Digital Analytics for Measuring and Improving Digital Marketing Performance

Iliyas Patel[1], Dr. Supriya Pathak[2]

[1]PhD Scholar, Faculty of Management, Commerce and Media Studies, Oriental University, Indore, Madhya Pradesh, India.
[2]Professor, Faculty of Management, Commerce and Media Studies, Oriental University, Indore, Madhya Pradesh, India.

Abstract
Every click, visit and purchase made online leaves a record behind. Digital analytics is the practice of collecting these records and turning them into useful information for marketing decisions. This study looks at how the use of digital analytics helps firms in Indore to measure and improve the performance of their digital marketing. Primary data were collected from 50 marketing professionals working in e-commerce, education, service, retail and IT/start-up firms of Indore city through a structured questionnaire on a five-point Likert scale. Three variables were measured: Digital Analytics Usage (10 items), Campaign Optimization (8 items) and Digital Marketing Performance (10 items). The data were analysed with descriptive statistics, Pearson correlation, simple and multiple regression, a bootstrap test of the indirect effect, and one-way ANOVA. The results show a strong positive relationship between digital analytics usage and digital marketing performance ($r = 0.73$, $p < 0.001$). Digital analytics usage alone explains about 54 percent of the change in marketing performance. Firms that use analytics more also optimize their campaigns more ($r = 0.75$). However, when both variables are taken together, analytics usage remains the main predictor and the separate effect of campaign optimization is not significant. No significant difference was found across sectors or experience groups. The study suggests that firms in Indore should treat analytics as a regular working habit and not as an occasional report.

Keywords: Digital Analytics, Digital Marketing Performance, Campaign Optimization, Marketing KPIs, Data-Driven Decision Making, Indore.

Introduction

Marketing in India has changed a lot in the last ten years. Cheap mobile data, low-cost smartphones and the spread of UPI payments have brought a very large number of people online. Customers now search for products on Google, compare prices on shopping apps, watch reviews on YouTube and follow brands on Instagram before they buy. Because of this, businesses of every size, from a small coaching institute to a large online store, now spend a growing share of their marketing budget on digital channels.

Spending money on digital marketing is only one part of the story. The bigger question for any manager is simple: is this money giving results? In traditional marketing, such as a newspaper advertisement or a hoarding, it was very hard to know how many people saw the message and how many of them actually bought something. Digital marketing is different. Every action of the customer can be tracked. Tools such as Google Analytics, Meta Business Suite, Search Console and the dashboards of e-mail and CRM software record visits, clicks, time spent, sign-ups and sales. This set of tools and practices is called digital analytics.

Digital analytics helps a firm to do two things. First, it helps to measure performance through numbers such as website traffic, click-through rate (CTR), cost per lead, conversion rate and return on investment (ROI). Second, it helps to improve performance, because once a manager knows which advertisement, keyword or post is working, the budget and content can be changed in time. This second step is known as campaign optimization.

Indore is the commercial capital of Madhya Pradesh and has been ranked the cleanest city of India several times. The city has a strong base of traders, educational institutes, service providers and a fast-growing group of IT companies and start-ups. Many of these firms now market themselves online. Yet it is not clear how far these local firms actually use the data they collect, and whether this use leads to better marketing results. The present study tries to answer this question with primary data from 50 marketing professionals of Indore.

2. Review of Literature

2.1 Digital Analytics and Performance Measurement

Kaushik (2009) explained that web analytics should not stop at counting visitors. In his view, the real value comes when the numbers are linked with business outcomes such as leads and sales. Chaffey and Patron (2012) took this idea further and argued that firms should move "from web analytics to digital marketing optimization", meaning that data must be used to make actual changes in campaigns.

Järvinen and Karjaluoto (2015) studied industrial firms and found that web analytics helps managers to measure digital marketing performance, but only when the firm has clear goals, trained staff and support from top management.

Saura, Palos-Sánchez and Cerdá Suárez (2017) reviewed the key performance indicators (KPIs) used in digital marketing. They grouped them into indicators of traffic, engagement, conversion and cost, and showed that the choice of the right KPI matters as much as the tool itself.

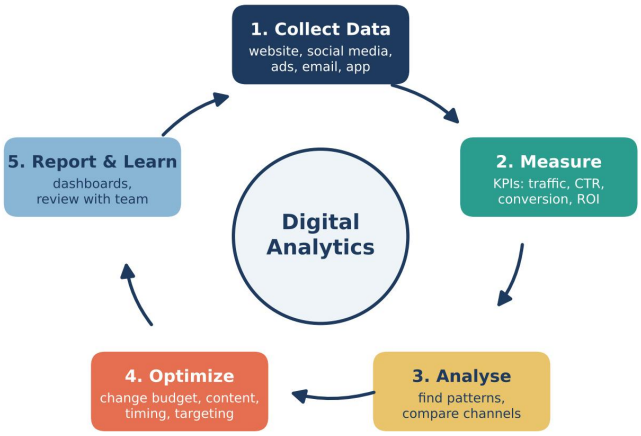

Figure 1: The Digital Analytics Cycle followed in Digital Marketing

2.2 Marketing Analytics and Firm Results

Davenport and Harris (2007) showed that firms which "compete on analytics" make faster and better decisions than their rivals. Germann, Lilien and Rangaswamy (2013) surveyed senior managers of large firms and found that the deployment of marketing analytics had a positive effect on firm performance, and this effect was stronger in industries with high competition and fast-changing customer needs. Wedel and Kannan (2016) described how the large amount of customer data now available has changed the way marketing decisions are made, from pricing to personalisation. Branda, Lala and Gopalakrishna (2018) introduced the idea of a "marketing analytics orientation", which means a firm culture where decisions are regularly based on data rather than on gut feeling.

2.3 Campaign Optimization

Kannan and Li (2017) presented a framework of digital marketing in which data from customer touch points feed back into the marketing mix. In practice, optimization means actions such as A/B testing of advertisements, changing keywords, shifting budget between platforms, re-targeting visitors who did not buy, and choosing the best time to post. Chaffey and Ellis-Chadwick (2019) describe this as a continuous loop of "plan, act, measure and improve". Leeflang, Verhoef, Dahlström and Freundt (2014), however, warned that many firms collect data but lack the skill to turn it into action, which they called the "talent gap".

2.4 Studies in the Indian Context

Kotler, Kartajaya and Setiawan (2017) pointed out that customers in emerging markets such as India move very quickly between online and offline channels. Most of the published work on analytics, however, is based on large firms in developed countries. Studies on Indian tier-2 cities, where small and medium firms form the bulk of business, are still few. This study tries to fill a part of this gap.

3. Research Gap

The review shows that digital analytics is widely accepted as useful, but three gaps remain. First, most studies focus on large firms in metro cities or abroad, and very little is known about firms in cities like Indore. Second, few studies have looked at usage of analytics, campaign optimization and marketing performance together in one model. Third, there is little evidence on whether the benefit of analytics differs by sector or by the experience of the marketing professional. The present study addresses these gaps.

4. Objectives of the Study

1. To study the level of digital analytics usage, campaign optimization and digital marketing performance among firms of Indore.
2. To examine the relationship between digital analytics usage and digital marketing performance.
3. To study the effect of digital analytics usage on campaign optimization, and of campaign optimization on marketing performance.
4. To test whether campaign optimization carries the effect of analytics usage on marketing performance.
5. To compare these variables across sectors and experience groups and to suggest practical steps for firms.

5. Hypotheses

Table 1: Hypotheses of the Study

No.	Null Hypothesis (H0)	Alternate Hypothesis (H1)
H1	Digital analytics usage has no significant effect on digital marketing performance.	Digital analytics usage has a significant positive effect on digital marketing performance.
H2	Digital analytics usage has no significant effect on campaign optimization.	Digital analytics usage has a significant positive effect on campaign optimization.
H3	Campaign optimization has no significant effect on digital marketing performance.	Campaign optimization has a significant positive effect on digital marketing performance.
H4	Campaign optimization does not mediate the link between analytics usage and performance.	Campaign optimization mediates the link between analytics usage and performance.
H5	There is no significant difference in the study variables across sectors.	There is a significant difference in the study variables across sectors.

6. Conceptual Framework

Based on the literature, the study proposes a simple model (Figure 2). Digital Analytics Usage (DAU) is the independent variable. Digital Marketing Performance (DMP) is the dependent variable. Campaign Optimization (CO) is placed in the middle, as the route through which data may turn into results. Sector and work experience are treated as group variables.

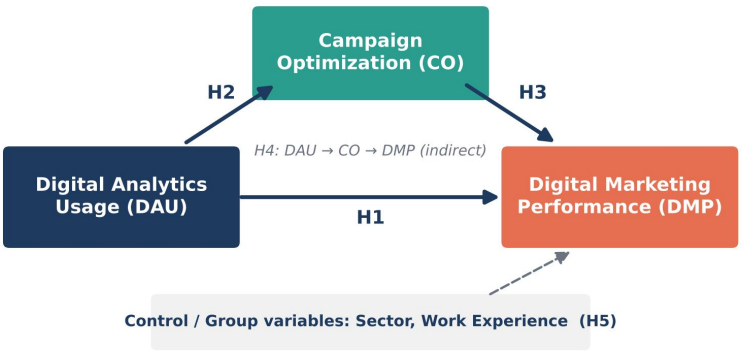

Figure 2: Conceptual Model of the Study

7. Research Methodology

The study is **descriptive and causal** in nature. Primary data were collected through a structured questionnaire filled by marketing professionals such as digital marketing executives, social media managers and business owners who handle the online marketing of their firm. The details are given in Table 2 and the steps followed are shown in Figure 3.

Table 2: Research Design at a Glance

Particular	Details
Research design	Descriptive and causal
Area of study	Indore city, Madhya Pradesh
Population	Marketing professionals of firms using digital marketing
Sample size	50 respondents
Sampling method	Convenience and purposive sampling
Sectors covered	E-commerce, Education, Service, Retail, IT/Start-up
Data collection tool	Structured questionnaire, five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree)
Variables (items)	Digital Analytics Usage (10), Campaign Optimization (8), Digital Marketing Performance (10)
Score range	DAU 10–50, CO 8–40, DMP 10–50

Particular	Details
Statistical tools	Mean, SD, Shapiro-Wilk test, Pearson correlation, simple and multiple regression, bootstrap mediation test, one-way ANOVA
Software	MS Excel and Python (SciPy, Statsmodels)



Figure 3: Flow of the Research Process

Measurement of variables. Digital Analytics Usage covers how often the firm uses tools like Google Analytics and social media insights, tracks KPIs, and uses reports in meetings. Campaign Optimization covers actions such as A/B testing, changing budget between platforms, re-targeting and changing content based on data. Digital Marketing Performance covers growth in website traffic, engagement, leads, conversion, cost per lead and return on marketing spend. Item scores were added to get a total score for each variable.

8. Data Analysis and Interpretation

8.1 Profile of Respondents

Table 3: Demographic Profile of Respondents (n = 50)

Variable	Category	Frequency	Percentage
Sector	E-commerce	12	24%
	Education	12	24%
	Service	12	24%
	Retail	9	18%
	IT/Start-up	5	10%
Work experience	1–3 years	12	24%
	4–6 years	14	28%
	7–10 years	24	48%
Total		50	100%

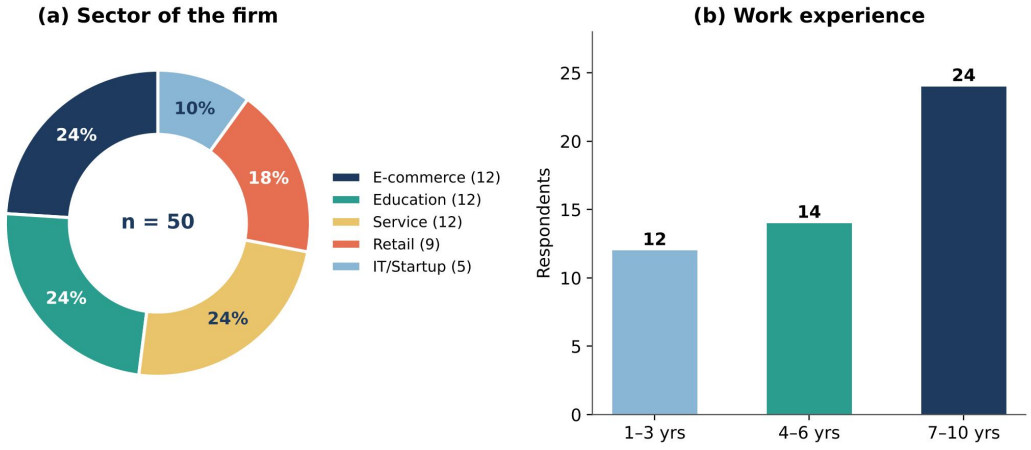

Figure 4: Sector-wise and Experience-wise Distribution of Respondents

Interpretation: E-commerce, education and service firms make up 24 percent each of the sample, followed by retail (18 percent) and IT/start-ups (10 percent). Almost half of the respondents (48 percent) have 7 to 10 years of experience, and the average experience is 5.88 years. So the sample is mostly made up of experienced people who know how marketing works in their firm.

8.2 Descriptive Statistics

Table 4: Descriptive Statistics of Study Variables

Variable	Items	Min	Max	Mean	SD	Mean per item	Skewness	Kurtosis
Digital Analytics Usage	10	24	47	34.96	5.52	3.50	-0.23	-0.46
Campaign Optimization	8	17	35	26.16	4.02	3.27	-0.09	-0.36
Digital Marketing Performance	10	22	45	32.74	4.93	3.27	-0.21	0.01
Experience (years)	–	1	10	5.88	2.83	–	-0.41	-1.03

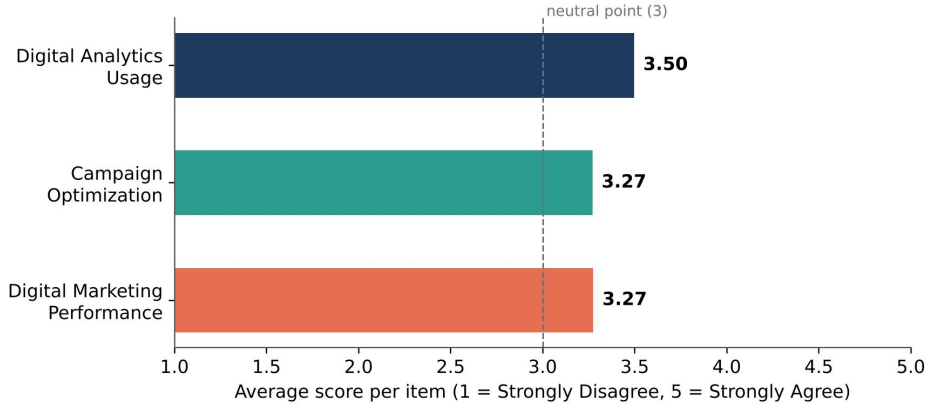

Figure 5: Average Item Score of the Three Variables

Interpretation: All three variables have a mean item score above the neutral point of 3. Digital analytics usage has the highest average (3.50), which means that most firms do use analytics tools to some degree. Campaign optimization and marketing performance both stand at 3.27. This small gap is worth noting: firms are collecting and looking at data a little more than they are acting on it. Skewness and kurtosis values lie well within ±1, so the data are close to a normal shape.

To see the level of each variable, the scores were divided into three bands on the 1–5 item scale: Low (below 2.33), Moderate (2.33 to 3.67) and High (above 3.67).

Table 5: Level-wise Distribution of Respondents

Variable	Low	Moderate	High
Digital Analytics Usage	0 (0%)	27 (54%)	23 (46%)
Campaign Optimization	2 (4%)	37 (74%)	11 (22%)
Digital Marketing Performance	2 (4%)	39 (78%)	9 (18%)

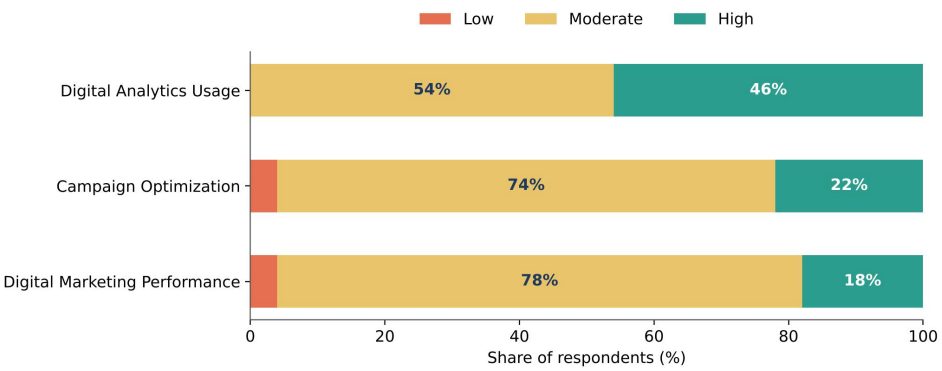

Figure 6: Level of Analytics Usage, Optimization and Performance

Interpretation: Not a single respondent falls in the low band for analytics usage, and 46 percent fall in the high band. But only 22 percent report high optimization and only 18 percent report high performance. Most firms are in the middle. In simple words, many Indore firms have started using analytics, but only a few have reached the stage where data regularly drives action and gives strong results.

8.3 Test of Normality

Table 6: Shapiro-Wilk Test of Normality

Variable	W statistic	p-value	Result
Digital Analytics Usage	0.974	0.325	Normal
Campaign Optimization	0.986	0.828	Normal
Digital Marketing Performance	0.972	0.291	Normal

Interpretation: The p-values of all three variables are above 0.05, so the data do not differ significantly from a normal distribution. This allows the use of parametric tests such as correlation, regression and ANOVA.

8.4 Correlation Analysis

Table 7: Pearson Correlation Matrix

Variable	Experience	DAU	CO	DMP
Experience	1			
Digital Analytics Usage (DAU)	0.179	1		
Campaign Optimization (CO)	0.172	0.747**	1	
Digital Marketing Performance (DMP)	0.087	0.734**	0.649**	1

** Correlation is significant at the 0.01 level (2-tailed). n = 50.

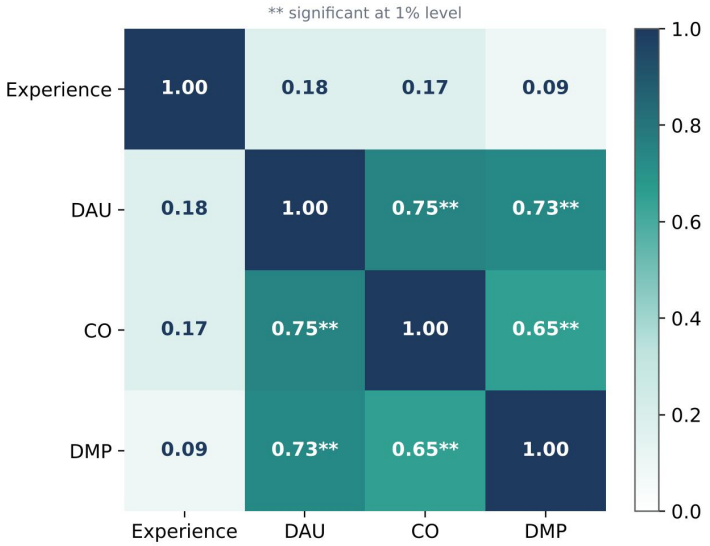

Figure 7: Correlation Heat Map of Study Variables

Interpretation: Digital analytics usage has a strong positive correlation with marketing performance ($r = 0.734$, $p < 0.001$) and with campaign optimization ($r = 0.747$, $p < 0.001$). Campaign optimization is also positively linked with performance ($r = 0.649$, $p < 0.001$). Work experience shows only a weak and non-significant link with all three variables. This means that what a firm does with data matters much more than how many years its marketing person has worked.

8.5 Simple Regression Analysis (H1, H2, H3)

Table 8: Results of Simple Linear Regression

Hyp.	Path	B	SE	β	t	p	R^2	F
H1	DAU → DMP	0.656	0.088	0.734	7.49	<0.001	0.539	56.10
H2	DAU → CO	0.544	0.070	0.747	7.79	<0.001	0.559	60.74
H3	CO → DMP	0.796	0.135	0.649	5.92	<0.001	0.422	34.99

B = unstandardised coefficient; β = standardised coefficient; df = (1, 48).

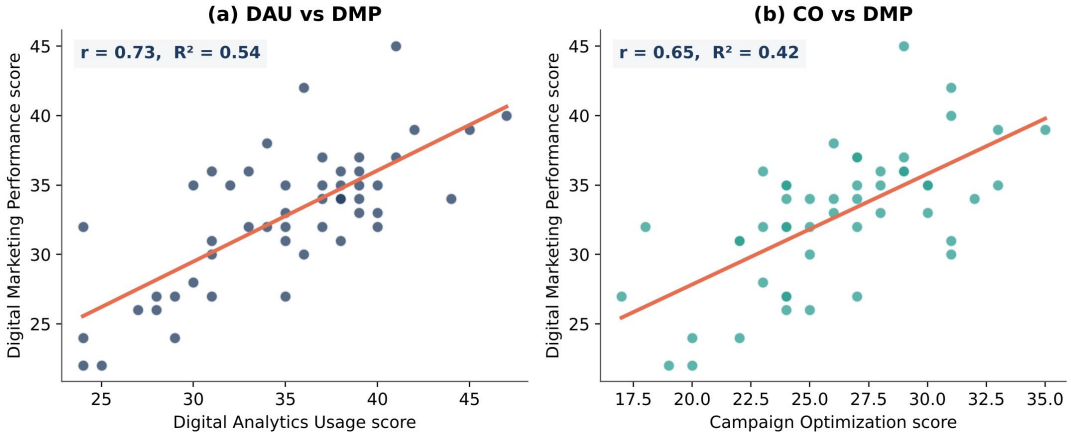

Figure 8: Scatter Plots with Regression Line

Interpretation: All three paths are positive and significant at the 1 percent level. **H1:** digital analytics usage alone explains 53.9 percent of the variation in marketing performance. A one-point rise in the analytics score is linked with a rise of about 0.66 points in the performance score. **H2:** analytics usage explains 55.9 percent of the variation in campaign optimization, which shows that firms which look at data more are also the ones that test and adjust their campaigns. **H3:** campaign optimization alone explains 42.2 percent of the variation in performance. So the null hypotheses H1, H2 and H3 are rejected.

8.6 Multiple Regression Analysis

To find out which variable matters more when both are present, a multiple regression was run with marketing performance as the dependent variable.

Table 9: Multiple Regression – Model Summary

R	R^2	Adjusted R^2	F (2, 47)	p-value	Durbin-Watson
0.750	0.562	0.543	30.14	<0.001	1.86

Table 10: Multiple Regression – Coefficients (Dependent: DMP)

Predictor	B	SE	β	t	p	VIF
Constant	7.826	3.305	–	2.37	0.022	–
Digital Analytics Usage	0.503	0.130	0.564	3.88	<0.001	2.27
Campaign Optimization	0.280	0.178	0.228	1.57	0.123	2.27

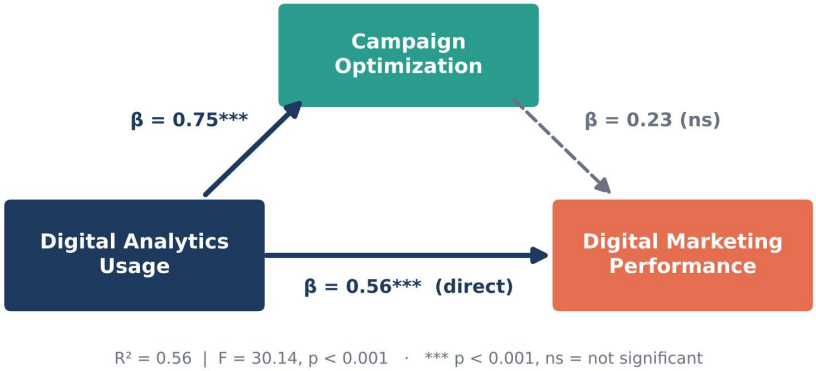

Figure 9: Path Diagram with Standardised Coefficients

Interpretation: The model is significant (F = 30.14, p < 0.001) and the two variables together explain 56.2 percent of the change in marketing performance. VIF values of 2.27 are far below the limit of 10, and the Durbin-Watson value of 1.86 is close to 2, so there is no serious problem of multicollinearity or autocorrelation. Digital analytics usage stays a strong and significant predictor (β = 0.564, p < 0.001). Campaign optimization has a positive sign but is no longer significant (β = 0.228, p = 0.123). This happens because both variables move closely together (r = 0.75): once analytics usage is known, campaign optimization adds only a small amount of new information. Adding experience as a third predictor did not change the result (β = -0.06, p = 0.58).

8.7 Mediation Analysis (H4)

To test whether campaign optimization is the route through which analytics improves performance, the indirect effect (a × b) was tested using 5,000 bootstrap samples, following Hayes (2018).

Table 11: Bootstrap Test of Indirect Effect

Effect	Path	Coefficient	95% Bootstrap CI	Result
Total effect (c)	DAU → DMP	0.656***	–	Significant
Direct effect (c′)	DAU → DMP (with CO)	0.503***	–	Significant
Indirect effect (a × b)	DAU → CO → DMP	0.152	-0.037 to 0.310	Not significant

*** p < 0.001. The indirect effect is significant only when the confidence interval does not include zero.

Interpretation: The indirect effect is positive (0.152), but its confidence interval includes zero. So, with this sample, mediation is **not supported** and H4 is not accepted. Most of the effect of analytics on performance is direct. A likely reason is that for many firms in the sample, using analytics and acting on it happen together as one habit, and a sample of 50 is too small to separate the two clearly.

8.8 Sector-wise Comparison (H5)

Table 12: Sector-wise Mean Scores and One-way ANOVA

Sector	n	DAU Mean (SD)	CO Mean (SD)	DMP Mean (SD)
E-commerce	12	35.33 (4.64)	26.25 (3.08)	34.50 (5.50)
Education	12	34.50 (6.14)	25.08 (4.52)	32.00 (4.99)
Service	12	36.42 (4.21)	27.00 (3.49)	33.75 (3.33)
Retail	9	33.56 (7.26)	25.78 (4.68)	31.44 (5.46)
IT/Start-up	5	34.20 (6.61)	27.20 (5.59)	30.20 (5.50)
F (4, 45)		0.39	0.43	1.07
p-value		0.813	0.786	0.383

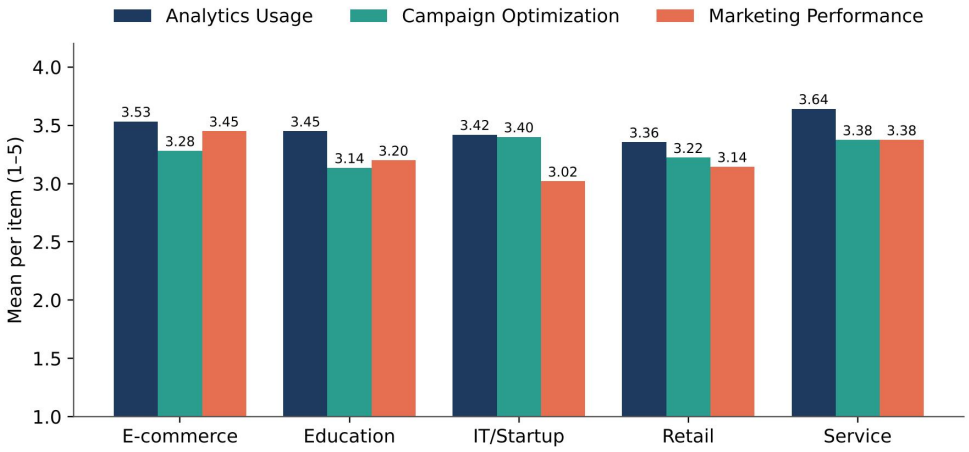

Figure 10: Sector-wise Average Item Scores

Interpretation: Service firms report the highest analytics usage and e-commerce firms the highest performance. IT/start-ups score lowest on performance, although they are only five in number. Still, the F-values are small and all p-values are above 0.05. Levene's test also confirmed equal variances ($p > 0.05$). So the null hypothesis H5 is accepted: the sector of the firm does not make a significant difference. The benefit of analytics seems to be general and not limited to one type of business.

8.9 Experience-wise Comparison

Table 13: Experience-wise Mean Scores and One-way ANOVA

Experience	n	DAU Mean (SD)	CO Mean (SD)	DMP Mean (SD)
1–3 years	12	32.92 (5.53)	24.25 (4.49)	30.50 (4.66)
4–6 years	14	34.50 (5.54)	27.00 (4.87)	33.86 (4.97)
7–10 years	24	36.25 (5.38)	26.62 (2.98)	33.21 (4.88)
F (2, 47)		1.56	1.88	1.76
p-value		0.221	0.163	0.184

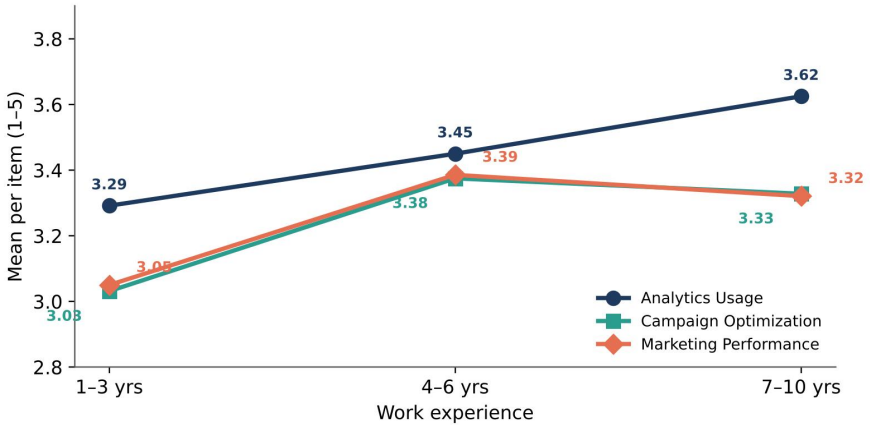

Figure 11: Trend of Scores across Experience Groups

Interpretation: Analytics usage rises steadily with experience, and professionals with 1–3 years of experience score lowest on all three variables. But the differences are not statistically significant (all $p > 0.05$). Experience helps a little, but it is not a substitute for a proper analytics practice.

9. Summary of Hypothesis Testing

Table 14: Summary of Hypothesis Testing

Hyp.	Statement	Test Used	Key Value	Decision
H1	DAU has a significant effect on DMP	Simple regression	$\beta = 0.734$, $p < 0.001$	Supported

Hyp.	Statement	Test Used	Key Value	Decision
H2	DAU has a significant effect on CO	Simple regression	β = 0.747, p < 0.001	Supported
H3	CO has a significant effect on DMP	Simple regression	β = 0.649, p < 0.001	Supported
H4	CO mediates DAU → DMP	Bootstrap (5,000)	CI: -0.037 to 0.310	Not supported
H5	Variables differ across sectors	One-way ANOVA	All p > 0.05	Not supported

10. Major Findings

- Firms in Indore show a moderate to high level of digital analytics usage (mean item score 3.50), while campaign optimization and marketing performance are at a moderate level (3.27 each).
- No respondent reported low analytics usage, but only 18 percent reported high marketing performance. There is a clear gap between having data and getting results from it.
- Digital analytics usage has a strong positive relationship with marketing performance (r = 0.73) and alone explains about 54 percent of the change in performance.
- Firms that use analytics more also optimize their campaigns more (r = 0.75).
- When both variables are considered together, analytics usage remains the main driver. Campaign optimization does not add a significant separate effect, and the mediation path is not supported in this sample.
- Sector and work experience do not make a significant difference. The value of analytics holds across e-commerce, education, service, retail and IT firms.

11. Discussion

The results agree with Germann et al. (2013) and Järvinen and Karjaluoto (2015), who also found that the use of analytics is linked with better marketing results. The strong link between analytics and optimization supports the view of Chaffey and Patron (2012) that analytics and optimization should be seen as one continuous process. The fact that optimization did not show a separate effect is interesting. Harjai et al. (2025) One way to understand it is this: in small and medium firms, the same person often reads the report and also changes the campaign. For such firms, "using analytics" already includes acting on it, so the two cannot be cleanly separated in a survey. The gap between high usage and moderate performance also supports the "talent gap" pointed out by Leeflang et al. (2014). Many firms look at dashboards, but fewer have a system to turn what they see into a planned change.

Key Takeaway

For Indore firms, the biggest gain does not come from buying a new tool. It comes from making analytics a regular habit: setting clear KPIs, checking them every week, and making at least one change in the campaign based on what the numbers say.

12. Suggestions and Managerial Implications

1. Set clear KPIs before starting a campaign. Every campaign should have two or three target numbers, such as cost per lead or conversion rate, so that success can be judged clearly.
2. Hold a short weekly data review. Marketing teams should spend 30 minutes every week on the dashboard and write down what they will change.
3. Train junior staff in analytics. Professionals with 1–3 years of experience scored lowest. Free courses such as Google Analytics certification can close this gap at low cost.
4. Use simple testing. Even small firms can test two versions of an advertisement or a landing page and keep the one that performs better.
5. Link online and offline data. Many Indore firms, especially in education and retail, close sales offline. Using a simple CRM or lead sheet to record the source of each customer will give a true picture of ROI.
6. Support from top management. Owners and senior managers should ask for data in decision meetings, so that analytics becomes part of the firm's culture.

13. Limitations and Scope for Future Research

The study has some limits. The sample of 50 respondents is small and was chosen by convenience, so the results should be generalised with care. The study covers only Indore city. The data are self-reported, and actual numbers such as sales or ROI were not checked from company records. The survey was done at one point in time, so cause and effect cannot be fully proven. Future studies may use a larger sample from several cities of Madhya Pradesh, use actual campaign data from firms, apply structural equation modelling, and study the role of new tools such as AI-based analytics and marketing automation. Sayyed et al. (2025)

14. Conclusion

This study set out to understand how digital analytics helps in measuring and improving digital marketing performance, using data from 50 marketing professionals of Indore. The answer is clear. Firms that use digital analytics more regularly report better marketing performance, and this link is strong in every sector studied. Analytics also goes

hand in hand with campaign optimization. However, the study shows that many firms are still in the middle stage: they have the tools and look at the data, but they have not yet turned this into a steady habit of action and improvement. Jasmine and Kissvar (2025) Closing this gap through clear goals, regular review, staff training and support from top management can help Indore firms get much more value from their digital marketing spend. In the end, data is useful only when it changes a decision.

References

1. Branda, A. F., Lala, V., & Gopalakrishna, P. (2018). The marketing analytics orientation (MAO) of firms: Identifying factors that create highly analytical marketing practices. Journal of Marketing Analytics, 6(3), 84–92.
2. Chaffey, D., & Ellis-Chadwick, F. (2019). Digital marketing: Strategy, implementation and practice (7th ed.). Pearson.
3. Chaffey, D., & Patron, M. (2012). From web analytics to digital marketing optimization: Increasing the commercial value of digital analytics. Journal of Direct, Data and Digital Marketing Practice, 14(1), 30–45.
4. Davenport, T. H., & Harris, J. G. (2007). Competing on analytics: The new science of winning. Harvard Business School Press.
5. Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big data consumer analytics and the transformation of marketing. Journal of Business Research, 69(2), 897–904.
6. Germann, F., Lilien, G. L., & Rangaswamy, A. (2013). Performance implications of deploying marketing analytics. International Journal of Research in Marketing, 30(2), 114–128.
7. Jasmine, C. N., & Kissvar, D. (2025). Digital marketing and its effectiveness in higher education. International Journal of Engineering Technologies and Management Research, 12(9), 42–48. https://doi.org/10.29121/ijetmr.v12.i9.2025
8. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate data analysis (8th ed.). Cengage Learning.
9. Hayes, A. F. (2018). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach (2nd ed.). Guilford Press.
10. Harjai, V., Nair, R., & Sharma, B. (2025). Is digital marketing simply communication evolved? A study on how digital platforms reshape brand–customer interaction. ShodhVichar: Journal of Media and Mass Communication, 1(2), 160–165. https://doi.org/10.29121/ShodhVichar.v1.i2.2025.54
11. Järvinen, J., & Karjaluoto, H. (2015). The use of web analytics for digital marketing performance measurement. Industrial Marketing Management, 50, 117–127.
12. Kannan, P. K., & Li, H. A. (2017). Digital marketing: A framework, review and research agenda. International Journal of Research in Marketing, 34(1), 22–45.
13. Kaushik, A. (2009). Web analytics 2.0: The art of online accountability and science of customer centricity. Wiley Publishing.
14. Kotler, P., Kartajaya, H., & Setiawan, I. (2017). Marketing 4.0: Moving from traditional to digital. John Wiley & Sons.
15. Leeflang, P. S. H., Verhoef, P. C., Dahlström, P., & Freundt, T. (2014). Challenges and solutions for marketing in a digital era. European Management Journal, 32(1), 1–12.
16. Sayyed, A. R., Jothi, L., & Sharma, B. (2025). A compreshensive study on social media marketing. ShodhVichar: Journal of Media and Mass Communication, 1(2), 181–187. https://doi.org/10.29121/ShodhVichar.v1.i2.2025.61
17. Saura, J. R., Palos-Sánchez, P., & Cerdá Suárez, L. M. (2017). Understanding the digital marketing environment with KPIs and web analytics. Future Internet, 9(4), 76.
18. Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. Journal of Marketing, 80(6), 97–121.