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Reinvesting Decisions on Marketing Activities: Leveraging Marketing Data Analytics for Sustainable Business Practices

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ABSTRACT:
This research explores the pragmatic domain of marketing management. As it explores the antecedents of reinvestment decisions in marketing activities, the importance of data usage satisfaction and marketing data analytics was also felt. To explore marketing data analytics, this research investigated its constituents, such as information quality and technology quality. A sample of 184 marketing managers was utilized, and the data was processed using SPSS 20.0 and Lisrel 10.0. Findings reveal that technology quality had a favorable influence on data usage satisfaction and, finally, on reinvesting decisions among marketing professionals. Moreover, a substantial and positive relationship exists between the quality of information and the level of satisfaction among marketing professionals, which was also observed. There is a favourable association between Data usage satisfaction with reinvesting plans. The findings have very serious and practical implications for the usage of marketing data analytics and decisions to reinvest in certain marketing practices of Big business corporations. The study acts as a cornerstone in this domain.

Keywords: Quality of Information, Quality of Technology, Marketing managers reinvest decisions, Data usage satisfaction.

1. Introduction

As of now, we are witnessing what is called the "Global Digital Revolution." The field of Marketing Data Analytics (MDA) is increasingly becoming characterized by its immersive nature. There is a growing interest among experts in examining the influence of data on the business sector, which is the new business interest. It is noteworthy that the issue of data availability does not pose a significant challenge. However, the efficacy of using Marketing Data Analytics (MDA) is contingent upon the quality of the information and the technological infrastructure employed, which might determine the degree of success in leveraging this precious resource. The aforementioned shift can be ascribed to the global digital revolution. The present study focuses on the examination of individual decision-making relevance based on data analytics. It is worth mentioning that marketing managers, who are users of business development (BD), exhibit a higher degree of criticality towards BD compared to BD analysts, who are primarily responsible for generating the data. This research article provides an introduction to the topic at hand. Organizations have exhibited significant investment and ongoing commitment toward the

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adoption and use of Marketing Data Analytics (MDA) (Business Wire, 2020; Columbus, 2017; Slesar, 2020).

With this kind of business scenario, Data Analytics is thriving in making marketing decisions. The rapid development of Marketing Data Analytics (MDA) has resulted in its widespread impact on several industries (Oracle, 2021). According to prior scholarly investigations, it has been posited that companies who allocate resources towards Marketing Data Analytics (MDA) exhibit a profitability advantage of around 5% to 6% in comparison to their counterparts who do not engage in MDA (McAfee et al., 2012). The efficacy of Marketing Data Analytics (MDA) is contingent upon the calibre of data, referred to as information quality, that is gathered, as well as the technologies employed for data analysis, known as technology quality (Mikalef et al., 2019). It must be noted that these two domains are the interests of the research in this study. Further investigation is required to explore the potential applications of big data in the realm of marketing, as suggested by Pantano et al. (2019). An examination of existing literature indicates that the majority has primarily focused on computational aspects such as algorithms, visualization, machine learning, geospatially, and data processing. However, the extent to which data research has been applied to decision-making in business, particularly in the realm of marketing, has not yet fully realized its potential (Mohammadi and Karami, 2020).

The need for this study was felt more than ever as the research investigates the influence of Marketing Data Analytics (MDA) on marketing managers' perceptions of data usage satisfaction and plans to reinvest. There is a dearth of research in this area. However, this study diverges from the works of Akter et al. (2017) in the following ways. Firstly, our investigation focuses on the perspective of marketing managers rather than that of BD analysts. Secondly, we employ an analysis of effect size in evaluating the model, rather than relying solely on testing for significance.

Thirdly, In the context of this research, a universal model was formulated with all the research variables examining them together, which was not done before. Fourthly, Prior studies in this field have mostly focused on visualization and related matters rather than investigating the interconnections within structural models between pertinent exogenous and endogenous characteristics (Amado et al., 2018). The objective of this investigation is to ascertain the impact and relevance of these relevant constructs. In general, there is a dearth of research in this domain that effectively showcases its advantages within the realm of marketing. Further investigation should be conducted to examine the effects of technology. Fifthly, Further investigation is necessary to ascertain the level of satisfaction among marketing professionals about the available Marketing Data Analytics (MDA) solutions since the potential for investment in such solutions shows promise (Buhalis and Volchek, 2021; Johnson et al., 2019). Finally, The assessment of data quality serves as a crucial determinant of the effectiveness of marketing endeavors. Previous studies have investigated big data quality instead of marketing data analytics (Fosso Wamba et al., 2018). This research emphasizes the incorporation of technical improvements that enable the process of informed decision-making within the marketing domain, as it allows for the utilization of enhanced data, leading to more logical and sensible decision-making outcomes. Moreover, it is also believed that marketing experts hold differing opinions concerning the quality of information produced by Data Analytics

(DA); therefore, data was collected to report their perceptions. According to Morales-Serazzi (2021), the two departments may exhibit varying degrees of reported satisfaction with the system. Therefore, the study will commence by doing a comprehensive literature review on MDA, followed by sections on research methodology, results, conclusions, and discussion. The paper will finish by providing a discussion on the implications, limits, and potential avenues for further study.

2. Literature Review

Marketing Data Analytics

Marketing data Analytics (MDA) refers to examining and evaluating customer behavior with the help of data algorithms. It includes the utilization of data in real-time processes in marketing planning due to its heightened capacity to address real-time uncertainties (Xu et al., 2016). The utilization of Marketing Data Analytics (MDA) empowers marketing managers to monitor and analyze consumer behavior effectively, hence facilitating the development of strategic approaches aimed at converting prospective clients into devoted patrons. In addition, the use of market segmentation aids marketing managers in the precise and efficient categorization of the market, enabling them to identify and choose the most suitable target categories meticulously. The implementation of Marketing Data Analytics (MDA) supports organizations in designing improved marketing practices. While the prevalence of MDA is on the rise, marketing managers in organizations must comprehend the connections between the quality of MDA and its effects on important user characteristics, including perceived happiness and other constructs. The field of marketing analytics specifically focused on big data, is an area of study that undertakes the processing of data and interpretation to gain insights and make informed decisions in marketing strategies. This can be achieved by improving information and technological advancements.

2.1. The quality of technology (TQ)

The data that is being created can be categorized as either structured or unstructured. Hence, the use of expert systems, such as predictive and diagnostic analytics, is imperative to efficiently and effectively transform data into algorithms and finally be used for marketing decision-making (Mikalef et al., 2019). The effective implementation of Marketing Data Analytics (MDA) necessitates the use of innovative technologies to capture and process substantial quantities of varied and rapidly changing data. The escalating volume and variety of data being created have led researchers to recognize the significance of high-quality systems for effective data applications (Ren et al., 2017).In this regard, Marketing Analytics (MDA) is a significant guiding tool at the firm level in the development of effective marketing strategies. To respond to this upsurge, it is important to expedite the enhancement of business development technology systems to acquire data in real-time from diverse sources effectively and analyze this data to provide significant marketing strategies. The level of technological excellence in MDA applications is a crucial factor in today's competitive scenario (Ren et al., 2017).

Prior studies have revealed that the technological advancement in Marketing Data Management and Analytics (MDA) is determined by the dependability, flexibility, integration, and privacy of the system. Nevertheless, possessing a superior technology infrastructure is not inherently enough, albeit important. Therefore, the study considered information quality to be a crucial constituent of this research (Ren et al., 2017). The connection, interoperability, and adaptability of an organization's technological infrastructure play a part in facilitating the remote sourcing of data from different locations and business activities. This enables the uninterrupted flow of data that is essential for the organization's operations. The integration of data from many sources by technological systems and the dedication of the IT department to preserving privacy are significant factors in this regard (Akter et al., 2017).

2.2. Information Quality (IQ)

The other constituent of marketing data analytics is the quality of information; it is an important aspect to consider in the context of MDA, and the performance of the systems is contingent upon the quality of input received. As pointed out by many researchers, including Fosso Wamba et al. (2018), the incorporation of data has a significant influence on the outcome, as this data is subsequently transformed into valuable business intelligence. The existing body of scholarly work acknowledges that to be considered valuable, information must possess the qualities of comprehensiveness, accuracy, and proper formatting and should be well organized (Wamba et al., 2019). Insufficient information quality has been found to lead to increased workloads, difficulties, and limited resources (Helfert and Ge, 2019), hence resulting in inefficiencies within the MDA domain. According to Haug and Arlbjørn (2010), the organization can get financial benefits through operational and strategic advantages when it ensures a high level of information quality in MDA. Hence, it is important to secure the assurance of information quality to enable managers to effectively address pertinent issues and consequently enhance their decision-making capabilities (Wamba et al., 2019). Hence, Information excellence is expected to play a crucial role in driving the effectiveness of Marketing Data and Analytics (MDA).

Many studies have suggested that information quality can have direct implications on data user satisfaction, leading to enhanced quality and decreasing costs (Wamba et al., 2019). It is worth mentioning that the participants in the study conducted by Fosso Wamba et al. (2018) consisted of individuals working in the field of business analysis and information technology rather than marketing managers inside the organizations. The potential influence of this factor on the efficacy and robustness of the suggested associations must be overlooked. This is the research gap our study tries to fill. The concept of information quality enables organizations to optimize their operational efficiency through the reorganization of internal processes and activities, employing innovative strategies to carry out essential tasks (Wamba et al., 2019). Hence, the quality of information in Big Data and Analytics (MDA) applications provides managers with opportunities to think innovatively and generate supplementary value for their clients.

2.3. Data Usage Satisfaction (DUST)

The constituents from the UTAUT model were derived for measuring satisfaction, Perceived usefulness, which refers to the enhancement of their job performance; second, the measurement of perceived ease of use, which pertains to the degree to which users perceive a system as effortless to operate; and third, the measurement of user attitude, which encompasses users' overall evaluation and emotional response towards a system. This study examines four key aspects related to information systems. Moreover, the evaluation may be approached from either a stakeholder perspective (in the context of this study, the user). The significance of the association between information quality and technology and user happiness has been emphasized in previous studies (Cleverley and Burnett, 2019; Cleverley et al., 2017). The significance of information and technology quality in fostering user happiness within MDA applications in organizations is evident. Previous studies have indicated that information quality and technology have a significant role in facilitating decision-making among managers (Wamba et al., 2019). Furthermore, it has been seen that a superior experience in this regard is positively associated with increased levels of satisfaction. Therefore, the subsequent Hypotheses are established:

H1. The technological Quality of MDA systems positively affects user satisfaction.

H2. Information Quality of MDA systems positively influences user satisfaction.

The function of satisfaction in marketing is crucial since it facilitates the production of value, which is a significant objective for companies seeking to achieve healthy returns (Armstrong, 2017). The present study centres its attention on user satisfaction, as opposed to customer satisfaction, within the context of marketing professionals utilizing MDA. User satisfaction is identified as a fundamental construct in MDA applications, as highlighted by Akter et al. (2017). Within the realm of information technology, prior scholarly investigations have established a conceptualization of the model. This study adopts the user-defined satisfaction method as opposed to the attribute-satisfaction model proposed by Zviran and Erlich (2003).

Reinvesting Decisions (RD)

The genesis of the desire to reinvest in the construct may be traced back (Oliver, 1999). Likewise, the concept of intent to reinvest may be characterized as a strongly ingrained dedication to constantly reinvest in a chosen MDA system in the future, resulting in ongoing purchases of the MDA system. This commitment remains steadfast despite various situational pressures and marketing endeavors that may tempt individuals to move to other systems. Further uses of Data Management and Analytics (MDA) can be explored. As a result, managers may allocate reduced amounts of effort towards monitoring information, opting instead to prioritize the creation of timely reports and the generation of accurate projections.

The utilization of Marketing Data Analytics (MDA) is beneficial for organizations in the acquisition and retention of clients (Artun and Levin, 2015). According to Furtado et al. (2017), the use of high-quality Management of Data and Analytics (MDA) has the potential to integrate various data sources, leading to enhanced operational efficiency. This, in turn, may positively influence the inclination to reinvest.

Upon achieving contentment with the current MDA system, the organization may contemplate reinvesting in supplementary MDA apps and systems to attain an enhanced understanding of the consumer (Visconti et al., 2017). Therefore, the subsequent Hypotheses are established:

H3. User satisfaction derived from MDA systems positively influences reinvest intentions (RD).

3. Results

A robust research method was applied to this research, ensuring the reliability and validity of all research methods. The structural model refers to a model based on a conceptual framework that represents all the research variables. The findings of the literature review confirmed the development of the structural model depicted in Table 01. It should be emphasized that this study paper's structural model makes use of multidimensional interactions under inquiry and increased parsimony, according to prior research. It should be emphasized that this technique requires that the higher-order constructs be conceptualized and specified using previous research (Sarstedt, Hair et al., 2018). It should be highlighted that more abstraction—that is, more derived constructs—may result in the loss of important data and, thus, insufficient essential insights. Therefore, care must be taken in this respect (Hair et al., 2018). Therefore, The SEM method was used to analyze the model. More specifically, the analytical tool was Lisrel 9.00. The purpose and measuring philosophy of the study vary between various approaches (Hair et al., 2018). SEM was utilized as the study purpose is not connected to testing a theory but rather to predicting important target constructs and finding important driving constructs. Ringle et al. (2018) used the most recent PLS-SEM criteria for the structural analysis as fit indices become irrelevant for PLS-SEM (Hair, 2017).

3.1. Characteristics of the Sample and Respondents

The data collection process involved soliciting input from marketing experts who possess expertise in Marketing Analytics (MDA) by administering questionnaires to their verified e-mails. During approximately 3 months in the year 2023, a total of 470 responses were gathered, primarily from participants at a significance level of $p < 0.01$. All participants in the study were a minimum of 18 years of age. The ultimate sample consisted of 184 valid replies during different phases of data collection.

3.2. Measurement and the creation of questionnaires

The research instrument was designed in the light of pertinent literature. All the research constructs were identified from the Marketing Data Analytics literature. Measures were drawn to assess the quality of technology and information, data usage satisfaction and reinvestment decisions. The responses were measured on 5 5-point Likert Scale, with one as Strongly disagree and five as strongly Agree. The dimensionality, reliability, and validity were ensured for the estimation of the measurement model. The study employed Factor Analysis (FA), Principal Component Analysis (PCA), and Structural Equation Modeling (SEM) sequentially to ensure methodological rigor. FA and PCA were used to explore construct dimensionality and extract components explaining over 77% of the variance (Hair et al., 2017; Sarstedt et al., 2019). SEM then tested the hypothesized relationships, addressing latent variables and structural paths simultaneously (Kline, 2004;

Hair et al., 2018). This combination ensures robust findings by integrating exploratory insights with structural validation, aligning with established practices in marketing analytics (Akter et al., 2017; Mikalef et al., 2019).

3.3. Measurement Model

Companies contacted were in the manufacturing, construction, real estate, information and culture, banking, and insurance sectors; the respondents came from a range of designated backgrounds, such as marketing specialists, Marketing managers, marketing heads, Area Marketing heads, etc. employed by the above-mentioned companies. Initially, or to be precise, at this stage*, t-tests* between early and late responders were performed to rule out response and non-response bias; this is the first step in evaluating the measurement model. Then, all the scales were tested for Common method bias; 11 factors emerged from the PCA analysis, and the factor explains more than 28% of Variance (Shown in Table 01). Thereafter, all the scales were examined to ensure dimensionality, reliability and validity. The findings for dimensionality show that every loading was significant to the relevant construct and larger than 0.50. Since the indicator variables were over the cut-off point of 0.50, there was no need to exclude any of them (Rosenbusch et al., 2018).

Table 01: Showing the total Variance explained by EFA

Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	15.633	28.92	28.983	15.613	28.9	28.988
2	5.843	10.823	39.813	5.841	10.8	39.811
3	4.193	7.762	47.576	4.191	7.76	47.571
4	3.353	6.202	53.776	3.351	6.20	53.778
5	2.637	4.922	58.696	2.617	4.92	58.699
6	2.433	4.542	63.248	2.413	4.54	63.241
7	1.938	3.661	66.907	1.918	3.66	66.905
8	1.539	2.922	69.826	1.519	2.92	69.828
9	1.532	2.834	72.665	1.512	2.83	72.665
10	1.224	2.363	75.027	1.274	2.36	75.025
11	1.241	2.315	77.349	1.231	2.31	77.341
Principal Component Analysis.						

The evaluation of reliability comes next (Table 2, with a goal range of 0.70 and 0.95 for all measures) and tends to overestimate the dependability of internal consistency. Accordingly, the true reliability lies in the range between both parameters, the dependability can be deemed adequate based on this. Using t values, convergent validity was evaluated and found to be satisfactory (Refer to Table 02).

Table 02: Scale Reliability of the Study Scales

CONSTRUCT	CRONBACH ALPHA	CONSTRUCT RELIABILITY	AVE
TQ	.78	.78	.50
IT	.83	.98	.60
DUST	.87	.88	.62
RD	.87	.89	.52

Assessing discriminant validity, which shows how much a concept varies from other constructs, is the next stage in evaluating the measurement model (Hair et al., 2017). As a result, bootstrapping techniques should be utilized to determine the significance of the HTMT correlation (Hair et al., 2017). There is no discriminant validity if the AVE is less than shared Variance; therefore, discriminant validity is supported (Refer Table 03). The evaluation of the measuring model was ensured at this stage.

Table 03: Correlations, Shared Variance and AVE for all measures.

CONSTRUCT	IQ	QT	DUST	RD
TQ	.807	.042	.026	.019
IT	.205	.678	.669	.373
DUST	.161	.818	.543	.497
RD	.137	.611	.705	.636

3.4. Evaluation of the structural model

The evaluation of collinearity comes first in the assessment of the structural model. The variance inflation factors (VIF) are typically used to evaluate the presence of collinearity. There was no collinearity problem since every VIF value in the model was below the strict acceptance value of 0.3 (Hair et al., 2011). The following stage involves evaluating the structural model's predictive validity; the path values were 0.80, 0.20, and 0.16, respectively (as shown in Table 04).

Table 04: Showing Path Values, t values, p values and VIF for all study scales

Relationship	Path Value	T value	p-value	VIF
TQ----DUST	.80	3.5555	.000	.019
IT-----DUST	.20	12.678	.000	.13
DUST---RD	.16	10.818	.000	.24

Testing Hypotheses

Estimating the path coefficients for testing the hypothesis is shown in table 04. All hypotheses H1, H2, and H3 were Accepted.

4. Discussion

The association between the quality of the information and satisfaction is negligible in previous works (Akter et al., 2017). In this study, however, the association is healthy; the reason for the discrepancy may be that the present study's participants were marketing professionals, not big data experts (Morales-Serazzi, 2021). In this context, the difference in perception makes much difference in the findings. It also ensures that this data is valued by the organization—as determined by users rather than data generators.

In line with other studies, the technology quality construct significantly and favorably affected perceived user satisfaction (Shahbaz et al., 2020). However, there was little correlation between user happiness and the quality of the technology. This weak connection result deviates from earlier studies (Akter et al., 2017). Once more, the findings of this study showed much lower route coefficients than many research studies in the field. Akter et al. (2017) study confirmed that marketing managers' and BD analysts' perceptions of MDA are very different. Therefore, it is likely that variations in how consumers (marketing managers) and information creators (IT staff) perceive the advantages of different levels of technology quality are the source of user satisfaction gaps (Morales-Serazzi, 2021).

From a theoretical perspective, data usage satisfaction must be present when evaluating marketing plans, as prior studies have validated the presence of user satisfaction. Now, however, the correlations' significance and impact sizes are also verified. But rather were outside the company. Patterson and Spreng (1997) discuss pre-purchase scenarios in which intentions are directly influenced by perceived value, ignoring pleasure. This makes sense because the clients are unable to express satisfaction or dissatisfaction because they have no experience with the goods or services. Intentions to reinvest were positively and significantly impacted by user satisfaction with medium effect sizes. Lastly, in line with earlier studies, it is substantially connected to customer satisfaction. As a result, these correlations seem stable, in contrast to the previous ones, which vary based on whether information creators or users are being discussed. For this reason, the data must be reliable, standardized, full, and up-to-date (Langenberg et al., 2012). In terms of technological quality, data privacy needs to be safeguarded when systems are capable of integrating data from many sources and being both dependable and flexible (Fosso Wamba et al., 2018).

Marketing Data Analytics (MDA) effectiveness varies across cultures and nations (Hofstede, 1980; Buhalis & Volchek, 2021). High power distance limits decentralized insights, while low power distance enables localized strategies (Mikalef et al., 2019). Regulatory frameworks like GDPR restrict data sharing, impacting adoption (Wamba et al., 2019). Advanced economies benefit from superior infrastructure, enhancing MDA use. High uncertainty avoidance cultures prefer robust analytics to mitigate risks (Zeithaml, 2000). Comparative studies can further optimize MDA across diverse contexts (Amado et al., 2018).

5. Conclusion

This study is examining several important consequences. First, there is actually not much of a direct relationship between intentions to reinvest. On the other hand, the overall effect significantly rises when you include the indirect influence through the user satisfaction construct. Second, there is little correlation between the information quality concept and data usage satisfaction. However, the overall benefit is more substantial. Third, the technological quality construct has no discernible direct impact on user satisfaction. This study looked at how an MDA's technology and information quality affected customer happiness and, ultimately, reinvestment intentions. The sample was made up of marketing experts with MDA expertise. The links in this research were examined through SEM from the perspective of the marketing staff rather than the BD analysts, which is in contrast to earlier studies.

Along with the significance tests, other tests of significance were also performed. Additionally, the structural model regarded the construct "intentions to reinvest" as dependent rather than being taken as a mediating or independent construct. According to the paper's findings, data usage satisfaction and plans to reinvest are all impacted by the IQ and TQ of MDA. In other words, MDA's information quality positively and significantly affects data user satisfaction. MDA is also favorably and dramatically impacted by technology quality. Further, this study demonstrates that user satisfaction strongly influences reinvestment intentions in Marketing Data Analytics (MDA). Enhancing system quality and user experience can drive satisfaction and foster continued investment (Fosso Wamba et al., 2018; Morales-Serazzi, 2021). The findings align with prior research on satisfaction's role in behavioral intentions (Patterson & Spreng, 1997) and highlight its mediating effect in reinvestment decisions (Akter et al., 2017).

6. Implications

The study also looked at how technology and information quality affected data usage satisfaction and, finally, reinvesting decisions. The lack of high-quality information in MDA apps might negatively impact users' pleasure and, ultimately, their intent to reinvest in MDA. Its direct or indirect effects on MDA marketing managers' evaluations were substantial. Similarly, IQ and TQ had a substantial and favorable indirect impact on DUST. Therefore, it is essential to guarantee that the data in MDA applications is correct, up-to-date, full, and in a format that can be used (Harrison, 2016). Higher satisfaction would result from improved knowledge, even if managers did not use this to justify spending more money. Organizations utilize IT to assist them in identifying their target markets, developing relationships with customers, and making smart decisions that lead to increased sales for the company. Moreover, when it comes to judging the worth and usefulness of the information gathered (and the insights that follow), marketing managers only seldom concur with data analysts. This conclusion suggests that, given the setting of the research, it is critical to evaluate the perspectives of all pertinent stakeholders since there may be substantial variations in those opinions.

The study's conclusions also show that, for MDA marketing customers, user satisfaction is positively and strongly correlated with reinvest decisions. Better technological quality is required for MDA, which helps process a lot of different types of data. Technology quality should be prioritized to meet evolving consumer demands and market situations (Tallon & Pinsonneault, 2011). This is because technology quality has a beneficial effect on customers' views about the Company; getting a good Company's product is, after all, rather fulfilling. Therefore, although it may not have a direct effect on satisfaction, high-quality technology does. Lastly, because the domains of MDA are quickly changing, businesses need to continuously search for novel solutions to help management create cutting-edge responses to managerial and marketing problems. In this process, the significance of high-quality information and technology takes primacy.

7. Limitations

Like all other research, some areas remain untouched through this research; the majority of the data included in this study comes from marketing experts with MDA implementation expertise. Although there were no discernible differences between research conducted in different contextual settings, it would be interesting to replicate the study in different nations and cultural contexts. As was already indicated, a lot of past studies have concentrated on the perspectives of the IT specialists working on the MDA applications rather than marketing professionals' perceptions (which were included in this research). Therefore, conducting a comparative study with a sample of IT and marketing experts would be fascinating. Further, this research is cross-sectional; a longitudinal study can be conducted to obtain results regarding trend analysis. Methodological research gaps can be overcome if more time and effort are put into research in these areas. Future research should examine how AI and blockchain enhance data accuracy and security in MDA, particularly in resource-constrained SMEs (Wamba et al., 2019). This study also has the limitations of including differing perceptions of data quality between marketing and IT teams, which may hinder MDA effectiveness (Morales-Serazzi, 2021; Mikalef et al., 2019). Interventions like cross-functional training were not explored but could align these perspectives (Akter et al., 2017). Lastly, reliance on self-reported data may introduce bias, suggesting a need for longitudinal studies (Wamba et al., 2019).

8. Future research avenues

Future research should prioritize investigating the direct application of big data analytics in decision-making processes, particularly within marketing strategies (Ledro et al., 2022). Studies could examine how data-driven insights translate into actionable strategies, such as market segmentation, pricing decisions, and customer relationship management (Vecchio et al., 2022). Furthermore, integrating big data with emerging technologies like AI and IoT may offer novel solutions for real-time decision-making, addressing the dynamic nature of consumer behavior (Filieri & Mariani, 2021). Exploring cross-functional collaborations between data scientists and marketing managers can also shed light on how analytical outputs are interpreted and implemented in practical scenarios (Wamba et al., 2019). Lastly, marketing researchers may consider conducting different types of systematic reviews (Fakhar et al., 2023; Khan, Anas, et al., 2024; Khan, Uddin, et al., 2024; Rashid et al., 2024) on the literature existing on the conjunction of sustainability and marketing data analytics.

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