

Leveraging Digital Analytics to Strengthen Marketing Decisions and Campaign Outcomes

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Abstract: *Many firms now have more marketing data than they can use. This paper asks a practical question: does the use of digital analytics actually lead to better marketing decisions, and do these better decisions show up in campaign results? A survey was carried out among 50 marketing professionals from education, e-commerce, IT/digital agency, service and retail firms in Indore. Three constructs were measured on a five-point scale: Digital Analytics Utilization (10 items), Marketing Decision Quality (8 items) and Campaign Outcomes (10 items). Correlation, group comparison (ANOVA and t-test), hierarchical regression and a bootstrap mediation test were applied. The results show that analytics utilization is very closely linked with decision quality ($r = 0.79$) and also with campaign outcomes ($r = 0.64$). Respondents in the high-usage group reported campaign outcome scores about 8 points higher than those in the low-usage group. Hierarchical regression shows that analytics adds 32 percent explained variance over experience, and decision quality adds a further 7 percent. The indirect path through decision quality is significant (effect = 0.29, 95% CI 0.02 to 0.60), which means that analytics improves results mainly by improving the decisions managers take. Experienced professionals use analytics more and decide better, but sector makes no difference. For firms in a growing city like Indore, the study shows that the payoff from analytics comes only when data is brought into the decision room. A dashboard that nobody acts on adds little to results.*

Keywords: Data-driven decisions, Digital analytics utilization, Marketing decision quality, Campaign outcomes, Mediation, Indore.

Introduction

1.1 Background

Ask any marketing manager in Indore how a campaign went and the answer is often a feeling: "it did well" or "response was low". Yet behind each campaign there is now a large pile of numbers. Facebook and Instagram report reach and cost per result, Google Ads shows which keyword brought a lead, the website records where visitors came from, and WhatsApp Business shows how many people read a message. The problem today is not a shortage of data. The problem is that data and decisions often live in two separate rooms.

Digital analytics utilization means the extent to which a firm actually uses these tools and numbers in its day-to-day marketing work. It is different from simply having an account on an analytics platform. A firm may install Google Analytics on its website and never open it. Utilization is about opening it, reading it and bringing it into planning.

The main idea of this paper is that analytics does not improve campaigns by itself. It improves **decisions**, such as which audience to target, how much to spend on which platform, when to stop a weak advertisement and what message to use, and these decisions then shape campaign outcomes. Figure 1 shows this chain from raw data to final outcome.

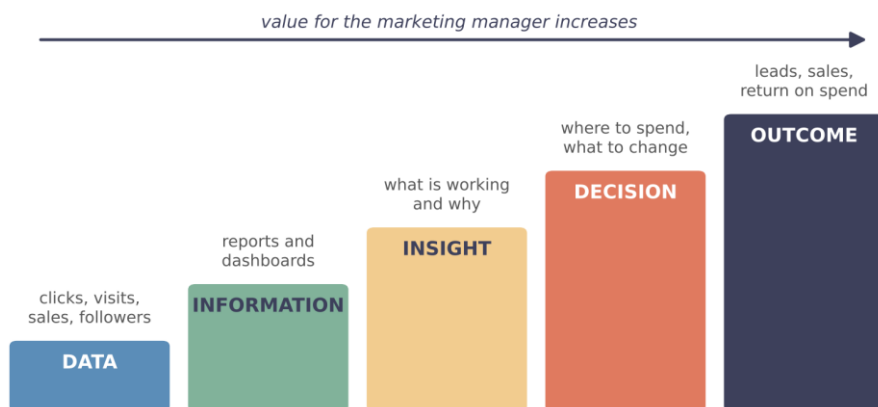


Figure 1: From Data to Campaign Outcome – the Value Ladder of Analytics

1.2 Need for the Study

Indore has a lively mix of coaching and education institutes, online sellers, digital agencies, service firms and retail stores, and most of them now promote themselves online. Small and medium firms here often work with tight budgets, so every rupee spent on advertising needs to show a return. Knowing whether analytics helps them decide better, and whether this shows up in results, is useful both for these firms and for the agencies and trainers who work with them. Studies that test this full chain, from analytics to decisions to outcomes, using data from a tier-2 Indian city are still rare.

Theoretical Background

Three well-known ideas from management theory support the model of this study.

- **Information Processing View** (Galbraith, 1974): firms face uncertainty, and they perform better when they build ways to collect and process information that reduce this uncertainty. Digital analytics is one such way for the marketing function.
- **Resource-Based View** (Barney, 1991): a firm gains an advantage from resources that are valuable and hard to copy. Data alone is easy to get, but the skill to use it well in decisions is not, so analytics use can work as such a resource.
- **Dynamic Capabilities** (Teece, Pisano and Shuen, 1997): firms need the ability to sense change and adjust quickly. Analytics helps marketers sense what customers are doing and adjust campaigns while they are still running. Harjai et al. (2025)

Taken together, these views suggest that analytics creates value through the decision-making process, and not merely because the data exists.

Review of Literature

Table 1 brings together the main studies that guide this research, followed by a short discussion.

Table 1: Summary of Key Studies

Author(s) & Year	Focus	Main Finding
McAfee & Brynjolfsson (2012)	Big data and management	Firms that call themselves data-driven performed better on objective measures of financial and operational results.
Mintz & Currim (2013)	Use of metrics by marketing managers	Greater use of marketing and financial metrics was linked with better performance of marketing-mix activities.
Provost & Fawcett (2013)	Data-driven decision making	Data science creates value only when it is used to support decisions; the decision is the point of contact with business value.
Cao, Duan & Li (2015)	Business analytics and decision making	Business analytics improved decision-making effectiveness through a data-driven environment and better information processing.
Brynjolfsson & McElheran (2016)	Adoption of data-driven decisions	Use of data-driven decision making spread quickly among US firms and was associated with higher productivity.
Gupta & George (2016)	Big data analytics capability	Analytics capability depends on tangible, human and intangible resources, and it is linked with firm performance.

Author(s) & Year	Focus	Main Finding
Wamba et al. (2017)	Analytics capability and performance	Analytics capability had a direct effect on firm performance and also an indirect effect through dynamic capabilities.
Mikalef et al. (2019)	Analytics and innovation	The effect of analytics capability on innovation passed through dynamic capabilities, not only directly.

Analytics and decisions. A clear line runs through this literature. Provost and Fawcett (2013) argue that the value of data science is created at the moment of decision. Cao, Duan and Li (2015) found that business analytics improves decision-making effectiveness, and Mintz and Currim (2013) showed that marketing managers who rely more on metrics make better marketing-mix decisions. Ambler (2003) had earlier argued that marketing loses credibility in the boardroom when it cannot show its results in numbers.

Indirect routes to results. Several studies show that analytics affects performance partly through another process. Wamba et al. (2017) and Mikalef et al. (2019) found that dynamic capabilities carry a part of the effect. This suggests that, in marketing too, the effect of analytics on campaign results may pass through the quality of decisions.

What is missing. Most of these studies are based on large firms in the US, Europe or China and look at overall firm performance. Few test the specific route from analytics to marketing decision quality to campaign outcomes, and fewer still use data from Indian tier-2 cities. This study responds to that gap.

Research Questions and Objectives

Table 2: Research Questions and Matching Objectives

Research Question	Objective
RQ1: How much do Indore firms use digital analytics, and how good are their marketing decisions and campaign outcomes?	To measure the level of the three study variables.
RQ2: Does analytics utilization improve marketing decision quality and campaign outcomes?	To test the effect of analytics on decisions and on outcomes.
RQ3: Is the effect of analytics on outcomes carried through better decisions?	To test the mediating role of decision quality.
RQ4: Do experience and sector make a difference?	To compare the variables across experience groups and sectors.

Research Model and Hypotheses

The model (Figure 2) places Digital Analytics Utilization (DAU) as the starting point, Marketing Decision Quality (MDQ) as the link in the middle, and Campaign Outcomes (CO) as the end result. Shankar et al. (2025) The following hypotheses are framed in the alternate form:

- 1. **H1:** Digital analytics utilization has a significant positive effect on marketing decision quality.
- 2. **H2:** Digital analytics utilization has a significant positive effect on campaign outcomes.
- 3. **H3:** Marketing decision quality has a significant positive effect on campaign outcomes.
- 4. **H4:** Marketing decision quality mediates the relationship between analytics utilization and campaign outcomes.
- 5. **H5:** There is a significant difference in the study variables between less and more experienced professionals.
- 6. **H6:** There is a significant difference in the study variables across sectors.

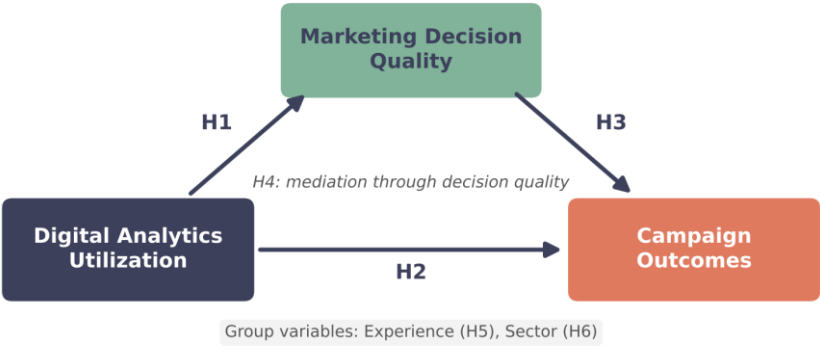


Figure 2: Proposed Research Model

Research Methodology

The study follows a quantitative, cross-sectional survey design. A structured questionnaire was given to people who plan or run digital marketing in their firms, such as owners, marketing heads, digital executives and agency account managers in Indore. The questionnaire had two parts: Part A asked about the sector and years of experience, and Part B contained 28 statements on the three constructs, each rated from 1 (Strongly Disagree) to 5 (Strongly Agree). The scores of each construct were added to form a total score.

Table 3: Constructs and What They Measure

Construct	Items	Score Range	Sample Areas Covered
Digital Analytics Utilization (DAU)	10	10–50	Regular use of web and social media analytics, KPI tracking, dashboards, use of reports in planning

Construct	Items	Score Range	Sample Areas Covered
Marketing Decision Quality (MDQ)	8	8–40	Decisions based on evidence, speed of decisions, budget allocation, targeting accuracy, fewer wrong guesses
Campaign Outcomes (CO)	10	10–50	Reach, engagement, quality of leads, conversion, cost per result, return on spend

The sample consists of 50 respondents selected through purposive sampling, since only those who actually handle digital marketing could answer the questions. Data were analysed using MS Excel and Python (SciPy and Statsmodels). The steps of the work are shown in Figure 3.



Figure 3: Stages of the Research Work

Results

7.1 Who Responded

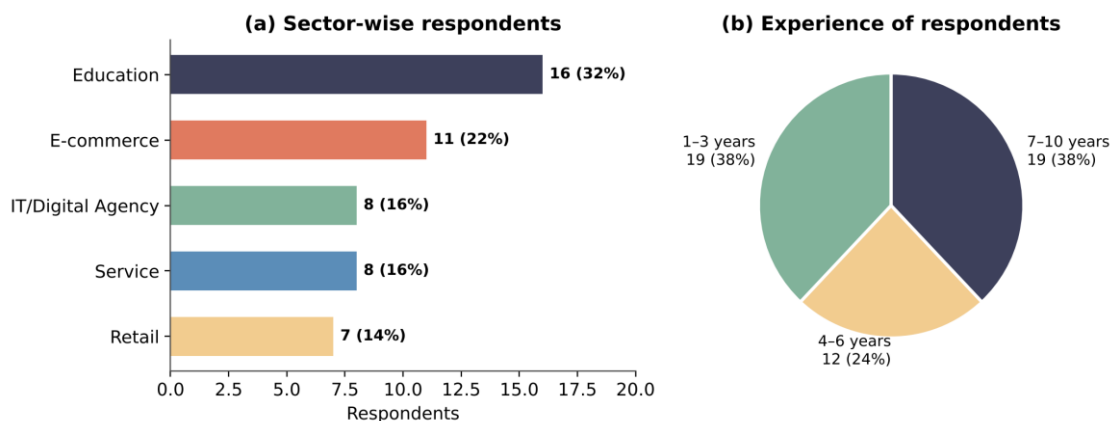


Figure 4: Profile of the 50 Respondents

Education firms form the largest group (32 percent), which fits Indore's image as a coaching and education centre for central India. E-commerce follows with 22 percent, then IT/digital agencies and service firms (16 percent each) and retail (14 percent). The experience of respondents ranges from 1 to 10 years with an average of 5.24 years; 38 percent are early-career (1–3 years), 24 percent mid-level and 38 percent senior (7–10 years). This balance allows a fair comparison between experience groups.

7.2 How the Variables Behave

Table 4: Summary Statistics and Normality Test

Construct	Mean	SD	Median	Range	Item Mean	Skew	Shapiro-Wilk W (p)
Analytics Utilization	32.14	5.58	32.5	20–42	3.21	-0.07	0.973 (0.310)
Decision Quality	27.18	4.61	26.5	17–37	3.40	0.00	0.979 (0.505)
Campaign Outcomes	32.24	5.29	32.0	20–44	3.22	-0.02	0.982 (0.647)

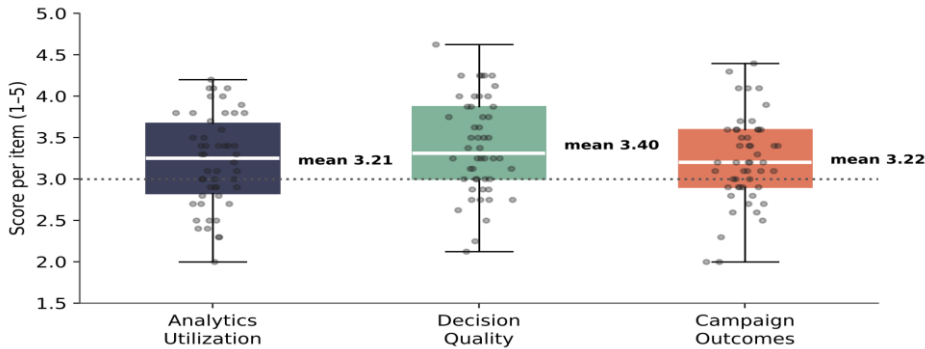


Figure 5: Spread of Scores on the Three Constructs (per-item scale)

All three constructs sit a little above the middle point of the scale. Decision quality has the highest item mean (3.40), while analytics utilization (3.21) and campaign outcomes (3.22) are slightly lower. The box plots show a wide spread: some respondents score close to 2 and others above 4, which means that Indore firms are at very different stages of analytics use. The Shapiro-Wilk test is not significant for any construct ($p > 0.05$), so the data can be treated as normal and parametric tests are suitable.

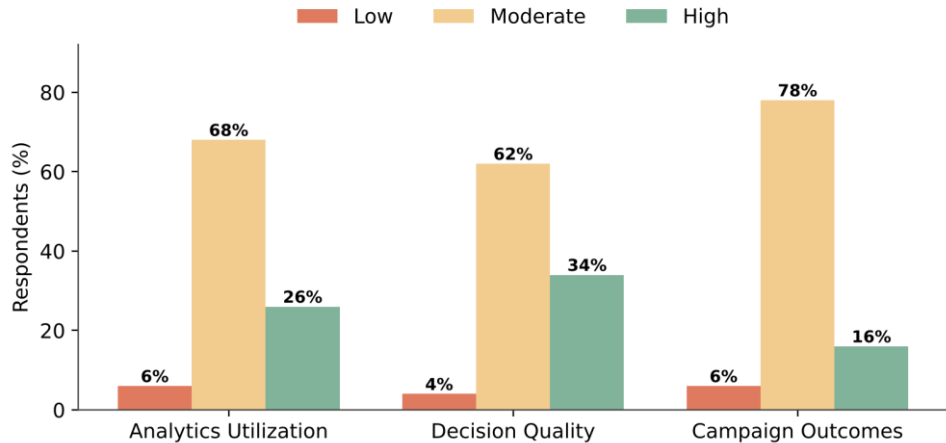


Figure 6: Low, Moderate and High Levels of Each Construct

Using cut-points of 2.33 and 3.67 on the item scale, most respondents fall in the moderate band for all three constructs. Gupta et al. (2025) A third of them (34 percent) report high decision quality, but only 16 percent report high campaign outcomes. So even firms that feel confident about their decisions do not always see this in their results.

7.3 How the Variables Are Related

Table 5: Correlation Matrix (Pearson r)

	Experience	DAU	MDQ	CO
Experience	—			
Analytics Utilization (DAU)	0.514**	—		
Decision Quality (MDQ)	0.569**	0.793**	—	
Campaign Outcomes (CO)	0.303*	0.642**	0.654**	—

** $p < 0.01$; * $p < 0.05$ (two-tailed); $n = 50$.

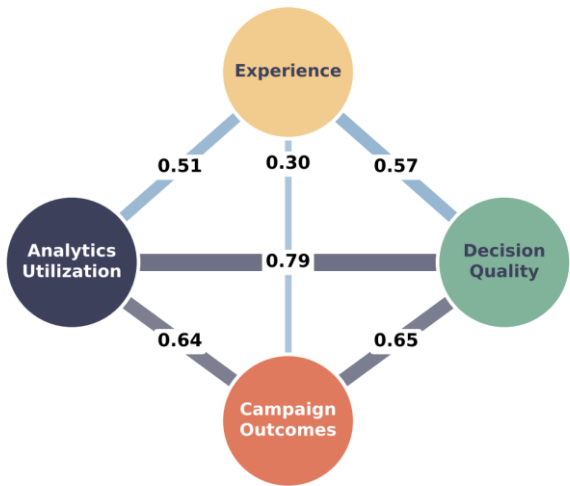


Figure 7: Correlation Network (thicker line = stronger relationship)

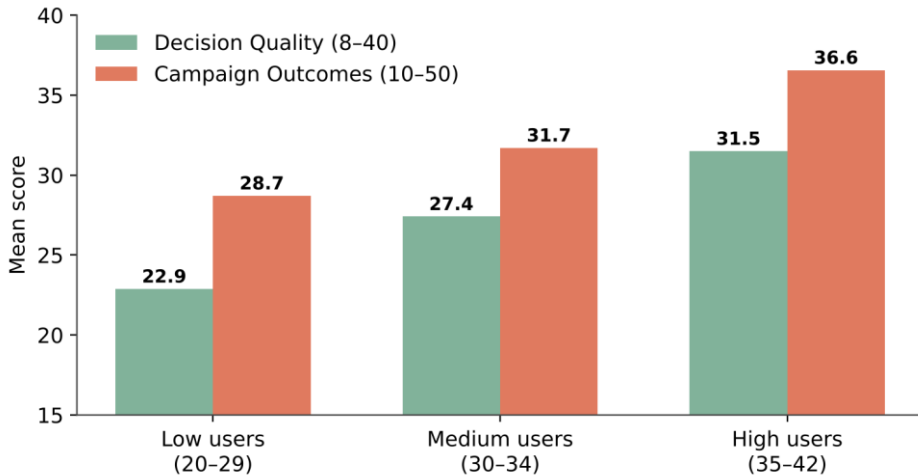
The strongest link in the data is between analytics utilization and decision quality ($r = 0.793$). Both are also strongly linked with campaign outcomes (0.642 and 0.654). Experience is moderately related to analytics use (0.514) and decision quality (0.569) but only weakly to campaign outcomes (0.303). In plain terms, experienced people use data more and take better decisions, but experience alone does not move results much.

7.4 Comparison by Level of Analytics Use

To see the effect in a simple way, respondents were divided into three nearly equal groups by their analytics score: low users (20–29), medium users (30–34) and high users (35–42).

Table 6: Decision Quality and Campaign Outcomes by Analytics Usage Group

Usage Group	n	MDQ Mean (SD)	CO Mean (SD)
Low users	17	22.88 (3.08)	28.71 (4.93)
Medium users	17	27.41 (2.72)	31.71 (2.44)
High users	16	31.50 (3.27)	36.56 (4.98)
F (2, 47)		33.54	14.15
p-value		< 0.001	< 0.001

**Figure 8: Decision Quality and Campaign Outcomes Rise with Analytics Use**

Both decision quality and campaign outcomes rise step by step as analytics use increases, and the differences are highly significant. The Tukey post-hoc test shows that high users score significantly higher on campaign outcomes than both low users (difference = 7.86, $p < 0.001$) and medium users (4.86, $p = 0.006$). The gap between low and medium users (3.00) is not significant ($p = 0.112$). This suggests that a firm needs to cross a certain level of analytics use before the benefit clearly shows in its results.

7.5 Testing H1, H2 and H3: Regression Analysis

Table 7: Simple Regression Results

Path	B	SE	β	t	R ²	F (1, 48)	p
DAU → MDQ (H1)	0.656	0.073	0.793	9.03	0.629	81.53	< 0.001
DAU → CO (H2)	0.609	0.105	0.642	5.81	0.413	33.70	< 0.001
MDQ → CO (H3)	0.750	0.125	0.654	5.99	0.428	35.88	< 0.001

All three paths are positive and significant. Analytics utilization alone explains 62.9 percent of the variation in decision quality, which is a very large share for a single factor. It also explains

41.3 percent of the variation in campaign outcomes. Decision quality alone explains 42.8 percent of the variation in outcomes. H1, H2 and H3 are therefore accepted.

Since experience is related to both analytics use and decision quality, a **hierarchical regression** was run to check whether analytics still matters after experience is taken into account. Experience was entered first, analytics utilization second and decision quality third.

Table 8: Hierarchical Regression on Campaign Outcomes

Predictor	Model 1 β	Model 2 β	Model 3 β
Experience	0.303*	-0.037	-0.135
Analytics Utilization		0.661***	0.356*
Decision Quality			0.449*
R ²	0.092	0.413	0.481
Adjusted R ²	0.073	0.389	0.447
Change in R ²	0.092	0.321	0.067
F change (p)	4.87 (0.032)	25.75 (< 0.001)	5.98 (0.018)

*** $p < 0.001$; * $p < 0.05$. VIF values: 1.50 to 2.98. Durbin-Watson = 1.95.

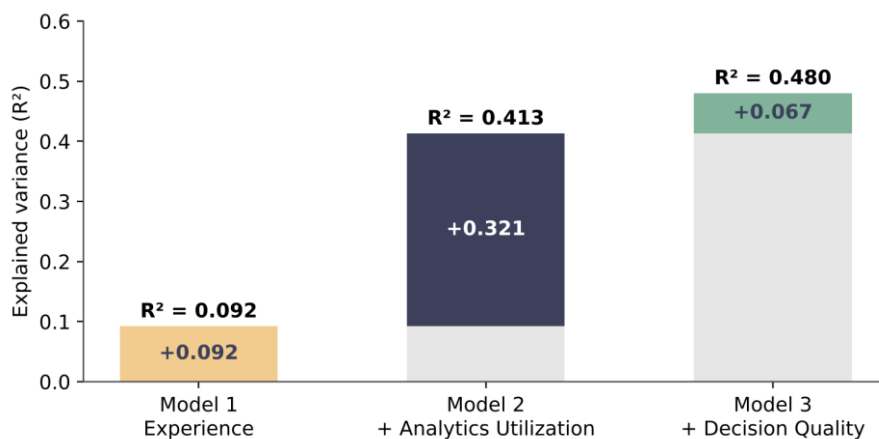


Figure 9: Step-wise Gain in Explained Variance

Experience on its own explains only 9.2 percent of campaign outcomes. When analytics utilization is added, the explained share jumps by 32.1 percentage points, and the effect of experience disappears ($\beta = -0.037$). This means that experienced people get better results mainly because they use analytics more, not because of their experience as such. Adding decision quality in Model 3 adds a further 6.7 percentage points, which is significant ($p = 0.018$). In the final model, decision quality ($\beta = 0.449$) is a slightly stronger predictor than analytics utilization ($\beta = 0.356$). VIF values below 3 and a Durbin-Watson value of 1.95 show that the model is statistically sound.

7.6 Testing H4: Does Decision Quality Carry the Effect?

Mediation was tested with the regression approach of Baron and Kenny (1986), and the indirect effect was checked with 5,000 bootstrap samples as suggested by Preacher and Hayes (2008).

Table 9: Mediation Results

Path	Coefficient	SE	p	95% Bootstrap CI
a: DAU → MDQ	0.656	0.073	< 0.001	—
b: MDQ → CO (controlling DAU)	0.447	0.200	0.030	—
c: Total effect DAU → CO	0.609	0.105	< 0.001	—
c': Direct effect DAU → CO	0.316	0.166	0.063	—
a × b: Indirect effect	0.293	—	—	0.017 to 0.604

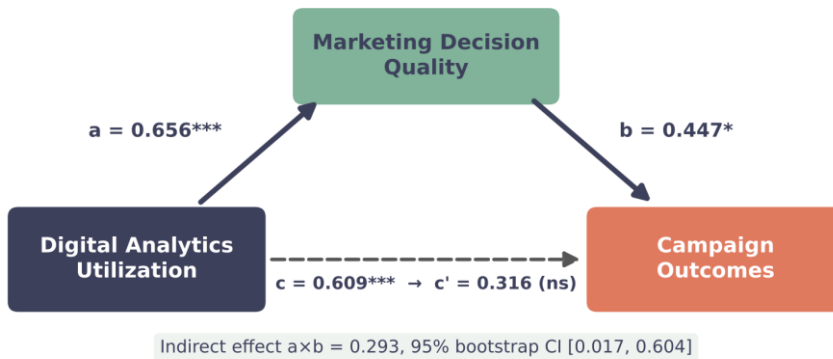


Figure 10: Mediation Model with Path Coefficients

The indirect effect of 0.293 is significant because its bootstrap confidence interval does not include zero. Once decision quality is in the model, the direct effect of analytics on outcomes falls from 0.609 to 0.316 and is no longer significant at the 5 percent level ($p = 0.063$). About 48 percent of the total effect (0.293 out of 0.609) passes through decision quality. H4 is accepted. Put simply, analytics helps campaigns mainly because it helps managers take better decisions.

7.7 Testing H5: Role of Experience

Table 10: Independent Samples t-test by Experience

Construct	Up to 5 yrs (n = 27) Mean (SD)	Above 5 yrs (n = 23) Mean (SD)	t (48)	p
Analytics Utilization	29.89 (5.60)	34.78 (4.34)	3.41	0.001
Decision Quality	25.07 (4.41)	29.65 (3.55)	3.99	< 0.001

Construct	Up to 5 yrs (n = 27) Mean (SD)	Above 5 yrs (n = 23) Mean (SD)	t (48)	p
Campaign Outcomes	31.63 (5.68)	32.96 (4.82)	0.88	0.383

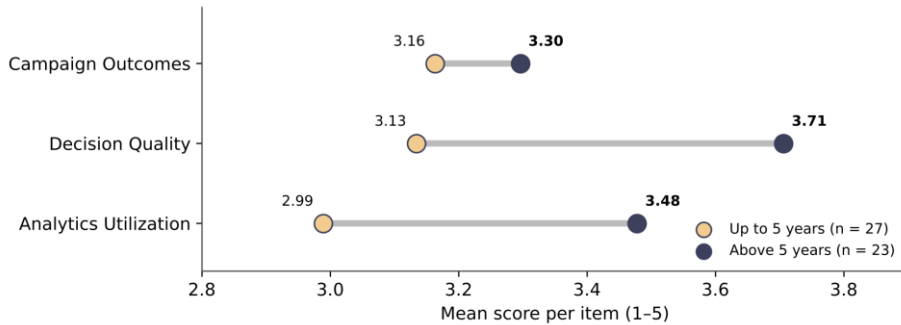


Figure 11: Gap between Less and More Experienced Professionals

Professionals with more than five years of experience score significantly higher on analytics utilization and decision quality. Levene's test confirmed equal variances in all three cases ($p > 0.05$). Their campaign outcomes, however, are only slightly higher and the difference is not significant. **H5 is partly accepted.** The likely reason is that campaign results also depend on budget, product and market conditions, which experience alone does not control.

7.8 Testing H6: Role of Sector

Table 11: Sector-wise Means and One-way ANOVA

Sector (n)	DAU	MDQ	CO
Education (16)	30.25 (5.85)	25.06 (4.89)	32.06 (5.30)
E-commerce (11)	32.00 (6.63)	27.18 (4.71)	31.91 (7.13)
IT/Digital Agency (8)	32.75 (4.56)	28.38 (4.21)	31.75 (5.01)
Service (8)	34.38 (4.84)	28.88 (3.31)	32.38 (3.62)
Retail (7)	33.43 (5.06)	28.71 (4.82)	33.57 (5.16)
F (4, 45) / p	0.89 / 0.478	1.50 / 0.219	0.13 / 0.969

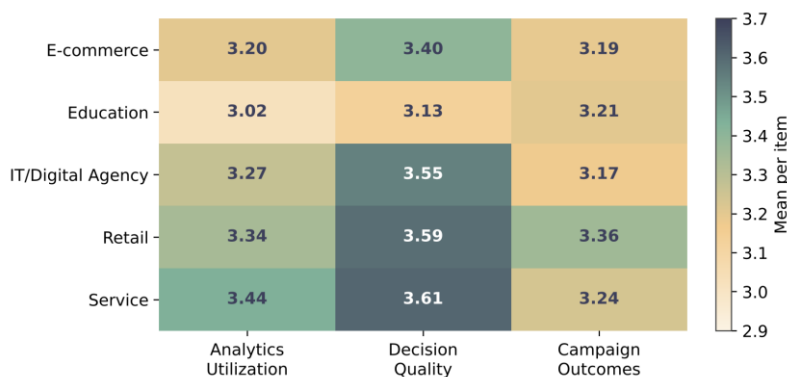


Figure 12: Heat Map of Sector-wise Mean Scores (per item)

Service and retail firms report somewhat higher analytics use and decision quality, while education firms are lowest on both. Even so, none of the differences is significant (all $p > 0.05$). **H6 is not accepted.** Whether a firm sells courses, products or services, the link between analytics, decisions and outcomes works in much the same way.

Summary of Hypotheses

Table 12: Decision on Hypotheses

No.	Hypothesis	Evidence	Decision
H1	DAU → MDQ	$\beta = 0.793, p < 0.001$	Accepted
H2	DAU → CO	$\beta = 0.642, p < 0.001$	Accepted
H3	MDQ → CO	$\beta = 0.449, p = 0.018$ (Model 3)	Accepted
H4	MDQ mediates DAU → CO	Indirect = 0.293, CI [0.017, 0.604]	Accepted
H5	Difference by experience	Significant for DAU, MDQ; not for CO	Partly accepted
H6	Difference by sector	All $p > 0.05$	Not accepted

Discussion

The central message of this study is that the decision is the bridge between data and results. The very strong link between analytics use and decision quality ($r = 0.79$) supports the claim of Provost and Fawcett (2013) and Cao et al. (2015) that analytics earns its value at the point of decision. The significant indirect effect fits with the findings of Wamba et al. (2017) and Mikalef et al. (2019), who also found that analytics works through another process rather than only directly.

The experience findings are also worth noting. Senior professionals use analytics more and decide better, yet their campaign results are not much higher. The hierarchical regression

explains why: the benefit of experience is mostly carried by analytics use. A young marketer who uses data well can therefore reach results close to those of a senior colleague. This fits the Resource-Based View, since the capability that matters is the skill of using data and not simply the years of service.

Finally, the threshold effect in Table 6, where results rise clearly only for high users, suggests that occasional or shallow use of analytics does not help much. Firms need to go beyond looking at likes and reach and start using data for budget, audience and content choices.

Practical Insight

Analytics pays off through better decisions. Firms in Indore should ask not "Do we have the data?" but "**Which decision did this data change this week?**"

Implications

10.1 For Managers and Business Owners

- Tie each report to a decision. Every weekly report should end with one or two clear actions, such as pausing an advertisement, moving budget or changing the audience.
- Aim to become a high user. Since benefits appear clearly only at higher levels of use, firms should track a fixed set of KPIs regularly instead of checking data now and then.
- Train young staff early. Fresh marketers lag behind in analytics use; short training in Google Analytics, Meta Ads Manager and basic Excel dashboards can close this gap quickly.
- Education firms need special attention. Coaching institutes and schools scored lowest on analytics use. Simple lead tracking from enquiry to admission can help them a great deal.

10.2 For Researchers and Educators

- Marketing decision quality should be treated as a key link in future models of analytics and performance.
- Business schools in the region can build practical analytics and decision-making modules into their commerce and management courses.

Limitations and Future Research

This study is based on 50 respondents from one city, chosen purposively, so its results should be read as indicative. All responses are self-reported, and campaign outcomes were not checked against actual company figures. The cross-sectional design limits firm claims about cause and effect. Future research can use a larger and random sample across Madhya Pradesh, collect real campaign data from ad platforms, use structural equation modelling, and test whether firm size, budget or the use of AI-based tools changes the strength of these links.

Conclusion

This paper examined whether digital analytics strengthens marketing decisions and campaign outcomes among firms in Indore. The answer is yes, and the route is clear. Firms that use analytics more take better marketing decisions, and these better decisions carry close to half of the effect of analytics on campaign results. The benefit appears across sectors and is not simply a matter of experience. The lesson for firms is simple: analytics is useful only when it reaches the decision. Firms that make data a part of every marketing choice, about whom to target, where to spend and when to change course, are the ones most likely to see stronger campaign outcomes.

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