

AN ANALYSIS OF FACTORS AFFECTING LEAD-TO-CUSTOMER CONVERSION OF FINANCIAL PRODUCTS AT ADITYA BIRLA CAPITAL LIMITED

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INTRODUCTION

India's financial services sector has undergone significant transformation, moving from a highly regulated system towards a more open, competitive, and digitally enabled environment. Government initiatives such as the Pradhan Mantri Jan Dhan Yojana, along with digital platforms such as Aadhaar and UPI, have expanded access to formal financial services. This growth has increased consumer participation in products such as mutual funds, insurance, and loans, creating new opportunities as well as greater competition for financial service providers.

In this competitive environment, lead-to-customer conversion has become an important measure of sales effectiveness. A lead may show interest in a financial product through a form, telephone call, digital enquiry, or branch visit, but converting that interest into an actual purchase depends on several factors. Trust in the advisor and company, clarity of communication, quality of customer service, and suitability of the product to the customer's needs can strongly influence the final purchase decision. Although digital technologies and data-driven tools are increasingly being used to identify and engage potential customers, trust remains an important element in financial decision-making.

This study focuses on Aditya Birla Capital Limited (ABCL), a diversified financial services organisation offering products such as mutual funds, insurance, and loans. The study examines the factors influencing the conversion of leads into customers, with particular focus on trust, communication, service quality, product fit, satisfaction, and demographic characteristics. The research is based on primary data collected during a marketing internship with ABCL's Life Insurance and Health Insurance teams.

The study aims to provide practical insights into how ABCL can strengthen its sales process, improve lead engagement, and increase customer conversion. It also seeks to understand whether conversion-related factors differ across customer characteristics such as age, gender, occupation, and income. By examining these factors together, the study provides an evidence-based understanding of the lead-to-customer conversion process and identifies areas that can support more effective sales and customer relationship strategies.

LITERATURE REVIEW

2.1 Lead Generation and Lead Management

Across the reviewed literature, lead-to-customer conversion is consistently framed as a multi-stage, effort-dependent process rather than a single event. At the technical end, patent filings for an automated conversion-prediction system (U.S. Patent No. 11,244,257, 2022; U.S. Patent No. 11,977,996, n.d.) show that lead attributes — type, submission method, urgency, vendor classification — combined with historical booking data can estimate conversion probability. These patents establish technical feasibility rather than managerial practice, and neither addresses how predictions should be acted upon by a sales organisation.

In a B2B, high-technology context, found sales effort itself accelerates conversion-cycle time, strongest among smaller, non-key accounts — suggesting effort allocation matters most where relationships are least established. Karthik et al. (2020), applying logistic regression to leads from Google, JustDial, and Sulekha for a training institute, found distance, referral channel, working status, and prospect-response type significantly predicted conversion, with Google-sourced leads converting roughly ten times more often than the other channels. Yadav and Kumar (2022) documented those Policybazaar alone accounts for approximately 70 percent of India's online life-insurance leads, underscoring how concentrated lead generation has become in Indian financial services.

2.2 Lead Scoring and Predictive Prioritisation

A closely related stream addresses how leads, once generated, should be scored and prioritised, moving decisively from static, manually assigned rules toward machine-learning-based scoring. Jadli et al. (2022) showed models trained on historical lead and sales-interaction data identify conversion-relevant patterns more effectively than manual scoring, with multi-channel leads scoring systematically higher. Sharma et al. (2023) reached a similar conclusion using deep-learning on website-visitor data, reporting faster prioritisation of high-value prospects. Extending this to the weighting problem, González-Flores et al. (2025) developed a

B2B lead-scoring model assigning differentiated weights to interaction types, again finding multi-channel engagement associated with higher scores and realised conversion.

2.3 Customer Relationship Management and Conversion Performance

Customer relationship management (CRM) research on financial services broadly converges on analytical CRM improving retention, satisfaction, and profitability, though authors disagree on how completely institutions have realised these benefits. Perwej (2012), comparing CRM at RBC and Wells Fargo, found analytical CRM enhances retention and supports tailored product development, but concluded banks still struggle toward a unified, product-agnostic customer view. Baser and Thakar (2015), synthesising roughly 40 articles on banking CRM, linked robust CRM implementation to customer loyalty and profitability, while calling for empirical validation of this largely literature-based consensus.

2.4 Customer Trust, Perceived Risk and Purchase Intention

Trust and perceived risk form the most researched theme in this literature, converging on one pathway: trust reduces perceived risk, which raises purchase intention. Rachbini (2018), using structural equation modelling on Indonesian e-commerce consumers, found trust reduced perceived risk and raised purchase decisions while mediating product-quality and price effects. Mahliza (2020) confirmed both a direct and risk-mediated effect of trust on purchase intention via path analysis. In insurance, Chaturvedi and Vijaykarthigeyan (2025), surveying 710 Indian respondents, found trust central to reducing risks around data protection, information accuracy, and claims validity, while Elangovan and Premkumar (2025a, 2025b) found trustful belief, perceived benefit, and perceived risk together explained 73.3 percent of the variance in life-insurance purchase intention.

2.5 Customer Buying Behaviour and Purchase Decisions

A smaller body of research addresses how financial-services customers behave as buyers rather than what drives purchase intention. Beckett et al. (2000) proposed a typology of four consumer types — Repeat-Passive, Rational-Active, Relational-Dependent, and No Purchase — arguing simplified interactions encourage more positive adoption attitudes, with relevant behavioural constructs varying between new and established products. Zhang and Jin (2022) found perceived convenience, risk value, and communication satisfaction all significantly predicted purchase behaviour among bank financial-product buyers, with risk value the strongest predictor.

2.6 Customer Service, Follow-up and Retention

Literature on customer service and follow-up spans both ends of the relationship: what builds satisfaction and retention, and what drives customers away. Kumar and Sharma (2016), synthesising e-banking satisfaction research, traced a shift from branch-based factors toward technology-driven dimensions such as accessibility, security, and speed. Hadiyanto (2021), analysing data from 2,858 financial-services customers, found branch proximity and loan-to-value ratio bore a highly significant relationship with retention, while days-past-due and income did not.

Where service and follow-up fail, the consequences are severe. Ahmed et al. (2025), surveying 405 Bangladeshi mobile financial-services customers, found excessive pricing, poor service quality, poor reputation, and loss of loyalty drove switching, itself a multi-step process rather than a single trigger.

2.7 Digital Marketing and Customer Acquisition

Research on digital marketing and customer acquisition agrees that digital channels have lowered acquisition costs and expanded reach, while diverging on which channels are responsible. Sharma (2022) found digital channels drove down acquisition costs, with companies using the savings to accelerate growth, while Melinevskyi et al. (2023) identified virtual space, competitive intensity, internet accessibility, and marketing-personnel shortages as the structural factors shaping how effectively digital marketing converts engagement into customers.

A more recent, financial-services-specific study complicates the assumption that digital investment translates uniformly into acquisition. Sanesh et al. (2025), surveying 712 digital-banking users on five components, found email marketing, app/website usability, online advertising, and social media marketing significantly influenced acquisition, while search engine marketing — often treated as foundational — had no significant effect; the model explained 42.8 percent of variance, with online advertising the strongest predictor.

2.8 Cross-Selling and Relationship Marketing

Cross-selling occupies a contested position: practitioner sources treat it as a durable competitive advantage, while customer-facing survey research often finds it a source of friction. JM Financial's (2023) institutional research on ABCL concludes that cross-selling across its NBFC, housing-finance, asset-management, and insurance segments, combined with its AAA-rated parentage, forms a genuine competitive moat, widened by its digital channels. Jarrar and Neely (2002) similarly argued successful cross-selling requires enterprise-wide CRM support and a customer-profitability lens, an organisational capability rather than a transactional tactic.

2.9 Artificial Intelligence and Chatbots in Customer Conversion

A growing, increasingly empirical literature examines whether AI-based chatbots improve customer outcomes in financial services, generally with encouraging but qualified results. Widayanti et al. (2025), surveying 340 chatbot users at Bank X, found chatbot service positively affected satisfaction, engagement, and perceived service efficiency, with satisfaction and engagement — but not efficiency itself — significantly mediating the effect on loyalty (78.6 percent of variance explained). Nguyen and Le (2024), studying 336 Vietnamese banking

chatbot users, found understandability, personalisation, and intimacy significantly increased extrinsic and intrinsic value, whereas intrusiveness reduced intrinsic value, with satisfaction and value together explaining 63 percent of variance in continued-use intention.

RESEARCH OBJECTIVES

- To identify key factors affecting lead conversion into customers.
- To study the link between demographics and customer trust, satisfaction, and purchase decisions.
- To examine how customer service and advisor trust affect satisfaction.
- To analyse how trust, satisfaction, and ease of process influence lead conversion.

Research Methodology

The study adopted a descriptive, cross-sectional research design with a quantitative approach to examine lead-to-customer conversion for financial products at ABCL. Both primary and secondary data were used, with primary data collected through a structured questionnaire from 103 respondents, including 59 respondents who had been contacted by ABCL. Convenience and purposive sampling techniques were used for respondent selection.

DATA ANALYSIS AND INTERPRETATION

4.1 Demographic and Descriptive Profile of Contacted Leads

The sample is mainly male and consists mostly of young adults. Students form the largest occupational group, while respondents are fairly distributed across income groups. Most leads were first contacted through agent/advisor visits and phone calls. Mutual Fund/SIP and Life Insurance were the most discussed products.

4.2 Inferential Statistics and Hypothesis Testing

Having profiled the sample descriptively, the analysis now turns to the inferential techniques identified in Section 3.9 — One-Way ANOVA, Chi-Square, the Independent Samples t-Test, Pearson Correlation, and Regression — to formally test the relationships implied by the study's research objectives. All tests were conducted at the conventional 5 percent level of significance ($\alpha = 0.05$); a p-value below 0.05 leads to rejection of the null hypothesis (H_0) in favour of the alternative hypothesis (H_1).

4.2.1 One-Way ANOVA

One-Way ANOVA was used to test whether mean scores on a continuous, Likert-scale outcome differ across three or more groups defined by a categorical demographic variable. Two such comparisons were of direct relevance to the study's objectives: whether Satisfaction varies by age, and whether the perceived ease of the Buying Process varies by income.

Test 1: Satisfaction Across Age Groups

Objective of the Test: To examine whether overall Satisfaction with the sales experience differs across the five age groups, addressing the study's second objective of relating demographic characteristics to satisfaction outcomes.

Null Hypothesis (H_0): There is no significant difference in mean Satisfaction score across age groups.

Alternative Hypothesis (H_1): There is a significant difference in mean Satisfaction score across age groups.

Table 4.8: One-Way ANOVA – Satisfaction Across Age Groups

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	5.094	4	1.274	1.122	.356
Within Groups	61.313	54	0.936		
Total	66.407	58			

Decision: Since $p = 0.356$ is greater than 0.05, the null hypothesis is accepted.

Interpretation: Leads of different ages reported similarly favourable, or unfavourable, levels of satisfaction with the sales experience; age on its own does not explain differences in how satisfied a lead felt.

Test 2: Buying Process Ease Across Income Groups

Objective of the Test: To examine whether the perceived ease of the buying process differs across the four monthly household income brackets.

Null Hypothesis (H_0): There is no significant difference in mean Buying Process rating across income groups.

Alternative Hypothesis (H_1): There is a significant difference in mean Buying Process rating across income groups.

Table 4.9: One-Way ANOVA – Buying Process Ease Across Income Groups

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.526	3	2.842	2.395	.078
Within Groups	65.271	55	1.187		

Source	Sum of Squares	df	Mean Square	F	Sig.
Total	73.797	58			

Decision: Since $p = 0.078$ is greater than 0.05, the null hypothesis is retained, though the result sits close to the threshold.

Interpretation: Income group does not produce a statistically significant difference in how easy leads found the buying process, but the near-threshold significance value suggests a mild trend that a larger sample might confirm — higher-income leads may experience the process somewhat differently from lower-income leads.

4.2.2 Chi-Square Test

The Chi-Square Test of Independence was applied to two categorical-by-categorical relationships central to the study's objectives: whether occupation and gender, respectively, are associated with the binary purchase (conversion) outcome.

Test 1: Occupation and Purchase (Conversion)

Objective of the Test: To examine whether occupation type is associated with whether a contacted lead went on to purchase the product.

Null Hypothesis (H_0): There is no association between occupation type and whether the lead purchased.

Alternative Hypothesis (H_1): There is an association between occupation type and whether the lead purchased.

Table 4.10: Chi-Square Test – Occupation × Purchase

Test	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	15.081	6	.020
Likelihood Ratio	16.784	6	.010
N of Valid Cases	59		

Note: 8 cells (57.1%) have an expected count of less than 5, with a minimum expected count of 0.34, reflecting the small number of respondents in categories such as Homemaker, Other, Retired, and Self-employed. This result should therefore be read as indicative rather than definitive.

Decision: Since $p = 0.020$ is less than 0.05, the null hypothesis is rejected.

Interpretation: Occupation is significantly associated with conversion outcome. Business Owners and Salaried Employees converted at a noticeably higher rate than Students and, especially, Self-employed respondents in this sample.

Test 2: Gender and Purchase (Conversion)

Objective of the Test: To examine whether gender is associated with whether a contacted lead went on to purchase the product.

Null Hypothesis (H_0): There is no association between gender and whether the lead purchased.

Alternative Hypothesis (H_1): There is an association between gender and whether the lead purchased.

Table 4.11: Chi-Square Test – Gender × Purchase

Test	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	0.202	1	.653
Likelihood Ratio	0.199	1	.656
N of Valid Cases	59		

Decision: Since $p = 0.653$ is greater than 0.05, the null hypothesis is accepted.

Interpretation: There is no significant association between gender and conversion outcome; male and female leads converted at broadly similar rates in this sample.

4.2.3 Independent Samples t-Test

The Independent Samples t-Test was used to compare mean scores between two distinct groups. Two comparisons were carried out: Trust in the Advisor between male and female leads, and the overall Composite Factor Score between leads who purchased and those who did not. In both cases, Levene's Test for Equality of Variances was examined first to determine which row of the t-Test output to read.

Test 1: Trust in the Advisor by Gender

Objective of the Test: To check whether male and female leads report significantly different levels of trust in the advisor who contacted them.

Null Hypothesis (H_0): There is no significant difference in mean Trust in the Advisor between genders.

Alternative Hypothesis (H_1): There is a significant difference in mean Trust in the Advisor between genders.

Table 4.12: Group Statistics – Trust in the Advisor by Gender

Gender	N	Mean	Std. Deviation	Std. Error Mean
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Gender	N	Mean	Std. Deviation	Std. Error Mean
Male	50	3.4200	1.1445	.1619
Female	9	3.3333	1.0000	.3333

Table 4.13: Independent Samples Test – Trust in the Advisor by Gender

Variance Assumption	Levene's F	Levene's Sig.	t	df	Sig. (2-tailed)	Mean Diff.
Equal variances assumed	0.18	0.673	0.213	57	.832	.0867
Equal variances not assumed			0.234	12.71	.819	.0867

Decision: Levene's Test supports the equal-variances assumption ($p = 0.673$); on that basis, since $p = 0.832$ is greater than 0.05, the null hypothesis is accepted.

Interpretation: Male and female leads reported statistically indistinguishable levels of trust in their advisor, with mean scores of 3.42 and 3.33 respectively on the five-point scale.

Test 2: Composite Factor Score by Purchase

Objective of the Test: To check whether purchasers and non-purchasers differ significantly in their overall (composite) blended score across the eight experience-based factors measured in the questionnaire.

Null Hypothesis (H_0): There is no significant difference in mean Composite Factor Score between purchasers and non-purchasers.

Alternative Hypothesis (H_1): There is a significant difference in mean Composite Factor Score between purchasers and non-purchasers.

Table 4.14: Group Statistics – Composite Factor Score by Purchase

Purchase	N	Mean	Std. Deviation	Std. Error Mean
Yes	32	3.6458	1.0028	.1773
No	27	3.3498	0.8731	.1680

Table 4.15: Independent Samples Test – Composite Factor Score by Purchase

Variance Assumption	Levene's F	Levene's Sig.	t	df	Sig. (2-tailed)	Mean Diff.
Equal variances assumed	0.756	0.388	1.198	57	.236	.2960
Equal variances not assumed			1.212	56.06	.230	.2960

Decision: Since $p = 0.236$ is greater than 0.05, the null hypothesis is accepted.

Interpretation: Purchasers reported a somewhat higher composite factor score ($M = 3.65$) than non-purchasers ($M = 3.35$), but the difference is not statistically significant. A single blended average across all eight experience factors does not, by itself, distinguish converters from non-converters.

4.2.4 Correlation Analysis

Trust in the Advisor and Overall Satisfaction

Objective of the Test: To examine the strength and direction of the relationship between Trust in the Advisor and overall Satisfaction, addressing the study's third objective on the role of advisor trust in shaping the sales experience.

Null Hypothesis (H_0): There is no significant correlation between Trust in the Advisor and Satisfaction.

Alternative Hypothesis (H_1): There is a significant correlation between Trust in the Advisor and Satisfaction.

Table 4.16: Correlation – Trust in the Advisor and Satisfaction

	Trust in the Advisor	Satisfaction
Trust in the Advisor — Pearson Correlation	1	.753**
Trust in the Advisor — Sig. (2-tailed)		.000
Satisfaction — Pearson Correlation	.753**	1

	Trust in the Advisor	Satisfaction
Satisfaction — Sig. (2-tailed)	.000	
N	59	59

** Correlation is significant at the 0.01 level (2-tailed).

Decision: Since $p = 0.000$ is less than 0.05, the null hypothesis is rejected.

Interpretation: The correlation coefficient ($r = 0.753$) indicates a strong, positive, and statistically significant relationship between Trust in the Advisor and overall Satisfaction. Leads who trusted their advisor more also reported substantially higher satisfaction with the sales experience.

4.2.5 Regression Analysis

Effect of Customer Service Quality on Overall Satisfaction

Objective of the Test: To assess the extent to which Customer Service quality explains and predicts variation in overall Satisfaction, addressing the study's third and fourth objectives on service quality and its link to the sales outcome.

Null Hypothesis (H_0): There is no significant effect of Customer Service quality on overall Satisfaction.

Alternative Hypothesis (H_1): There is a significant effect of Customer Service quality on overall Satisfaction.

Table 4.17: Regression Model Summary – Customer Service and Satisfaction

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.871 ^a	.759	.755	.539

a. Predictors: (Constant), Customer Service

Figure 4.10: Variance in Satisfaction Explained by Customer Service Quality

Table 4.18: Regression ANOVA – Customer Service and Satisfaction

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	52.145	1	52.145	179.4	.000 ^b
Residual	16.565	57	0.291		
Total	68.712	58			

a. Dependent Variable: Satisfaction b. Predictors: (Constant), Customer Service

Table 4.19: Regression Coefficients – Customer Service and Satisfaction

Model	B	Std. Error	Beta	t	Sig.
(Constant)	.593	.233		2.542	.014
Customer Service	.834	.062	.871	13.394	.000

Decision: Since $p = 0.000$ is less than 0.05, the null hypothesis is rejected.

Interpretation: Customer Service quality has a very strong, positive, and statistically significant effect on overall Satisfaction, explaining 75.9 percent of the variation in Satisfaction scores ($R^2 = 0.759$, $F = 179.4$, $p = 0.000$). For each one-point increase in the Customer Service rating, Satisfaction increases by approximately 0.83 points ($B = 0.834$, $p = 0.000$).

KEY FINDINGS

The study shows that most contacted leads are young, male, and students, indicating limited diversity in ABCL's reach. Gender does not appear to be a major barrier to sales, while occupation shows some differences, with business owners and salaried employees more likely to purchase than students. Age and income have limited influence on satisfaction and ease of the buying process. Offline channels, particularly agent visits and phone calls, generate most leads, while digital channels have lower reach. Mutual Funds/SIPs and Life Insurance receive the highest interest, whereas Health Insurance and Personal Loans have lower engagement. Since only around half of the contacted leads convert into customers, there is scope to improve conversion. The findings also highlight the importance of advisor trust and customer service in improving customer satisfaction and the overall sales experience.

CONCLUSION

The study concludes that advisor trust and customer service quality are the most important factors influencing customer satisfaction and lead-to-customer conversion at ABCL. While occupation shows some influence on conversion, age, gender, and income have limited impact on customer behaviour. Agents and phone calls remain the major sources of leads, with Mutual Funds/SIPs and Life Insurance receiving the highest interest.

With just over half of the contacted leads converting, ABCL has clear scope to improve conversion by strengthening advisor relationships, service quality, and cross-selling opportunities.

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