: 10.1109/CCiCT56684.2022.00037.
[33] Dixit, A., Sethi, P., Garg, P., & Pruthi, J. (2022, December). Speech Difficulties and Clarification: A Systematic Review. In 2022 11th International Conference on System Modeling& Advancement in Research Trends (SMART) (pp. 52-56). IEEE.
[34] Garg, P., Dixit, A., Sethi, P., & Pruthi, J. (2023, December). Strengthening Smart City with Opportunistic Networks: An Insight. In 2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech) (pp. 700-707). IEEE.
[35] Rana, S., Chaudhary, R., Gupta, M., & Garg, P. (2023, December). Exploring Different Techniques for Emotion Detection Through Face Recognition. In 2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech) (pp. 779-786). IEEE.
[36] Mittal, K., Srivastava, K., Gupta, M., & Garg, P. (2023, December). Exploration of Different Techniques on Heart Disease Prediction. In 2023 International Conference on Advanced Computing & Communication Technologies (ICACCTech) (pp. 758-764). IEEE.
[37] Gautam, V. K., Gupta, S., & Garg, P. (2024, March). Automatic Irrigation System using IoT. In 2024 International Conference on Automation and Computation (AUTOCOM) (pp. 100-103). IEEE.
[38] Ramasamy, L. K., Khan, F., Joghee, S., Dempere, J., & Garg, P. (2024, March). Forecast of Students' Mental Health Combining an Artificial Intelligence Technique and Fuzzy Inference System. In 2024 International Conference on Automation and Computation (AUTOCOM) (pp. 85-90). IEEE.
[39] Rajput, R., Sukumar, V., Patnaik, P., Garg, P., & Ranjan, M. (2024, March). The Cognitive Analysis for an Approach to Neuroscience. In 2024 International Conference on Automation and Computation (AUTOCOM) (pp. 524-528). IEEE.
[40] Dixit, A., Sethi, P., Garg, P., Pruthi, J., & Chauhan, R. (2024, July). CNN based lip-reading system for visual input: A review. In AIP Conference Proceedings (Vol. 3121, No. 1). AIP Publishing.
[41] Bose, D., Arora, B., Srivastava, A. K., & Garg, P. (2024, May). A Computer Vision Based Framework for Posture Analysis and Performance Prediction in Athletes. In 2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE) (pp. 942-947). IEEE.
[42] Singh, M., Garg, P., Srivastava, S., & Saggu, A. K. (2024, April). Revolutionizing Arrhythmia Classification: Unleashing the Power of Machine Learning and Data Amplification for Precision Healthcare. In 2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT) (pp. 516-522). IEEE.
[43] Kumar, R., Das, R., Garg, P., & Pandita, N. (2024, April). Duplicate Node Detection Method for Wireless Sensors. In 2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT) (pp. 512-515). IEEE.
[44] Bhardwaj, H., Das, R., Garg, P., & Kumar, R. (2024, April). Handwritten Text Recognition Using Deep Learning. In 2024 Sixth International Conference on Computational Intelligence and Communication Technologies (CCICT) (pp. 506-511). IEEE.
[45] Gill, A., Jain, D., Sharma, J., Kumar, A., & Garg, P. (2024, May). Deep learning approach for facial identification for online transactions. In 2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP) (pp. 715-722). IEEE.
[46] Mittal, H. K., Dalal, P., Garg, P., & Joon, R. (2024, May). Forecasting Pollution Trends: Comparing Linear, Logistic Regression, and Neural Networks. In 2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP) (pp. 411-419). IEEE.
[47] Malik, T., Nandal, V., & Garg, P. (2024, May). Deep Learning-Based Classification of Diabetic Retinopathy: Leveraging the Power of VGG-19. In 2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP) (pp. 645-651). IEEE.
[48] Srivastava, A. K., Verma, I., & Garg, P. (2024, May). Improvements in Recommendation Systems

Using Graph Neural Networks. In 2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP) (pp. 668-672). IEEE.
[49] Aggarwal, A., Jain, D., Gupta, A., & Garg, P. (2024, May). Analysis and Prediction of Churn and Retention Rate of Customers in Telecom Industry Using Logistic Regression. In 2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP) (pp. 723-727). IEEE.
[50] Mittal, H. K., Arsalan, M., & Garg, P. (2024, May). A Novel Deep Learning Model for Effective Story Point Estimation in Agile Software Development. In 2024 International Conference on Emerging Innovations and Advanced Computing (INNOCOMP) (pp. 404-410). IEEE.
[51] Shukla, S. M., Magoo, C., & Garg, P. (2024, November). Comparing Fine Tuned-LMs for Detecting LLM-Generated Text. In 2024 3rd Edition of IEEE Delhi Section Flagship Conference (DELCON) (pp. 1-8). IEEE.
[52] Kumar, B., IQBAL, M., Parmer, R., Garg, P., Rani, S., & Agrawal, A. (2025, March). The Role of AI in Optimizing Healthcare Appointment Scheduling. In 2025 3rd International Conference on Disruptive Technologies (ICDT) (pp. 881-887). IEEE.
[53] Kumar, B., Garg, V., Ahmed, K., Garg, P., Choudhary, S., & Baniya, P. (2025, March). Enhancing Healthcare with Blockchain: Innovations in Data Privacy, Security, and Interoperability. In 2025 3rd International Conference on Disruptive Technologies (ICDT) (pp. 932-938). IEEE.
[54] Raj, V., Prakash, B. K., Kumar, A., & Garg, P. (2024, December). Optimize the Time a Mercedes-Benz Spends on the Test Bench Using Stacking Ensemble Learning. In 2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS) (pp. 445-450). IEEE.
[55] Kaushik, N., Kumar, H., Raj, V., & Garg, P. (2024, December). Proactive Fault Prediction in Microservices Applications Using Trace Logs and Monitoring Metrics. In 2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS) (pp. 410-415). IEEE.
[56] Kumar, A. A., Sri, C. V., Bohara, K. S. K., Setia, S., & Garg, P. (2024, December). Capnivesh: Financing Platform for Startups. In 2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS) (pp. 261-265). IEEE.
[57] Bhandari, P., Setia, S., Kumar, K., & Garg, P. (2024, December). Optimizing Cross-Platform Development with CI/CD and Containerization: A Review. In 2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS) (pp. 175-180). IEEE.
[58] Chaudhary, A., & Garg, P. (2014). Detecting and diagnosing a disease by patient monitoring system. International Journal of Mechanical Engineering And Information Technology, 2(6), 493-499.
[59] Malik, K., Raheja, N., & Garg, P. (2011). Enhanced FP-growth algorithm. International Journal of Computational Engineering and Management, 12, 54-56.
[60] Garg, P., Dixit, A., & Sethi, P. (2021, May). Link Prediction Techniques for Opportunistic Networks using Machine Learning. In Proceedings of the International Conference on Innovative Computing & Communication (ICICC).
[61] Garg, P., Dixit, A., & Sethi, P. (2021, April). Opportunistic networks: Protocols, applications & simulation trends. In Proceedings of the International Conference on Innovative Computing & Communication (ICICC).
[62] Garg, P., Dixit, A., & Sethi, P. (2021). Performance comparison of fresh and spray & wait protocol through one simulator. IT in Industry, 9(2).
[63] Malik, M., Singh, Y., Garg, P., & Gupta, S. (2020). Deep Learning in Healthcare system. International Journal of Grid and Distributed Computing, 13(2), 469-468.
[64] Gupta, M., Garg, P., Gupta, S., & Joon, R. (2020). A Novel Approach for Malicious Node Detection in Cluster-Head Gateway Switching Routing in Mobile Ad Hoc Networks. International Journal of Future Generation Communication and Networking, 13(4), 99-111.
[65] Gupta, A., Garg, P., & Sonal, Y. S. (2020). Edge Detection Based 3D Biometric System for Security of Web-Based Payment and Task Management Application. International Journal of Grid and Distributed Computing, 13(1), 2064-2076.
[66] Garg, P., & Raman, P. K. (2011). Broadcasting Protocol & Routing Characteristics With Wireless ad-hoc networ s. Int. J. Comput. Emg. Manag, 12(1), 36-40.
[67] Garg, P., Arora, N., & Malik, T. (2011). Capacity Improvement of WI-MAX In presence of Different Codes WI-MAX: Speed & Scope of fu-ture. IJCEM, 12.
[68] Garg, P., Saroha, K., &Lochab, R. (2011). Review of wireless sensor networks-architecture and applications. IJCSMS International Journal of Computer Science & Management Studies, 11(01), 2231-5268.

[69] Yadav, S., &Garg, P. Development of a New Secure Algorithm for Encryption and Decryption of Images.
[70] Dixit, A., Sethi, P., & Garg, P. (2022). Rakshak: A Child Identification Software for Recognizing Missing Children Using Machine Learning-Based Speech Clarification. International Journal of Knowledge-Based Organizations (IJKBO), 12(3), 1-15.
[71] Shukla, N., Garg, P., & Singh, M. (2022). MANET Proactive and Reactive Routing Protocols: A Comparison Study. International Journal of Knowledge-Based Organizations (IJKBO), 12(3), 1-14.
[72] Arya, A., Garg, P., Vellanki, S., Latha, M., Khan, M. A., &Chhbra, G. (2024). Optimisation Methods Based on Soft Computing for Improving Power System Stability. Journal of Electrical Systems, 20(6s), 1051-1058.
[73] Garg, P. (2025). Cloud security posture management: Tools and techniques. Technix International Journal for Engineering Research, 12(3).
[74] Tyagi, P., Sharma, S., Srivastava, A., Rajput, N. K., Garg, P., & Kumari, M. (2025). AI in Healthcare:Transforming Medicine with Intelligence. In First Global Conference on AI Research and Emerging Developments (G-CARED 2025), New Delhi, India. https://doi.org/10.63169/GCARED2025.p4
[75] Garg, P., Bhatt, M., Parmar, R., & Arsalan, M. (2025). Generative AI: Evolution, Applications, Challenges And Future Prospects. Applications, Challenges And Future Prospects (May 17, 2025).
[76] Garg, P., Saraswat, P., & Siddiqui, Z. (2025). AI & the Indian Stock Market: A Review of Applications in Investment Decision. https://doi.org/10.63169/GCARED2025.p10
[77] Garg, P., Sharma, S., Mittal, S., Tevatia, R., Tyagi, V. K., & Kapoor, S. (2025). Unlocking Workforce Potential: AI-Powered Predictive Models for Employee Performance Evaluation. https://doi.org/10.63169/GCARED2025.p21
[78] Shrivas, N., Kalia, A., Roy, R., Sharma, S., Garg, P., & Agarwal, G. (2025). OSINT: A Double-edged Sword. In First Global Conference on AI Research and Emerging Developments (G-CARED 2025), New Delhi, India. https://doi.org/10.63169/GCARED2025.p22
[79] Garg, P., Aditi, A., & Roy, B. (2025). A System of Computer Network: Based On Artificial Intelligence. https://doi.org/10.63169/GCARED2025.p24
[80] Parmar, R., Kapoor, S., Saifi, S., & Garg, P. (2025). Case Study on Intelligent Factory Systems for Improving Productivity and Capability in Industry 4.0 with Generative AI. In First Global Conference on AI Research and Emerging Developments (G-CARED 2025), New Delhi, India. https://doi.org/10.63169/GCARED2025.p28
[81] Singh, R., Sharma, R., Kumar, R., Nafis, A., Siddiqui, M. A. M., & Garg, P. (2025). Detection of Unauthorize Construction using Machine Learning: A Review. In First Global Conference on AI Research and Emerging Developments (G-CARED 2025), New Delhi, India. https://doi.org/10.63169/GCARED2025.p30
[82] Garg, P., Kapoor, S., Singh, V., Sharma, S., & Ankita, A. (2025). A Bridge between Blockchain and Decentralized Applications Web3 and Non-Web3 Crypto Wallets. https://doi.org/10.63169/GCARED2025.p35
[83] Verma, M., Sharma, S., Garg, P., & Singh, A. (2025). The Hidden Dangers of Prototype Pollution: A Comprehensive Detection Framework. In First Global Conference on AI Research and Emerging Developments (G-CARED 2025), New Delhi, India. https://doi.org/10.63169/GCARED2025.p36
[84] Sharma, A., Sharma, S., Garg, P., & Bhardwaj, P. (2025). LockTalk: A Basic Secure Chat Application. In First Global Conference on AI Research and Emerging Developments (G-CARED 2025), New Delhi, India.
[85] Arora, K., Bawane, R., Gupta, C., Ahmed, K., & Garg, P. (2025). Detection and Prevention of Cyber Attack and Threat using AI. In First Global Conference on AI Research and Emerging Developments (G-CARED 2025), New Delhi, India. https://doi.org/10.63169/GCARED2025.p38
[86] Garg, P., Dhruv, D., Rahman, A. A., Rai, A., Siddiqui, M., & Yadav, D. (2025). Easeviewer: An Esports Production Tool. https://doi.org/10.63169/GCARED2025.p46
[87] Garg, P., Lakshita, L., Mehwish, M., Nazia, N., & Ahmed, K. (2025). Emerging Trend in Computational Technology: Innovations, Applications, and Challenges. Applications, and Challenges (May 17, 2025). https://doi.org/10.63169/GCARED2025.p51
[88] Chauhan, S., Singh, M., & Garg, P. (2021). Rapid Forecasting of Pandemic Outbreak Using Machine Learning. Enabling Healthcare 4.0 for Pandemics: A Roadmap Using AI, Machine Learning, IoT and Cognitive Technologies, 59-73.
[89] Gupta, S., & Garg, P. (2021). An insight review on multimedia forensics technology. Cyber Crime and Forensic Computing: Modern Principles, Practices, and Algorithms, 11, 27.
[90] Shrivastava, P., Agarwal, P., Sharma, K., & Garg, P. (2021). Data leakage detection in Wi-Fi

networks. Cyber Crime and Forensic Computing: Modern Principles, Practices, and Algorithms, 11, 215.
[91] Meenakshi, P. G., & Shrivastava, P. (2021). Machine learning for mobile malware analysis. Cyber Crime and Forensic Computing: Modern Principles, Practices, and Algorithms, 11, 151.
[92] Nanwal, J., Garg, P., Sethi, P., & Dixit, A. (2021). Green IoT and Big Data: Succeeding towards Building Smart Cities. In Green Internet of Things for Smart Cities (pp. 83-98). CRC Press.
[93] Gupta, M., Garg, P., & Agarwal, P. (2021). Ant Colony Optimization Technique in Soft Computational Data Research for NP-Hard Problems. In Artificial Intelligence for a Sustainable Industry 4.0 (pp. 197-211). Springer, Cham.
[94] Magoo, C., & Garg, P. (2021). Machine Learning Adversarial Attacks: A Survey Beyond. Machine Learning Techniques and Analytics for Cloud Security, 271-291.
[95] Garg, P., Srivastava, A. K., Anas, A., Gupta, B., & Mishra, C. (2023). Pneumonia Detection Through X-Ray Images Using Convolution Neural Network. In Advancements in Bio-Medical Image Processing and Authentication in Telemedicine (pp. 201-218). IGI Global.
[96] Gupta, S., & Garg, P. (2023). 14 Code-based post-quantum cryptographic technique: digital signature. Quantum-Safe Cryptography Algorithms and Approaches: Impacts of Quantum Computing on Cybersecurity, 193.
[97] Prakash, A., Avasthi, S., Kumari, P., & Rawat, M. (2023). PuneetGarg 18 Modern healthcare system: unveiling the possibility of quantum computing in medical and biomedical zones. Quantum-Safe Cryptography Algorithms and Approaches: Impacts of Quantum Computing on Cybersecurity, 249.
[98] Gupta, S., & Garg, P. (2024). Mobile Edge Computing for Decentralized Systems. Decentralized Systems and Distributed Computing, 75-88.
[99] Gupta, M., Garg, P., & Malik, C. (2024). Ensemble learning-based analysis of perinatal disorders in women. In Artificial Intelligence and Machine Learning for Women's Health Issues (pp. 91-105). Academic Press.
[100] Malik, M., Garg, P., & Malik, C. (2024). Artificial intelligence-based prediction of health risks among women during menopause. Artificial Intelligence and Machine Learning for Women's Health Issues, 137-150.
[101] Garg, P. (2024). Prediction of female pregnancy complication using artificial intelligence. In Artificial Intelligence and Machine Learning for Women's Health Issues (pp. 17-35). Academic Press.
[102] Pokhrel, L., Arsalan, M., Rani, P., Garg, P., & Pinheiro, P. R. (2026). AI-Powered Healthcare Solutions: Bridging the Medical Gap in Underserved Communities Worldwide. In Applied AI and Computational Intelligence in Diagnostics and Decision-Making (pp. 57-86). IGI Global Scientific Publishing.
[103] Kapoor, S., Parmar, R., Sharma, N., Garg, P., & Singh, N. J. (2026). AI and Computational Intelligence in Healthcare: An Introductory Guide. In Applied AI and Computational Intelligence in Diagnostics and Decision-Making (pp. 1-26). IGI Global Scientific Publishing.
[104] Pokhrel, L., Kumar, A., Garg, P., Anand, N., & Singh, N. (2026). AI and IoT in Global Health: Ethical Lessons From Pandemic Response. In Development and Management of Eco-Conscious IoT Medical Devices (pp. 367-394). IGI Global Scientific Publishing.
[105] Parmar, R., Singh, A., Garg, P., Sharma, T., & Pinheiro, P. R. (2026). Blockchain for Ethical Supply Chains: Transparency in Medical IoT Manufacturing. In Development and Management of Eco-Conscious IoT Medical Devices (pp. 337-366). IGI Global Scientific Publishing.
[106] Gupta, S., Garg, P., Agarwal, J., Thakur, H. K., & Yadav, S. P. (2024). Federated learning based intelligent systems to handle issues and challenges in IoVs (Part 1). https://doi.org/10.2174/9789815313031124030l
[107] Gupta, S., Chaudhary, G., & Garg, P. (2013). Modified AODV Routing Protocol through Cache Memory for Finding New Routing Paths in MANETs. International Journal of Computer Science & Management Studies, 13(3).
[108] Gupta, A., & Garg, P. (2021). Emerging Techniques for Handling Pandemic Challenges. Enabling Healthcare 4.0 for Pandemics: A Roadmap Using AI, Machine Learning, IoT and Cognitive Technologies, 189-209.
[109] Chaudhary, A. P., Mishra, A., Kumar, D., & Garg, P. (2023, April). Human Emotion Recognition using Deep Learning. In 2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN) (pp. 191-197). IEEE.
[110] Nagpal, S., Garg, P., Gaba, S., & Aggarwal, A. (2023). 13 An improved genetic quantum cryptography model for network communication. Quantum-Safe Cryptography Algorithms and Approaches: Impacts of Quantum Computing on Cybersecurity, 177.

[111] Yadav, M., Swami, V., Kumar, N., & Garg, P. (2025). Comparative study of Repairable Juice Plants using RPGT. Reliability: Theory & Applications, 20(2 (84)), 776-783.
[112] Gupta, A., Garg, P., & Yadav, P. (2025). Role of Generative AI Towards Education and Learning: Present & Future. TPM–Testing, Psychometrics, Methodology in Applied Psychology, 32(S6 (2025): Posted 15 Sept), 1059-1076.
[113] Dalal, P., Beniwal, G., Sharma, V., Garg, P., & Ahmed, K. (2025). Predicting Student Motivation and Engagement through Machine Learning Models. TPM–Testing, Psychometrics, Methodology in Applied Psychology, 32(S7 (2025): Posted 10 October), 393-411.
[114] Gupta, A., Mund, A., Roy, S., Garg, P., & Yadav, D. K. (2025). Trust in AI Systems: A Social-psychological Investigation of Human–AI Collaboration. TPM–Testing, Psychometrics, Methodology in Applied Psychology, 32(S7 (2025): Posted 10 October), 428-446.
[115] Bhardwaj, A., Das, A., Garg, P., & Yadav, S. (2025). Material-Driven Performance Analysis of a Vertical Nanowire Tunnel FET for Analog Applications: Bhardwaj, Das, Garg, and Yadav. Journal of Electronic Materials, 1-12.
[116] Dalal, P., Sharma, B., Sharma, T., Garg, P., & Ahmed, K. (2025). Explainable AI for Understanding Human Decision Making Patterns. TPM–Testing, Psychometrics, Methodology in Applied Psychology, 32(S7 (2025): Posted 10 October), 412-427.
[117] Sharma, K. K., Verma, P. K., Garg, P., &Shrotriya, V. K. (2025, October). Predicting costs and benefits of IoT-based energy management for optimizing sustainable energy storage in rural areas. In AIP Conference Proceedings (Vol. 3343, No. 1, p. 040017). AIP Publishing LLC.
[118] Ahmed, K., Baranwal, A., Sharma, N., Garg, P., & Singh, N. (2026). The Role of Federated Learning in AI-Powered Integrated Healthcare Solutions. In Enabling Collaborative Health Intelligence With Federated Learning (pp. 421-448). IGI Global Scientific Publishing.
[119] Gupta, S., Garg, P., Agarwal, J., Thakur, H. K., & Yadav, S. P. (2025). Federated learning based intelligent systems to handle issues and challenges in IoVs (Part 2). Bentham Science Publishers. https://doi.org/10.2174/9789815322241250301
[120] Garg, P., Pranav, S., & Prerna, A. (2021). Green internet of things (G-IoT): A solution for sustainable technological development. In Green Internet of Things for Smart Cities (pp. 23-46). CRC Press.
[121] Malik, A., Nandal, D., Gupta, V., Garg, P., & Nandal, V. INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING.
[122] Gupta, S., Garg, P., Agarwal, J., Thakur, H. K., & Yadav, S. P. (Eds.). (2025). Federated learning based intelligent systems to handle issues and challenges in IoVs (Part 2).
[123] Garg, P., Bhatt, M., Parmar, R., & Arsalan, M. (2025). Generative AI: Evolution, Applications, Challenges And Future Prospects. Applications, Challenges And Future Prospects (May 17, 2025).
[124] Kumar, N., Kumar, Y., Khurana, D., Kumar, S., & Garg, P. (2025, November). A Hybrid Ensemble Learning Framework for Interpretable Student Performance Prediction Using Academic and Extracurricular Factors. In 2025 International Conference on Innovations and Emerging Technologies In AI & Communication Systems (IETACS) (pp. 666-672). IEEE.
[125] Khurana, D., Kumar, Y., Kumar, N., Kumar, S., & Garg, P. (2025, November). Transformer-Based Movie Recommendation System with Autoencoder-Enhanced Feature Compression. In 2025 International Conference on Innovations and Emerging Technologies In AI & Communication Systems (IETACS) (pp. 685-690). IEEE.
[126] Garg, P. (2025, November). Comparative Analysis of Various Neural Networks for Galaxies Classification. In 2025 International Conference on Innovations and Emerging Technologies In AI & Communication Systems (IETACS) (pp. 697-701). IEEE.
[127] Saggu, A. K., Babbar, N., & Garg, P. (2025, November). Health-Guard AI: Integrated Health Report Management and Analysis. In 2025 International Conference on Innovations and Emerging Technologies In AI & Communication Systems (IETACS) (pp. 614-623). IEEE.
[128] Kumar, S., Kumar, Y., Kumar, N., Khurana, D., & Garg, P. (2025, November). Hybrid FCM-DNN Model for Uncertainty-Aware Air Quality Classification Using Multi-Pollutant Data. In 2025 International Conference on Innovations and Emerging Technologies In AI & Communication Systems (IETACS) (pp. 679-684). IEEE.
[129] Babbar, N., Singh, H. V., Bendale, S., & Garg, P. (2025, November). Stock Market Price Prediction Using Big Data Analysis: A Performance Evaluation Study. In 2025 3rd International Conference on Computational Intelligence and Network Systems (CINS) (pp. 1-6). IEEE.
[130] Singh, A. K., Kori, G., Garg, P., & Srivastava, G. (2025, November). Bank Churn Prediction Using Machine Learning. In 2025 IEEE 7th International

Conference on Computing, Communication and Automation (ICCCA) (pp. 1-6). IEEE.
[131] Bhardwaj, A., Das, A., Garg, P., & Yadav, S. (2026). Material-Driven Performance Analysis of a Vertical Nanowire Tunnel FET for Analog Applications. Journal of Electronic Materials, 55(1), 1099-1110.
[132] Srivastava, A. K., Shankdhar, D., Ror, R., & Garg, P. (2026). Harnessing YOLOv5 for real-time object detection: A cloud-based approach. In Recent Advances in Computational Methods in Science and Technology (pp. 441-450). CRC Press.
[133] Srivastava, A. K., Shukla, A., Gupta, H., Saxena, K., & Garg, P. (2026). Towards intelligent attendance management system with face recognition using LBPH algorithm. In Recent Advances in Computational Methods in Science and Technology (pp. 8-15). CRC Press.
[134] Srivastava, A. K., Garg, P., & Pandey, H. (2026). Vedcure: Towards intelligent ayurvedic drug recommendation and disease prediction. In Recent Advances in Computational Methods in Science and Technology (pp. 16-23). CRC Press.
[135] Upadhyay, D., Garg, P., & Babbar, N. (2026). Blockchain and IoT based smart contract framework for efficient and secure product life management. Discover Internet of Things.
[136] Singh, A., Parmar, R., Bhardwaj, P., Sharma, V., & Garg, P. (2026). Fusion of Aerial Networks with Advanced Computing Paradigms. Edge Computing and Aerial Platforms, 355-367.
[137] Kumari, M., Baranwal, A., Sonal, & Garg, P. (2026). Application of Aerial Edge Computing in Disaster Management. Edge Computing and Aerial Platforms, 103-122.
[138] Aditi, Saraswat, P., Sharma, V., & Garg, P. (2026). Advances in Aerial Platforms and Edge Computing. Edge Computing and Aerial Platforms, 123-143.
[139] Garg, P., Arora, K., Bawane, R., Gupta, C., & Ahmed, K. (2025). Detection and Prevention of Cyber Attack and Threat using AI.
[140] Ahmed, K., Ahmed, A., Khan, J., Garg, P., Seth, S., & Mallik, S. (2025). Principal Component Analysis Based Clustering of Insecticides and Molecular Docking of Pyrethroids Insecticides.
[141] Kumar, B., Kumar, A., Nanwal, J., Garg, P., & Patnaik, P. (2025, November). Ensemble of YOLOv5 and Segment Anything Model for Brain Tumor Detection. In 2025 2nd International Conference on Advanced Computing and Emerging Technologies (ACET) (pp. 1-5). IEEE.
[142] Arsalan, M., Anas, M., & Garg, P. (2025). Transparent AI for Drug Discovery and Development. Available at SSRN 5844242.
[143] Singh, A., Bhardwaj, P., Garg, P., & Singh, N. (2026). Introduction to explainable artificial intelligence in healthcare. In Explainable AI in Clinical Practice (pp. 23-44). Academic Press.
[144] Kapoor, S., Singh, A., Garg, P., & Ramasamy, L. K. (2026). Explainable artificial intelligence in a diagnostic support system. In Explainable AI in Clinical Practice (pp. 131-145). Academic Press.
[145] Ahmed, K., Anas, M., & Garg, P. (2026). Case studies on unlocking the potential of Industry 4.0 for sustainable manufacturing through generative AI-driven innovations. Available at SSRN 6356958.
[146] Garg, P., & Oruganti, S. K. (2026, March). AI Assisted Routing Optimization in Opportunistic IoT Networks using Machine Learning: A Comprehensive review on Protocols & Simulators. In Sustainable Global Societies Initiative (Vol. 1, No. 4). Vibrasphere Technologies.
[147] Arsalan, M., Pokhrel, L., & Garg, P. (2026). Architecture, Components, and tools in Integrated AI-Augmented Intelligence: A design perspective. Components, and tools in Integrated AI-Augmented Intelligence: A design perspective (March 19, 2026).
[148] Singh, H., Ahmed, K., & Garg, P. (2026). Human Versus Machine Customer Behaviour and Functional Differences. Available at SSRN 6441098.
[149] Saraswat, P., & Garg, P. (2026). Soft Computing In AI Agents.
[150] Saraswat, P., & Garg, P. (2026). Water Quality Prediction Using IOT Sensors and Deep Networks.
[151] Arsalan, M., Ahmed, K., & Garg, P. (2026). Machine learning for Anomaly detection in sensor networks. Available at SSRN 6441518.
[152] Kumari, M., & Garg, P. (2026). Hybrid Cloud Infrastructure: Models, Benefits and Security And Challenges. Benefits and Security and Challenges (March 19, 2026).
[153] Singh, H., & Garg, P. (2026). Demystifying Artificial Distributed Intelligence (ADI). Available at SSRN 6442698.
[154] Saraswat, P., & Garg, P. (2026). Human AI Collaboration the future of clinical decision making.
[155] Saraswat, P., & Garg, P. (2026). Breaking Data Boundaries Federated Learning in Digital Healthcare.
[156] Singh, A., Parmar, R., Bhardwaj, P., Sharma, V., & Garg, P. (2026). Fusion of Aerial Networks with Advanced Computing Paradigms. Edge Computing and Aerial Platforms, 355-367.
[157] Kumari, M., Baranwal, A., Sonal, & Garg, P. (2026). Application of Aerial Edge Computing in

Disaster Management. Edge Computing and Aerial Platforms, 103-122.
[158] Aditi, Saraswat, P., Sharma, V., & Garg, P. (2026). Advances in Aerial Platforms and Edge Computing. Edge Computing and Aerial Platforms, 123-143.
[159] Garg, P. (2026). Zero-Trust Security Enforcement through AI-Powered Anomaly Detection in Cloud Systems. Journal of Artificial Intelligence in Governance and Public Policy (JAIGPP), 1(1), 1-8.
[160] Singh, A. P., Sharma, A., & Garg, P. (2026, January). AI-Powered Adaptive Mock Interview Generation System. In 2026 International Conference on AI-Driven Smart Systems and Ubiquitous Computing (ICAUC) (pp. 1421-1426). IEEE.
[161] Raghav, A., Mishra, A., & Garg, P. (2026, January). Enhancing Healthcare Access: An AI-driven Chatbot for Doctor Appointment Management. In 2026 International Conference on AI-Driven Smart Systems and Ubiquitous Computing (ICAUC) (pp. 910-914). IEEE.
[162] Kumar, B., Chauhan, D., Singh, H., Verma, H., Sahu, K., & Garg, P. (2026, January). Decoding Linear A with Artificial Intelligence: A Comprehensive Machine Learning and NLP Framework. In 2026 International Conference on AI-Driven Smart Systems and Ubiquitous Computing (ICAUC) (pp. 1-7). IEEE.
[163] Gupta, V., Chakravarti, L., Akhtar, M. M., Maheshwari, P., Garg, P., & Tiwari, D. (2026, January). A Sentence-Level Risk Estimator for Identifying Hallucinations in Generative AI. In 2026 International Conference on AI-Driven Smart Systems and Ubiquitous Computing (ICAUC) (pp. 1619-1626). IEEE.
[164] Patnaik, P., & Garg, P. (2026). Principles of Artificial Intelligence: Cognitive Architectures, Large Language Models, and Computational Limits. Deep Science Publishing.
[165] Singh, K., & Garg, P. (2026). Trustworthy Deep Learning: Robustness, Uncertainty Quantification, and Adversarial Resilience. Deep Science Publishing.
[166] Garg, P. (2026). Survey of Load Balancing Strategies in Fog-Cloud Architectures for IoT Integration. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 9(2), 595-604.
[167] Tiwari, D., Bhati, B. S., Garg, P., & Babbar, N. (2026). A novel lexicon dictionary and CNN-LSTM employed hybrid approach for sentiment detection of COVID-19 vaccines. Scientific Reports.
[168] Sethi, P., Kumar, B., Garg, P., & Yadav, P. (2026, February). Graph Neural Networks for Causal Inference in Climate Science: A Novel Approach to Model Modeling Complex Interactions. In 2026 International Conference on Intelligent Computing and Automation for Sustainable Solutions (ICASS) (pp. 1-7). IEEE.
[169] Kumar, B., Garg, P., Garg, A., Nanwal, J., & Yadav, P. (2026, February). An AI-Centric Multimodal Framework for Cognitive Productivity and Digital Wellbeing. In 2026 International Conference on Intelligent Computing and Automation for Sustainable Solutions (ICASS) (pp. 1-7). IEEE.
[170] Ahmed, K., Mathur, T., Chaudhary, Y., Anshika, A., Garg, P., & Tiwari, D. (2026, April). ParseRAG: Layout-Aware Open-Source Alternative. In 2026 Eight International Conference on Computational Intelligence and Communication Technologies (CCICT) (pp. 799-804). BM Institute of Engineering & Technology.
[171] Yadav, P., Raj, M., Kaushik, S., Goel, P., Garg, P., & Tiwari, D. (2026, April). Employing Enhanced LSTM and Large Language Models for Stock Price Prediction Using Sentiment Analysis. In 2026 Eight International Conference on Computational Intelligence and Communication Technologies (CCICT) (pp. 617-622). BM Institute of Engineering & Technology.
[172] Gupta, V., Sharma, H., Nagpal, N., Garg, P., & Tiwari, D. (2026). Feel Frames: An Emotion Based Video Summarization using Multimodal Deep Learning. Procedia Computer Science, 282, 715-724.
[173] Singh, H., Ahmed, K., Kumar, U., & Garg, P. (2026, July). Comparative Analysis of Machine Learning and Large Language Model Architectures for Intelligent Medical Diagnosis and Clinical Decision Support Systems. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 125-138).
[174] Singh, H., Ahmed, K., Prajapati, P., & Garg, P. (2026, July). Federated Learning with Differential Privacy: A Comprehensive Framework for Privacy-Preserving Distributed Machine Learning. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 139-155).
[175] Singh, H., Ahmed, K., & Garg, P. (2026, July). Survey on Internet of Things (IOT) Forensics: Challenges, Approaches, Privacy-Aware Frameworks and Open Issues. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 156-170).
[176] Singh, H., Ahmed, K., & Garg, P. (2026, July). Supply Network Disruption Prediction using

Heterogeneous Graph Neural Networks and Temporal Embeddings. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 171-186).
[177] Saraswat, P., Kumari, S., & Garg, P. (2026, July). Future Directions in Digital Social Linguistics. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 187-203).
[178] Saraswat, P., Yadav, A., & Garg, P. (2026, July). Comparing Supervised and Unsupervised Learning Approaches for Specific Tasks. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 220-236).
[179] Saraswat, P., Aishwarya, S., & Garg, P. (2026, July). Foundation of Self-Learning AI for Drones. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 237-254).
[180] Ahmed, K., Singh, H., Anas, M., & Garg, P. (2026, July). The Future of Artificial Intelligence in Healthcare. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 255-270).
[181] Ahmed, K., & Garg, P. (2026, July). AI-DRIVEN FAULT DETECTION AND DIAGNOSTICS. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 271-292).
[182] Kumari, M., Pandey, S., & Garg, P. (2026, July). Quantum AI for Drug Discovery and Material Science. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1).
[183] Kumari, M., Jha, S. K., & Garg, P. (2026, July). Opportunities and Challenges of AI in Education. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 328-341).
[184] Pokhrel, L., Kumar, A., & Garg, P. (2026, July). Impact of AI on Employment and Workforce Transformation. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 342-356).
[185] Singh, H., Ahmed, K., Kumar, A., & Garg, P. (2026, July). AI-Driven Optimization in Supply Chain Operations: A Machine Learning Framework for Demand Forecasting and Inventory Management. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 357-371).
[186] Saraswat, P., Kumar, R., & Garg, P. (2026, July). Human Perception and Virtual Reality: What Is the Connection?. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 409-427).
[187] Ahmed, K., Arsalan, M., Sharma, P. K., & Garg, P. (2026, July). Quantum Technology in Medical Diagnosis. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 428-448).
[188] Saraswat, P., Sharma, P., & Garg, P. (2026, July). The Challenges of AI Implementation in Business. In Adroid Conference Series: Engineering and Technology (Vol. 2, No. 1, pp. 204-219).
[189] Trivedi, S., Beri, T., Arora, A., & Garg, P. (2026, June). NoduleNet: Deep Learning-Based Computational Model for Thyroid Cancer Detection. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-7). IEEE.
[190] Joshi, V., Tyagi, U., Jakhar, V., Gaur, M., & Garg, P. (2026, June). HealthQ: A Retrieval-Augmented Health Policy Query Chatbot. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-6). IEEE.
[191] Saraswat, P., Sharma, V., & Garg, P. (2026, June). Energy Optimization In Smart IOT Enabled Smart Home System Through Machining Learning Techniques. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-6). IEEE.
[192] Saraswat, P., Tiwari, B., & Garg, P. (2026, June). An Empirical Study on Salary Determinants Using Machine Learning. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-5). IEEE.
[193] Pokhrel, L., Arsalan, M., Tiwari, B., & Garg, P. (2026, June). Food Delivery Time Prediction Using Machine Learning Algorithms: A Comparative Study with Hybrid XGBoost-LSTM Architecture. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-7). IEEE.
[194] Garg, P., & Kumar, V. (2026, June). Millimeter-Wave 60 GHz On-Chip Dipole Antenna with Silicon Lens Integration in SiGe Technology. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-5). IEEE.
[195] Arora, A., Trivedi, S., Tyagi, R., & Garg, P. (2026, June). LungVision: Classifying lung diseases using CNN ensembles. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-6). IEEE.

[196] Arora, A., Trivedi, S., Sharma, R., Tiwari, R., Chaudhary, S., & Garg, P. (2026, June). Comparative Study of ResNet-152 and ViTPose-G for Human Pose Detection on the COCO Yoga Dataset. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-6). IEEE.
[197] Kaur, M., Chhillar, V., Kumar, V., & Garg, P. (2026, June). Exploration and Recognition of Autism Spectrum Disorder through Machine Learning Approaches. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-6). IEEE.
[198] Singh, R., Singh, G., Kumar, V., Kumari, M., Kumar, A., & Garg, P. (2026, June). Optimization of Battery Electric Vehicle Thermal Management System Using MATLAB Simscape for Enhanced Charging Efficiency. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-6). IEEE.
[199] Chauhan, A., Singh, G., Kumar, V., Kumari, M., Kumar, A., & Garg, P. (2026, June). An Intelligent Thermal Control and Optimization Framework for Efficient and Safe Battery Charging in Electric Vehicles. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-6). IEEE.
[200] Kumar, S., Kumar, Y., Khurana, D., Kumar, N., & Garg, P. (2026, June). AI-Driven Discovery of Cybercrime Insights from Diverse Web Data. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-6). IEEE.
[201] Chaudhary, N., Tyagi, N., Sharma, N., Gupta, M., & Garg, P. (2026, June). BusOptima-Bus Scheduling & Route Management System. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-6). IEEE.
[202] Srivastava, A. K., Singh, A., Umrao, A., & Garg, P. (2026, June). A Retrieval-Augmented Framework for Context-Aware Document Querying. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-7). IEEE.
[203] Gupta, T., Bhargava, D., & Garg, P. (2026, June). A Comprehensive Survey on Malware Botnet Detection Using Deep Learning in IoT and Android Platforms with Edge AI. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-7). IEEE.
[204] Trivedi, S., Shukla, B., Garg, Y., Satish, T., & Garg, P. (2026, June). Enhancing Social Media Security Through Explainable Ensemble Learning. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-6). IEEE.
[205] Arora, P., Arora, R., Tiwari, D., & Garg, P. (2026, June). Automated Brain Tumor Classification from MRI Images Through InceptionNet Architecture. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-6). IEEE.
[206] Srivastava, S., Singh, S., Goswami, S., Gupta, M., & Garg, P. (2026, June). SignSpeak: A Real-Time Deep Learning Framework for Bidirectional Sign Language Translation. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-7). IEEE.
[207] Srivastava, A. K., Garg, P., & Singh, A. (2026, June). ExplainFusion: An Ensemble Explainable AI Framework with Evidence-Grounded LLM-Based Clinical Explanations. In 2026 6th International Conference on Emerging VLSI and Semiconductor Technology for AI and Computing Applications (EVST) (pp. 1-8). IEEE.