Digital Lead Generation, Lead Quality, Conversion, and Perceived Sales Revenue Outcomes: Evidence from an Indian EdTech Firm

Dr. K.G. Senthilkumar[1], Ms. B. Srimathi[2]

[1]Professor, Department of Management Studies, KGiSL Institute of Technology, Coimbatore, Tamil Nadu, India

[2]Department of Management Studies, KGiSL Institute of Technology, Coimbatore, Tamil Nadu, India

DOI: https://doi.org/10.51244/IJRSI.2026.1310000193

Received: 26 October 2026; Accepted: 31 October 2026; Published: 13 November 2026

ABSTRACT

Digital lead generation has become central to customer acquisition in EdTech, yet high enquiry volume does not necessarily translate into qualified leads, conversion, or revenue-related outcomes. This study examines the relationships among digital channel activity, lead quality, conversion, and perceived sales revenue outcomes in a Indian EdTech firm. A quantitative, cross-sectional survey was conducted with 165 employees and customer-facing staff from sales, digital marketing, marketing, CRM/customer support, and related functions using a 26-item five-point Likert instrument. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to assess the measurement and structural models. The reported measurement model showed acceptable convergent and discriminant validity (AVE = 0.51–0.64; composite reliability = 0.81–0.89; construct reliability α = 0.77–0.84; maximum HTMT = 0.84). Harman's single-factor result (29.8%) indicated that no single factor dominated the item variance, although this test alone cannot rule out common-method bias. Digital Channels were positively associated with Lead Quality ($\beta = 0.518$, $p < 0.001$), Lead Quality with Conversion ($\beta = 0.482$, $p < 0.001$), and Conversion with Perceived Sales Revenue Outcomes ($\beta = 0.601$, $p < 0.001$). The direct Digital Channels→Perceived Sales Revenue path was not significant ($\beta = 0.092$, $p = 0.194$). The model explained 41.3% of the variance in Lead Quality, 36.7% in Conversion, and 58.6% in Perceived Sales Revenue Outcomes. Supplementary analyses showed no significant age-based variation in perceived sales performance. Experience was associated with responses to a lead-quality/conversion item, but this should not be interpreted as statistical moderation. The findings suggest that qualifying enquiries and managing conversion warrant greater attention than lead volume alone. They contribute a stage-separated interpretation of the digital acquisition funnel and practical priorities for source-level tracking, responsible CRM follow-up and sustainable channel spending. Because the supplied indirect-effect statistics were internally inconsistent with the reported path coefficients, formal mediation is not claimed in this revised article pending verification of the original SmartPLS output.

Keywords: Digital Lead Generation; Edtech; Lead Quality; Conversion; Perceived Sales Revenue; PLS-SEM; Digital Marketing; India

INTRODUCTION

India's EdTech sector has expanded alongside rising smartphone adoption, internet connectivity, digital learning acceptance, and demand for flexible higher education and professional certification. Reviews of the Indian EdTech ecosystem identify digital infrastructure and changing learning behaviour as major growth drivers while also noting regulatory, accessibility, and business-model challenges (Bajaj & Mathur, 2022; Bansal, Pophalkar, & Vidani, 2023). Digital marketing has therefore become an important mechanism for attracting prospective learners, creating engagement, and supporting customer acquisition.

A central managerial problem is that digital reach and lead volume are not equivalent to commercial value. A campaign may generate traffic or enquiries but still produce weak buying intent or low conversion. In the Indian education vertical, Naveen Kumar and Hariharanath (2021) demonstrate the value of distinguishing

qualified from unqualified prospects through lead scoring. González-Flores, Rubiano-Moreno, and Sosa-Gómez (2025) likewise show that lead-source and engagement information can improve the prioritisation of prospects with greater conversion potential. These findings imply that digital-channel performance should be evaluated across the funnel rather than at the enquiry stage alone.

The present study examines this problem in an Indian EdTech firm using employee and customer-facing staff perceptions of digital channel effectiveness, lead quality, conversion, and revenue-related outcomes. The study does not use audited financial revenue by channel; accordingly, the dependent construct is described throughout as Perceived Sales Revenue Outcomes. The study evaluates a sequential structural logic in which Digital Channels are associated with Lead Quality, Lead Quality with Conversion, and Conversion with Perceived Sales Revenue Outcomes.

THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Theoretical Foundations

The study is informed by the hierarchy-of-effects perspective and the Resource-Based View (RBV). Lavidge and Steiner's (1961) hierarchy-of-effects framework conceptualises advertising response as a progression from cognitive awareness and knowledge through affective evaluation toward behavioural purchase. Applied to digital customer acquisition, the framework supports treating channel exposure, lead qualification, conversion, and purchase/revenue outcomes as related but distinct stages rather than as a single outcome.

RBV proposes that sustained performance differences can arise from valuable organisational resources and capabilities (Barney, 1991). Day (1994) extends this logic to market-driven capabilities, including market sensing and customer linking. Digital marketing channels can therefore be viewed not merely as promotional tools but as part of a customer-acquisition capability whose value depends on the organisation's ability to attract suitable prospects, qualify them, nurture them, and convert them into paying customers.

Together, these perspectives yield a stage-specific explanation of the proposed links. The hierarchy-of-effects view suggests that digital contact can initiate awareness and interest, but those responses must be screened for relevance before they translate into sales opportunities. The resource-based view explains why firms differ in their ability to qualify enquiries, maintain timely CRM follow-up and convert interested prospects. Accordingly, H1 concerns the association between digital-channel activity and perceived lead quality; H2 concerns the association between quality and perceived conversion; H3 links conversion with perceived revenue outcomes; and H4 examines whether digital-channel activity has an additional direct association with perceived revenue after accounting for the funnel stages. The sequence is a conceptual ordering, not proof of temporal or causal mediation.

Indian EdTech and the Digital Marketing Environment

Indian EdTech growth has been associated with improved connectivity, smartphone penetration, favourable digital adoption, and demand for online learning (Bajaj & Mathur, 2022; Bansal et al., 2023). Kaushik and Bindal (2025) further describe digital marketing as an important mechanism linking learners with educational resources and highlight search visibility, personalisation, and engagement as important components of the emerging education ecosystem. These developments make digital customer acquisition strategically important, but they do not establish that every digital channel contributes equally to enrolment or revenue.

Evidence from EdTech case research illustrates this distinction. Shrivastava and Kumar (2022), in their study of BYJU'S advertising strategies, describe a broad mix of digital and traditional promotion and note that some digital enquiries may lack strong purchase intention because the information seeker and final payer can be different people. This is especially relevant in education markets, where students may influence the decision while parents or employers make the final payment.

ISSN No. 2321-2705 | DOI: 10.51244/IJRSI |Volume XIII Issue X October 2026

Channel Effectiveness and Customer Engagement

Different digital channels appear to influence different stages of customer decision-making. Ruangkanjanases et al. (2022), using structural equation modelling with prospective higher-education students, found that social-media marketing activities were positively associated with brand equity and behavioural engagement. Abu Seman and Segar (2023), in a non-education consumer setting, found positive relationships for social-media and search-engine marketing but a negative relationship for email marketing, demonstrating that channel effects are heterogeneous rather than uniform.

Contemporary electronic word-of-mouth further expands the channel environment. Filieri, Christodoulides, and Nicolau (2025) show that eWOM now includes influencer content, video, live and interactive formats, social commerce, and AI-enabled communication. Their review emphasises trust, authenticity, format, source, and audience characteristics as important determinants of digital response. In EdTech, these considerations imply that social engagement metrics should not automatically be interpreted as sales outcomes.

Personalisation can increase digital engagement, but engagement is not the same as lead conversion. Agrawal, Athey, Kanodia, and Palikot (2022) found in a randomised controlled trial that personalised recommendations increased consumption within the personalised section of an educational app by about 60% and overall app use by 14%. The study supports the value of data-driven personalisation for engagement but does not directly test CRM follow-up, lead quality, or revenue.

Lead Quality, Lead Scoring, and Conversion

The distinction between lead quantity and lead quality is particularly well supported. Naveen Kumar and Hariharanath (2021) developed a lead-scoring model for digital marketing firms in the Indian education vertical using 1,900 leads and explicit, implicit, and negative behavioural parameters. Their model classified prospects into hot, warm, and cold categories and illustrates why enquiry volume alone is an inadequate measure of marketing effectiveness.

González-Flores et al. (2025) provide more recent evidence from B2B sales using real CRM data and machine-learning classification. Their study shows that lead-source and lead-status information are useful for identifying higher-quality prospects and improving prioritisation. This directly supports the present study's treatment of Lead Quality as a distinct construct between channel activity and conversion.

Lead quality also depends on what happens after the enquiry. Marketing research increasingly treats qualification, CRM follow-up, response time, and sales execution as part of an integrated conversion process. Accordingly, a high-quality lead should not be expected to generate revenue automatically; conversion depends on the organisation's ability to respond, nurture, and close the opportunity.

Digital Channels and Revenue-Related Outcomes

Research linking digital channels directly to financial outcomes remains less common than studies of traffic, engagement, or purchase intention. Batsakis, Konara, and Theoharakis (2023), using longitudinal evidence from 122 retail multinational enterprises, show that digital-sales intensity can support broader firm growth, although their context is retail diversification rather than EdTech lead generation. Their findings nevertheless reinforce the strategic value of digital-channel capability at the firm level.

The literature therefore supports a sequential interpretation of digital customer acquisition: channels create visibility and enquiries; lead-quality processes distinguish commercially relevant prospects; conversion activities transform qualified prospects into customers; and completed sales contribute to revenue. Existing studies tend to examine individual segments of this process rather than the integrated sequence, especially in Indian EdTech.

Research Gap and Hypotheses

The reviewed literature provides limited empirical evidence integrating digital channel activity, lead quality, conversion, and revenue-related outcomes within one structural model in an Indian EdTech setting. It also reports conflicting channel-level findings: social media and search are effective in some contexts, while traffic or enquiries from the same channels do not always translate into purchase. This suggests that lead quality and conversion should be treated as distinct stages rather than assuming a direct channel-to-revenue relationship.

Hypotheses	Statement
H_1	Digital Channel activity is positively associated with Lead Quality.
H_2	Lead Quality is positively associated with Conversion.
H_3	Conversion is positively associated with Perceived Sales Revenue Outcomes.
H_4	Digital Channel activity has a positive direct association with Perceived Sales Revenue Outcomes.

Table 1. Core structural hypotheses. Demographic comparisons are treated as supplementary analyses rather than core causal hypotheses.

RESEARCH METHODOLOGY

Research Design and Study Setting

A quantitative, cross-sectional explanatory design with a predictive-structural orientation was adopted. Data were collected in a single Indian EdTech organisation providing online higher education and professional-certification programmes. Because the design is cross-sectional and the variables are perception-based, the results are interpreted as associations and predictive relationships rather than causal effects.

Sampling and Data Collection

Convenience sampling was used. The final sample comprised 165 employees and customer-facing staff from Sales (36.7%), Digital Marketing (21.1%), Marketing (20.5%), CRM/Customer Support (13.9%), and other functions (7.8%). Participation was voluntary. Convenience sampling limits probabilistic generalisation beyond the organisation. A formal a priori power analysis was not undertaken. Given the relatively simple structural model and the achieved sample of 165 respondents, the sample was considered adequate for the present exploratory-predictive analysis; nevertheless, future studies should determine sample size prospectively using statistical power analysis.

Primary data were collected through a structured questionnaire containing demographic items and 26 construct items measured on five-point Likert scales. The analytical model grouped the items into Digital Channels (4 items), Lead Quality (4 items), Conversion (7 items), and Perceived Sales Revenue Outcomes (5 items). Other descriptive channel items were retained for supplementary analysis but were not treated as separate structural constructs.

Of the 26 questionnaire items, the four constructs described here account for 20 items (4 + 4 + 7 + 5); the remaining six items were not included in these four structural constructs. Their exact content and analytic treatment should be documented in an instrument appendix before publication.

Measurement Model

Because the instrument is multidimensional, construct-level reliability is more informative than a single overall Cronbach's alpha for all 26 items. The reported PLS-SEM measurement model showed construct alpha values from 0.77 to 0.84, composite reliability from 0.81 to 0.89, and AVE from 0.51 to 0.64. Reported outer loadings ranged from 0.62 to 0.86. The maximum reported HTMT value was 0.84, below the commonly used 0.85 threshold. These results provide acceptable evidence of internal consistency, convergent validity, and discriminant validity at the construct level.

Common-Method Bias

Harman's single-factor test was used as an initial diagnostic. The first unrotated factor accounted for 29.8% of total variance. This result indicates that no single factor dominated the covariance structure, but Harman's test alone cannot establish that common-method bias is absent (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). The self-report, single-source design remains a methodological limitation.

PLS-SEM and Supporting Analyses

PLS-SEM was estimated in SmartPLS 4. Measurement-model assessment considered outer loadings, AVE, composite reliability, and HTMT. The structural model was assessed using standardised path coefficients, bootstrapped t statistics and p values, R^2, Q^2, f^2, and VIF. The reported source output used 5,000 bootstrap resamples.

The supplied manuscript also contained a sequential mediation table. However, the reported indirect effect (0.221) does not reconcile with the product of the reported standardised structural paths ($0.518 \times 0.482 \times 0.601 \approx 0.150$). Formal mediation is therefore not reported in this revised article until the original SmartPLS 'Specific Indirect Effects' output is verified. Supplementary analyses included chi-square association tests with Monte Carlo exact-test correction where expected counts were sparse, and one-way ANOVA for age-group differences in perceived sales performance. These demographic analyses are interpreted as descriptive association tests rather than moderation tests.

RESULTS

Respondent Profile

Variable	Category	n	%
Age	Below 25	81	49.4
	25–30	62	37.3
	31–35	13	7.8
	Above 35	9	5.4
Gender	Female	102	61.8
	Male	63	38.2
Experience	Less than 1 year	40	24.1
	1–3 years	55	33.7
	3–5 years	53	31.9
	Above 5 years	17	10.2
Department	Sales	60	36.4
	Digital Marketing	35	21.2
	Marketing	34	20.6
	CRM/Customer Support	23	13.9
	Others	13	7.9

Table 2. Demographic profile of respondents (N = 165).

Measurement Model

Construct	Items	AVE	CR	α	Mean*	SD
Digital Channels	4	0.64	0.89	0.84	15.39	3.36
Lead Quality	4	0.58	0.85	0.81	14.13	3.21
Conversion	7	0.51	0.81	0.77	19.50	4.21
Perceived Sales Revenue Outcomes	5	0.55	0.86	0.82	17.86	3.78

Table 3. Measurement-model statistics. *Means are summed construct scores. Reported outer loadings = 0.62–0.86; maximum HTMT = 0.84.

Structural Model

The structural model explained 41.3% of the variance in Lead Quality ($R^2 = 0.413$), 36.7% in Conversion ($R^2 = 0.367$), and 58.6% in Perceived Sales Revenue Outcomes ($R^2 = 0.586$). Reported Q^2 values were positive for all endogenous constructs (Lead Quality = 0.261; Conversion = 0.219; Perceived Sales Revenue Outcomes = 0.398). Maximum VIF was 1.57, indicating no apparent collinearity problem among the reported structural predictors.

Path	β	SE	t	p	f^2	Decision
Digital Channels → Lead Quality	0.518	0.065	7.92	<0.001	0.37	Supported
Lead Quality → Conversion	0.482	0.078	6.21	<0.001	0.30	Supported
Conversion → Perceived Sales Revenue Outcomes	0.601	0.066	9.04	<0.001	0.58	Supported
Digital Channels → Perceived Sales Revenue Outcomes	0.092	0.071	1.30	0.194	0.01	Not supported

Table 4. PLS-SEM structural-path results (N = 165).

Digital Channels were positively associated with Lead Quality, Lead Quality was positively associated with Conversion, and Conversion was positively associated with Perceived Sales Revenue Outcomes. The direct Digital Channels→Perceived Sales Revenue path was small and statistically non-significant. The pattern is consistent with a sequential funnel logic.

In the reported model, the largest standardized coefficient among paths ending in Perceived Sales Revenue Outcomes is Conversion → Perceived Sales Revenue Outcomes ($\beta = 0.601$, $f^2 = 0.58$, $p < 0.001$), whereas Digital Channels → Perceived Sales Revenue Outcomes is small and not statistically significant ($\beta = 0.092$, $f^2 = 0.01$, $p = 0.194$). Across stages, Digital Channels → Lead Quality ($\beta = 0.518$, $f^2 = 0.37$) is larger than Lead Quality → Conversion ($\beta = 0.482$, $f^2 = 0.30$). These coefficients should be compared within their respective outcomes; they are not shares of revenue, and the cross-sectional estimates do not demonstrate a causal conversion funnel.

Descriptive Channel Findings

At the item level, Social Media Lead Generation recorded the highest reported mean (M = 4.36, SD = 1.12), whereas Email Marketing Customer Reach (M = 2.12), Webinars and Online Events (M = 2.15), Social Media Marketing Customer Acquisition (M = 2.18), and Paid Advertisements Sales Inquiries (M = 2.20) were among the lowest-rated items. These are perceptual ratings rather than objective channel ROI measures and should not be interpreted as evidence that a channel is inherently effective or ineffective.

Supplementary Demographic Analyses

Association	χ^2	df	Pearson p	Exact/Monte Carlo p	Interpretation
Gender × Social Media Lead Generation	8.016	4	0.091	0.097	Not significant
Department × Perceived Digital Lead-Generation Revenue Item	22.620	16	0.124	0.142	Not significant
Experience × Lead-Quality/Conversion Item	21.424	12	0.045	0.041	Significant association
Department × Paid Digital Campaign Performance Item	22.319	16	0.133	0.151	Not significant

Table 5. Supplementary categorical association tests. These results do not constitute moderation tests.

Experience was significantly associated with response distributions for the lead-quality/conversion item (exact p = 0.041). This finding indicates heterogeneity in perceptions across experience categories, but it does not establish that experience moderates the structural relationship between Lead Quality and Conversion.

One-way ANOVA found no significant age-group difference in perceived sales performance, $F(3,161) = 0.509$, $p = 0.677$, $\eta^2 = 0.009$. Levene's test was non-significant ($p = 0.928$), and the reported Tukey comparisons were also non-significant.

DISCUSSION

Lead Quality and Conversion as Distinct Stages

The structural results support the theoretical separation of lead generation, lead quality, conversion, and revenue-related outcomes. Digital-channel activity has a strong relationship with Lead Quality, and Lead Quality is in turn associated with Conversion. Conversion shows the strongest direct relationship with Perceived Sales Revenue Outcomes. This sequence is consistent with Naveen Kumar and Hariharanath's (2021) emphasis on qualification and González-Flores et al.'s (2025) evidence that engagement and lead-status information can improve conversion-oriented prioritisation.

The non-significant direct Digital Channels→Perceived Sales Revenue path is also substantively important. It suggests that high channel activity alone should not be equated with commercial performance. However, because the formal indirect-effect statistics require verification, the present study stops short of claiming full sequential mediation.

For managers, the pattern differentiates three operational tasks: generating relevant enquiries, qualifying those enquiries, and converting qualified prospects. Channel activity may produce a pool of leads, but lead quality reflects fit, purchase intent and readiness, while conversion also requires lead assignment, responsive counselling, timely follow-up and credible programme information. This helps explain why the reported conversion-to-revenue relationship is stronger than the direct channel-to-revenue relationship. These mechanisms are theoretically plausible interpretations, rather than independently tested process mechanisms or observed financial effects.

Interpreting Channel-Level Ratings

Social-media lead generation received the highest item-level perception score, which is broadly consistent with evidence that social-media marketing can promote engagement among prospective higher-education students (Ruangkanjanases et al., 2022). Yet the low ratings for some email, webinar, and paid-advertising items should be interpreted cautiously. Abu Seman and Segar (2023) demonstrate that channel effectiveness can vary substantially by context, while Filieri et al. (2025) show that digital response depends on source, format, trust, and audience characteristics. The current survey does not contain channel-level cost, actual enrolment, or ROI data and therefore cannot rank channels financially.

Experience-Related Heterogeneity

The significant experience association suggests that response distributions differed significantly across experience categories for the lead-quality/conversion item. It is reasonable for future research to investigate whether experience affects lead-evaluation judgement, but the present chi-square result does not test a moderation effect. A true moderation analysis would require multi-group structural modelling or an interaction term with adequate measurement invariance and statistical power.

Theoretical and Managerial Implications

Theoretical Contributions: The findings extend the hierarchy-of-effects perspective to a four-construct, employee-perception model of EdTech customer acquisition: Digital Channels, Lead Quality, Conversion and Perceived Sales Revenue Outcomes. Rather than treating digital contact as a direct proxy for revenue, the model distinguishes awareness-generation capability from qualification and conversion capability. This separation adds a useful analytical lens to digital marketing and lead-management literature, where traffic and enquiries may otherwise be conflated with commercial results. Consistent with the resource-based view, the relationships suggest that channel access alone is insufficient without processes for evaluating and nurturing

enquiries. The non-significant direct Digital Channels-to-Revenue path is therefore substantively informative; it does not establish mediation, because the reported indirect-effect results require verification.

Managerial and Business Implications: EdTech managers should manage a measurable lead funnel rather than optimise raw enquiry counts. At the acquisition stage, the firm can distinguish website, search, social, email and webinar enquiries using source tagging and transparent attribution. At the qualification stage, sales and CRM teams can use a documented lead rubric based on programme fit, eligibility, expressed interest, readiness and contactability, with periodic checks for bias or exclusion. At the conversion stage, teams can assign ownership promptly, monitor first-response time, use consistent counselling scripts, schedule appropriate follow-up, and record reasons for conversion or non-conversion. These are practical recommendations derived from the model and literature; the present survey does not estimate the causal improvement from implementing them. A management dashboard should monitor qualified-lead rate, lead-to-enrolment conversion, time to contact, cost per qualified lead, cost per enrolment and verified revenue per acquired customer, segmented by source and campaign.

Sustainability of Digital Channels: Sustainable growth requires attention to financial efficiency, learner welfare and data stewardship, not simply the volume of paid enquiries. The firm should regularly reallocate spending from persistently low-quality traffic to channels demonstrating verified qualified leads and enrolments; test improvements in landing pages and follow-up before increasing advertising expenditure; and invest in reusable educational content, organic search, referrals and permission-based communication to reduce dependence on rising paid-acquisition costs. Consent-based CRM practice, data minimisation, transparent programme claims and reasonable contact frequency can reduce reputational and compliance risks. Channel portfolios should be evaluated for cost stability, customer acquisition cost, subsequent enrolment quality, refunds and retention across cohorts. The study did not measure these sustainability outcomes; they are implementation priorities to be verified with transaction-level records.

Broader EdTech Relevance: Although these findings arise from one Indian EdTech firm, the distinction between enquiry generation, qualification and conversion may inform how other course providers formulate hypotheses and design dashboards. The precise strength of associations should not be transferred to other companies, regions, products or customer segments without replication. Providers with different fee levels, programme lengths, institutional trust and learner-payer arrangements may face different qualification and conversion bottlenecks.

LIMITATIONS AND FUTURE RESEARCH

The study is limited by its single-organisation convenience sample, cross-sectional design and self-reported perceptual measures. In particular, the dependent construct represents perceived sales revenue outcomes rather than audited channel-level revenue. The findings cannot establish causal effects or actual return on advertising expenditure. Harman's single-factor result is only a preliminary diagnostic and does not exclude common-method bias. An a priori sample-size power analysis was not documented, and full item-loading and HTMT matrices are not presented, limiting independent scrutiny of the measurement model. The reported sequential indirect-effect statistic (0.221) does not reconcile with the product of the listed standardized path coefficients (approximately 0.150); consequently, mediation cannot be claimed without recovering and verifying the SmartPLS specific-indirect-effects output. Demographic chi-square associations should not be interpreted as evidence of structural moderation.

Future research should link lead source, lead-quality classifications, follow-up timestamps, actual enrolment conversions, marketing expenditure and realised revenue in CRM and accounting systems. Prospective multi-firm designs with probabilistic or appropriately stratified samples could test generalisability across EdTech segments and evaluate channel sustainability over time. Longitudinal cohorts could clarify temporal ordering, learner retention and customer lifetime value. Future PLS-SEM studies should report complete measurement matrices, prospective power analysis, bootstrapped specific indirect effects and confidence intervals, and measurement-invariance tests before formal multi-group moderation comparisons.

CONCLUSION

The study set out to evaluate how digital-channel activity, lead quality and conversion relate to perceived sales revenue outcomes in an Indian EdTech firm. Its main findings support positive associations between Digital Channels and Lead Quality (β = 0.518), Lead Quality and Conversion (β = 0.482), and Conversion and Perceived Sales Revenue Outcomes (β = 0.601), whereas the direct Digital Channels-to-Revenue relationship was not significant (β = 0.092, p = 0.194). The model accounts for 41.3%, 36.7% and 58.6% of variance in Lead Quality, Conversion and Perceived Sales Revenue Outcomes, respectively. Of the reported direct paths to the revenue-related outcome, conversion has the largest coefficient and f^2, underlining the importance of downstream funnel management rather than enquiry volume alone.

Theoretically, the findings contribute a stage-separated account of digital customer acquisition consistent with the hierarchy-of-effects and resource-based perspectives; they do not establish causal sequential mediation. Practically, EdTech firms can improve decisions by monitoring source-attributed lead quality, contact timeliness, conversion and verified acquisition costs, and by supporting sustainable, consent-based channel strategies rather than relying exclusively on paid lead volume. These implications provide a testable framework for other education providers, not universal effect-size estimates. Because the evidence comes from one convenience-sampled organisation and self-reported cross-sectional perceptions, it cannot establish actual revenue growth or causality. Future multi-firm and longitudinal research should connect digital-channel interactions with CRM conversion records, marketing expenditure, audited sales and long-term learner value, and verify the currently inconsistent indirect-effect estimate before drawing mediation conclusions.

REFERENCES

1. Abu Seman, N. A., & Segar, V. (2023). The impact of digital marketing channels on consumer buying decision. Journal of International Business, Economics and Entrepreneurship, 8(1), 42–53. https://doi.org/10.24191/jibe.v8i1.23145
2. Agrawal, K., Athey, S., Kanodia, A., & Palikot, E. (2022). Personalized recommendations in EdTech: Evidence from a randomized controlled trial (Working Paper No. 4105). Stanford Graduate School of Business. https://doi.org/10.48550/arXiv.2208.13940
3. Agresti, A. (2018). An introduction to categorical data analysis (3rd ed.). Wiley.
4. Bajaj, V., & Mathur, M. (2022). Indian EdTech ecosystem: Drivers and challenges. Siddhanta Journal of Decision Making, 22, 148–154. https://doi.org/10.5958/2231-0657.2022.00014.3
5. Bansal, A., Pophalkar, S., & Vidani, C. J. (2023). A review of Ed-Tech sector in India. International Journal of Management Analytics, 1(1), 63–84. https://doi.org/10.59890/ijma.v1i1.102
6. Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108
7. Batsakis, G., Konara, P., & Theoharakis, V. (2023). Digital sales channels and the relationship between product and international diversification: Evidence from going digital retail MNEs. Global Strategy Journal, 13(4), 830–856. https://doi.org/10.1002/gsj.1465
8. Cochran, W. G. (1954). Some methods for strengthening the common χ^2 tests. Biometrics, 10(4), 417–451. https://doi.org/10.2307/3001616
9. Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.
10. Day, G. S. (1994). The capabilities of market-driven organizations. Journal of Marketing, 58(4), 37–52. https://doi.org/10.1177/002224299405800404
11. Filieri, R., Christodoulides, G., & Nicolau, J. L. (2025). Emerging sources, formats, channels, devices, and audiences in modern eWOM communications. Psychology & Marketing, 42(9), 2430–2443. https://doi.org/10.1002/mar.22239
12. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104

13. González-Flores, L., Rubiano-Moreno, J., & Sosa-Gómez, G. (2025). The relevance of lead prioritization: A B2B lead scoring model based on machine learning. Frontiers in Artificial Intelligence, 8, 1554325. https://doi.org/10.3389/frai.2025.1554325
14. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Sage.
15. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
16. Kaushik, N., & Bindal, M. (2025). The role of digital marketing in the new education ecosystem in India. Journal of East-West Thought, 15(1). https://doi.org/10.7492/xsz43c39
17. Lavidge, R. J., & Steiner, G. A. (1961). A model for predictive measurements of advertising effectiveness. Journal of Marketing, 25(6), 59–62. https://doi.org/10.1177/002224296102500611
18. Naveen Kumar, G., & Hariharanath, K. (2021). Designing a lead score model for digital marketing firms in education vertical in India. Indian Journal of Science and Technology, 14(16), 1302–1309. https://doi.org/10.17485/IJST/v14i16.290
19. Nunnally, J. C. (1978). Psychometric theory (2nd ed.). McGraw-Hill.
20. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
21. Ringle, C. M., Wende, S., & Becker, J.-M. (2022). SmartPLS 4. SmartPLS GmbH. https://www.smartpls.com
22. Ruangkanjanases, A., Sivarak, O., Wibowo, A., & Chen, S.-C. (2022). Creating behavioral engagement among higher education's prospective students through social media marketing activities: The role of brand equity as mediator. Frontiers in Psychology, 13, 1004573. https://doi.org/10.3389/fpsyg.2022.1004573
23. Shrivastava, A., & Kumar, R. (2022). To study the advertising strategies for EdTech startup (with special reference to BYJU'S). Journal of Public Relations and Advertising, 1(1), 27–35.