



LEVERAGING DIGITAL MARKETING ANALYTICS TO ENHANCE RETURN ON MARKETING INVESTMENT: A STUDY OF STARTUPS IN VIJAYAWADA

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ABSTRACT :

Digital marketing has become an important tool for startups to promote their products and services, reach target customers, and improve business performance. Startups in Vijayawada are increasingly using digital marketing platforms such as Instagram, Facebook, Google Ads, websites, and email marketing to attract customers and increase sales. However, spending money on digital marketing does not always guarantee the expected results. Marketing analytics therefore plays an important role in measuring campaign performance and understanding whether marketing investments are generating positive returns.

This study examines how digital marketing analytics may help startups in Vijayawada improve their Return on Marketing Investment (ROMI). **An important note on the data:** the empirical analysis uses 83 simulated questionnaire responses, not data collected from real startups. The study should therefore be read as an illustrative, simulation-based application of the research design, and its results do not describe real startups. The responses were analysed using frequencies, means, one-sample Wilcoxon tests, Spearman correlation, multiple regression, and Kruskal–Wallis and Mann–Whitney tests.

In the simulated dataset, social media marketing (79.5%), content marketing (53.0%), and email marketing (44.6%) are the most used channels. Analytics use is moderate (mean 3.20 out of 5), and perceived improvement in ROMI is moderately positive (mean 3.33; 49.4% agree). Use of analytics is strongly and positively related to ROI measurement ($\rho = .74$), marketing performance ($\rho = .73$), budget efficiency ($\rho = .62$), improved ROMI ($\rho = .55$), and staff analytical capability ($\rho = .50$). Analytics use is the strongest predictor of ROMI improvement in regression ($\beta = .47$), and staff capability and channel insight add to the explanation of overall outcomes. Reported challenges, firm age, firm size, role, and number of channels are not significantly related to analytics use. Intention to increase analytics use is high (mean 4.05) and is unrelated to current use. The paper discusses what such a pattern would imply for startups if it were confirmed with real data, and recommends that the same instrument be administered to real startups in Vijayawada.

Keywords: Digital Marketing Analytics, Return on Marketing Investment (ROMI), Startups, Marketing Performance, Data-Driven Decision-Making, Customer Engagement, Digital Marketing Strategies, Vijayawada.

1: INTRODUCTION

1.1 Introduction

In the present business environment, digital marketing has become an essential part of business growth and development. The increasing use of the internet, smartphones, and social media has changed the way businesses communicate with customers. Digital marketing allows businesses to promote their products and services through online platforms such as social media, search engines, websites, email, and online advertisements. Compared with traditional marketing methods, digital marketing can provide businesses with opportunities to reach specific customer groups, communicate quickly, and monitor campaign performance.

Startups play an important role in creating employment opportunities, introducing new products and services, and supporting economic development. However, startups often face challenges such as limited financial resources, strong competition, low brand awareness, and difficulties in attracting customers. For these businesses, using marketing budgets effectively is important. They need to select suitable marketing channels and understand which activities contribute to customer acquisition, sales, and business growth.

Digital marketing analytics helps businesses collect, measure, and analyse data generated through their online marketing activities. It provides information about customer behaviour, advertisement performance, website visits, social media engagement, leads, conversions, and sales. Tools such as Google Analytics, Meta Business Suite, and advertising dashboards help businesses evaluate their marketing campaigns and identify areas that require improvement.

One of the important concepts associated with marketing analytics is Return on Marketing Investment (ROMI). ROMI helps businesses evaluate the financial benefits generated by their marketing expenditure. By comparing the returns from marketing activities with their associated costs, startups can better understand whether their campaigns are contributing to business objectives. For example, a startup can use analytics to compare the performance of Instagram advertisements and Google Ads and determine which channel generates more valuable leads or sales relative to its cost.

Despite the availability of digital marketing tools, some startups may find it difficult to interpret marketing data, choose appropriate performance indicators, or connect online engagement with actual revenue. Limited technical knowledge, financial constraints, and a lack of skilled employees may also affect the effective use of analytics. As a result, some startups may continue spending on marketing campaigns without clearly understanding their financial returns.

Vijayawada is an important commercial centre in Andhra Pradesh, with businesses operating in areas such as retail, food services, education, technology, fashion, and other service industries. As startups in the city adopt digital marketing to reach local and wider markets, understanding the role of analytics in improving marketing returns becomes increasingly relevant.

Therefore, the present study, titled “Leveraging Digital Marketing Analytics to Enhance Return on Marketing Investment: A Study of Startups in Vijayawada,” aims to examine the use of digital marketing analytics among startups in Vijayawada and understand how analytical practices influence marketing performance and investment returns. The study also seeks to identify the challenges faced by startups and suggest ways to improve their marketing decisions through data-driven strategies.

1.2 Statement of the Problem

Startups invest in digital marketing with limited budgets, yet it is uncertain whether they use analytics to judge the returns on that spending. Engagement, website traffic, and leads do not always translate into revenue, and startups may lack the skills, tools, or money to connect marketing data with financial results. It is therefore necessary to examine how far analytics is used, whether its use is associated with better ROMI, budget allocation, and marketing performance, and what challenges limit its use. Existing studies are general, concern other regions, or focus on adoption and not on ROMI. This study addresses these questions for startups in Vijayawada.

1.3 Significance of the Study

- For startup founders and marketing managers, the study shows how analytics practices can be linked to investment returns, budget decisions, and channel choice.
- For policymakers and incubators, it indicates the capability and cost challenges that may need support.
- For researchers and students, it provides a worked example of a measurement and analysis framework for analytics and ROMI that can be applied to real data.

1.4 Research Objectives

1. To study the use of digital marketing analytics among startups in Vijayawada.
2. To examine the impact of digital marketing analytics on Return on Marketing Investment (ROMI).
3. To identify the key digital marketing channels used by startups to attract customers and increase sales.
4. To analyse how marketing analytics helps startups improve marketing performance and allocate marketing budgets effectively.
5. To suggest suitable strategies for improving marketing effectiveness and investment returns through data-driven decision-making.

1.5 Research Hypotheses

- **H1:** Use of digital marketing analytics is positively and significantly related to improvement in ROMI.
- **H2:** Use of digital marketing analytics is positively and significantly related to budget efficiency (reduced unnecessary spending and more effective allocation).
- **H3:** Use of digital marketing analytics is positively and significantly related to marketing performance (customer acquisition, sales or revenue,

and conversion).

- **H4:** Staff analytical capability is positively and significantly related to the use of analytics.
- **H5:** Perceived challenges (data difficulties, lack of technical knowledge, tool cost, and limited skills) are negatively and significantly related to the use of analytics.
- **H6:** Startup characteristics (age, size, industry, and respondent's role) are significantly associated with the use of analytics.
- **H7:** The number and type of digital marketing channels used are significantly associated with the use of analytics and with ROMI.

1.6 Scope of the Study

The study concerns startups in Vijayawada that use digital marketing, in industries such as technology, retail, professional services, food and hospitality, healthcare, and manufacturing. It examines perceived use of analytics, perceived outcomes, and challenges as reported by founders, owners, and marketing and operations staff. It does not compute actual ROMI from financial records, and it does not evaluate particular campaigns or tools.

2: REVIEW OF LITERATURE

2.1 Introduction

The review of literature provides an understanding of previous research related to digital marketing, marketing analytics, startup growth, and marketing investment returns. It helps identify important findings from earlier studies and determine the research gap addressed by the present study.

2.2 Anwar and Daniel (2016): Entrepreneurial Marketing in Online Businesses

Anwar and Daniel examined entrepreneurial marketing practices in online businesses, focusing on the role of digital marketing in improving customer engagement and business growth. The study highlighted the importance of online marketing for businesses operating with limited financial resources. Digital marketing was found to offer opportunities to reach customers at relatively low costs. However, the study did not specifically examine how marketing analytics can be used to measure Return on Marketing Investment among Indian startups.

2.3 Banerjee and Banerjee (2017): Determinants of Analytics Process Adoption in Emerging Economies

Arindam Banerjee and Tanushri Banerjee studied the factors influencing the adoption of analytics processes in emerging economies. Their research highlighted the importance of analytical capabilities in supporting business decision-making and improving marketing performance. The study indicated that organisations can benefit from using data to understand business activities and make informed decisions. However, it did not specifically focus on the financial returns generated by marketing investments in startups.

2.4 France and Ghose (2018): Marketing Analytics: Methods, Practice, Implementation, and Links to Other Fields

Stephen L. France and Sanjoy Ghose reviewed different marketing analytics methods, their practical applications, and their connections with other business disciplines. Their work highlighted the importance of using analytical techniques to understand marketing performance and support evidence-based decision-making. The study provides a useful foundation for understanding how businesses can apply analytics to marketing activities. However, it does not provide specific empirical evidence concerning startups in India or the measurement of ROMI in Vijayawada.

2.5 Banerji and Reimer (2019): Start-up Founders and Their LinkedIn Connections

Banerji and Reimer examined the relationship between startup founders' LinkedIn connections and startup-related outcomes. The study drew attention to the role of digital networking in building professional relationships, increasing visibility, and supporting entrepreneurial development. It suggests that online platforms can contribute to opportunities for startups. However, the study does not directly investigate marketing analytics or measure the financial returns generated by digital marketing campaigns.

2.6 Sharma and Goyal (2020): Entrepreneurial Marketing Strategies for Start-up Companies in India

Sarika Sharma and D. P. Goyal explored entrepreneurial marketing strategies used by startup companies in India. The study highlighted the importance of selecting suitable marketing approaches to improve business performance while managing limited resources. Digital marketing can help startups promote their products, reach target customers, and compete in changing markets. However, further research is required to understand how startups use marketing analytics to evaluate campaign profitability and improve ROMI.

2.7 Hawaldar et al. (2021): Digital Marketing Influences on Sales for B2B Start-Ups in South Asia

Hawaldar and colleagues investigated the influence of digital marketing on sales performance among business-to-business startups in South Asia. The study provided insights into the contribution of digital marketing to business development and sales outcomes. Its regional focus makes it relevant to understanding the role of online marketing in startup performance. However, the study does not specifically examine marketing investment returns among startups operating in Vijayawada.

2.8 Chakraborti, Dutta and Jana (2022): Digital Marketing Adoption among Startups in India

Jayanta Chakraborti, Anirban Dutta, and Bhaswati Jana examined digital marketing adoption among startups in India. The study highlighted the importance of digital marketing in customer acquisition, business visibility, and startup competitiveness. It also points to the growing relevance of analytical capabilities in digital marketing. However, there is a need for more location-specific empirical research on how startups in Vijayawada use analytics to measure marketing effectiveness and improve their Return on Marketing Investment.

2.9 Research Gap

Geographical gap: Limited location-specific evidence has been identified on the use of digital marketing analytics among startups in Vijayawada.

Measurement gap: Earlier studies discuss digital marketing adoption and performance, but the supplied literature provides limited direct evidence on how startups measure ROMI.

Practical gap: More understanding is needed of how startups use analytical tools to evaluate campaigns, compare marketing channels, and allocate their budgets effectively.

Financial performance gap: Customer engagement, website traffic, and lead generation do not always translate into revenue. The relationship between these indicators and marketing investment returns requires further investigation.

Implementation gap: Startups may face difficulties related to analytical skills, access to tools, data interpretation, and limited budgets. These challenges need to be examined in the local startup context.

3: RESEARCH METHODOLOGY

3.1 Research Design

The study follows a quantitative, descriptive, and cross-sectional survey design. The instrument is a structured questionnaire whose items measure the use of analytics, its perceived outcomes, and challenges.

3.2 Data Used and Its Status

The dataset contains **83 simulated responses** and no real respondents. Each row of the response file carries the label “SIMULATED — not collected from real respondents.” The responses follow the structure of the 30-question questionnaire described in Section 3.3. Because the data were generated, sampling method, response rate, and data collection period cannot be reported, and the timestamps in the file are part of the simulation. The results show how the analysis would operate and what interpretation would follow, but they cannot be generalised to startups in Vijayawada. The analysis code and tables can be re-run on real responses without change to the design.

3.3 Questionnaire Design

Table 3.1 Structure of the questionnaire

Part	Questions	Content
A. Startup and respondent profile	Q1–Q5	Role, years of operation, primary industry, number of employees, digital marketing channels used (multiple response)
B. Use of analytics	Q6–Q11	Regular monitoring, use of tools, understanding customers, tracking key metrics, analysing campaigns, data-based decisions
C. Channel insight and capability	Q12–Q15	Identifying effective channels and campaigns, staff knowledge, difficulty collecting and analysing data

Part	Questions	Content
D. ROMI measurement and outcomes	Q16–Q25	Measuring return, reducing unnecessary spending, budget allocation, identifying highest-ROI campaigns, spending effectiveness, customer acquisition, sales, conversion, cost–result comparison, overall ROMI
E. Challenges and future	Q26–Q30	Lack of technical knowledge, tool cost, limited skilled employees, plan to increase use, belief that analytics improves ROMI

3.4 Measurement and Constructs

Q6 to Q30 were measured on a five-point Likert scale (Likert, 1932) coded Strongly Disagree = 1 to Strongly Agree = 5. Composite scores are means of related items (Table 3.2). The ROMI measure is a **perceived** measure (Q25) and does not compute return from financial figures.

Table 3.2 Constructs and items

Construct	Items	Cronbach's α
Analytics use	Q6–Q11 (6 items)	.79
Channel / campaign insight	Q12, Q13	.56
Budget efficiency	Q17, Q18, Q20	.51
ROI measurement	Q16, Q19, Q24	.65
Marketing performance	Q21, Q22, Q23	.67
Improved ROMI	Q25 (single item)	–
Outcome index (all outcomes)	Q16–Q25 (10 items)	.86
Staff capability	Q14 (single item)	–
Challenges	Q15, Q26, Q27, Q28 (4 items)	.11
Future intention and belief	Q29, Q30	–.76

The analytics use, ROI measurement, performance, and overall outcome scores show acceptable internal consistency, while the budget efficiency and channel insight scores are modest. The challenge items ($\alpha = .11$) and the two future items ($\alpha = -.76$) do not form scales, so these items are analysed individually as well as in the combined challenge index. The challenge index is used cautiously, and Q29 and Q30 are never combined in tests. The 25 items together give $\alpha = .87$.

3.5 Tools of Analysis

- **Descriptive statistics:** frequencies, percentages, means, and standard deviations.
- **One-sample Wilcoxon signed-rank test:** to test whether item and construct scores differ from the neutral value of 3.
- **Spearman rank correlation:** to test H1 to H7.
- **Multiple regression:** to estimate the effect of analytics use on ROMI and on the outcome index, controlling for capability, challenges, number of channels, firm size, and firm age.
- **Kruskal–Wallis and Mann–Whitney tests:** to compare groups by role, age, size, industry, and channel.

Non-parametric tests were chosen for the main comparisons because the responses are ordinal. All tests used the 5% level of significance and were run in Python.

3.6 Data Preparation

There were no missing values and no duplicate rows. Channel names written in two forms (for example, “Search Engine Optimization (SEO)” and “SEO”, “Search Engine Marketing (SEM)” and “SEM”) were merged. For the channel question, a respondent could select several channels, so percentages are of respondents and do not add to 100. Employee categories and years of operation were coded as ordered scores for the correlations.

3.7 Ethical Considerations

Because no real respondents are involved, there are no participant-protection issues in the present analysis. If the questionnaire is later administered to real startups, informed consent, confidentiality, and anonymity of firms and respondents should be ensured.

4: DATA ANALYSIS AND INTERPRETATION

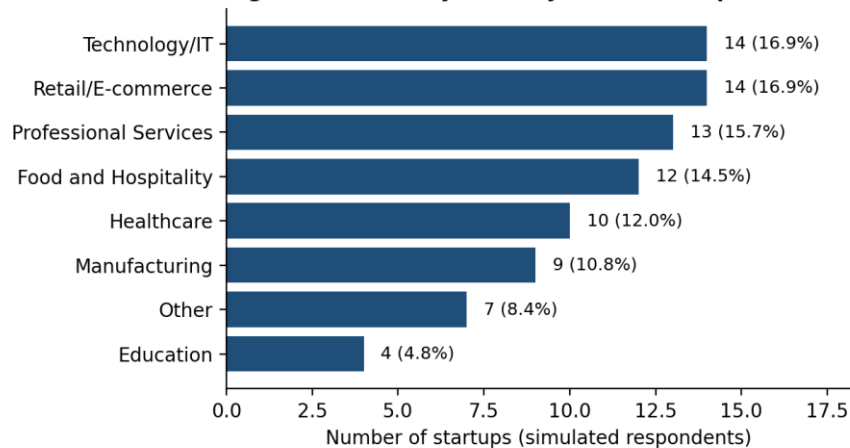
This chapter analyses the 83 **simulated** responses (see Chapter 3). Every result describes the simulated dataset. Section 4.1 describes the profile, Sections 4.2 to 4.5 present descriptive results by objective, and Sections 4.6 and 4.7 report the hypothesis tests.

4.1 Profile of Respondents and Startups

Table 4.1 Profile of simulated respondents and startups (n = 83)

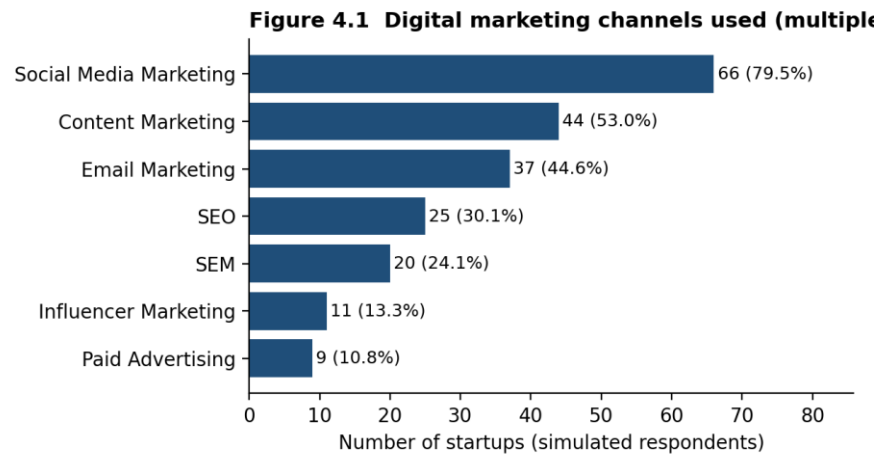
Variable	Category	Number	%
Role	Marketing Manager	30	36.1
	Founder/Co-founder	21	25.3
	Business Owner	10	12.0
	Operations Manager	9	10.8
	Digital Marketing Executive	8	9.6
	Other	5	6.0
Years of operation	Less than 1 year	22	26.5
	1–2 years	22	26.5
	3–5 years	25	30.1
	More than 5 years	14	16.9
Employees	1–10	26	31.3
	11–25	23	27.7
	26–50	18	21.7
	51–100	7	8.4
	More than 100	9	10.8

Figure 4.2 Primary industry of the startup



The simulated respondents are mostly marketing managers (36.1%) and founders or co-founders (25.3%), so 83.1% are founders, owners, or marketing staff in a position to know about marketing practice. The startups are young (53.0% under three years) and small (59.0% have 25 or fewer employees). Industries are well spread, led by technology/IT and retail/e-commerce (16.9% each), professional services (15.7%), and food and hospitality (14.5%).

4.2 Digital Marketing Channels Used (Objective 3)



Social media marketing is used by 79.5% of the startups, well ahead of content marketing (53.0%) and email marketing (44.6%). SEO (30.1%) and SEM (24.1%) follow, while influencer marketing (13.3%) and paid advertising (10.8%) are the least used. Startups use between one and four channels (mean 2.55, SD 0.87): 8 use one channel, 34 use two, 28 use three, and 13 use four. The pattern shows reliance on low-cost, organic channels (social media, content, email) rather than paid advertising, which fits the limited budgets that startups are described as having.

4.3 Use of Analytics (Objective 1)

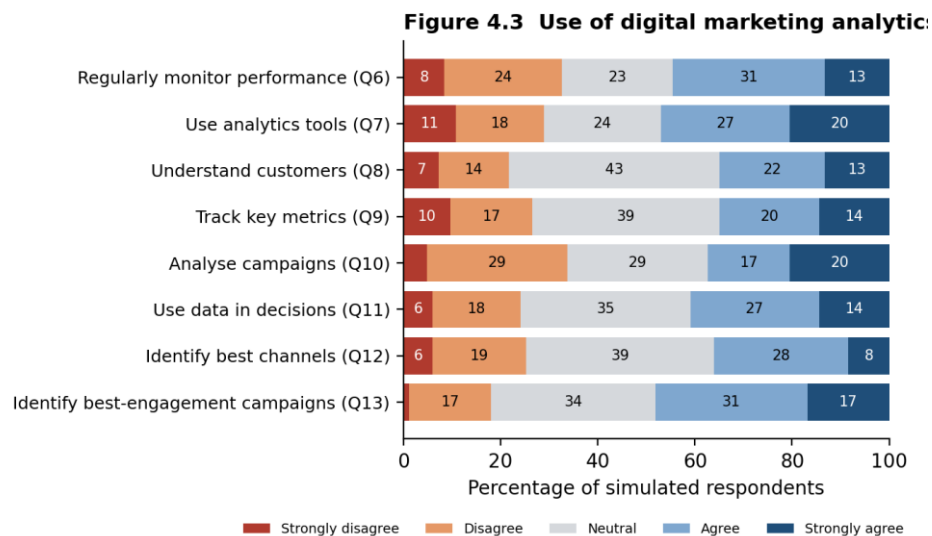


Table 4.2 Descriptive statistics of the analytics use and insight items

Statement	Mean	SD	% agree	% neutral	% disagree	p (vs 3)
Regularly use analytics to monitor performance (Q6)	3.17	1.19	44.6	22.9	32.5	.202
Use analytics tools (Q7)	3.28	1.28	47.0	24.1	28.9	.057
Analytics helps understand customers (Q8)	3.19	1.08	34.9	43.4	21.7	.113
Track key metrics (Q9)	3.13	1.16	34.9	38.6	26.5	.299
Analyse campaign performance (Q10)	3.19	1.20	37.3	28.9	33.7	.083
Use data in marketing decisions (Q11)	3.25	1.10	41.0	34.9	24.1	.040
Identify most effective channels (Q12)	3.13	1.02	36.1	38.6	25.3	.251
Identify campaigns with highest engagement (Q13)	3.46	1.00	48.2	33.7	18.1	< .001

Analytics use is moderate and close to neutral. The mean of the six use items is 3.20 (SD 0.82) and only marginally above 3 (Wilcoxon $p = .045$). Agreement ranges from 34.9% to 47.0%, with large neutral and disagreeing shares: about one third (28.9% to 33.7%) disagree that they regularly monitor performance, use tools, or analyse campaigns. The only item significantly above neutral is the identification of campaigns with the highest engagement (mean 3.46, 48.2% agree). Identifying the most effective channels (mean 3.13) is not above neutral. In the simulated data, therefore, analytics is used by a large minority of startups but is far from universal.

4.4 Outcomes: Measurement of Return, Budget Allocation, and Performance (Objectives 2 and 4)

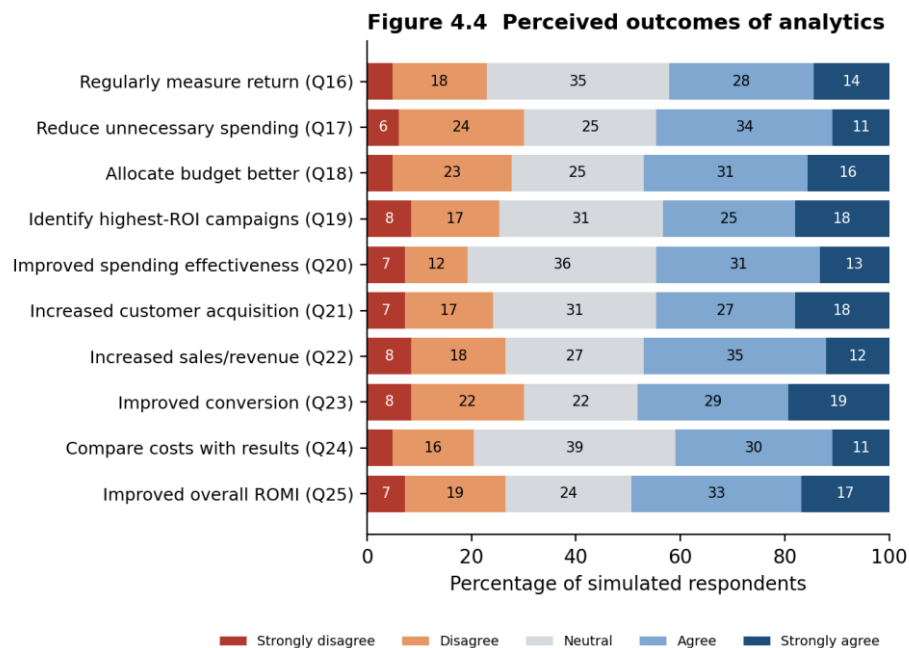


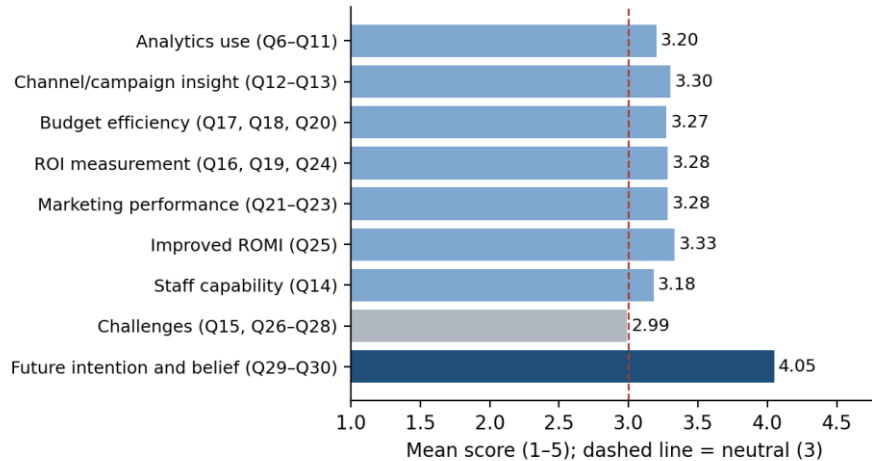
Table 4.3 Descriptive statistics of outcome items

Statement	Mean	SD	% agree	% neutral	% disagree	p (vs 3)
Regularly measure return from marketing (Q16)	3.29	1.08	42.2	34.9	22.9	.017
Reduce unnecessary marketing expenditure (Q17)	3.19	1.11	44.6	25.3	30.1	.119
Allocate marketing budget more effectively (Q18)	3.30	1.13	47.0	25.3	27.7	.017
Identify highest-ROI campaigns (Q19)	3.28	1.19	43.4	31.3	25.3	.040
Improved effectiveness of marketing spending (Q20)	3.31	1.08	44.6	36.1	19.3	.016
Increased customer acquisition (Q21)	3.31	1.17	44.6	31.3	24.1	.018
Increased sales or revenue (Q22)	3.24	1.14	47.0	26.5	26.5	.073
Improved conversion of customers (Q23)	3.29	1.24	48.2	21.7	30.1	.037
Compare marketing costs with results (Q24)	3.27	1.01	41.0	38.6	20.5	.023
Improved overall ROMI (Q25)	3.33	1.18	49.4	24.1	26.5	.016

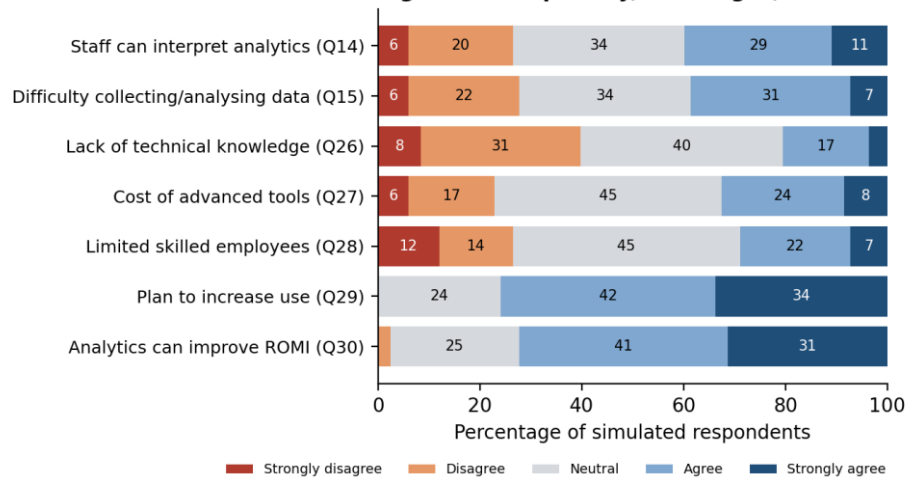
Outcome ratings are modestly positive. The ten outcome items average 3.28 (SD 0.75, $p = .002$), and 49.4% agree that analytics improved their overall ROMI (mean 3.33), while 26.5% disagree. Eight of the ten items are significantly above neutral, the exceptions being reduction of unnecessary expenditure (mean 3.19) and increased sales or revenue (mean 3.24), which are the two items closest to actual financial results. This pattern is consistent with the financial performance gap identified in Chapter 2: it is easier to report better campaign insight and spending effectiveness than a visible increase in sales.

Table 4.4 Mean scores of constructs

Construct	Mean	SD	p (vs 3)
Analytics use (Q6–Q11)	3.20	0.82	.045
Channel / campaign insight (Q12, Q13)	3.30	0.84	.002
Budget efficiency (Q17, Q18, Q20)	3.27	0.79	.004
ROI measurement (Q16, Q19, Q24)	3.28	0.84	.006
Marketing performance (Q21–Q23)	3.28	0.92	.009
Improved ROMI (Q25)	3.33	1.18	.016
Outcome index (Q16–Q25)	3.28	0.75	.002
Staff capability (Q14)	3.18	1.07	.131
Challenges (Q15, Q26–Q28)	2.99	0.53	.882
Future intention and belief (Q29, Q30)	4.05	0.48	< .001

Figure 4.6 Mean scores of the main construct:

4.5 Capability, Challenges, and Future Intention

Figure 4.5 Capability, challenges, and future i

Staff capability is not clearly strong: only 39.8% agree that staff can interpret analytics (mean 3.18, not significantly different from neutral), and 38.6% report difficulty in collecting and analysing data (mean 3.12). Specific challenges are less strongly endorsed. Lack of technical knowledge has the lowest mean (2.76), with 39.8% disagreeing and only 20.5% agreeing, and is significantly below neutral ($p = .027$). Tool cost (mean 3.12) and limited skilled employees (mean 2.98) are not significantly different from neutral; 32.5% agree that tool cost is a challenge and 28.9% that skilled employees are limited,

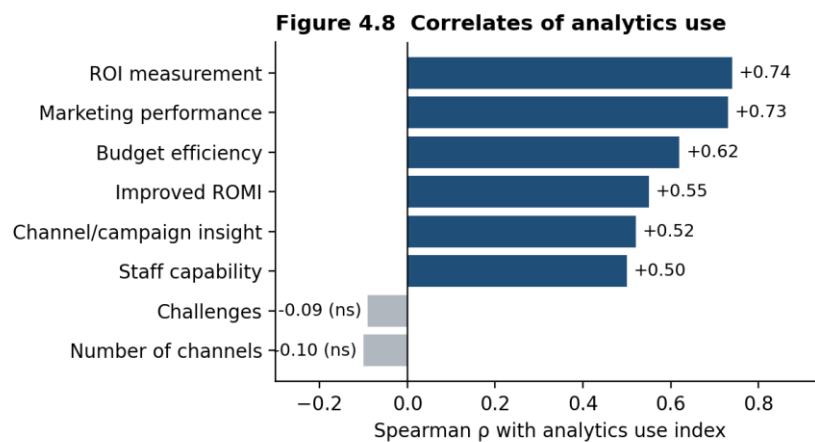
and 44.6% are neutral on each. Challenges are therefore moderate and not dominant. By contrast, intention and belief are strongly positive: 75.9% plan to increase their use of analytics (mean 4.10) and 72.3% believe analytics can significantly improve ROMI (mean 4.01); no respondent disagrees with the plan and only 2.4% disagree with the belief ($p < .001$ for both).

4.6 Hypothesis Testing

H1 to H3: Analytics use, ROMI, budget efficiency, and performance

Table 4.5 Spearman correlations with the analytics use index (n = 83)

Variable	ρ	p-value	Result
ROI measurement (Q16, Q19, Q24)	.74	< .001	Significant
Marketing performance (Q21–Q23)	.73	< .001	Significant
Budget efficiency (Q17, Q18, Q20)	.62	< .001	Significant
Improved ROMI (Q25)	.55	< .001	Significant
Channel / campaign insight (Q12, Q13)	.52	< .001	Significant
Staff capability (Q14)	.50	< .001	Significant
Challenges (Q15, Q26–Q28)	–.09	.444	Not significant
Future intention and belief (Q29, Q30)	–.01	.926	Not significant
Number of channels used	–.10	.387	Not significant
Years of operation	–.05	.675	Not significant
Number of employees	–.04	.726	Not significant



Analytics use is strongly related to improved ROMI ($\rho = .55$, $p < .001$), to budget efficiency ($\rho = .62$), and to marketing performance ($\rho = .73$). **H1, H2, and H3 are supported.** The relationships among the outcome constructs are also strong: ROMI improvement correlates with budget efficiency ($\rho = .58$), performance ($\rho = .55$), and ROI measurement ($\rho = .53$), all $p < .001$. When startups are grouped by their analytics use index, the mean ROMI rating rises from 2.62 for low users (index up to 2.5, $n = 21$) to 3.22 for medium users ($n = 37$) and 4.08 for high users (index above 3.5, $n = 25$); the difference is significant (Kruskal–Wallis $H = 17.66$, $p < .001$). The outcome index shows the same gradient (2.53, 3.26, and 3.94; $H = 38.94$, $p < .001$).

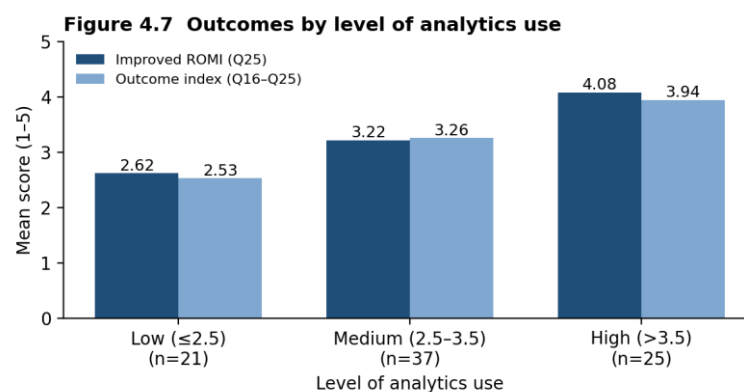


Table 4.6 Multiple regression: effect of analytics use on ROMI and on the outcome index

Predictor	ROMI (Q25) B	β	p	Outcome index B	β	p
Constant	0.198		.834	0.621		.117
Analytics use	0.674	.47	< .001	0.529	.58	< .001
Channel / campaign insight	0.086	.06	.601	0.163	.18	.019
Staff capability	0.142	.13	.241	0.165	.24	.001
Challenges	0.129	.06	.543	0.039	.03	.660
Number of channels	0.132	.10	.314	0.029	.03	.597
Number of employees (coded)	−0.042	−.05	.626	−0.067	−.12	.063
Years of operation (coded)	−0.163	−.15	.121	−0.052	−.07	.226

In both models, analytics use is the strongest predictor ($\beta = .47$ for ROMI and $\beta = .58$ for the outcome index). For the outcome index, staff capability ($\beta = .24$, $p = .001$) and channel and campaign insight ($\beta = .18$, $p = .019$) also contribute significantly, whereas challenges, number of channels, firm size, and firm age do not. The very high explained variance of the outcome model (73.4%) partly reflects the fact that the predictors and outcomes were reported by the same respondent in the same questionnaire, and some outcome items overlap in meaning with the insight items; it should not be read as a causal effect size.

H4: Staff capability

Staff capability (Q14) is positively and significantly related to analytics use ($p = .50$, $p < .001$) and to the outcome index ($p = .58$, $p < .001$), and to improved ROMI ($p = .39$, $p < .001$). **H4 is supported.** Startups reporting that their staff can interpret analytics report more use of analytics and better outcomes.

H5: Challenges

The challenge index is not significantly related to analytics use ($p = -.09$, $p = .444$) or to the outcome index ($p = -.11$, $p = .314$). **H5 is not supported.** Reported challenges do not distinguish heavy from light users in this dataset. The challenge items also do not form a reliable scale ($\alpha = .11$), so this result should be treated cautiously.

H6: Startup characteristics

Table 4.7 Group comparisons (Kruskal–Wallis tests, p-values)

Grouping variable	Analytics use	Outcome index	ROMI (Q25)	Challenges
Role of respondent (6 groups)	.332	.714	.720	.527
Years of operation (4 groups)	.123	.553	.225	.123
Industry (8 groups)	.560	.648	.095	.021
Number of employees (5 groups)	.464	.239	.134	.304

None of the startup characteristics is significantly related to analytics use or to the outcome index. The only significant difference is for challenges by industry ($p = .021$): challenges are highest in education (3.62, but only four startups), healthcare (3.20), and manufacturing (3.31), and lowest in food and hospitality (2.79), retail/e-commerce (2.80), and technology/IT (2.80). Because 16 comparisons were made and the groups are small, this single result may be due to chance. Some non-significant patterns are worth noting: startups operating for 1 to 2 years report the highest analytics use (3.48) and those operating more than five years the lowest (2.89); operations managers report the lowest use (2.65, $n = 9$), and the 11 to 25 employee group the highest ROMI (3.83). **H6 is not supported.**

H7: Channels**Table 4.8 Mean scores by channel used**

Channel	Startups using	Analytics use	Outcome index	ROMI (Q25)
Social Media Marketing	66	3.25	3.30	3.35
Content Marketing	44	3.04	3.22	3.30
Email Marketing	37	3.10	3.27	3.46
SEO	25	3.17	3.30	3.32
SEM	20	3.48	3.51	3.60
Influencer Marketing	11	3.20	3.07	3.00
Paid Advertising	9	2.96	2.99	3.00

The number of channels used is not significantly related to analytics use ($\rho = -.10$, $p = .387$), the outcome index ($\rho = -.01$, $p = .920$), or ROMI ($\rho = .07$, $p = .559$). Mann–Whitney tests comparing users and non-users of each channel found no significant differences in analytics use, outcomes, or ROMI at the 5% level; the nearest to significance is content marketing, whose users report lower analytics use (3.04 versus 3.39, $p = .062$). SEM users have the highest average scores (3.48 for use and 3.60 for ROMI), and influencer marketing and paid advertising users the lowest, but these groups are small and the differences are not significant. **H7 is not supported.**

Table 4.9 Summary of hypothesis tests

Hypothesis	Test	Result	Decision
H1: Analytics use and ROMI	Spearman; regression	$\rho = .55$; $\beta = .47$, $p < .001$	Supported
H2: Analytics use and budget efficiency	Spearman	$\rho = .62$, $p < .001$	Supported
H3: Analytics use and performance	Spearman	$\rho = .73$, $p < .001$	Supported
H4: Staff capability and analytics use	Spearman	$\rho = .50$, $p < .001$	Supported
H5: Challenges and analytics use	Spearman	$\rho = -.09$, $p = .444$	Not supported
H6: Startup characteristics	Kruskal–Wallis; Spearman	All $p \geq .12$ for use	Not supported
H7: Channels	Spearman; Mann–Whitney	All $p \geq .06$	Not supported

All results in Table 4.9 describe the simulated dataset only.

5: FINDINGS, SUGGESTIONS AND CONCLUSION

5.1 Findings

1. Analytics use is moderate: the mean of the use items is 3.20 out of 5, with 34.9% to 47.0% agreeing on each practice and about one third disagreeing that they regularly monitor, use tools, or analyse campaigns.
2. The only use item clearly above neutral is identifying campaigns with the highest engagement (mean 3.46).
3. 49.4% agree that analytics improved their overall ROMI (mean 3.33), while 26.5% disagree.
4. Analytics use is strongly related to improved ROMI ($\rho = .55$) and is the strongest predictor in regression ($\beta = .47$). Low, medium, and high users report mean ROMI ratings of 2.62, 3.22, and 4.08.
5. Social media (79.5%), content (53.0%), and email marketing (44.6%) are the most used channels; influencer marketing and paid advertising are the least used. Startups use 2.55 channels on average.
6. Neither the number nor the type of channel is significantly related to analytics use or ROMI.
7. Challenges are moderate: lack of technical knowledge is below neutral (mean 2.76), tool cost (3.12) and limited skilled employees (2.98) are near neutral. Challenges are not significantly related to analytics use.
8. Intention to increase analytics use (75.9% agree) and belief that analytics can improve ROMI (72.3%) are strongly positive, but are unrelated to current use.
9. Firm age, size, role, and industry are not significantly related to analytics use.

5.2 Suggestions

The following suggestions are conditional on the findings being confirmed with real data from Vijayawada startups, and address Objective 5.

- Startups should link campaign data to revenue and cost for each channel and compute ROMI, because the weakest outcomes concern money and not engagement.
- Training, shared dashboards, or a trained marketing person can help, since capability is the factor most closely linked to use and outcomes.
- Set a regular review of key metrics (traffic, leads, conversions, and cost per customer) so that planned use becomes practice.
- Free platform insights and basic dashboards address cost concerns and allow comparison of social media, content, and email campaigns.
- . Compare cost and result by channel, and move spending from channels with low returns to those with higher returns.
- Local incubators and business associations could offer workshops on analytics and ROMI measurement.

5.3 Scope for Further Research

The most important next step is to administer the same questionnaire to real startups in Vijayawada, using a defined sampling frame (for example, startups registered with incubators or recognised under a startup programme), and to repeat this analysis. Further work could collect actual marketing spend and revenue to compute ROMI, add multi-item measures of capability and challenges, include interviews with founders, compare analytics tools and channels, and use structural equation modelling to test the framework.

5.4 Conclusion

This paper has set out the design and analysis of a study of digital marketing analytics and Return on Marketing Investment among startups in Vijayawada, and applied it to a simulated dataset of 83 responses. In that dataset, social media, content, and email marketing are the most used channels, analytics use is moderate, and perceived ROMI improvement is modestly positive. Analytics use is strongly related to ROI measurement, budget efficiency, performance, and ROMI, and staff capability is related to both use and outcomes. Reported challenges, firm characteristics, and channel mix are not related to use, and strong intentions to use analytics are not matched by current practice.

Because the responses are simulated, these results illustrate the method and the kind of conclusions that the design can support; they do not establish how real startups in Vijayawada use analytics. The paper's value is in the framework, the instrument, and the analytical procedure, which are ready to be applied to real responses. The conclusions should be confirmed by repeating the analysis with real data before any claim is made about startups in Vijayawada.

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