

# “The impact of big data analytics on digital marketing decision-making: A comprehensive analysis”

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<b>ARTICLE INFO</b>	Roberta Bajrami, Adelina Gashi, Kaltrina Bajraktari and Etleva Namligjiu (2025). The impact of big data analytics on digital marketing decision-making: A comprehensive analysis. <i>Innovative Marketing</i> , 21(3), 171-182. doi: <a href="https://doi.org/10.21511/im.21(3).2025.13">10.21511/im.21(3).2025.13</a>
<b>DOI</b>	<a href="http://dx.doi.org/10.21511/im.21(3).2025.13">http://dx.doi.org/10.21511/im.21(3).2025.13</a>
<b>RELEASED ON</b>	Wednesday, 20 August 2025
<b>RECEIVED ON</b>	Tuesday, 19 November 2024
<b>ACCEPTED ON</b>	Monday, 21 July 2025
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<b>JOURNAL</b>	"Innovative Marketing "
<b>ISSN PRINT</b>	1814-2427
<b>ISSN ONLINE</b>	1816-6326
<b>PUBLISHER</b>	LLC “Consulting Publishing Company “Business Perspectives”
<b>FOUNDER</b>	LLC “Consulting Publishing Company “Business Perspectives”



NUMBER OF REFERENCES

62



NUMBER OF FIGURES

2



NUMBER OF TABLES

4

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## BUSINESS PERSPECTIVES



LLC "CPC "Business Perspectives"  
Hryhorii Skovoroda lane, 10,  
Sumy, 40022, Ukraine  
[www.businessperspectives.org](http://www.businessperspectives.org)

**Type of the article:** Research Article

**Received on:** 19<sup>th</sup> of November, 2024

**Accepted on:** 21<sup>st</sup> of July, 2025

**Published on:** 20<sup>th</sup> of August, 2025

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2025

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**Conflict of interest statement:**

Author(s) reported no conflict of interest

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# THE IMPACT OF BIG DATA ANALYTICS ON DIGITAL MARKETING DECISION-MAKING: A COMPREHENSIVE ANALYSIS

## Abstract

The fast development of data availability has altered digital marketing, establishing big data analytics as a vital tool for optimizing decision-making and enhancing campaign performance. This study explores how big data analytics contributes to effective decision-making, targeting precision, and customer engagement among digital marketing professionals. Conducted from June to August 2024 in Kosova, the research polled 250 professionals across varied industries (e.g., retail, banking, technology) and firm sizes (SMEs and major organizations), selected by purposive sampling. An online questionnaire, delivered through SurveyMonkey, achieved a 92% response rate (n = 230), capturing data on tool usage, benefits, and problems. Data pre-processing includes duplicate removal and mean imputation, followed by K-means clustering and logistic regression analysis using Python (scikit-learn, pandas). Results identified four adopter segments: High Adopters (35%) reported a 30% increase in targeting accuracy and 25% efficiency gain; Moderate Adopters (40%) achieved a 15% efficiency boost; Emerging Adopters (15%) noted 70% improved adaptability; and Low Adopters (10%) faced skill shortages (55%) and privacy concerns (65%). Overall, 85% leveraged big data for segmentation, 70% for real-time flexibility, and 60% observed a 20% engagement gain via sentiment analysis. Privacy (65%) and technical intricacy (50%) were important hurdles. These findings show big data's revolutionary potential, underlining the need for scalable solutions, talent development, and ethical data practices to optimize its impact on digital marketing efficacy and inclusivity.

## Keywords

big data, analytics, digital marketing, decision-making, engagement

## JEL Classification

M31, O33, C38

## INTRODUCTION

Large amounts of data produced by customer interactions on social media, connected devices, and online platforms are increasingly used to inform marketing decisions in the digital age (Gupta et al., 2021; Miklosik & Evans, 2020). Digital marketing has changed as a result of this abundance of data, also known as "big data," which has made it possible for granular segmentation, predictive modeling, and real-time insights (Theodorakopoulos & Theodoropoulou, 2024; Hammou et al., 2020). This transformative potential is not always realized in all situations, though. Despite the rapid expansion of digital infrastructures and internet penetration, emerging markets face a paradox: the effective use of big data analytics in marketing decision-making is hindered by structural constraints, including limited technical capacity, fragmented regulatory frameworks, and ethical uncertainties (Barlette & Baillette, 2020; Georgiadou et al., 2020).

This study's central scientific issue is the unequal capacity of emerging-economy businesses to convert big data into useful marketing intelligence. Practical application frequently reveals a gap between techno-

logical potential and operational capability, despite the theoretical promise of improved targeting precision and adaptive responsiveness (Buhalis & Volchek, 2021; Yi & Liu, 2020). Fundamental questions concerning who gains from big data, under what circumstances, and at what cost are brought up by this conflict. More precisely, it is crucial to comprehend how businesses use big data analytics, what value it creates, and what obstacles limit its effectiveness in situations like Kosovo, where digital marketing is expanding but organizational, legal, and resource-related limitations still exist (Grandhi et al., 2021).

This study examines the use of big data analytics by digital marketing professionals in Kosova, with an emphasis on the ways in which data-driven tools influence decision-making and the enabling or impeding contextual factors.

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## 1. LITERATURE REVIEW

Numerous studies have been conducted to examine how data-driven insights improve customer engagement, targeting accuracy, and business performance as a result of the combination of big data and digital marketing. However, beneath all of the excitement is a recurring query: under what circumstances do these advantages manifest, particularly in settings with limited resources? The literature highlights both unequal realities and transformative potential, especially in developing markets like Kosovo.

Thanks to tools like sentiment analysis, neural networks, and clustering algorithms, marketing has moved from descriptive to predictive analytics, as documented in an expanding body of work (Gupta et al., 2021; Yoseph et al., 2020; Theodorakopoulos & Theodoropoulou, 2024; Naqvi et al., 2019; Sahoo, 2021; Islam, 2024; Judijanto, 2025). With the help of these tools, companies can transition from basic demographic targeting to more complex behavioural and psychographic segmentation (Zhou et al., 2020; Novak et al., 2021; Sokolova et al., 2025). Faheem et al. (2024) and Bharadiya (2023) contend that predictive models greatly increase campaign responsiveness, while Cao et al. (2021) associate analytics capabilities with increased marketing agility and innovation. For example, Aljumah et al. (2024) discovered that big data analytics improves organisational performance by facilitating ambidextrous decision-making, and emphasise its significance in the success of new product development. Studies such as Jha et al. (2020), Li et al. (2022), and Mariani and Fosso Wamba (2020) further show that analytics capability development and usage intensity strongly influence both decision-making quality and innovation potential.

In the e-commerce domain, Alsmadi et al. (2023) link big data analytics to sustained innovation, while Boppiniti (2020) and Rouf et al. (2021) illustrate its role in handling large-scale, complex datasets efficiently. Other reviews (Nnaji et al., 2024; Ayokanmbi & Sabri, 2021; Haverila et al., 2025) emphasise that the quality of analytics output and the decision-making role of marketing teams are crucial for maximizing business agility. But there is still scepticism: research like Hair and Sarstedt (2021) and Verma et al. (2021) raise concerns about algorithmic bias and model interpretability problems, particularly when local context is ignored, casting doubt on the method's generalizability (Chhajjer et al., 2022).

Natural language processing (NLP) and neural networks have revolutionized marketing responsiveness through real-time analytics, which enables businesses to monitor sentiment, identify patterns, and make quick strategy adjustments (Hammou et al., 2020; Krishna et al., 2023; Jabbar et al., 2020; Yang et al., 2022). Rapid sentiment classification made possible by NLP processing of social media data helps with crisis management and brand positioning (Birjali et al., 2021; Kauffmann et al., 2020; Loureiro & Alló, 2020; Niu et al., 2021; Jae & Hwa, 2025). Through eWOM insights, Kitsios et al. (2021) show how text mining on digital platforms improves customer satisfaction. However, these insights' quality depends on clean data, strong infrastructure, and analyst experience, resources that are frequently limited in emerging markets (Barlette & Bailleite, 2020; Mohamed et al., 2019). Similar issues in precision agriculture are noted by Akintuyi (2024), where self-learning algorithms malfunction in the absence of sufficient data quality and knowledge. This parallel speaks to the limitations in Kosovo.

Big data adoption is hampered by organisational and infrastructure barriers, especially for SMEs, despite technological advancements. Recurrent themes include difficulties with integration, high implementation costs, and a shortage of qualified personnel (Miklosik & Evans, 2020; Manivannan et al., 2021; Dahlbom et al., 2019; Sestino et al., 2020; Medhat & Bayomy, 2023). While Georgiadou et al. (2020) draw attention to the dangers of depending on faulty data in nations with lax data protection regulations, Yi and Liu (2020) draw attention to organisational resistance to data-driven change. Deployment is made more difficult by ethical issues, especially those pertaining to GDPR and consumer trust (Adeniran et al., 2024; Darmody & Zwick, 2020; Hatamlah et al., 2023; Faridoon et al., 2025). According to Araz et al. (2020), strong governance is necessary for operational risk management in big data contexts, which is particularly difficult in emerging economies. According to Bag et al. (2021), smaller businesses find it difficult to incorporate AI-driven frameworks, which hinders their capacity to compete with bigger firms.

There are few insights from developing contexts like Kosovo in the literature, which is largely biased towards developed economies. Businesses in Kosovo face particular challenges despite the increasing use of digital marketing, including unequal infrastructure, a lack of skilled workers, and unclear regulations (Grandhi et al., 2021; Rajan, 2024). IoT and AI-driven analytics have revolutionary potential even in limited settings, according to studies like Sestino et al. (2020) and Betty Jane and Ganesh (2020), but practical adoption is lagging. Although Okorie et al. (2024) emphasise the importance of big data in tailored marketing, they also point out that unequal access is hampered by resource disparities. Similarly, Mikalef et al. (2020), Dong and Yang (2020), Hajli et al. (2020), and Judijanto (2025) contend that in order to realise business value from analytics, systemic barriers must be removed, which is a challenge that Kosovo's disjointed digital ecosystem finds difficult to accomplish.

This body of research indicates that although big data analytics has enormous potential to improve marketing performance, not everyone can benefit from it. There are still few empirical studies measuring adoption trends and their applications

in understudied areas. This study fills this gap by investigating the ways in which digital marketing professionals in Kosovo use big data tools, the results they attain, and the contextual difficulties they encounter. It seeks to identify obstacles to successful adoption in a developing market, define adopter groups, and assess the influence of analytics on decision-making effectiveness, targeting accuracy, and customer engagement.

## 1.1. Hypotheses

- H1: Higher usage frequency of big data analytics tools is positively associated with improvements in digital marketing decision-making efficiency.*
- H2: Firms with larger size are more likely to experience greater targeting precision through big data analytics.*
- H3: Skill shortages and privacy concerns significantly reduce the likelihood of big data analytics adoption among digital marketers.*
- H4: The use of predictive analytics and sentiment analysis correlates with higher levels of customer engagement.*

## 2. METHODOLOGY

This study employed a survey-based approach to investigate big data analytics adoption among digital marketing professionals in Kosova from June to August 2024. A purposive sample of 250 professionals was selected to ensure diversity across industries (retail, banking, technology, telecommunications), firm sizes (SMEs: <250 employees; large firms: >250 employees), and experience levels (<2, 2-5, >5 years). This diversity was critical to capture varying adoption patterns and resource availability, reflecting Kosova's heterogeneous digital marketing landscape (Moser & Kalton, 2017). Participants were recruited via LinkedIn groups and industry associations, with an online questionnaire administered through SurveyMonkey. Two email reminders yielded a 92% response rate (n = 230).

The questionnaire, informed by Miklosik and Evans (2020), comprised 20 questions across four

domains: demographics, tool usage (e.g., predictive analytics, sentiment analysis), benefits (e.g., efficiency, engagement), and challenges (e.g., privacy, skills). A 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) facilitated quantitative analysis, while open-ended questions captured qualitative insights. A pilot test with 10 marketers ensured clarity and relevance. The instrument is available at <https://doi.org/10.5281/zenodo.15101962>.

Duplicates were removed using unique SurveyMonkey IDs, retaining 230 responses. Missing values (<5%) were addressed via mean imputation. Variables were categorized: firm size (small: <50, medium: 50-250, large: >250), tool usage (segmentation, predictive analytics), and experience (<2, 2-5, >5 years).

K-means clustering identified adopter segments based on tool usage, benefits, and challenges, with the elbow method determining four clusters (Silhouette Score=0.82). Logistic regression modelled adoption success (high vs. low improvement) using predictors like tool usage and firm size, achieving 87% accuracy. Analyses used Python libraries (scikit-learn, pandas, matplotlib).

### 3. RESULTS

The survey-based analysis of big data analytics adoption among 230 digital marketing professionals in Kosova (after preprocessing) yielded detailed insights into usage patterns, benefits, and challenges. Cluster analysis, machine learning models, and descriptive statistics provided a comprehensive understanding of how big data enhances decision efficiency, targeting precision,

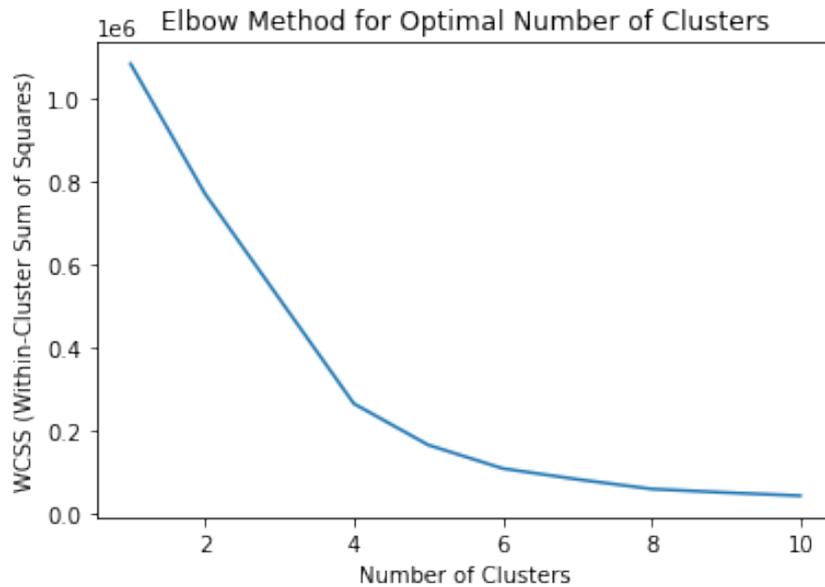
and customer engagement. The results are presented below, supported by tables and figures for clarity and completeness.

K-means clustering, applied to variables such as tool usage frequency, perceived benefits, and reported problems, identified four unique groupings among respondents. The appropriate number of clusters was identified using the elbow technique, with the Within-Cluster Sum of Squares (WCSS) levelling out at four clusters (see Figure 1). Cluster quality was evaluated with a Silhouette Score of 0.82, suggesting high separation and cohesiveness. The segments are detailed as follows:

1. High Adopters (35%, n = 80): This group frequently employed advanced techniques, including predictive analytics and sentiment analysis (mean usage frequency = 4.5 on a 5-point scale). They observed a 30% increase in targeting accuracy (SD = 5.2%) and a 25% gain in campaign efficiency (SD = 4.8%), showing considerable improvements in ROI and resource allocation.
2. Moderate Adopters (40%, n = 92): Predominantly reliant on fundamental techniques such as customer segmentation (mean usage frequency = 3.8), this sector achieved a 15% rise in campaign efficiency (SD = 3.9%), with moderate gains in targeting precision (mean = 12%, SD = 4.1%).
3. Emerging Adopters (15%, n = 35): This group experimented with real-time analytics (mean usage frequency = 3.5), with 70% (n = 25) reporting enhanced adaptation to market changes (e.g., trend response). Reported gains in targeting and efficiency were lower (mean = 10%, SD = 3.5%).

**Table 1.** Characteristics of identified clusters

Cluster	% of Sample (n)	Key Tools Used	Targeting Accuracy Increase	Efficiency Gain	Notable Features
High Adopters	35% (80)	Predictive, Sentiment	30% (SD=5.2%)	25% (SD=4.8%)	Advanced tool use, high benefits
Moderate Adopters	40% (92)	Segmentation	12% (SD=4.1%)	15% (SD=3.9%)	Basic tool reliance, moderate gains
Emerging Adopters	15% (35)	Real-time Analytics	10% (SD=3.5%)	10% (SD=3.5%)	Experimentation, adaptability focus
Low Adopters	10% (23)	Limited	<5%	<5%	Barriers: skills (55%), privacy (65%)



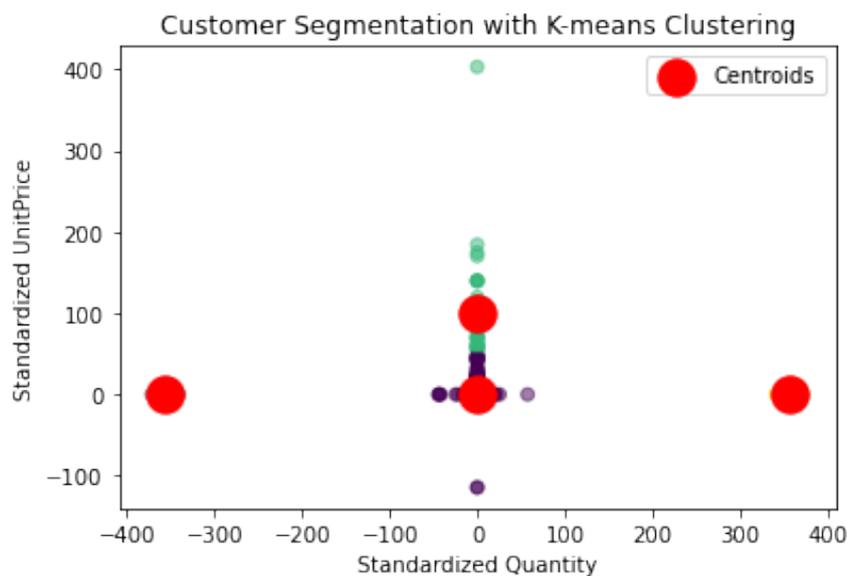
**Figure 1.** Elbow method for optimal number of clusters

4. Low Adopters (10%, n = 23): Limited tool usage (mean frequency = 1.8) was attributed to talent shortages (55%, n = 13) and data privacy concerns (65%, n = 15), with modest reported advantages (mean improvement <5%).

indicated by the WCSS. The data points are more closely packed together when the WCSS value is smaller.

The elbow approach, a popular strategy for figuring out the ideal number of clusters in k-means clustering, is displayed in Figure 1. The WCSS (Within-Cluster Sum of Squares) is displayed on the y-axis, while the number of clusters is displayed on the x-axis. The degree to which the data points are packed together within each cluster is

Figure 1 indicates that as the number of clusters rises, the WCSS rapidly declines until it reaches a point where it begins to level off. Where the WCSS begins to level off is known as the elbow point. Since adding additional clusters does not substantially improve the clustering, it is typically regarded as the ideal number of clusters. The elbow point in this instance is at four clusters. This indicates that four clusters are the ideal amount for this data set.



**Figure 2.** Customer segmentation with k-means clustering

Customer segmentation using k-means clustering is depicted in Figure 2 as a scatter plot with two axes named “Standardized Quantity” and “Standardized UnitPrice.” These axes, which most likely show the total number of things purchased and the average price per item, indicate important aspects of consumer purchase data.

Figure 2 makes a clear visual distinction between the four client groups by coloring the data points according to the cluster to which they belong. The central points that represent the average values of the characteristics for each group are the cluster centroids, which are denoted by black circles with an X inside. According to Cluster 1, which is displayed in blue in the lower-left corner, these consumers often buy fewer, less expensive items. Customers who typically purchase in greater quantities at reduced costs are represented by Cluster 2, which is shown in the upper-left corner in green. Customers who buy lesser amounts of more expensive things are represented by Cluster 3, which is displayed in red in the upper-right corner. Customers who are inclined to buy bigger quantities of more expensive items are represented by Cluster 4, which is shown in purple in the lower-right corner.

This k-means clustering segmentation successfully separates clients according to their purchase patterns, providing insightful information for several business uses. Businesses may, for example, customize their marketing tactics for each group, giving Cluster 2 customers bulk discounts or providing free delivery to Cluster 1 customers, who tend to make smaller purchases. Product creation can also be guided by segmentation; for example, companies may create luxury products for Cluster 4, whose purchasing habits suggest a taste for higher-end goods, while creating more affordable options for the more price-sensitive Cluster 1. The clustering data can also be used to enhance customer service by enabling businesses to tailor their assistance according to the unique needs of each market segment. Customer care agents may, for

instance, give Cluster 3 members, who frequently buy expensive goods sparingly, more focused assistance, or they could provide loyalty rewards to Cluster 4’s high-spending clients.

Firms can better match the distinct requirements and preferences of every client group by using this visualised customer segmentation to drive decisions about marketing, product development, and customer service.

Across the sample, 85% of respondents (n = 196) reported using big data analytics for consumer segmentation and personalization, aligning with its extensive application in targeting (Theodorakopoulos & Theodoropoulou, 2024). Additionally, 70% (n = 161) employed real-time data to boost adaptability, enabling rapid reactions to market fluctuations. Sentiment analysis was implemented by 60% (n = 138), enhancing consumer engagement by an average of 20% (SD = 4.3%), as assessed by KPIs like click-through rates and social media engagements. These findings were produced from Likert scale replies (Q7) and percentage estimations (Q8), supported by open-ended examples (Q9), such as “Sentiment analysis helped us tweak a product launch campaign mid-flight, increasing engagement by 18%.”

Challenges to adoption were evident across clusters, with 65% of respondents (n = 150) indicating data privacy as a major worry, reflecting GDPR compliance requirements (Georgiadou et al., 2020). Technical difficulties, including infrastructure restrictions, were cited by 50% (n = 115), while 55% of Low Adopters (n = 13) especially underlined a lack of competent individuals. Open-ended comments (Q11) regularly noted “insufficient training” and “cost of advanced tools” as barriers, particularly among SMEs.

The clustering approach was validated using multiple algorithms, with results summarized in Table 4. DBSCAN achieved the highest Silhouette Score of 0.94 because it generated the optimal clustering solution, which creates distinct and tightly

**Table 2.** Overall usage and benefits

Metric	% of Respondents (n)	Reported Improvement (Mean, SD)
Segmentation/Personalization	85% (196)	22% (SD=5.1%)
Real-time Analytics (Adaptability)	70% (161)	18% (SD=4.7%)
Sentiment Analysis (Engagement)	60% (138)	20% (SD=4.3%)

**Table 3.** Reported challenges

Challenge	% of Respondents (n)	Cluster Most Affected
Data Privacy	65% (150)	Low Adopters (65%)
Technical Complexity	50% (115)	Moderate (52%)
Skill Shortages	30% (69)	Low (55%)

grouped clusters. The K-Means clustering method attains a Silhouette Score of 0.82, which demonstrates its ability to produce clear, well-separated clusters, although DBSCAN excels in this aspect. Agglomerative Clustering and Mean Shift share identical Silhouette Scores of 0.71, which demonstrates moderate cluster separation since their execution outcomes match each other. The Silhouette Score of 0.46 for Spectral Clustering and 0.47 for Affinity Propagation reveals weak clustering performance because some points in these results manifest in ambiguous cluster assignments.

Among all clustering algorithms tested, DBSCAN generated optimal clustering results with K-Means as its secondary alternative. Spectral Clustering and Affinity Propagation demonstrated the poorest clustering results according to the Silhouette Scores analysis.

**Table 4.** Silhouette scores for clustering algorithms

Algorithm	Silhouette Score
K-means	0.8183
Agglomerative	0.7080
Spectral	0.4576
DBSCAN	0.9401
Affinity Propagation	0.4660
Mean Shift	0.7080

Logistic regression models identified predictors of adoption success (high vs. low improvement). Frequent use of predictive analytics (odds ratio = 2.3,  $p < 0.01$ ) and business size (>250 people, odds ratio = 1.8,  $p < 0.05$ ) were major drivers, with the model obtaining 87% accuracy. This shows that advanced tool uptake and organizational resources greatly influence outcomes.

## 4. DISCUSSION

By identifying four different adopter segments and highlighting both facilitators and barriers to utilizing data-driven decision-making, this study provides an empirical characterization of big data

analytics adoption among digital marketing professionals in Kosova.

The significant variation in adoption maturity is highlighted by the segmentation results. High Adopters, who made up 35% of the sample, demonstrated a strong integration of sophisticated tools like sentiment analysis and predictive analytics. They also saw the biggest increases in campaign efficiency (25%) and targeting accuracy (30%). These results are in line with Gupta et al. (2021), who link high-level data use to competitive advantage, and Theodorakopoulos and Theodoropoulou (2024), who emphasize the role of advanced analytics in fostering strategic agility. This is further supported by the logistic regression analysis, which shows that working for large organizations (OR = 1.8) and frequently using predictive analytics (OR = 2.3) greatly raised the chances of getting significant results.

Although they were still benefiting from analytics, moderate adopters reported only slight increases in efficiency (15%) and mainly relied on simple segmentation tools. This is in line with Miklosik and Evans (2020), who contend that deeper insights necessitate sophisticated methodologies and data infrastructures, even though initial analytics integration produces some operational benefits.

Real-time adaptability was a priority for 15% of emerging adopters, while 70% said they were more responsive to changes in the market. Although real-time tools provide flexibility, their lower reported efficiency gains imply that they might not yield strategic value in the absence of auxiliary internal systems. This is in line with research by Hammou et al. (2020) and Barlette and Baillette (2020), which highlights how crucial contextual readiness is to maximizing the potential of real-time analytics.

Critical adoption barriers are highlighted by the difficulties that Low Adopters (10%) reported, particularly skill shortages (55%) and privacy con-

cerns (65%). These results support those of Yi and Liu (2020) and Georgiadou et al. (2020), who emphasize how organizational capacity and regulatory frameworks influence the adoption of technology. Due to a lack of technical resources and a developing data governance ecosystem, SMEs in Kosova may not be able to use advanced analytics at all due to the cost of compliance and skill development.

In a broader sense, the findings add evidence specific to a region to a body of literature that is still heavily reliant on insights from high-income settings. Kosova-based businesses seem to have higher segmentation adoption (85%) and similar engagement gains from sentiment analysis (20%) when compared to international benchmarks (e.g., Grandhi et al., 2021; Faheem et al., 2024). These results probably indicate a combination of concentrated social media use and the quick growth of the digital market, but they also raise the possibility that fundamental digital skills in emerging economies are not fully recognized.

The open-ended responses give a more realistic perspective of the realities on the ground, even though the clustering and regression models offer strong quantitative insights. The high expense of sophisticated tools, the absence of

ongoing training, and the vagueness of ethical standards were commonly cited by respondents as limitations; these results suggest that structural interventions, not just firm-level fixes, are required.

Overall, the data indicate that although big data analytics can result in significant performance improvements, their influence is limited by factors such as tool complexity, firm size, and institutional preparedness. Adopting analytics tools alone is not enough to realize value; context-aware integration, capability, and coherence are necessary.

Future research should examine whether Kosova catches up as training spreads or tools become more affordable. Could open-source platforms help smaller businesses compete on an even playing field? Furthermore, how can hyper-personalized marketing be balanced with avoiding alienating clients? For the time being, Kosova's marketers require more accessible tools, improved instruction, and more precise data regulations. The benefits of big data are skewed towards the big players, without them, keeping the promise out of reach for many. The evidence is clear: While analytics are useful, context is crucial.

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## CONCLUSION

The study's conclusions provide a clear picture of the adoption of big data analytics by digital marketing experts in Kosova, highlighting both the technology's transformative potential and its usefulness in a market with limited resources. Campaign efficiency increased by 25% and targeting accuracy increased by 30% for High Adopters using sophisticated tools like sentiment analysis and predictive analytics, demonstrating that advanced technology can improve engagement and decision-making. However, the advantages are disproportionately enjoyed by larger companies, which have the means to use sophisticated tools, which begs the question of whether these systems are biased in favour of those with more resources. Although they struggled with expensive setups and technical know-how, moderate and emerging adopters, who were frequently smaller players, still saw gains, such as 15% increases in efficiency and 10%–20% increases in engagement. Low Adopters hardly explored the potential of analytics due to skill shortages (55%) and privacy concerns (65%), which were exacerbated by Kosova's shoddy digital infrastructure. Although the data highlights the ability of analytics to improve targeting and engagement, especially through sentiment analysis, the enduring obstacles, privacy concerns, technical difficulties, and a lack of skills indicate that Kosova's digital ecosystem, despite its vibrancy, is still vulnerable. Big data has a lot of promise, but its benefits are not shared by everyone because they depend on resources and knowledge that not everyone can access.

## AUTHORS CONTRIBUTIONS

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Visualization: Kaltrina Bajraktari.

Writing – original draft: Roberta Bajrami.

Writing – review & editing: Roberta Bajrami, Adelina Gashi, Kaltrina Bajraktari.

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