

Generative AI and Copyright in India: An Empirical Study of Stakeholder Perceptions on Consent, Licensing, Transparency, Compensation and Legal Reform

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Abstract

Generative AI has brought a practical copyright question to the centre of Indian policy: on what terms, if any, should copyright-protected works be used in training models? This paper reports an exploratory mixed-method study of 105 respondents drawn from five stakeholder groups - software professionals, lawyers and academicians, authors, content creators, and students or researchers. Nineteen Likert-scale items and three open-ended questions were used to examine views on permission, licensing, compensation, disclosure, research use, trust, enforcement and legal reform. Mandatory licensing attracted the strongest support (M=4.39; 85.7% agreement), followed by AI-specific legislative reform (M=4.36; 84.8%), legal prohibition of unauthorised training (M=4.34; 82.9%), training-data disclosure (M=4.30; 81.0%) and creator compensation (M=4.29; 78.1%). Seventeen of the 19 items differed significantly from the neutral midpoint after false-discovery-rate correction. The two status-quo items - adequacy of the present Copyright Act and sufficiency of existing enforcement - did not show a clear departure from neutrality. The responses also show that support for creator protection is compatible with more lenient treatment of genuine non-commercial research and with recognition of AI's social benefits. Professional-category differences did not remain significant after multiple-testing correction. The findings should not be read as nationally representative, but they provide stakeholder evidence relevant to the current Indian debate on AI training, copyright licensing, transparency and reform.

Keywords: Generative AI, Copyright, India, AI Training, Licensing, Compensation, Transparency, Text and Data Mining, Empirical Legal Studies, AI Governance

1. Introduction

The copyright issue raised by generative AI begins before any model output is produced. Training large language and multimodal systems commonly requires the acquisition and computational processing of very large datasets. Those datasets may contain books, articles, images, music, code and other protected material obtained from public websites, licensed collections, repositories or archives. The legal analysis therefore has an input-side dimension as well as the more familiar question of whether a generated output reproduces protected expression. [15].

For India, the legal position remains unsettled. The Copyright Act, 1957 contains specific exceptions, including fair dealing for defined purposes, but it does not create a general text-and-data-mining exception for commercial model training [3]. At the policy level, the India AI Governance Guidelines place responsible and accountable AI development within a broader national governance framework [4], while the Department for Promotion of Industry and Internal Trade has opened a dedicated policy process on generative AI and copyright, including licensing and the use of protected works for training [5]. These developments make the question more immediate than it was even a few years ago.

Most legal writing on AI training has understandably concentrated on doctrine: whether copying occurs, whether an exception applies, and whether a licensing rule or other statutory response is justified. That literature is essential, but it does not by itself show how relevant stakeholder groups assess the legitimacy or practicality of different regulatory choices. Questions such as disclosure, remuneration, collective licensing and research exceptions involve not only legal doctrine but also transaction costs, bargaining power and institutional design.

This study was undertaken to add an empirical layer to that debate. The survey included 105 respondents across five professional or academic categories and asked whether they distinguish ethical objection from legal prohibition; how they assess the current statutory and enforcement framework; whether they support licensing, compensation and disclosure; whether they treat commercial and genuine research uses differently; and whether professional background or familiarity with AI and copyright is associated with different attitudes.

The results do not point to a simple anti-AI position. Strong support for licensing, disclosure, compensation and legislative reform sits alongside substantial support for genuine academic or non-commercial research use. Respondents are also more confident about the desirability of licensing than about its practical implementation. The paper uses these tensions as the basis for discussing what an Indian regulatory response would need to solve in practice, rather than treating the survey as a referendum for or against generative AI.

2. Research Context and Literature

2.1 Copyright, AI training and regulatory choice

Jurisdictions have taken materially different approaches to the use of copyrighted works for computational analysis and AI training. In the United States, the central debate has developed through fair use and litigation. The European Union created specific text-and-data-mining exceptions in Articles 3 and 4 of Directive (EU) 2019/790, with Article 4 allowing rights reservation for certain uses [8]. The EU AI Act adds provider-level obligations for general-purpose AI models, including a copyright-compliance policy and a public summary of training content [9]. Singapore expressly permits computational data analysis, including machine-learning uses, subject to conditions such as lawful access [10]. Japan has adopted a comparatively broad information-analysis approach, though its limits remain relevant to particular uses. Comparative scholarship therefore cautions against treating 'TDM' as a single regulatory model [6].

The debate is also moving beyond the binary question of permission. Control, compensation, transparency and legal certainty recur across comparative analyses [6]. Pasquale and Sun argue for a framework in which creator consent and compensation play a more explicit role in generative-AI copyright governance [11]. WIPO's recent work on copyright infrastructure similarly emphasises that licensing and compensation depend on workable systems for rights information, provenance, attribution

and transparency [14]. This matters because a licensing rule can exist on paper while remaining difficult to administer at the scale of modern training datasets.

India's current policy discussion reflects the same tension. The DPIIT working paper addresses the use of copyrighted material in generative-AI training and considers mechanisms intended to balance innovation with the interests of rightholders [5]. The practical questions are therefore not limited to whether permission should be required. They include how rights would be identified, how licences could be obtained or administered, what information developers should disclose, and whether genuine research should be treated differently from commercial foundation-model development.

2.2 Emerging empirical evidence

Empirical evidence on these questions is beginning to develop. Liang, Crosby and McKenzie surveyed 419 members of the Australian Society of Authors and found that perceived fairness, replacement risk and patterns of AI use were associated with authors' willingness to permit training and with compensation expectations [12]. Kyi and colleagues, using interviews with creative workers in visual art, writing and programming, similarly identify consent, credit and compensation as recurring governance concerns [13]. These studies suggest that stakeholder attitudes are conditional: views can change with purpose, compensation, perceived risk and the degree of control retained by creators.

The present study adds a different perspective in two ways. First, it is situated in the Indian legal and policy context. Secondly, the sample is deliberately multi-stakeholder rather than creator-only: it includes technology professionals, legal and academic respondents, authors, content creators, and students or researchers. The 19-item instrument also covers a wider regulatory set of issues - ethics, legality, statutory adequacy, disclosure, licensing, compensation, research treatment, trust, feasibility, vulnerability, economic impact, specialised oversight and enforcement - rather than asking only whether a participant would permit use of a work.

3. Research Questions

1. To what extent do respondents support permission, licensing, compensation and transparency for the use of copyrighted works in generative-AI training?
2. How confident are respondents that the present Indian copyright and enforcement framework adequately addresses AI training?
3. Do respondents distinguish commercial AI training from genuine non-commercial or academic research?
4. Does greater transparency appear to function as a trust-enhancing governance mechanism?
5. Do attitudes toward AI-copyright regulation differ materially across professional stakeholder groups?
6. What additional concerns and opportunities emerge from the open-ended responses?

4. Methodology

4.1 Design and sample

The study uses a cross-sectional mixed quantitative-qualitative survey design. The present paper reports the final analysed data cut-off of 105 valid respondents. The sample is purposive and convenience-based, selected to obtain stakeholder diversity rather than population representativeness.

Table 1: Respondent Category Distribution

Respondent category	n	%
Software professional	32	30.5
Lawyer/academician	24	22.9
Student/researcher	21	20.0
Content creator	15	14.3
Author	13	12.4

The sample included 12 respondents aged 18-24, 21 aged 25-34, 34 aged 35-44, 26 aged 45-54 and 12 aged 55 or above. Professional or academic experience ranged from zero to 35 years (mean 14.0; median 15.0). These characteristics provide useful heterogeneity but do not justify national prevalence claims.

4.2 Instrument

Nineteen substantive propositions were measured on a five-point Likert scale: 1=Strongly Disagree, 2=Disagree, 3=Neither Agree nor Disagree, 4=Agree and 5=Strongly Agree. The instrument deliberately paired related but distinct propositions. Current statutory adequacy (Q3) was contrasted with demand for reform (Q11); mandatory licensing (Q5) with practical feasibility (Q12); baseline trust (Q9) with transparency-enhanced trust (Q18); and dedicated regulation (Q17) with confidence in existing enforcement (Q19). Three optional open-ended questions addressed desired legal reform, personal/professional experience of possible training use, and the principal risk and opportunity associated with generative AI.

4.3 Statistical analysis

All 105 respondents answered all 19 Likert items, yielding 1,995 closed-item observations with no item-level missingness. Means are reported as comparative summaries but are accompanied by medians, distributions and non-parametric inference because Likert responses are ordinal. Wilcoxon signed-rank tests evaluate departure from the neutral midpoint. The paired conceptual contrasts reported in Section 5.3 were also evaluated using within-respondent Wilcoxon signed-rank tests, with Benjamini-Hochberg false-discovery-rate (FDR) correction applied across that family of contrasts. Kruskal-Wallis tests examine professional-category differences. Spearman correlations explore associations between self-rated familiarity and policy attitudes. Benjamini-Hochberg FDR correction is applied to families of repeated tests [1]. Internal consistency is assessed only for conceptually coherent item clusters rather than by treating all 19 items as a single scale.

The open-ended questions produced 51 valid legal-reform narratives, 39 personal/professional-experience narratives and 44 risk-opportunity narratives. Open-ended responses were coded using a transparent keyword-assisted thematic framework followed by conceptual consolidation. Thematic coding was multi-label: one response could receive more than one code. The coding approach follows the principle that qualitative themes may overlap when a single narrative raises several distinct concerns [2]. Accordingly, thematic percentages are not mutually exclusive and should not be summed to 100 per cent. The qualitative coding is used for exploratory triangulation and is not presented as automated sentiment analysis or as a substitute for a full qualitative methodology.

4.4 Research Ethics

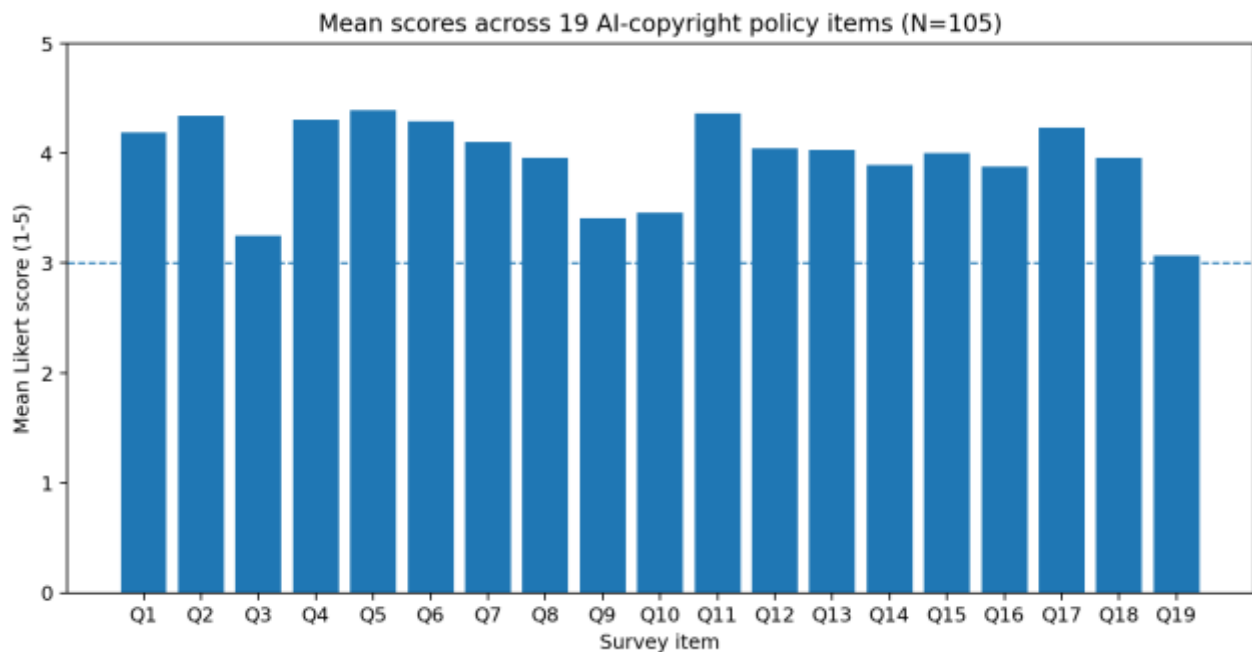
Participation in the survey was voluntary. The empirical component was designed to preserve respondent anonymity and to collect perceptions relevant to the research questions rather than

confidential commercial information. Responses were analysed in aggregate, and open-ended responses are reported through thematic categories rather than identification of individual participants. The underlying research documentation does not record a formal institutional ethics approval number; accordingly, no such approval is claimed in this paper.

5. Results

5.1 Overall pattern: regulated permission

Figure 1. Mean Likert scores across the 19 substantive items. Dashed line = neutral midpoint (3).



The ranking reveals a clear policy structure. Mandatory licensing (Q5) is the highest-scoring proposition (M=4.39; 85.7% agreement), followed by AI-specific legislative reform (Q11, M=4.36; 84.8%), legal prohibition of unauthorised training (Q2, M=4.34; 82.9%), training-data disclosure (Q4, M=4.30; 81.0%), creator compensation (Q6, M=4.29; 78.1%) and a dedicated regulator (Q17, M=4.23; 81.9%). Seventeen of the 19 items remain statistically distinguishable from neutrality after FDR correction. The exceptions are Q3, concerning adequacy of the present Copyright Act (M=3.25; adjusted $p=.074$), and Q19, concerning sufficiency of existing enforcement (M=3.07; adjusted $p=.598$). The defensible inference is not that the survey proves legal inadequacy, but that the sample provides no clear affirmative endorsement of the status quo.

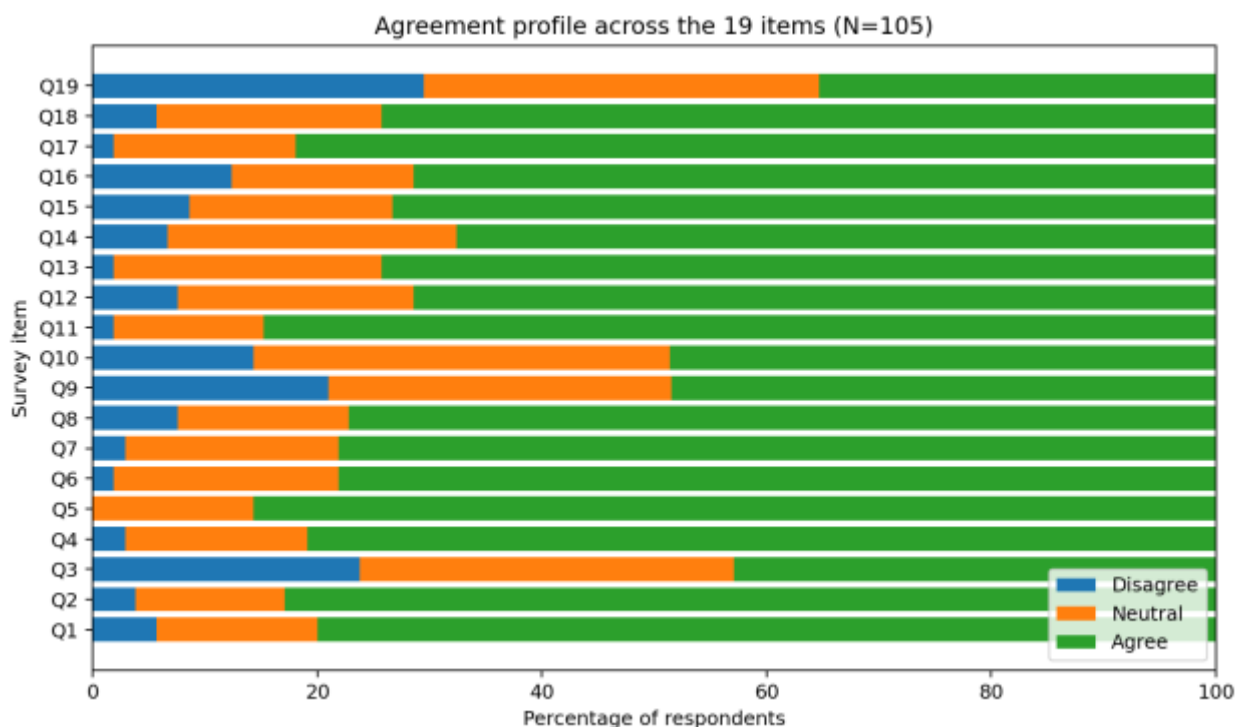
Table 2: Item-Level Likert Summary

Item	Short description	Mean	Agree %	Neutral %	Disagree %
Q1	Ethical wrongness	4.19	80.0	14.3	5.7
Q2	Desired legal prohibition	4.34	82.9	13.3	3.8
Q3	Current Act adequate	3.25	42.9	33.3	23.8
Q4	Training-data disclosure	4.30	81.0	16.2	2.9
Q5	Mandatory licensing	4.39	85.7	14.3	0.0
Q6	Creator compensation	4.29	78.1	20.0	1.9
Q7	Output resemblance concern	4.10	78.1	19.0	2.9

Item	Short description	Mean	Agree %	Neutral %	Disagree %
Q8	Research leniency	3.96	77.1	15.2	7.6
Q9	Trust in AI companies	3.41	48.6	30.5	21.0
Q10	Benefits outweigh risks	3.46	48.6	37.1	14.3
Q11	AI-specific legal reform	4.36	84.8	13.3	1.9
Q12	Licensing feasible in India	4.04	71.4	21.0	7.6
Q13	Small creators vulnerable	4.03	74.3	23.8	1.9
Q14	Professional/economic impact	3.89	67.6	25.7	6.7
Q15	Allow own work if compensated	4.00	73.3	18.1	8.6
Q16	Allow academic use uncompensated	3.88	71.4	16.2	12.4
Q17	Dedicated regulator	4.23	81.9	16.2	1.9
Q18	Transparency increases trust	3.96	74.3	20.0	5.7
Q19	Existing enforcement sufficient	3.07	35.2	35.2	29.5

5.2 Agreement, neutrality and disagreement

Figure 2. Agreement profile across all 19 survey items.



The distributional view reinforces the ranking. Q5 records no disagreement responses, making its consensus stronger than its high mean alone suggests. Q3 and Q19 contain substantial neutral and disagreeing shares, consistent with genuine uncertainty or division about current legal adequacy and enforcement. Q9 and Q10 are also comparatively dispersed, indicating that baseline corporate trust and

broad judgments about whether AI benefits outweigh copyright risks are materially less settled than the core reform mechanisms.

5.3 Four policy gaps

Adequacy-reform gap. Current Act adequacy (Q3, $M=3.25$) is substantially below demand for AI-specific reform (Q11, $M=4.36$), a paired difference of about 1.11 points (FDR $p<.001$). Respondents may not uniformly conclude that the existing Act is inadequate, yet they strongly favour a specific legislative response to AI training.

Licensing-feasibility gap. Mandatory licensing (Q5, $M=4.39$) exceeds confidence in practical licensing or royalty feasibility (Q12, $M=4.04$) by about 0.35 points (FDR $p=.002$). This is a critical design constraint: stakeholder legitimacy for licensing does not eliminate rights-identification, transaction-cost, valuation, cross-border and distribution problems.

Trust-transparency gap. Baseline trust in AI companies (Q9, $M=3.41$) is materially below the proposition that greater transparency would increase trust (Q18, $M=3.96$), a difference of about 0.55 points (FDR $p<.001$). Transparency therefore appears to have a legitimacy function in addition to its evidentiary role.

Regulator-enforcement gap. Support for a dedicated regulator (Q17, $M=4.23$) exceeds confidence in existing enforcement (Q19, $M=3.07$) by roughly 1.16 points (FDR $p<.001$). The survey does not identify the optimal institutional form, but it indicates demand for specialised capacity beyond reliance on ex post litigation alone.

5.4 Research flexibility and innovation

The sample is not simply hostile to AI. Q8, favouring more lenient treatment for genuine non-commercial research, reaches $M=3.96$ with 77.1% agreement. Q16, willingness to permit one's own work to be used without compensation for genuine academic research, reaches $M=3.88$ with 71.4% agreement. Q10, asking whether AI's societal benefits outweigh copyright risks, is positive but more modest ($M=3.46$). Strong creator-protection preferences therefore coexist with purpose-sensitive flexibility. The empirical pattern supports differentiated treatment rather than a universal rule applying identically to commercial foundation-model development and genuine academic research.

5.5 Reliability and exploratory structure

The broad rights-protection and regulatory-intervention scale comprises Q1, Q2, Q4, Q5, Q6, Q7, Q11, Q13, Q17 and Q18; it has Cronbach's $\alpha=.871$ and a mean score of approximately 4.22, indicating good internal consistency for exploratory research. For the broader reform-orientation index, Q3, Q9 and Q19 are reverse-coded while their raw item reporting remains unchanged; this index has $\alpha=.775$. The licensing-and-remuneration grouping comprises Q5, Q6, Q12 and Q15 and is more moderate ($\alpha=.688$), while the research-flexibility/innovation grouping comprises Q8, Q10 and Q16 and is weak ($\alpha=.389$), so it should not be treated as a single latent scale. For the 19-item correlation matrix, the KMO statistic is .854 and Bartlett's test of sphericity is significant (chi-square=830.6, $df=171$, $p<.001$), indicating sufficient shared covariance for exploratory dimensional inspection. These diagnostics are used descriptively and do not establish a validated or confirmatory factor structure; the 105-to-19 respondent-item ratio is too modest for strong confirmatory psychometric claims.

5.6 Professional groups and familiarity

Several professional-group comparisons have nominal p-values below .05 before correction, including disclosure, ethical wrongness, desired illegality, small-creator vulnerability and licensing. None survives FDR correction across the 19 professional-group tests. The more defensible result is therefore broad

cross-professional consensus on the principal regulatory propositions, not a stable 'developers versus creators' divide. Notably, software professionals in this sample are among the stronger supporters of licensing and disclosure.

Familiarity correlations are more nuanced. Greater self-rated familiarity with Indian copyright law is associated with somewhat greater trust in AI companies, greater perceived adequacy of the current Act, a more positive benefits-over-risks assessment, willingness to allow academic use and confidence in enforcement; it is negatively associated with desired illegality and mandatory licensing on some tests. Greater familiarity with LLM training is most strongly associated with willingness to permit uncompensated genuine academic research. These are cross-sectional associations and cannot establish causality, but they caution against treating regulatory disagreement as a simple product of ignorance.

5.7 Qualitative findings

The open-ended data independently reproduce several of the quantitative themes. Among 51 legal-reform narratives, transparency/disclosure was coded in 27.5%, ownership/authorship/attribution in 25.5%, AI-specific legal clarity or reform in 17.6%, licensing/permission/consent in 15.7%, human-centred protection in 13.7%, compensation/revenue sharing in 11.8%, accountability/specialised enforcement in 7.8% and international alignment in 7.8%. Because coding is multi-label, these percentages describe theme incidence rather than mutually exclusive categories.

Among 39 personal-experience narratives, a substantial group reported uncertainty about whether their work had been used for training. This uncertainty is analytically important: the inability to verify use mirrors the information asymmetry underlying demands for training-data transparency and provenance records. Responses also referenced written and creative content, software/code, attribution, ownership and confidentiality concerns.

The 44 risk-opportunity narratives reveal a dual rather than binary account. Job displacement or reduced opportunities was the most common risk theme (59.1%), followed by confidentiality/privacy/data-security concerns (27.3%). On the opportunity side, productivity/efficiency/automation appeared in 50.0%, faster research/drafting/coding/analysis in 38.6%, and accessibility in 18.2%. Participants therefore simultaneously recognise serious rights and labour concerns and substantial practical benefits.

6. Discussion

6.1 From prohibition to regulated permission

Taken together, the findings suggest a position that is more conditional than a simple rights-versus-innovation divide. Respondents strongly favour mechanisms that give creators greater legal and informational protection, but they also make room for genuine research and acknowledge benefits from AI. The phrase 'regulated permission' is used here to describe that combination: it refers to a preference for lawful access and accountability without treating all computational use as equivalent.

Licensing illustrates the difference between a normative preference and an implementable rule. Q5 records the highest level of support in the survey, yet confidence in the feasibility of a licensing or royalty system is lower. That difference is important. If India chooses a licensing-based route, the rule would still need workable answers on rights identification, repertoire coverage, rate setting, collective administration, cross-border uses and the distribution of payments. The survey therefore supports licensing as a policy direction more clearly than it supports any particular licensing mechanism.

Transparency raises a related point. Baseline trust in AI companies is modest, while respondents are considerably more positive about the proposition that transparency would increase trust. The policy

value of disclosure may therefore be practical as well as symbolic. Training-data information can assist licensing, rights reservation, auditing and dispute resolution. At the same time, disclosure rules would need to take account of legitimate trade-secret and security concerns. A useful approach may be to distinguish public-facing summaries from more detailed records available to regulators, auditors or courts when necessary [7, 9, 14].

6.2 Implications for India's current policy process

These findings arrive while India is actively considering both AI governance and the copyright treatment of model training [4, 5]. The survey does not resolve the doctrinal question of whether a particular act of training infringes copyright; that question depends on the facts and on the Copyright Act. What the survey adds is evidence about the kinds of regulatory mechanisms that this sample regards as legitimate or useful. It also shows that support for reform is stronger than confidence in the adequacy of the present framework.

Three implications follow from the data. Commercial training is the context in which respondents most clearly expect licensing, remuneration and disclosure. Research uses receive more accommodating treatment, which argues against applying identical compliance burdens to every form of computational analysis. Finally, the trust-transparency result suggests that information duties should be designed so that they can actually support provenance, verification and redress. This is consistent with the broader international shift toward copyright-compliance and training-content transparency obligations [7, 9, 14]. The subgroup results also deserve restraint. A few professional-category comparisons produce nominal p-values below .05, but none remains significant after FDR correction across the 19 tests. The data therefore do not support a strong claim that technology professionals and creative stakeholders form stable opposing camps. In this sample, support for several core interventions is shared across categories. A larger probability-based study would be needed before drawing stronger conclusions about profession-specific differences.

6.3 Comparison with emerging empirical literature

The Indian findings are broadly compatible with the emerging empirical literature, but the samples and questions are not directly comparable. Liang, Crosby and McKenzie show that Australian authors' willingness to permit AI training is associated with fairness perceptions and replacement risk, while compensation expectations vary with perceived economic threat [12]. Kyi and colleagues report that creative workers place substantial weight on consent, credit and compensation [13]. The present study extends that line of inquiry by using a multi-stakeholder Indian sample and by examining institutional questions such as statutory adequacy, enforcement, a dedicated regulator and the practical feasibility of licensing.

7. Policy Recommendations

1. Differentiate by purpose. The responses support more flexible treatment for genuine non-commercial or academic research than for commercial foundation-model development. Any Indian rule should preserve that distinction rather than assume that every computational use presents the same policy problem.
2. Treat licensing as an implementation problem as well as a legal rule. Because support for mandatory licensing is stronger than confidence in its feasibility, reform should address rights identification, standard licences, collective administration, rate setting, auditability, royalty distribution and the treatment of orphan or unidentifiable works.

3. Require proportionate training-data transparency. Developers should retain auditable information about major training-data sources and the legal basis relied upon for use. Public disclosure may appropriately operate at an aggregated level, while more detailed information could be available to regulators, auditors or courts where justified [9, 14].
4. Use transparency to support enforcement, not merely reporting. Disclosure requirements are most useful when they enable rights reservation, licensing, verification and dispute resolution. A formal transparency statement that cannot be connected to provenance or compliance records would have limited practical value.
5. Reduce transaction-cost disadvantages for smaller creators. Standard-form licensing, collective representation and accessible dispute-resolution mechanisms should be considered where individual negotiation is unrealistic. This is particularly relevant because respondents expressed concern about the vulnerability of small and independent creators.
6. Build specialised institutional capability. Whether this is achieved through an existing body or a new mechanism, copyright administration in the AI context will require technical as well as legal expertise. The survey's support for specialised oversight should be read as a demand for capability, not necessarily as proof that a new regulator is the only institutional solution.
7. Preserve lawful innovation and access. Reform should remain focused on copyright-relevant uses of protected expression. Public-domain material, openly licensed content and qualifying research uses should remain available, and copyright should not be expanded into a general right to control ideas, facts, methods or technological competition.

8. Limitations

The study is exploratory. The 105 respondents form a purposive/convenience sample and not a probability sample of India. National prevalence estimates, conventional population margins of error and statements that 'Indians believe' a proposition would therefore be inappropriate.

Self-selection may attract respondents with stronger views or greater interest in AI and copyright. Professional groups are unequal and modest in size, limiting subgroup power. Familiarity variables are self-rated. The cross-sectional design cannot establish causal relationships. Some legal propositions were simplified for accessibility, and survey preferences cannot substitute for statutory interpretation.

Likert responses are ordinal. Means are used as comparative summaries, but medians, distributions and non-parametric tests remain central. The open-ended coding is interpretive and multi-label. Finally, AI technology, litigation and Indian policy are developing rapidly; stakeholder attitudes may change following major judgments, legislation or licensing-market developments.

9. Conclusion

This study provides exploratory evidence on how a diverse Indian stakeholder sample views the copyright governance of generative-AI training. The clearest results concern licensing, legislative reform, disclosure, compensation and specialised oversight. By contrast, respondents do not give a clear affirmative endorsement to the adequacy of the present Copyright Act or to existing enforcement mechanisms. At the same time, the survey records substantial support for genuine academic and non-commercial research use.

The practical lesson is that the policy debate cannot end with a choice between 'permission' and 'exception'. Respondents may favour licensing, but they are less certain that a workable royalty system

can be implemented. They may have limited baseline trust in AI companies, yet they expect transparency to improve that trust. These differences point to implementation questions - rights identification, provenance, administration, disclosure and redress - that legislation would need to address if reform is to be effective.

The study has clear limits: it uses a purposive sample, measures perceptions rather than legal outcomes, and cannot establish national prevalence or causal relationships. Within those limits, it adds empirical evidence to an Indian debate that has so far been dominated by doctrinal and policy analysis. Further work with larger and more representative samples, together with testing of specific licensing and transparency models, would help determine which approaches are not only normatively attractive but workable in practice.

Conflict of Interest

The author declares that there is no conflict of interest in relation to the research, authorship, or publication of this paper. The research was conducted independently and was not sponsored or influenced by any individual, institution, organization, or commercial entity. The interpretation of the empirical findings and the conclusions presented in this paper are solely those of the author.

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The author remains solely responsible for the analysis, interpretation, arguments, conclusions, and any remaining errors in this paper.

14. References

1. Y. Benjamini, Y. Hochberg, "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing", Journal of the Royal Statistical Society: Series B, 1995, 57 (1), 289-300. <https://doi.org/10.1111/j.2517-6161.1995.tb02031.x>
2. V. Braun, V. Clarke, "Using Thematic Analysis in Psychology", Qualitative Research in Psychology, 2006, 3 (2), 77-101. <https://doi.org/10.1191/1478088706qp0630a>
3. Government of India, Copyright Act, 1957, especially sections 14, 51 and 52.
4. Ministry of Electronics and Information Technology, Government of India, "MeitY Unveils India AI Governance Guidelines under IndiaAI Mission to Ensure Safe, Inclusive, and Responsible Adoption of Artificial Intelligence across Sectors", Press Information Bureau, 5 November 2025. <https://www.pib.gov.in/PressReleasePage.aspx?PRID=2186639>

5. Department for Promotion of Industry and Internal Trade, Ministry of Commerce and Industry, Government of India, "Working Paper on Generative AI and Copyright: One Nation One License One Payment - Balancing AI Innovation and Copyright", December 2025. <https://www.dpiit.gov.in/static/uploads/2025/12/ff266bbeed10c48e3479c941484f3525.pdf>
6. K. de la Durantaye, "Control and Compensation: A Comparative Analysis of Copyright Exceptions for Training Generative AI", IIC - International Review of Intellectual Property and Competition Law, 2025, 56, 737-770. <https://doi.org/10.1007/s40319-025-01569-6>
7. J.P. Quintais et al., "Generative AI, Copyright and the AI Act", Computer Law & Security Review, 2025, 56, 106107. <https://doi.org/10.1016/j.clsr.2025.106107>
8. European Parliament and Council, Directive (EU) 2019/790 on Copyright and Related Rights in the Digital Single Market, 17 April 2019, especially Articles 3 and 4. <https://eur-lex.europa.eu/eli/dir/2019/790/oj/eng>
9. European Parliament and Council, Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence, 13 June 2024, especially Article 53. <https://eur-lex.europa.eu/eli/reg/2024/1689/oj/eng>
10. Singapore, Copyright Act 2021, especially sections 243-244 on computational data analysis. <https://sso.agc.gov.sg/Act/CA2021?ProvIds=pr243-,pr244->
11. F. Pasquale, H. Sun, "Consent and Compensation: Resolving Generative AI's Copyright Crisis", Virginia Law Review Online, 2024, 110, 207-247. <https://virginialawreview.org/articles/consent-and-compensation-resolving-generative-ais-copyright-crisis/>
12. S. Liang, P. Crosby, J. McKenzie, "Write Incentives? Authors' Sentiment on Generative AI", Applied Economics, published online 18 June 2026. <https://doi.org/10.1080/00036846.2026.2689494>
13. L. Kyi, A. Mahuli, M.S. Silberman, R. Binns, J. Zhao, A.J. Biega, "Governance of Generative AI in Creative Work: Consent, Credit, Compensation, and Beyond", Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, 2025, Article 197, 1-16. <https://doi.org/10.1145/3706598.3713799>
14. World Intellectual Property Organization, "Eleventh Session of the WIPO Conversation on Intellectual Property and Frontier Technologies: Copyright Infrastructure in the Age of Generative AI", Geneva, 23-24 April 2025. https://www.wipo.int/meetings/en/details.jsp?meeting_id=87571
15. World Intellectual Property Organization, "Generative AI: Navigating Intellectual Property", 2024. <https://www.wipo.int/edocs/pubdocs/en/wipo-pub-rn2024-8-en-generative-ai-navigating-intellectual-property.pdf>