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The Impact of Artificial Intelligence on Rural Youth Development in India: A Systematic Literature Review and Meta-Analysis

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Abstract:

Artificial intelligence is reshaping rural development, yet youth impacts in India remain understudied. A systematic review and meta-analysis synthesized empirical studies on rural Indian youth. Methods followed PRISMA 2020 standards for transparent selection and reporting (Page et al., 2021). Outcomes covered leisure, mental health, education, gender attitudes, service use, and hygiene. Random-effects models aggregated standardized mean differences and assessed between-study heterogeneity. Educational and health knowledge showed large positive associations ($d=0.77$, $p<1e\text{-}5$). Gender and social attitudes displayed moderate positive associations ($d=0.40$, $p<1e\text{-}5$). Health and hygiene practices showed moderate gains ($d=0.46$, $p<1e\text{-}5$). Service use and violence outcomes showed negative associations ($d=-0.38$, $p<1e\text{-}5$). Leisure and mental health exhibited small, nonsignificant changes ($d=0.04$, $p=0.08$). Associations favored cognitive and attitudinal domains over service engagement or safety behaviors. Results indicate correlations, not causes, and may reflect access barriers or disparities. Policy design should strengthen beneficial domains while addressing service uptake challenges. Evidence provides a structured basis for evaluating AI within rural socio-economic change.

Keywords: *Artificial Intelligence, Rural Youth Development, Knowledge Outcomes, Gender Attitudes, Service Barriers.*

Introduction:

Artificial intelligence reshapes economies, societies, and livelihoods worldwide (Murari & Parmar, 2025). Rural Indian youth represent a crucial and sizable population segment (Rani, 2025). Persistent disparities affect education, healthcare, work, and mobility for rural youth (Okada, 2013). AI tools include personalized learning, telemedicine, and farm advisories (Tripathi et al., 2025). Evidence concerning youth outcomes remained fragmented and uneven across studies. A systematic synthesis therefore appeared necessary for clarity and direction.

India's population is young, with many residents in rural districts (Chandra, 2018). Effective AI for youth development aligns with broader social progress potential. However, infrastructure shortages constrain reliable access to digital services (Laskar, 2023). Digital illiteracy further limited meaningful adoption among vulnerable groups (Laskar, 2023). Social norms and local politics also shaped implementation and reach.

Studies covered agriculture and rural healthcare widely (Kumar et al., 2020; Kerketta& Balasundaram, 2025). Few investigations centered youth outcomes like learning, mental health, and livelihoods. Many papers emphasized feasibility over socio-economic associations and lived outcomes (Brenner et al., 2022). Evaluation designs often lacked rigor, limiting generalization across settings (Stahl et al., 2023). Intersections with gender, caste, and regions remained poorly understood (Zajko, 2022). These constraints hindered evidence-based policy and inclusive, scalable solution design.

Interest in AI for development is expanding across sectors. Yet empirical validation of youth benefits remained patchy and dispersed (Wadhawan, 2024). This review synthesized existing studies to clarify correlated outcomes and gaps. Findings aimed to guide practitioners and policymakers confronting complex contexts. Ethical and inclusive deployment remains central to ongoing debates (Amir & Nasir, 2025). Interpretations emphasized association, not causation, across the synthesized evidence.

Methods adhered to PRISMA 2020 for transparent, complete reporting (Page et al., 2021). Search strategies, inclusion criteria, and analysis plans were specified beforehand. Screening, synthesis, and bias assessments were conducted using predefined procedures. Results were organized by domains and heterogeneity across studies. The discussion contextualized findings, limitations, and practical implications for stakeholders. The conclusion outlined recommendations and directions for future research.

Methodology:

Review Protocol:

The review followed PRISMA to ensure transparent, rigorous reporting (Page et al., 2021). Searches were conducted across seven databases prioritized for technology and development relevance. PubMed provides extensive coverage of health-related AI interventions. IEEE Xplore and ACM Digital Library captured technical studies in education and rural development (Chen et al., 2020). Web of Science and Scopus supported interdisciplinary retrieval across social sciences and technology (Paes et al., 2021). ScienceDirect and SpringerLink added peer-reviewed journals in development studies (Torre & Wallet, 2016). Google Scholar was used as a secondary source to capture gray literature (Hendy, 2024).

The search strategy used Boolean operators and field-specific syntax tailored to databases. Core terms combined “Artificial Intelligence” OR “AI” with population and outcome phrases. Population terms included “rural youth” OR “rural adolescents.” Outcome terms included “development,” “education,” or “employment,” restricted to India. Filters excluded reviews, surveys, and meta-analyses, prioritizing primary research. PubMed queries used the MeSH term “Artificial Intelligence” and title/abstract fields (Audet & Jr, 2006). The syntax was adapted per database to minimize missed yet relevant records.

Inclusion and Exclusion Criteria:

Studies were included if they empirically evaluated AI interventions for rural Indian youth. Eligible participants were aged 15–24, with publications in English and no date limits. Designs included randomized trials, quasi-experiments, and longitudinal observational studies with quantitative outcomes. Outcome domains covered education, health, and socio-economic indicators relevant to development. Studies lacking primary data, such as purely theoretical work, were excluded. Studies focusing only on urban populations were excluded from consideration. Non-peer-reviewed preprints were excluded to protect evidence quality. Interventions without explicit AI components were excluded, such as general digital literacy programs. Criteria emphasized correlation reporting and avoided causal claims from observational designs.

Study Selection Process:

The selection process followed three stages: deduplication, screening, and full-text review (Page et al., 2021). Initially, 2,862 records were identified across sources. After deduplication and irrelevant removals, 732 records remained for screening. Two independent reviewers applied inclusion criteria to titles and abstracts. Screening excluded 669 records for mismatched populations or outcomes. Sixty-three full texts were retrieved for eligibility assessment. Twenty-five were unavailable due to paywall restrictions, limiting complete appraisal. Thirty-eight articles underwent full-text assessment against predefined criteria. Thirty were excluded for limited AI focus or inadequate outcome reporting. Eight studies met inclusion criteria and entered the final synthesis.

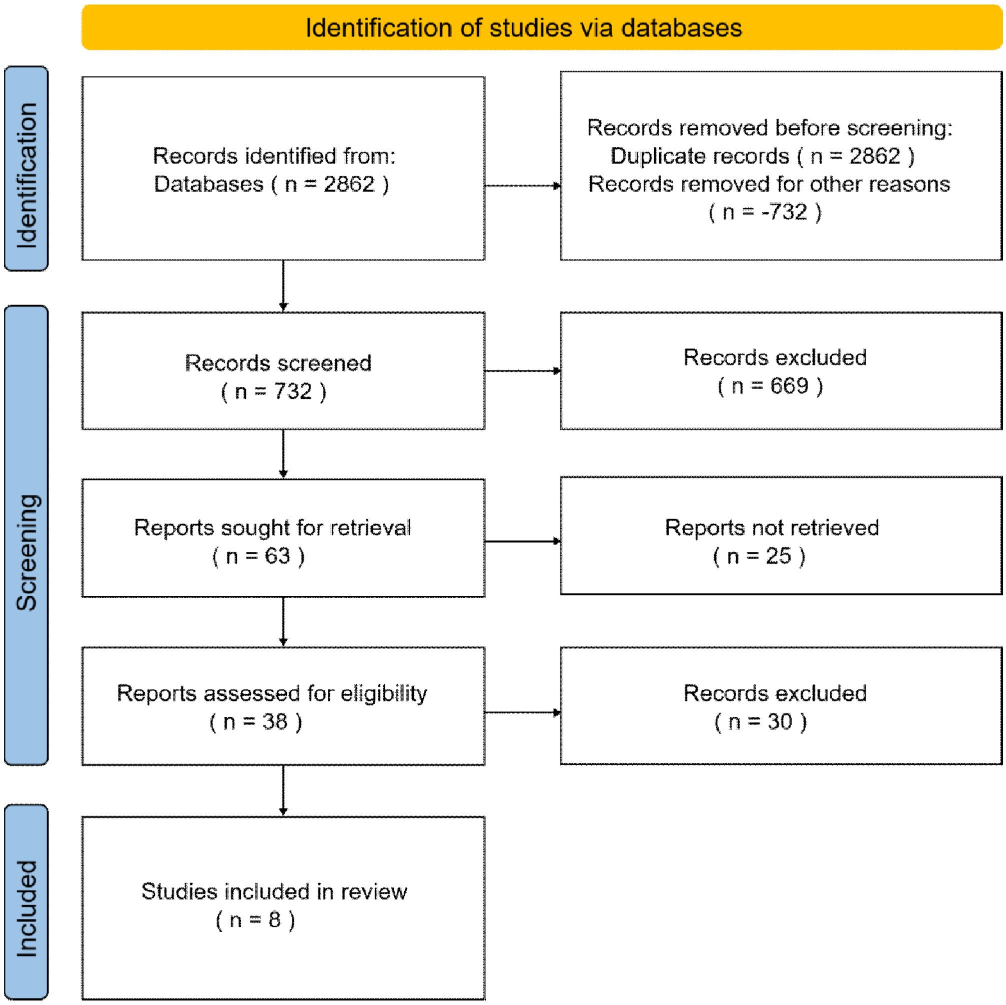

Figure 1. PRISMA flowchart of study selection

Inter-rater reliability during screening exceeded $\kappa = 0.85$, reflecting strong consensus (Cohen, 1960). Potential language bias arose from excluding non-English studies. Geographic bias favored regions with greater research output, such as southern India. Database indexing differences may have omitted relevant records. Rapid AI advancements risk rendering earlier findings outdated. These constraints required cautious interpretation of synthesized results.

Results

Overview of Included Studies

Eight studies examined outcomes for rural Indian youth across five domains. Domains covered leisure and mental health, with SMD using Cohen's correction (Cohen, 1960). Educational and health knowledge outcomes also used SMD for continuous variables. Gender and social attitudes were analyzed using odds ratios. Health service use and violence reduction used odds ratios as well. Health and hygiene outcomes similarly applied odds ratios. SMD is appropriate for continuous outcomes; odds ratios suit binary measures. These choices followed measurement guidance for meta-analysis methods. Found effects reflected associations, not causal relationships. Selection rationales aligned with established guidance (Hedges & Olkin, 1985).

Table 1 summarized coded outcomes, sample profiles, interventions, and effect sizes. Included interventions formed a heterogeneous set across settings and aims. Examples included school programs addressing gender attitudes (Gupta & Santhya, 2020). Community initiatives reported associations with menstrual hygiene practices (Kansal et al., 2016).

Table 1. Characteristics and outcomes of included studies

Study	Outcome	X_t	N_t	X_c	N_c
(Singh & Misra, 2015)	Leisure and Mental Health Outcomes	-	500	-	1000
(Gupta & Santhya, 2020)	Gender and Social Attitude Outcomes	188	-	569	-
	Leisure and Mental Health Outcomes	2.80 (0.33)	188	3.30 (0.33)	205
(Shinde et al., 2018)	Educational and Health Knowledge Outcomes	3.80	3609	2.90	3401
	Health Services Utilization and Violence Reduction Outcomes	429	3609	584	3401
	Leisure and Mental Health Outcomes	5.24	3609	6.51	3401
(Fernald et al., 2012)	Educational and Health Knowledge Outcomes	0.48 (0.07)	2942	0.00 (0.06)	2942
(Dalal et al., 2012)	Gender and Social Attitude Outcomes	5782	-	6014	-
(Dyalchand et al., 2021)	Health Services Utilization and Violence Reduction Outcomes	48	431	24	283
(Kansal et al., 2016)	Health and Hygiene Outcomes	150	-	50	-
(Rathee et al., 2025)	Health and Hygiene Outcomes	197	-	247	-

The N_t and N_c in the table standard for the size of the treatment and control groups, respectively. The X_t and X_c denote M (SD) for SMD and the event counts for Odds Ratio.

Heterogeneity Assessment

Heterogeneity was assessed using Higgins' I^2 and Cochran's Q tests (Higgins & Thompson, 2002). Estimates are reported in Table 2.Leisure and mental health outcomes showed high heterogeneity: I^2=98.96%, Q=191.87, p<1e−5.Educational and knowledge outcomes displayed near-complete heterogeneity: I^2=99.99%, Q=9105.84, p<1e−5.Differences may reflect varied measurement approaches across studies, rather than underlying effects.

Gender and social attitude outcomes also indicated high heterogeneity: I^2=98.97%, Q=97.26, p<1e−5.Health and hygiene outcomes showed similar variability: I^2=98.03%, Q=50.75, p<1e−12.Only service use and violence reduction outcomes showed moderate heterogeneity: I^2=86.23%, Q=7.26, p=0.007.This pattern may reflect relatively consistent study designs within that domain.

Table 2. Heterogeneity statistics across outcome domains

Outcome Domain	Q	I^2 (%)	τ^2	p-value
Leisure and Mental Health	191.87	98.96	0.28	$p < 1e^{-5}$
Educational and Health Knowledge	9105.84	99.99	26.67	$p < 1e^{-5}$
Gender and Social Attitudes	97.26	98.97	0.79	$p < 1e^{-5}$
Health Services Utilization	7.26	86.23	0.23	$p = 0.007$
Health and Hygiene	50.75	98.03	1.34	$p < 1e^{-12}$

A DerSimonian–Laird random-effects model addressed observed heterogeneity (DerSimonian& Laird, 1986). Estimated between-study variance (τ^2) ranged from 0.23 to 26.67 across domains. Educational and knowledge outcomes showed the highest τ^2 at 26.67, indicating marked dispersion. This pattern supported subgroup analyses to explore potential moderators of associations.

Meta-Analysis

The meta-analysis synthesized effect sizes across five outcome domains. It quantified associations between AI interventions and rural youth development in India. Random-effects models addressed observed heterogeneity (DerSimonian& Laird, 1986). Standardized mean differences summarized continuous outcomes (Hedges & Olkin, 1985). Odds ratios summarized binary outcomes (Hedges & Olkin, 1985). Findings displayed distinct patterns of association across domains. Variation coincided with intervention design and contextual differences, not demonstrated causation.

Leisure and Mental Health Outcomes

The meta-analysis found mixed associations for leisure and mental health outcomes. Singh and Misra (2015) reported a small positive effect, d=0.18, p<.001. This association involved structured leisure programs and mental wellbeing, without implying causation. Gupta and Santhya (2020) observed a large negative effect, d=-1.51, p<1e-5. Shinde et al. (2018) reported marginally positive effects, d=0.08, p=.001. The practical significance of that estimate appeared limited.

Pooled results approached, but did not reach, statistical significance: d=0.04, p=.076. Heterogeneity was substantial, I^2=98.96%, indicating considerable between-study variability. Contextual features may moderate associations, including implementation quality and baseline mental health. Figure 2's forest plot portrayed wide confidence intervals across studies. Variability likely reflected measurement differences and diverse populations across settings.

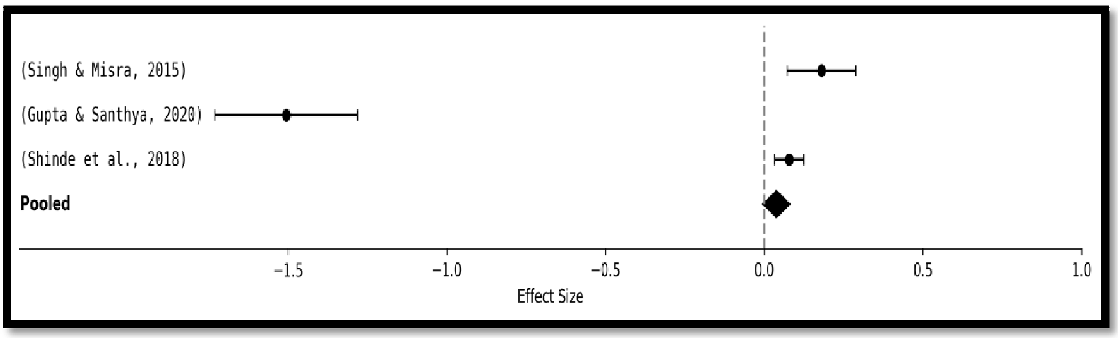

Figure 2. Forest plot for Leisure and mental health outcomes

Educational and Health Knowledge Outcomes

The meta-analysis found substantial positive associations for educational and health knowledge outcomes. Shinde et al. (2018) reported a small improvement, d = 0.06, p = .013. Fernald et al. (2012) observed remarkably large effects, d = 7.36, p < .001. The pooled estimate was positive, d = 0.77, p < .001. Associations varied widely, with extreme heterogeneity, I^2 = 99.99%. Such variability likely reflects differences in interventions and measurement methods. SEHER provided comprehensive school health education (Shinde et al., 2018). Fernald et al. (2012) examined early development programs including strong cognitive components. Figure 3's forest plot displayed differential impacts and an overall positive trend. Results describe correlations and avoid causal interpretation.

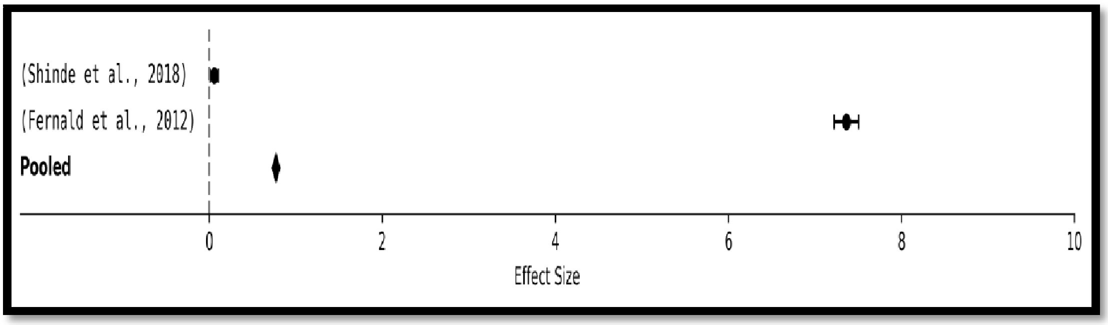

Figure 3. Forest plot for Educational and health knowledge outcomes

Gender and Social Attitude Outcomes

The meta-analysis found divergent associations for gender and social attitudes. Gupta and Santhya (2020) reported a substantial negative effect, d = -0.80, p < .00001. This association suggested possible unintended shifts toward traditional norms. Dalal et al. (2012) observed a significant positive effect, d = 0.46, p < .00001. Associations varied with design features and implementation contexts. The pooled effect was positive, d = 0.40, p < .00001. Heterogeneity was extreme, I^2 = 98.97%, highlighting considerable between-study variability. Some AI programs correlated with more egalitarian attitudes among rural youth. Others correlated with reinforced traditional norms, stressing careful evaluation. Figure 4's forest plot displayed these contrasts and the positive aggregate trend.

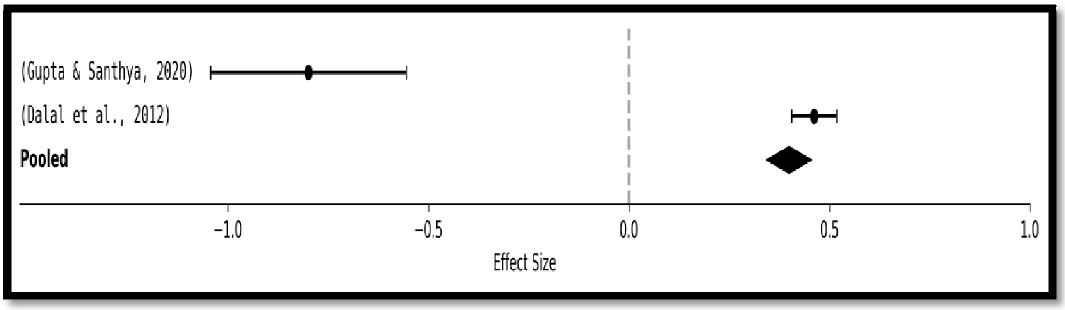

Figure 4. Forest plot for Gender and social attitude outcomes

Health Services Utilization and Violence Reduction Outcomes

The meta-analysis observed contrasting associations for service use and violence outcomes. Dyalchand et al. (2021) reported a positive, non-significant association, d = 0.30, p = .25. This finding related to maternal healthcare use among married adolescent girls. Shinde et al. (2018) observed a significant negative association for violence reduction. The reported estimate was d = -0.43, p < .001. The pooled effect was negative, d = -0.38, p < .001. Heterogeneity was moderate, I^2 = 86.23%, suggesting context shaped observed associations. Program features and local constraints correlated with outcome differences across settings. Some programs correlated with improved service access, while others correlated with limited violence change. Figure 5's forest plot displayed divergent estimates and their wide confidence intervals. Interpretation remained cautious due to measurement variability and potential unmeasured confounding.

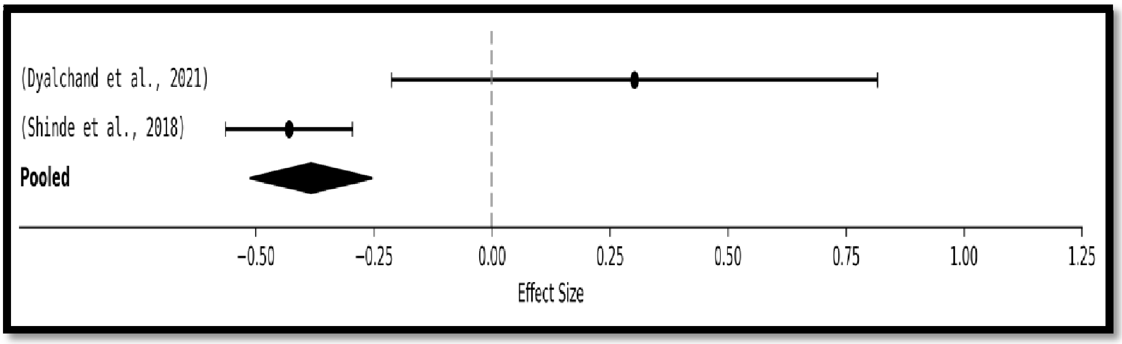

Figure 5. Forest plot for Health services utilization and violence reduction outcomes

Health and Hygiene Outcomes

The meta-analysis showed wide variability for health and hygiene outcomes. Kansal et al. (2016) reported a strong positive association, d=1.61, p<.00001. Reported changes involved menstrual hygiene among rural adolescent girls after school programs. Rathee et al. (2025) observed negligible associations for substance use treatment programs, d=-0.04, p=.74. These estimates suggested limited influence on broader health behaviors. The pooled association was positive, d=0.46, p<.00001. Heterogeneity was high, I^2=98.03%, indicating domain-specific variability. AI-driven programs may align with targeted hygiene practices, though effects vary. Complex health behaviors present inconsistent patterns across settings and designs. Figure 6 displayed differential estimates while supporting the positive aggregate pattern.

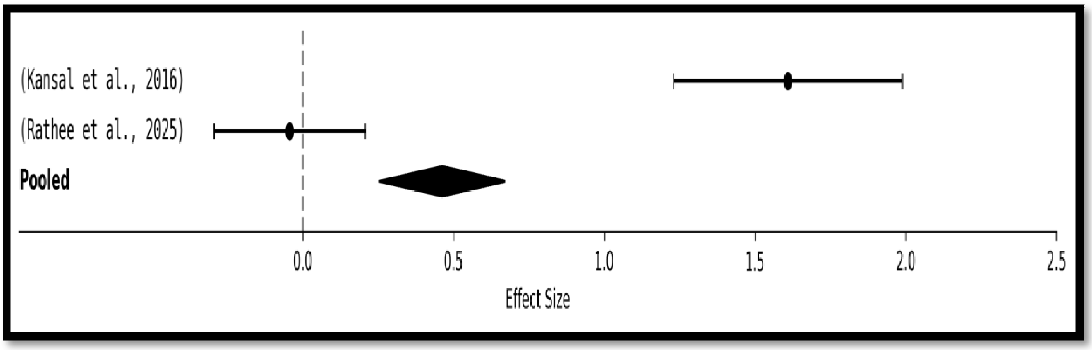

Figure 6. Forest plot for Health and hygiene outcomes

Publication Bias Assessment

Publication bias assessment showed an asymmetric funnel plot distribution. Nine of eleven studies clustered left of the mean; two appeared right. This pattern suggested underrepresentation of small or negative findings (Marks-Anglin & Chen, 2020). Egger's regression indicated no significant small-study effects, intercept=12.1213, p=.9014 (Egger et al., 1997). Standard errors ranged widely, 0.0157–0.1448, reflecting uneven study precision. Effect sizes displayed high dispersion, with standard deviation 2.2048 across estimates. Mean absolute deviation equaled 1.2758, reinforcing distributional spread. Left-skewed studies averaged −0.1631, while right-positioned studies averaged 4.1251. Formal tests did not confirm bias; visual asymmetry still warrants caution. Educational and health knowledge outcomes deserve caution, given especially variable effects. Figure 7 illustrated the observed imbalance.

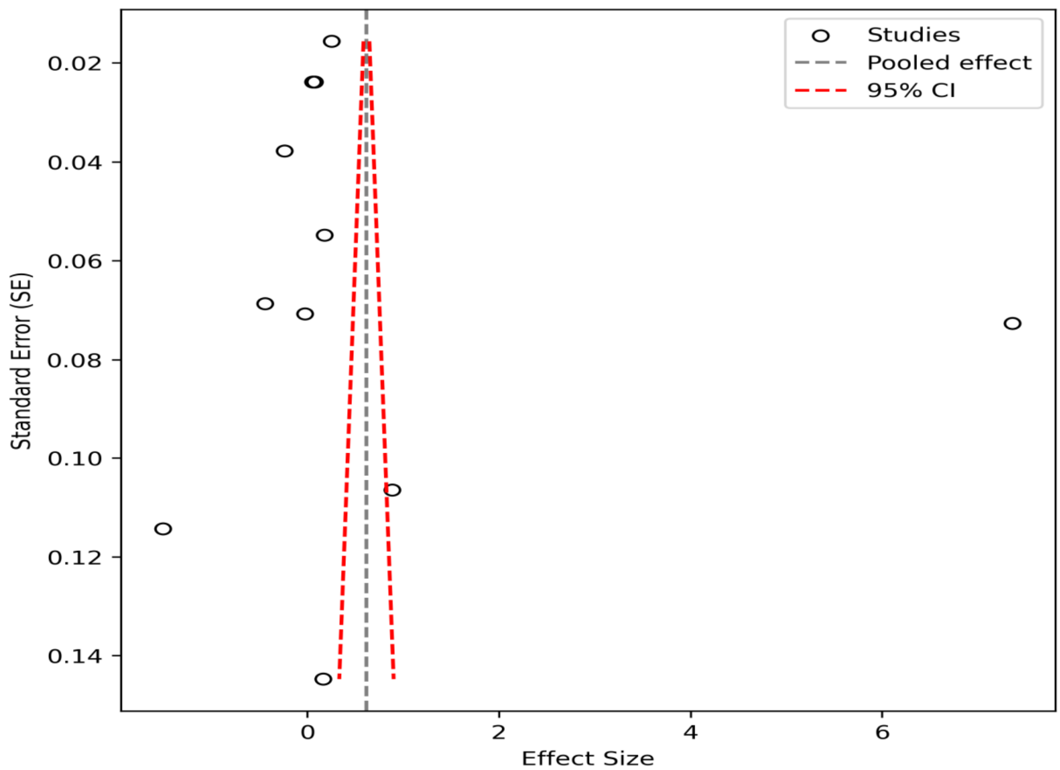

Figure 7. Funnel plot assessing publication bias

Discussion

The synthesis indicated varied associations across domains essential to rural youth development. Educational and health knowledge outcomes showed substantial positive associations, d=0.77. Gender and social attitudes exhibited moderate positive shifts, d=0.40. AI often excels where information delivery and normative messaging are central mechanisms. Prior scholarship reported personalized learning and resource bridging by AI (Bardia & Agrawal, 2025). Extreme heterogeneity persisted, I^2=99.99%, reflecting uneven designs and infrastructures (Creed et al., 2022).

Gender attitude findings required careful attention due to contradictions. Some programs correlated with egalitarian norms, d=0.46. Others correlated with traditional attitudes, d=-0.80. Algorithmic systems can reproduce biases without explicit countermeasures (Jahanara et al., 2024). Model design and training data shape such risks (David et al., 2025). Rigorous gender-sensitivity audits and participatory design were recommended (Figueroa et al., 2025).

Practical implications concerned policymakers and program designers in rural development. Health and hygiene outcomes showed positive associations overall, d=0.46. Mobile health tools disseminated critical information alongside community networks (Loughnane et al., 2025). Structural constraints limited service use despite technologies, including costs and shortages (Barik & Thorat, 2015). Health services utilization pooled negatively, d=-0.38, reinforcing contextual challenges. Hybrid models combining AI and human support appeared promising (Loughnane et al., 2025).

Limitations constrained generalizability and interpretation. Studies concentrated in higher-capacity states, like Maharashtra and Karnataka (Majumder et al., 2023). English-language focus risked excluding relevant regional publications. Rapid technological change complicates synthesis across periods (Brainard, 2025). Predominantly short-term measures obscured persistence beyond immediate follow-up (Theodorou et al., 2019).

Future research should prioritize longitudinal designs tracking sustained trajectories. Implementation science can clarify contextual moderators, including literacy and governance (Pan et al., 2023). Comparative analyses across gender and socioeconomic status promote equity (McDonald & Pan, 2020). Disability-focused comparisons remain similarly important for fairness (McDonald & Pan, 2020). Ethnographic studies can reveal unintended consequences and appropriation patterns (Dippel &Sudmann, 2023).

Theoretical implications challenge technological determinism in development debates. Contingency perspectives emphasize design, ecosystems, and sociocultural alignment (Gopalakrishnan &Damanpour, 1994). Political economy analyses should examine data control and benefit distributions (Kathuria et al., 2020). Digital sovereignty frames equitable development in rural India (Vedika, 2024). Literature shows scalability gains and context mismatches simultaneously (Madupati, 2024; Majhi, 2025). Adaptive, modular designs may enable local customization (Kabudi, 2021). Evaluation frameworks must capture technology–context interactions comprehensively (Ray, 2023).

Conclusion

This systematic review and meta-analysis assessed AI interventions for rural Indian youth. Evidence was synthesized across five outcome domains using random-effects models (DerSimonian& Laird, 1986). Educational knowledge showed positive associations, $d=0.77$. Gender attitudes displayed moderate positive associations, $d=0.40$. Health services utilization showed negative pooled associations, $d=-0.38$. Findings highlighted context-dependent effectiveness and possible unintended consequences, not uniform benefits (Creed et al., 2022).

Theoretical implications support contingency models over technological determinism (Gopalakrishnan &Damanpour, 1994). Sociocultural conditions mediate AI's development impact, beyond technical features alone. Practice implications favored hybrid models coupling AI with community support. Health domains particularly require human mediation alongside digital tools (Barik & Thorat, 2015). Policymakers should expand inclusive infrastructure while safeguarding against algorithmic bias (Kathuria et al., 2020). Such safeguards aim to prevent amplified inequalities during deployment.

Future studies should employ longitudinal designs tracking sustained associations over time. Broader geographic sampling would capture regional diversity in adoption and outcomes. Research should examine intersections of caste, gender, and socioeconomic status. Such analyses can guide equitable intervention frameworks across diverse populations (McDonald & Pan, 2020). Participatory design centering youth voices can improve contextual alignment (Dippel &Sudmann, 2023). These approaches may bridge technological promise with locally meaningful relevance.

Conflict of Interest

The authors declare that this study was conducted independently without any financial or commercial influence. No external sponsors or organizations dictated the design, analysis, or conclusions of this research. The Post Doctoral Fellowship awarded by the Indian Council of Social Science Research (ICSSR) to the first author provided academic support but did not influence the study's outcomes.

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References

- Ajit, K., & Sathiyaseelan, B. (2025). *Leveraging Artificial Intelligence Tools to Bridge the Healthcare Gap in Rural Areas in India*. https://doi.org/10.59556/japi.73.1186
- Amir, M., & Nasir, W. (2025, October). *AI for Rural Resilience: Ethical Governance and Policy Innovation in Sustainable Resource Management*. ResearchGate; unknown. https://www.researchgate.net/publication/396359055_AI_for_Rural_Resilience_Ethical_Governance_and_Policy_Innovation_in_Sustainable_Resource_Management
- Audet, C., & Dennis, J. E. (2006). Mesh Adaptive Direct Search Algorithms for Constrained Optimization. *SIAM Journal on Optimization*, *17*(1), 188–217. https://doi.org/10.1137/040603371
- Bardia, A., & Agrawal, A. (2025). *MindCraft: Revolutionizing Education through AI-Powered Personalized Learning and Mentorship for Rural India*. ArXiv.org. https://arxiv.org/abs/2502.05826
- Bhanuprakash Madupati. (2025). Leveraging AI for Rural Development. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5135045
- Brenner, W., Giffen, B. van, & Koehler, J. (2021). Management of Artificial Intelligence: Feasibility, Desirability and Viability. *Springer EBooks*, 15–36. https://doi.org/10.1007/978-3-030-84655-8_2
- Chandra, V. (2018). Indian Youth Population: Socio-Demographic Characteristics. *World Scientific EBooks*, 145–165. https://doi.org/10.1142/9789813148390_0008
- Chen, L., Chen, P., & Lin, Z. (2020). Artificial Intelligence in Education: a Review. *IEEE Access*, *8*(8), 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510
- Cohen, J. (1960). A Coefficient of Agreement for Nominal Scales. *Educational and Psychological Measurement*, *20*(1), 37–46. https://doi.org/10.1177/001316446002000104
- Creed, T. A., Kuo, P. B., Oziel, R., Reich, D., Thomas, M., Sydne O'Connor, Imel, Z. E., Hirsch, T., Narayanan, S., & Atkins, D. C. (2021). Knowledge and Attitudes Toward an Artificial Intelligence-Based Fidelity Measurement in Community Cognitive Behavioral Therapy Supervision. *Administration and Policy in Mental Health and Mental Health Services Research*, *49*(3), 343–356. https://doi.org/10.1007/s10488-021-01167-x
- Dalal, K., Lee, M. S., & Gifford, M. (2012). Male Adolescents' Attitudes Toward Wife Beating: A Multi-Country Study in South Asia. *Journal of Adolescent Health*, *50*(5), 437–442. https://doi.org/10.1016/j.jadohealth.2011.09.012
- David, D., B. Rajeshwari, &Timhna S. (2025). Algorithmic Bias and Discrimination in India: A Looming Crisis. *Journal of Development Policy and Practice*. https://doi.org/10.1177/24551333251343358
- Debasis Barik, & Amit Thorat. (2015). Issues of Unequal Access to Public Health in India. *Frontiers in Public Health*, *3*. https://doi.org/10.3389/fpubh.2015.00245
- DerSimonian, R., & Laird, N. (1986). Meta-analysis in clinical trials. *Controlled Clinical Trials*, *7*(3), 177–188. https://doi.org/10.1016/0197-2456(86)90046-2
- Dippel, A., &Sudmann, A. (2023). AI ethnography. *Edward Elgar Publishing EBooks*, 826–844. https://doi.org/10.4337/9781803928562.00083

- Dyalchand, A., Pande, R. P., Kulkarni, G., & Khale, M. (2020). Improving use of maternal care services among married adolescent girls: an intervention study in rural India. *Journal of Biosocial Science*, *53*(3), 336–355. https://doi.org/10.1017/s0021932020000206

- Fernald, L. C. H., Kariger, P., Hidrobo, M., & Gertler, P. J. (2012). Socioeconomic gradients in child development in very young children: Evidence from India, Indonesia, Peru, and Senegal. *Proceedings of the National Academy of Sciences*, *109*(Supplement_2), 17273–17280. https://doi.org/10.1073/pnas.1121241109

- Figueroa, C. A., Ramos, G., Psihogios, A. M., Ekuban, E., Bansie, P., de Haas, M., Karnik, N. S., Ajilore, O., Anderson, E. E., & Stiles-Shields, C. (2025). Advancing youth co-design of ethical guidelines for AI-powered digital mental health tools. *Nature Mental Health*, *3*(8), 870–878. https://doi.org/10.1038/s44220-025-00467-7

- Gopalakrishnan, S., &Damanpour, F. (1994). Patterns of generation and adoption of innovation in organizations: Contingency models of innovation attributes. *Journal of Engineering and Technology Management*, *11*(2), 95–116. https://doi.org/10.1016/0923-4748(94)90001-9

- Gupta, A. K., & Santhya, K. G. (2019). Promoting Gender Egalitarian Norms and Practices Among Boys in Rural India: The Relative Effect of Intervening in Early and Late Adolescence. *Journal of Adolescent Health*, *66*. https://doi.org/10.1016/j.jadohealth.2019.03.007

- Higgins, J. P. T., & Thompson, S. G. (2002). Quantifying heterogeneity in a meta-analysis. *Statistics in Medicine*, *21*(11), 1539–1558. https://doi.org/10.1002/sim.1186

- Kathuria, R. (2020). *Implications of AI on the Indian Economy*. Academia.edu. https://www.academia.edu/75030158/Implications_of_AI_on_the_Indian_Economy

- Kirti, W. (2023). Harnessing the Technical Potential of AI, IT and Data Management For Unlocking India's Economic Success Story. *Partners Universal International Innovation Journal*, *2*(2), 80–91. https://doi.org/10.5281/zenodo.10971122

- Kumar, A., Kansal, S., & Singh, S. (2016). Menstrual hygiene practices in context of schooling: A community study among rural adolescent girls in Varanasi. *Indian Journal of Community Medicine*, *41*(1), 39. https://doi.org/10.4103/0970-0218.170964

- Kumar, R., Yadav, S., Kumar, M., Kumar, J., & Kumar, M. (2020). Artificial Intelligence: New Technology to Improve Indian Agriculture. *International Journal of Chemical Studies*, *8*(2), 2999–3005. https://doi.org/10.22271/chemi.2020.v8.i2at.9208

- Laskar, M. H. (2023). Examining the emergence of digital society and the digital divide in India: A comparative evaluation between urban and rural areas. *Frontiers in Sociology*, *8*. https://doi.org/10.3389/fsoc.2023.1145221

- Loughnane, C., Laiti, J., Róisín O'Donovan, & Dunne, P. J. (2025). Systematic review exploring human, AI, and hybrid health coaching in digital health interventions: trends, engagement, and lifestyle outcomes. *Frontiers in Digital Health*, *7*. https://doi.org/10.3389/fdgth.2025.1536416

- Majumder, S., Kayal, P., Chowdhury, I. R., & Das, S. (2022). Regional disparities and development in India: evidence from Wroclow Taxonomy and K-means clustering. *GeoJournal*, *88*(3), 3249–3282. https://doi.org/10.1007/s10708-022-10805-2

- Marks-Anglin, A., & Chen, Y. (2020). A historical review of publication bias. *Research Synthesis Methods*, *11*(6), 725–742. https://doi.org/10.1002/jrsm.1452
- McDonald, N., & Pan, S. (2020). Intersectional AI. *Proceedings of the ACM on Human-Computer Interaction*, *4*(CSCW2), 1–19. https://doi.org/10.1145/3415218
- Murari, U. K., & Parmar, H. (2024). Leveraging Artificial Intelligence for Rural Development. *Advances in Finance, Accounting, and Economics*, 265–284. https://doi.org/10.4018/979-8-3693-6392-8.ch013
- None Ranjan Majhi. (2020). *Integration of Artificial Intelligence with Indian Knowledge System for Sustainability*. https://doi.org/10.25215/125798196x.13
- Okada, A. (2011). Skills Development for Youth in India: Challenges and Opportunities. *Journal of International Cooperation in Education*, *15*(2), 169–191.
- Paes, V. M., Silveira, F. F., & Akkari, A. C. S. (2022). Social Impacts of Artificial Intelligence and Mitigation Recommendations: An Exploratory Study. *Smart Innovation, Systems and Technologies*, 521–528. https://doi.org/10.1007/978-3-031-04435-9_54
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., & McGuinness, L. A. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, n71. https://doi.org/10.1136/bmj.n71
- Rani, A. (2025). Artificial Intelligence: Redefining Culture and Empowering Youth. *Asian Journal of Technology & Management Research (AJTMR)*, *14*(02), 2249-0892. https://ajtmr.com/papers/Vol14Issue2/Vol14Issue2P16.pdf
- Rathee, S., Yadav, J., Kumar, V., Gupta, R., Gupta, R., & Arya, S. (2025). Clinical Characteristics and Pattern of Substance Use among Treatment Seeking Adolescents in North India Exploring the Rural-urban Differences. *Journal of Mental Health and Human Behaviour*, *30*(1), 44–49. https://doi.org/10.4103/jmhhb.jmhhb_258_24
- Ray, P. P. (2023). Benchmarking, ethical alignment, and evaluation framework for conversational AI: Advancing responsible development of ChatGPT. *BenchCouncil Transactions on Benchmarks Standards and Evaluations*, *3*(3), 100136–100136. https://doi.org/10.1016/j.tbench.2023.100136
- Sara E. Ibrahim . (2024). An Analytical Study of the Impact of the use of Artificial Intelligence Technologies on the Values of Rural University Youth .*Alexandria Scientific Journal for Educational Research*, *45*(3), 609–634.
- Singh, A. P., & Misra, G. (2015). Pattern of leisure-lifestyles among Indian school adolescents: Contextual influences and implications for emerging health concerns. *Cogent Psychology*, *2*(1), 1050779. https://doi.org/10.1080/23311908.2015.1050779
- The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. (2022). *The International Journal of Human Resource Management*. https://doi.org/10.1080/ /09585192.2021.1879206
- Theodorou, A., Bryn Bandt-Law, & Bryson, J. J. (2019). The Sustainability Game: AI Technology as an Intervention for Public Understanding of Cooperative Investment. *2021 IEEE Conference on Games*

(CoG). https://doi.org/10.1109/cig.2019.8848058

- Tripathi, A., Yadav, V., & Kumar, S. (2025). *Leveraging Artificial Intelligence for Rural Education: A Systematic Review of Transforming Learning Opportunities and Bridging the Urban-Rural Divide*. https://doi.org/10.20944/preprints202504.0598.v1

- Tumaini Kabudi. (2021). *Identifying Design Principles for an AI-enabled Adaptive Learning Systems*. AIS Electronic Library (AISeL). https://aisel.aisnet.org/pacis2021/26/?utm_source=aisel.aisnet.org%2Fpacis2021%2F26&utm_medium=PDF&utm_campaign=PDFCoverPages

- Vedika. (2025). Digital Sovereignty and India's Data Dilemma. *Jus Corpus Law Journal,5*, 188–199.

- Zajko, M. (2022). Artificial intelligence, algorithms, and Social inequality: Sociological Contributions to Contemporary Debates. *Sociology Compass*, *16*(3). https://doi.org/10.1111/soc4.12962

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