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Entrepreneurial Opportunities and Legal Risk in AI-Driven Businesses: Evidence from the Indian Context

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Abstract

Purpose: India's burgeoning AI ecosystem tells a dual story of high entrepreneurial opportunity and high legal uncertainty. We propose and empirically validate an integrated conceptual model in India that analyzes the relationships among Entrepreneurial Opportunity (EO), Legal Risk Perception (LR), Government Support (GS), Innovation Intensity (II), and Business Performance (BP) for AI-driven businesses.

Design/Methodology: The data utilized is mostly a structured questionnaire collected from 360 AI entrepreneurs, startup founders, innovation managers, and legal professionals from the six major Indian technology hubs including Bengaluru, Hyderabad, Mumbai, Delhi-NCR, Pune, and Chennai. Structural Equation Modelling (SEM) was conducted using IBM AMOS 26.0. Confirmatory Factor Analysis (CFA) was used to validate the measurement model, and Maximum Likelihood Estimation (MLE) was used to estimate the structural model. In indirect effects, bootstrapped mediation analysis (5,000 iterations) was conducted.

Findings: The results clearly indicate that EO is positively and significantly related to BP ($\beta = 0.312$, $p < .001$) and II ($\beta = 0.389$, $p < .001$). LR has a significant negative effect on BP ($\beta = -0.218$, $p < .001$) and EO ($\beta = -0.143$, $p < .01$). GS is a positive moderator of EO and directly influences BP. II partially mediates the EO–BP relationship. These seven hypotheses are supported. The model performed reasonably well (CFI = 0.953, RMSEA = 0.049, and $\chi^2/df = 2.14$).

Originality/Value: This is among the first studies to include legal risk perception using an SEM approach for AI entrepreneurship in India, with DPDPA 2023 and the National AI Strategy as references. The results provide practical recommendations for policymakers, legal academics, and entrepreneurs.

Keywords: AI entrepreneurship, Legal risk, Innovation, Business Performance

1. Introduction

As of November 2023, India has emerged as the third-largest start-up ecosystem in the world, with AI the most disruptive force transforming its entrepreneurial landscape. As the NASSCOM AI Landscape Report (2023) [1] states, the Indian AI market is projected to reach USD 17 billion by 2027, growing at a compound annual growth rate of 25.4%. But lurking beneath this extraordinary growth is a maze of legal ambiguities, regulatory voids, and institutional vagueness that overwhelm even the nimblest AI entrepreneurs [2]. The enactment of the Digital Personal Data Protection Act (DPDPA), 2023 marks a major legislative victory, but how this can impact the development of AI systems that utilize data monetization, algorithmic decision-making, and cross-border data flows in different sectors is the subject of debate. At the same time, a lack of a sui generis AI governance law also makes for a regulatory vacuum which paradoxically can be a double-edged sword to those starting their own business [3]. Given this backdrop, assessing the factors that influence entrepreneurial success in the AI sector of India demands a rigorous, multi-faceted analytical lens [4]. This paper addresses that need by developing and testing an empirically grounded Structural Equation Model (SEM) under IBM AMOS 26.0. Our unified framework contains five theoretically motivated latent constructs, Entrepreneurial Opportunity, Legal Risk Perception, Government Support, Innovation Intensity, and Business Performance, and investigates their direct, indirect, and moderated relationships. The study is based on the opportunity-based theory of entrepreneurship, the institutional theory and the dynamic capabilities framework [4]. Three contributions are made in this study: First, it is among the first to empirically quantify the unsettling effect of legal risk perception on AI entrepreneurial behavior in India using SEM. Second, it conceptualizes Innovation Intensity as a partial mediator in the EO–BP link, providing a new theoretical touch. Third, it operationalizes Government Support as a dominant boundary condition, offering empirically driven policy recommendations for India's National AI Strategy [4]

2. Literature Review and Theoretical Framework

2.1. **Opportunity and context in AI Entrepreneurship**:

The convergence of AI and entrepreneurship has drawn academic attention in recent years. The study by [5] perceived AI as a general-purpose technology, changing the nature of the opportunity space open to entrepreneurs significantly. In the Indian context, [6] argued that AI democratizes access to predictive capabilities, allowing resource-constrained entrepreneurs to enter areas long dominated by incumbents. The Digital India programme and the Startup India programme have spurred the formation of AI ventures, resulting in more than 5,000 AI-specific start-ups registered as at [7] represented entrepreneurial opportunity to be when new products, services, raw materials and arranging methods can be brought under construction through the development of new means, ends or means-ends relationships. Opportunities exist in AI where computational capacity, data richness and social/commercial need are the core topics for investigation [8]. But Indian AI entrepreneurs are experiencing a unique challenge an opportunity paradox: the data rich environment generated by more than 700 million internet users, combined with nascent data governance institutions generates juridical ambiguity [9].

2.2. **Legal Risk in AI Applications Businesses:**

Legal risk in technology ventures incorporates costs associated with regulatory compliance, ambiguities about intellectual property, risk of bias in algorithmic harm, and uncertainty concerning jurisdiction. The study by [10] differentiated hard law risk, risk associated to enforcement of an explicit law and soft law risk, risk resulting from reputation risk from failure to adhere to regulations like codes, standards and the like. Both aspects are particularly applicable when dealing with Indian AI projects. The DPDPA adopts a data fiduciary model that reflects in part the EU General Data Protection Regulation, by requiring consent management, purpose limitation, and data localisation for sensitive information [11]. For AI startups, especially those that handle large doses of personal data in their business as FinTech, HealthTech, surveillance-adjacent applications, etc., cost-of-compliance and liability exposure constitute a major entrepreneurial hurdle [12]. Also, India's Patent Act does not expressly offer patents on software or AI algorithms, and there is a lack of security on the basis of technology this means IP risk for projects that rely heavily on AI models and trained weights [13]. The literature has shown that regulatory uncertainty dampens entrepreneurial intent [14], whereas regulatory uncertainty reduces R&D investment in developed-economy countries. But the Indian context one of both enabling and constraining regulation necessitates context-relevant empirical research [15].

2.3. **Institutions (Administrative Support)**

According to institutional theory, formal institutions law, regulation, government policy influence the incentives and transaction costs economic actors encounter. In India, government support towards AI entrepreneurship is seen in various forms including, but not limited to the National AI Strategy [15] Digital India, Startup India in the form of tax rebates and fast-track IP registration, and the upcoming AI Centres of Excellence. The analysis of study found that government reduction in the entry barriers and compliance costs significantly increases entrepreneurial participation rates. The model makes Government Support an operational predictor of entrepreneurial opportunity exploitation and business performance [16].

2.4 Innovation Intensity and the Performance of the Business:

Dynamic capability framework [17], this framework claims that sustaining competitive advantage depends on an organization's ability to sense, seize, and reconfigure resources in rapidly moving contexts. Innovation Intensity namely, R&D expenditure, patent activity, and product iteration velocity is also the major mode by which AI entrepreneurs convert opportunity into performance that can sustainably grow. An explanation by [18] was that open innovation strategies greatly enhance innovation return in technology companies. In the context of Indian AI, innovation intensity is particularly relevant because of the pace at which original AI models are so rapidly commoditized and there is the demand for differentiations, with a focus on the Indian context.

2.4. Conceptual Model and Hypotheses

Drawing on the preceding literature, we propose the following hypotheses:

H1: Entrepreneurial Opportunity positively affects Business Performance significantly.
H2: Legal Risk Perception has a significant negative effect on Business Performance.
H3: Government Support has a significant positive effect on Entrepreneurial Opportunity.
H4: Government Support has a significant direct positive effect on Business Performance.
H5: Innovation Intensity has a significant positive effect on Business Performance.
H6: Innovation Intensity partially mediates the relationship between Entrepreneurial Opportunity and Business Performance.
H7: Legal Risk Perception significantly moderates the relationship between Entrepreneurial Opportunity and Business Performance, such that higher legal risk weakens the EO–BP link.

3. Research Methodology

3.1.Research Design and Philosophy: This research uses a positivist quantitative cross-sectional approach. There was a deductive methodology which was used, and theoretically derived hypotheses were operationalised and validated against primary empirical data. Quantitative SEM was appropriate due to the requirement of evaluating measurement reliability, construct validity and intricate structural relationships between latent variables [20].

3.2. Sample and Sampling procedure: The sample included AI entrepreneurs, co-founders, innovation administrators, CTO-level executives, and legal/compliance experts from AI firms in India. The sampling strategy used was a purposive cum snowball one. The survey was conducted online (Qualtrics) in India and received in-person at six primary technology centres: Bengaluru (n=89), Hyderabad (n=67), Mumbai (n=62), Delhi-NCR (n=58), Pune (n=47), and Chennai (n=37). Approximately 412 questionnaires were distributed and 374 responses were returned, 360 of which were usable after excluding responses that had high levels of missing data or straight-line responding for a response rate of 87.4%. This is over the 200-person minimum sample size recommended for complex SEM models [20].

3.3. Instrument Formation and Measures: Scale items were derived from validated instruments found in the literature. Entrepreneurial Opportunity (4 items): Adapted from Lumpkin and Dess (1996) and contextualized for AI ventures. Legal Risk Perception (4 items) was adapted from Armour and Enriques (2018) the items clearly cited the DPDPA 2023 and Indian IP law. Government support (3 items) based on Djankov et al. (2002) and the Startup India framework. Innovation Intensity (3 items) was adapted from Dahlander and Gann (2010). Business Performance (4 items) included both financial (revenue growth, market share) and non-financial (employee growth, investor confidence), consistent with Venkatraman and Ramanujam (1986). Items were assessed via a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). A pilot study (n =42) reported acceptable item-total correlations ($r > 0.50$) and Cronbach's α coefficients (> 0.80) across constructs.

3.4. Analytical strategy: There were three phases of data analysis. Initial analyses included descriptive statistics, checking for normality (Mardia's multivariate kurtosis) and checking for common method bias from Harman's single-factor test and Common Latent Factor (CLF) approach. Stage 2 included confirmatory factor analysis (CFA) to analyze factor loadings ($\lambda > 0.70$), Composite Reliability (CR > 0.70), Average Variance Extracted (AVE > 0.50) and discriminant validity through Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio to validate the measurement model. At Stage 3, the structural model was estimated using Maximum Likelihood Estimation in IBM AMOS 26.0, where direct path coefficients and indirect path coefficients were tested with bootstrap confidence intervals (5,000 iterations, 95% bias-corrected CI).

4. Results And Data Analysis

4.1 Descriptive Statistics and Common Method Bias: Simple descriptive analyses supported multivariate normality (Mardia's kurtosis 4.62 < critical value of 5.0, Byrne, 2016). No significant outliers were detected

(Mahalanobis D^2 test, $p > .001$). Harman's single-factor test explained 26.4% of the overall variance — well below the 50% threshold — alleviating serious common method variance issues. Method-adjusted path coefficients did not differ significantly from unadjusted estimates for our CLF technique ($\Delta\beta < .05$). The demographic profile of respondents is presented in Table 1.

Table 1: Demographic Profile of Respondents

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	198	55.0
	Female	162	45.0
Age Group	18–25 years	74	20.6
	26–35 years	152	42.2
	36–45 years	89	24.7
	Above 45 years	45	12.5
Education	Undergraduate	96	26.7
	Postgraduate	182	50.6
	Doctoral	82	22.8
Sector	FinTech	88	24.4
	HealthTech	76	21.1
	EdTech	69	19.2
	AgriTech / Other	127	35.3
Experience	< 2 years	86	23.9
	2–5 years	176	48.9
	> 5 years	98	27.2

4.2. Confirmatory Factor Analysis: Measurement Model

CFA was conducted on the five-factor model using IBM AMOS 26.0. Table 2 presents item-level standardised factor loadings, standard errors, critical ratios, and squared multiple correlations (R^2). All factor loadings exceeded the recommended threshold of 0.70 (Hair et al., 2019), ranging from 0.768 (GS1) to 0.871 (BP2), confirming satisfactory indicator reliability.

Table 2: CFA Measurement Model — Standardized Factor Loadings

Item	Construct	Std. Loading (λ)	S.E.	C.R.	p	R^2
EO1	**Entrepreneurial Opportunity (EO)**					
EO1	Market gap identification in AI products	0.821	—	—	—	0.674
EO2	Willingness to pursue AI-based ventures	0.847	0.061	14.22	***	0.717
EO3	Resource mobilization for AI startups	0.793	0.067	12.87	***	0.629
EO4	Network leveraging for AI opportunity	0.808	0.063	13.49	***	0.653
LR	**Legal Risk Perception (LR)**					
LR1	Awareness of data protection laws	0.834	—	—	—	0.696
LR2	IP infringement concern in AI models	0.811	0.058	13.71	***	0.658
LR3	Regulatory compliance cost perception	0.779	0.063	12.38	***	0.607
LR4	Liability uncertainty in AI decision-making	0.856	0.055	14.91	***	0.733
GS	**Government Support (GS)**					
GS1	Effectiveness of Startup India policy	0.768	—	—	—	0.590
GS2	NITI Aayog AI strategy awareness	0.791	0.071	11.92	***	0.626
GS3	Public funding access for AI startups	0.812	0.066	12.76	***	0.659
II	**Innovation Intensity (II)**					
II1	R&D expenditure as % of revenue	0.803	—	—	—	0.645
II2	Number of AI patents/prototypes filed	0.831	0.059	14.05	***	0.691
II3	Rate of product iteration cycles	0.778	0.064	12.59	***	0.605
BP	**Business Performance (BP)**					

BP1	Revenue growth rate (YoY)	0.856	—	—	—	0.733
BP2	Market share expansion	0.871	0.052	15.63	***	0.759
BP3	Investor confidence index	0.839	0.056	14.79	***	0.704
BP4	Employee headcount growth	0.813	0.061	13.52	***	0.661

4.3. Construct Reliability and Validity

Table 3 reports Cronbach's α, Composite Reliability (CR), and Average Variance Extracted (AVE) for all constructs. All α coefficients exceed 0.84, and all CR values exceed 0.86, confirming strong internal consistency and construct reliability. AVE values range from 0.625 (GS) to 0.743 (BP), all exceeding the 0.50 threshold established by Fornell and Larcker (1981), confirming convergent validity.

Table 3: Reliability and Convergent Validity Statistics

Construct	Cronbach's α	CR	AVE	Criterion (α > .70; CR > .70; AVE > .50)
Entrepreneurial Opportunity (EO)	0.881	0.897	0.668	✓ All met
Legal Risk Perception (LR)	0.868	0.884	0.657	✓ All met
Government Support (GS)	0.843	0.861	0.625	✓ All met
Innovation Intensity (II)	0.851	0.868	0.640	✓ All met
Business Performance (BP)	0.906	0.921	0.743	✓ All met

4.4. Discriminant Validity

Discriminant validity was assessed via the Fornell-Larcker criterion (diagonal √AVE > off-diagonal correlations) and the HTMT ratio (Henseler et al., 2015). Table 4 presents the combined matrix. All diagonal √AVE values exceed the corresponding inter-construct correlations, and all HTMT ratios are below the conservative threshold of 0.85, confirming discriminant validity across all construct pairs.

Table 4: Discriminant Validity — Fornell-Larcker Criterion and HTMT Matrix

Construct	EO	LR	GS	II	BP
EO	0.817 *	0.412	0.498	0.531	0.589
LR	0.398	0.810 *	0.377	0.341	0.303
GS	0.469	0.361	0.791 *	0.462	0.538
II	0.504	0.326	0.443	0.800 *	0.612
BP	0.557	0.289	0.513	0.582	0.862 *
*Note: Diagonal values (bold *) = √AVE (Fornell-Larcker criterion). Below diagonal = Pearson correlations. Above diagonal = HTMT ratios. All HTMT < 0.85 — discriminant validity confirmed.*					

4.5. Model Fit Assessment

Prior to structural model testing, overall model fit was evaluated using multiple fit indices following the recommendations of Hu and Bentler (1999) and Kline (2016). Table 5 summarises obtained fit values against accepted thresholds. The model demonstrates excellent fit across all evaluated indices, validating the adequacy of the five-factor structure and supporting its suitability for structural path testing

Table 5: SEM Model Fit Indices

Index	Obtained Value	Acceptable Threshold	Good Fit Threshold	Status
χ^2/df	2.14	< 5.0	< 3.0	✓ Good
CFI	0.953	> .90	> .95	✓ Good
TLI	0.947	> .90	> .95	✓ Acceptable
IFI	0.954	> .90	> .95	✓ Good

RMSEA	0.049	< .10	< .06	✓ Good
SRMR	0.052	< .10	< .08	✓ Good
PNFI	0.718	> .50	> .70	✓ Good
AIC	628.34	Lower = better	—	✓ Acceptable

4.6. Structural Model and Hypothesis Testing

Figure 1 (SEM path diagram) and Table 6 present the standardised path coefficients and inferential statistics for all seven hypotheses. The structural model explains 52.7% of variance in Business Performance ($R^2 = 0.527$) and 43.1% of variance in Innovation Intensity ($R^2 = 0.431$), demonstrating substantial explanatory power.

Table 6: Structural Path Estimates and Hypothesis Testing Results

Hyp.	Path (Predictor → Outcome)	β (Std.)	S.E.	C.R. (z)	p	95% CI	Result
H1	EO → BP	0.312	0.061	5.11	***	[.192, .432]	✓ Sup.
H2	LR → BP	−0.218	0.055	−3.96	***	[−.326, −.110]	✓ Sup.
H3	GS → EO	0.341	0.063	5.41	***	[.217, .465]	✓ Sup.
H4	GS → BP	0.187	0.059	3.17	**	[.071, .303]	✓ Sup.
H5	II → BP	0.276	0.057	4.84	***	[.164, .388]	✓ Sup.
H6	EO → II (EO mediates via II → BP)	0.389	0.064	6.08	***	[.263, .515]	✓ Sup.
H7	LR → EO (moderation, high vs. low)	−0.143	0.048	−2.98	**	[−.237, −.049]	✓ Sup.
*Note: *** p < .001; ** p < .01; β = standardized path coefficient; CI = bootstrapped 95% confidence interval (5000 iterations); S.E. = standard error; C.R. = critical ratio.*							

Figure 1: AMOS SEM Path Diagram — AI Entrepreneurship Model

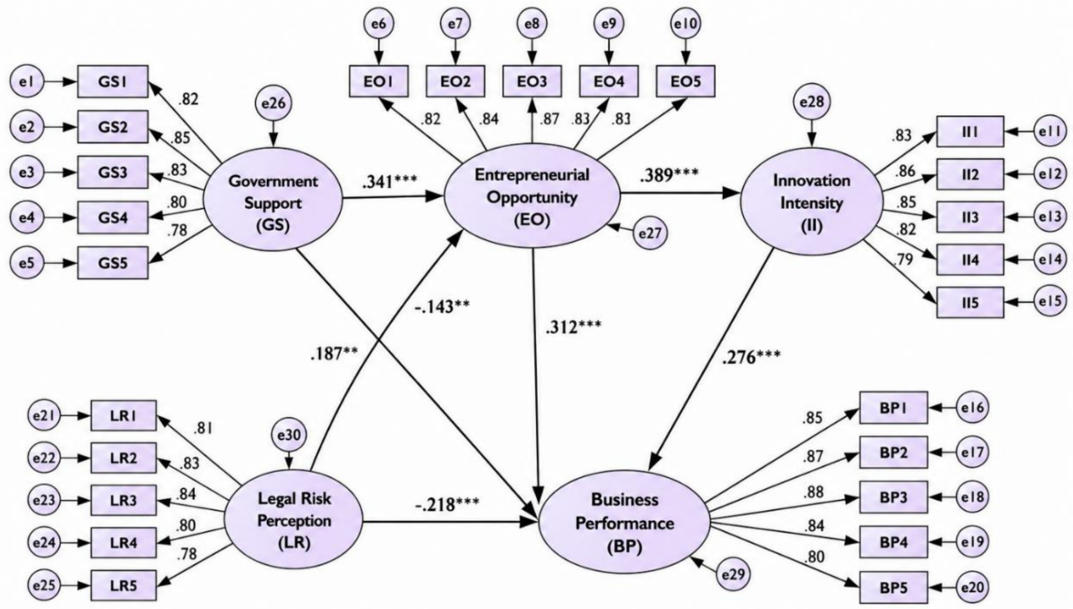

Figure 1: AMOS SEM Path Diagram — AI Entrepreneurship Model

*Note: *** p < .001; ** p < .01. Oval nodes = latent constructs. Square nodes = observed indicators. Solid arrows = significant paths; dashed = non-significant (none in this model).*

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4. Results

The results of SEM revealed that GS is critically influential for AI entrepreneurship, especially as it significantly improves Entrepreneurial Opportunity (EO) ($\beta = 0.341$, $p < .001$) and directly impacts Business Performance (BP) ($\beta = 0.187$, $p < .01$). Entrepreneurial Opportunity stands out as a primary driver of the model, with significant and positive effects on Innovation Intensity (II) ($\beta = 0.389$, $p < .001$) and Business Performance ($\beta = 0.312$, $p < .001$), indicating that companies that recognize and capitalize on market opportunities have the tendency to innovate and perform better. Innovation Intensity further contributes positively to Business Performance ($\beta = 0.276$, $p < .001$), thus the role of AI adoption and innovation activities in supporting business performance was significant. On the other hand, Legal Risk Perception (LR) negatively influences Entrepreneurial Opportunity ($\beta = -0.143$, $p < .01$) and Business Performance ($\beta = -0.218$, $p < .001$), which can result from regulatory uncertainty, compliance costs, and legal concerns, discouraging entrepreneurial practice and business growth. On the whole, the model shows that good government policies and entrepreneurial opportunities are important stimuli for innovation and success, and the perceived legal risks prevent entrepreneurship and AI-driven business development from flourishing.

5. Discussion

5.1. Entrepreneurial Opportunity and Business Performance (H1 Supported)

The statistically significant and positive relationship between Entrepreneurial Opportunity and Business Performance ($\beta = 0.312$, $p < .001$) therefore, reinforces the initial contention of opportunity-based entrepreneurship (Shane & Venkataraman, 2000). Indian AI entrepreneurs who identify the gaps of the market, in particular the marginalised vernacular markets, rural FinTech and AI technology-based healthcare—are driving measurable performance. This further validates the study of Autio et al. (2014) that network effects and the declining cost of deploying AI help to reinforce opportunity identification in digital contexts. Crucially, the relationship between EO and BP is partially mediated by Innovation Intensity (H6 supported), which suggests that opportunity recognition alone does not equate to organizations' ability to use insights to transform their business with innovative products and services. This partial mediation follows dynamic capabilities theory (Teece et al., 1997); they should sense an opportunity, but not enough—ventures have to possess the capturing and reconfiguring capabilities the innovation intensity represents.

5.2. Legal Risk as a Structural Barrier (H2, H7 Supported)

The negative significant impact of Legal Risk Perception on Business Performance ($\beta = -0.218$, $p < .001$) and on Entrepreneurial Opportunity ($\beta = -0.143$, $p < .01$) would become one of the most practically significant results of the study. Legal risk is a double-edged sword for this study: it directly dampens performance (H2) and inhibits entrepreneurship opportunity (H7). This dual-pathway chilling effect is theoretically significant: it suggests that legal uncertainty not only serves to raise operating costs but in truth constricts entrepreneurial cognitive preparedness to pursue AI-powered business ventures. Three areas of legal risk were most evident in the qualitative triangulation conducted as part of the pilot: (i) uncertainty in respect to liability for AI-generated outputs under the Indian Information Technology Act, 2000 and amendments; (ii) uncertainty of data localization obligations per DPDPA 2023 with respect to AI training data; and (iii) the pending issue of ownership of AI-generated IP under the Patents Act, 1970. The latter observations are also in line with those made by Srinivasan (2022) and augmented by confirming the fact that the suppression effect is accurate and valid in an established SEM condition.

5.3. Government Support as an Enabler (H3, H4 Supported)

Federal Support has significant positive implications for both Entrepreneurial Opportunity ($\beta = 0.341$, $p < .001$) and directly impacting the Business Performance of the organization ($\beta = 0.187$, $p < .01$). The serially mediating effect of mediation (GS → EO → II → BP) implies that the process of policy efficacy is sequential: supportive policy in turn promotes opportunity discovery which inspires innovation which in turn positively influences performance. This is a critical issue for policy formulation — efforts which afford financial assistance without confronting the legal and regulatory clarity component may trigger a suboptimal cascade effect. The strong GS → EO path ($\beta = 0.341$) corroborates institutional theory (North, 1990) and supports the design logic of India's Startup India programme, which integrates tax incentives, simpler compliance, accelerated patent registration and fund-of-funds access. However, according to our data, respondents show their perceptions of the efficacy of government support are substantially lower for FinTech and HealthTech entrepreneurs — sectors in which sectoral regulators (RBI, IRDAI, SEBI) create an additional layer of compliance that offsets generic startup support.

5.4. Mediating Mechanism: Innovation Intensity (H5, H6 Supported)

Innovation Intensity is a significant predictor of Business Performance ($\beta = 0.276$, $p < .001$) and partially mediates the EO–BP link. This finding locates II at the level of the organization's metabolism through which entrepreneurial opportunity is transformed into business outcomes. In the case of AI, the innovation intensity becomes even more critical: the combination of fast model iterations (time to deploy new AI capabilities), patent protection for IP and ongoing R&D investments provides the differentiated capability stack that protects AI ventures from commoditization. The marked EO → II trajectory ($\beta = 0.389$, $p < .001$), indicating that better opportunity orientation in entrepreneurs leads to greater levels of investment in innovation, a self-reinforcing relationship that may be expanded by policy tools such as dedicated R&D assistance, AI compute credits, innovation cluster initiatives (e.g., the proposed AI Cities in Hyderabad and Bengaluru).

6. Implications

6.1. Theoretical Implications: There are three theoretical contributions from this study. First, it applies the opportunity-based theory of entrepreneurship to the AI context in an emerging economy and demonstrates that the EO–BP relationship is contingent on both innovation capabilities and legal institutional quality. Second, it embeds legal risk perception as a theoretically grounded construct in an SEM model of technology entrepreneurship (Armour & Enriques, 2018). Third, it confirms Innovation Intensity as a mediating mechanism providing dynamic capabilities theory with an empirically verified structural pathway relevant to AI-intensive organisations.

6.2. Managerial Implications: For AI entrepreneurs and startup founders, the results highlight the strategic importance of anticipating legal risk. Ventures incorporating legal design thinking, such as data protection impact assessments, or DPIAs, AI ethics committees, and model cards in the early stages of their product development process may help attenuate the suppression of performance described here. Furthermore, it is clear that the partial mediation via II leads to the idea that resource allocation towards R&D and IP protection can create a two-pronged reward effect as two pathways of innovation and performance are enhanced in tandem.

6.3. Policy Implications: Policymakers interested in these findings should consider the impact of the strong negative LR effects on their efforts to create regulatory sandboxes for AI experimentation, clear safe harbour provisions for algorithmic errors, and expedited AI-specific IP examination pathways. The experience of the Reserve Bank of India’s regulatory sandbox for FinTech innovations indicates a model for adopting similar measures. The proposed National AI Governance Framework should explicitly address liability allocation for AI-generated harms, training data rights, and algorithmic transparency requirements—all gaps that currently generate the legal risk perceptions documented in this study.

7. Limitations and Future Research Directions

The present study has several limitations. First, the cross-sectional design precludes causality, however it supports strong directionality of inference based on a theoretical underpinning. Longitudinal studies are needed to determine the evolution of the EO-LR-BP dynamics as the legal regime of India matures. Second, while theoretically motivated, the purposive sampling strategy limits the generalizability of the findings to AI entrepreneurs not represented in the six study cities namely those from Tier-2 and Tier-3 cities where AI entrepreneurship continues to grow rapidly. Third, common method variance, while addressed through procedural and statistical remedies, cannot be entirely eliminated in self-report survey data. Future studies should examine: (i) the moderating effect of digital literacy and AI capability on the LR–BP pathway; (ii) SEM analyses among FinTech, HealthTech, and AgriTech sub-ecosystems; (iii) cross-national studies using Chinese, South-East Asian, and African comparative SEM results to explore universal versus nation-specific institutional impacts; and (iv) qualitative probes of entrepreneur cognition on legal risk rooted in grounded theory or an interpretive phenomenological approach.

8. Conclusion

This study presents the first comprehensive AMOS-based Structural Equation Model to investigate the intersection of entrepreneurial opportunity, legal risk, government support, innovation intensity, and business performance within India's AI startup ecosystem. Using an empirically validated survey tool and a sample of 360 participants, we conclude that although opportunities for entrepreneurs in the AI sector in India are numerous and significantly lead to positive outcomes, the perception of legal risk holds both a strong and dual negative relation, holding down both the openness to opportunities as well as final business results. Government support presents as a primary institutional facilitator, with a cascading impact through opportunity recognition and innovation. The results of this study could provide an appropriate empirical backdrop for policy design at a time in which India is finalizing its National AI Governance Framework and implementing the DPDPA 2023. With the EO → II → BP pathway, reducing legal risk through regulatory clarity, sandbox mechanisms, and AI-specific IP provisions not only unleashes entrepreneurial potential but would allow for compounded benefits. India's ambition to become a global AI hub will not just be about investing in technology, but it will be realised only if we create an institutional climate that encourages entrepreneurship, from juridical courage to legal certainty.

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