Overview of Marketing Analytics and Public Policy for improving Consumer Behaviour in the Digital Economy

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Abstract

As Trinidad and Tobago aspires to become a Caribbean leader in digital transformation, there is a growing need to understand consumer engagement within the digital economy, particularly in relation to state-provided, subsidised services that address basic citizen needs. Despite ongoing efforts, these services have been met with increasing public dissatisfaction, often reflected in negative consumer feedback. This underscores a critical gap in the application of marketing analytics to public policy, especially in the effective promotion and management of state-subsidised services. While marketing analytics has proven valuable in influencing consumer behaviour in the private sector—such as through de-marketing harmful products or promoting essential services—it remains underutilised in the public sector context. This literature review explores the intersection of marketing analytics and public policy, aiming to improve consumer perceptions of government agencies. By employing predictive analysis and machine learning techniques, the research seeks to identify key factors influencing consumer behaviour toward ministerial services. Guided by the Stimulus-Organism-Response (S-O-R) theory, the study proposes the development of marketing strategies that can shape cognitive and affective consumer responses, ultimately leading to more favourable behavioural outcomes. The overarching objective is to contribute to a conceptual model that integrates marketing analytics into public policy frameworks, enhancing citizen engagement and supporting more responsive and effective governance.

Keywords: Marketing Analytics, Predictive Analysis, Machine Learning, Stimulus-Organism-Theory, Policy Development

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Introduction

Policy making has traditionally been the subject of research with decision analysts introducing traditional methodologies to assist policymakers in making better judgments. Recently, the subject of decision analysis has been significantly impacted by the "analytics" perspective, which blends advanced data mining and machine learning methodologies that lend support to the decision-making process (Davis et al. 2021). The field of analytics serves as a foundational component in facilitating data-driven decision-making and advancing business intelligence across modern organisations (Emma, 2024). However, in public decisions, matters such as social values, behaviour, culture, and public engagement play a major role in the public policy cycle (Baltussen et al., 2020) of design, testing, implementation, evaluation, and review. This has revealed that public policy creation is a more socially complex process as previously investigated by most analytical techniques and applications (Almquist et al., 2012).

Marketing analytics, when applied to large data sets, can shed light on policy concerns and produce practical recommendations (Davis et al., 2021). For instance, policymakers can utilise big data and artificial intelligence (AI) to develop predictive models that inform marketing strategies aimed at

promoting healthier behaviours and improving patient habits. Marketing analytics frequently integrates numerous fields (for example, customers, products, time, geospatial locations, and channels) from many data sources, then adopts large-scale data mining approaches (Bradlow et al., 2017). Analytics also enables researchers to investigate vulnerable populations for whom primary data collection is limited **(**O'Connor, 2020). When the COVID-19 virus became a pandemic in March 2020, unusual retail consumer behaviour such as hoarding toilet paper and food was recorded across the world (Wang et al., 2020). The perceived cause was not only the imminent health threat posed by COVID-19 and the potential for quarantine, but also concerns about factory shutdowns and disruptions to global supply chains. The S-O-R framework was utilized to examine how the environmental stimuli of online information sources led to these behaviours on COVID-19.

According to Comuzzi and Patel (2016), data culture in public organisations describes how big data is viewed not just as an IT problem but also as something that needs to be supported by organisational-wide structures and skills. In particular, it highlights how crucial it is that policymakers and civil servants know where to look for, evaluate, and use big data as well as how to support this with institutional frameworks like data sharing or training across government agencies (Giest, 2017).

In the sphere of marketing, public policy is an expansive topic. According to Andrews et al. (2022), marketing and public policy covers areas of consumer protection issues, data privacy, consumer vulnerability, diversity, communication, education, and competition, just to name a few. Kopalle and Lehmann (2021) provided general perceptive in "Big Data, Marketing Analytics, and Public Policy: Implications for Health Care." They indicated that the availability of big data is spawning data-driven decision cultures, providing organisations with competitive advantages that can have a significant effect on policy decisions. Their analysis, together with Chen, Sridhar, and Mittal's (2021), offers practical guidance on how analytics might leverage data and technology to derive marketing insights. Applying marketing analytics to large-scale data sets can also reveal policy challenges and provide recommendations that can be put into practice.

Making accurate and reliable predictions about actions or behaviours is crucial for organisations to survive and achieve competitive advantage in dynamic settings (Banerjee & Chandrasekaran, 2023). In numerous applications, machine learning algorithms have demonstrated a high degree of accuracy in predicting human decisions (Kleinberg et al., 2018; Mullainathan & Spiess, 2017; Plonsky et al., 2019). The question to answer is how public policy can use marketing analytics to improve consumer behaviour in the digital economy.

Existing research pays significant attention to investigating the driving factors for a specific behaviour, and it overlooks the multiple reasons for certain behavioural choices that the consumer faces (Fang et al., 2018). Although there have been many studies on the understanding and

prediction about the volume differences of customer engagement behaviours among posts, that is, predicting the amount of responses for a particular post (Lee et al., 2018; Mariani et al., 2016), there is little knowledge or evidence on how public policy can use marketing analytics to support the goals and strategic objective of State-managed projects that would harvest positive responses from the public using the Stimulus-Organism-Response (S-O-R) framework.

This study aims to explore the inherent connection between the stimuli, such as perceived information quality and social presence, resulting from online and social media reviews, and the subsequent response, namely public acceptance. The findings can provide valuable insights for the design, implementation, and evaluation of public policies. By doing so, this research has the potential to mitigate potential inefficiencies in public sector investment, thereby improving the overall quality of public services.

Background

Marketing Analytics

Marketing analytics has evolved significantly. With the exponential increase in data availability in the digital economy over the past two decades, businesses have come to realize the significant competitive edge that analytics can provide. This realisation has fuelled the continuous development and adoption of analytics strategies within firms. A study done by Morgado et al. (2023) emphasises that integrating various technologies into company systems is crucial for achieving a sustainable competitive advantage through data-driven marketing.

Wedel and Kannan (2016) highlighted that the evolution of data-driven analytics in marketing, spanning from approximately 1900 to the advent of the World Wide Web in 1995, can be outlined within three key phases:

(1) Initially, marketers focused on depicting market conditions through basic statistical methods, aiming to describe trends.
(2) Subsequently, there was a shift towards constructing models that employed economic and psychological theories to offer insights and diagnostics.
(3) The final stage involved assessing marketing strategies, wherein the effects of these strategies were forecasted, and decision-making was facilitated through the application of statistical, econometric, and operations research approaches.

As the volume of retail data sets grows, there is a significant potential for gaining policy insights, particularly when common elements like zip codes are linked with data detailing maladaptive consumption, such as tobacco usage (Davis & Grier, 2015). Additionally, analytics enables researchers to explore vulnerable populations, such as adolescents, where primary data collection may be limited, by leveraging secondary data sources (O'Connor, 2020).

Policy Analytics

Decision analysts must draw from a wide range of existing data and knowledge, including factual information, scientific knowledge, and expert knowledge in its many forms, in order to support policy makers in a way that is meaningful (i.e. adds value to the process), operational (meaning that it is practically feasible), and legitimizing (i.e. ensuring transparency and accountability). They must also combine this with a constructive approach to surfacing, modelling, and understanding the opinions, values, and judgments of the range of relevant stakeholders. The combination of these abilities, approaches, technologies, and methods is referred as "policy analytics" (Tsoukias et al., 2013). The goal is to assist pertinent parties involved in the policy cycle to have access to insightful and useful foresight, insight, and hindsight.

According to Tsoukias et al. (2013), policy analytics has two main responsibilities in terms of data requirements. These are investigating already-existing data sets and collecting information, building new databases, and investigating specific topics that are important to decision-makers. Tsoukias et al. (2013) also indicated that analysts must acknowledge that benchmarks cannot be easily defined by examining data that already exists (such as citizen votes, preferences and demands, their relationship to demographics, etc.). There are multiple stakeholders involved who are affected by a decision and multiple objectives pursued by the policy makers. Therefore, in order to support decisions made within the policy cycle, policy analytics must concentrate on constructive methods (building step by step), such as constructive benchmarking and learning. Understanding the stakeholders' beliefs is necessary to create standards, which are needed in the analysis' design rather than just basing them on observed performances or behaviours. In order to foster constructive learning, it is necessary to emphasise models for learning that will promote active engagement and knowledge construction (Almulla, 2023) as opposed to models that provide the "correct" answer. It is also important to acknowledge that analytical models have a constructive role to play, encouraging learners to build their own understanding (Daodu et al., 2024).

Consider the Water and Sewerage Authority (WASA) of Trinidad and Tobago being evaluated based on the number of communities receiving a regular water supply. In addition to a variety of surrounding elements, this seemingly straightforward indicator is open to several social and political interpretations. For instance, tighter water schedules may mean "poor" infrastructure which may lead to the inefficiency of the water authority to supply water to many of the communities; or it could mean "prudent" and "effective" management of limited water resources. It is crucial to remember that, depending on the environment, values, and culture, the same statistical information may be interpreted in several ways. A policy must satisfy these various, sometimes conflicting, concerns in order to be considered "legitimate." This is where "analytics" become important, as they offer not only supporting data but also validating data (e.g., demonstrating that an increase in water schedules can ultimately lead to a significant decline in water resources.

Another important point is that, unlike business analytics, which is frequently very data-driven, policy analytics must emphasise value-driven analysis that can assist value-driven decision-making (Costa et. al., 2016). Value-driven analysis recognises that the various policies are ways to accomplish the goals and values that society is trying to realise. Since these values frequently reflect the goals of various stakeholders, different policies will have varying effects on how much these values are realised or upheld. Additionally, these policies may have uneven effects on different societal sectors. In connection with this, policy analysis has failed to promote the creation of improved policies from the standpoint of value-driven analysis (Cinelli et al., 2022).

In the policy analytic cycle, there is a significant opportunity to incorporate analyses to support decision-making. Examples of such analyses include assisting with issue identification, forecasting potential policy impacts, supporting policy design, simulating policy implementation, and assisting with the evaluation and monitoring of implemented policies.

S-O-R framework in Marketing Analytics

The S-O-R (Stimulus-Organism-Response) framework in marketing analytics is a conceptual model used to understand and analyse consumer behaviour. The following is a breakdown for the S-O-R framework:

- **Stimulus (S)** - Stimuli are external factors that influence consumer behaviour, such as marketing messages, product features, pricing, promotions, and environmental cues (Kotler & Armstrong, 2017).

- **Organism (O)** - The organism refers to the internal psychological processes of the consumer, including perceptions, attitudes, motivations, emotions, and personality traits, which shape their response to stimuli (Solomon, 2019).

- **Response (R)** - Responses are the observable behaviours or actions taken by consumers in reaction to stimuli and their internal psychological processes, such as purchasing decisions, brand loyalty, engagement with marketing channels, and advocacy (Kotler & Keller, 2015).

The overall goal is to measure and analyse consumer responses to different stimuli to understand their preferences, intentions, and purchase behaviour. By applying the S-O-R framework in policy analysis, researchers can systematically analyse the interactions between policy stimuli, organisms, and responses to understand the effectiveness, efficiency, equity, and unintended consequences of policy interventions (Bridgman, Davis, & Ferguson, 2018). This framework helps in evaluating the design, implementation, and outcomes of policies, thereby informing evidence-based decision-making and improving policy outcomes.

Application of Marketing Analytics to Policy Development

In today's data-driven world, the application of marketing analytics is extending beyond commercial realms into the domain of public policy. By harnessing advanced analytical techniques, state agencies can gain valuable insights into the needs, preferences, and behaviours of their stakeholders. These insights, as evidenced by Carter and Lee (2019), allow agencies to craft policies that are more aligned with the priorities of the communities they serve. Moreover, the utilisation of marketing analytics facilitates the identification of policy objectives and goals. Through the analysis of trends, patterns, and data gaps, as highlighted by Shaw (2018), state agencies can develop policies that are not only responsive to current challenges but also forward-looking in addressing emerging issues.

One of the significant advantages of marketing analytics in policy development lies in its ability to target and tailor interventions to specific population segments. Davis and Meyer (2019) mentioned that state agencies can leverage demographic and behavioural data to design policies that resonate with the unique characteristics and needs of diverse communities. Furthermore, marketing analytics equips state agencies with robust tools and methodologies for measuring policy outcomes and effectiveness. Harris and Dennis (2019) emphasised the importance of tracking Return on Investment (ROI) in policy initiatives, enabling agencies to optimise resource allocation and maximise impact.

The iterative nature of marketing analytics promotes continuous learning and improvement in policy development. As advocated by Carreno (2024), integrating sentiment analysis, employee listening platforms, and pulse surveys can create a multidimensional feedback system. Such systems enable organisations, including state agencies, to make data-driven adjustments, maintain engagement, and align change initiatives with workforce needs. State agencies can adapt policies dynamically to evolving societal needs and challenges. The integration of marketing analytics into policy development processes offers state gencies a powerful toolkit for addressing complex societal challenges and enhancing service delivery. By leveraging data-driven insights, agencies can achieve better outcomes for their constituents while fostering a more responsive and adaptable governance framework.

Recognition Techniques in Marketing Analytics that aids Policy Development

In the realm of policy development, the utilisation of advanced analytics techniques is revolutionising the way policymakers gather insights and make informed decisions. From text analytics to voice, image, and video analytics, each method offers a different lens through which policymakers can dissect complex data and extract actionable intelligence. The following is an account of some main recognition techniques that can be utilised by policymakers.

1. Text Analytics: Deciphering the Narrative

Text analytics serves as a formidable tool for policymakers, enabling the analysis of vast troves of textual data from diverse sources such as policy documents, public consultations, and social media interactions (Karanasios et al., 2020). By harnessing natural language processing (NLP) techniques, policymakers can unravel key themes, sentiments, and trends hidden within textual data. This empowers them to grasp public opinions, evaluate policy impacts, and fine-tune interventions to better align with societal needs.

2. Voice Analytics: Amplifying Public Discourse

Voice analytics offers a window into spoken language and vocal patterns, allowing policymakers to glean insights from recordings of public meetings, interviews, and stakeholder consultations (King et al., 2019). Through sophisticated speech recognition and sentiment analysis algorithms, policymakers can distil valuable insights from verbal exchanges. This enables them to gauge public sentiment, identify areas of concern, and refine communication strategies for greater impact.

3. Image and Video Analytics: Illuminating Visual Narratives

Image and video analytics unlock the potential of visual content, enabling policymakers to dissect images and videos from public events, protests, and surveillance footage (Zhu et al., 2021). By leveraging techniques like object detection, facial recognition, and emotion analysis, policymakers can unravel nuanced insights into public behaviour, emerging trends, and the societal impact of policies.

4. Face Recognition: Putting a Face to Policy Insights

Facial recognition technology empowers policymakers to identify individuals based on facial features, offering a novel approach to analysing images and videos in policy development (Dantcheva et al., 2019). By integrating face recognition with other analytics techniques, policymakers can gain deeper insights into public engagement, demographic trends, and community dynamics, enabling more targeted and effective policy interventions.

Related Works

Davis, Grewal, and Hamilton (2021) discussed contemporary analytics techniques addressing policy and marketing challenges which identified six key areas for marketing analytics and public policy. These areas include retail analytics, social media analytics, marketing-mix analytics, services and healthcare, non-profits and politics, alongside AI and robotics. The analysis emphasised the exclusion of analytic approaches in literature on social problems and suggests exploring additional areas like criminality, finance, and public utilities. Dai and Wang (2021) focused on predicting customer engagement behaviour in response to social media marketing posts using machine learning. The widespread use of social media platforms has significantly transformed the dynamics of customer-brand interactions. The selection of appropriate strategies

for social media marketing to elicit diverse forms of customer engagement is a crucial consideration. To enhance our comprehension of customer behaviours within the context of social media marketing, we leverage the Stimulus-Organism-Response theory. The study done by Dai and Wang (2021) conceptualises and delineates marketing posts across six dimensions to capture various features as stimuli. These dimensions include format, interactivity, content theme, emotionality, posting time and content length. These stimuli, in turn, prompt or activate customers' cognitive and affective states to varying degrees, ultimately resulting in distinct behavioural responses. Machine learning algorithms can be used to predict customer engagement behaviours in response to marketing posts. The success of social media marketing initiatives is primarily determined by the engagement behaviour of customers.

Wedel and Kannan (2016) examined the history of data and analytics in marketing, emphasising the diverse requirements across subdomains. They stressed the importance of understanding marketing modelling approaches and highlighted potential organisational barriers and opportunities for successful implementation of rich marketing data analytics. Advertising, promotions, product development, and branding are just a few of the subdomains in marketing that have different data and analytics requirements. Therefore, it is unlikely to be effective to use one-size-fits-all analytical solutions. Because of this, analysts need to be well-versed in marketing modelling techniques for personalisation, marketing-mix optimisation, and forecasting marketing response. Ngai and Wu (2022) aimed to create a conceptual framework for machine learning applications in marketing. They identified machine learning tools and technologies for marketing development. McCarthy's 7Ps of marketing mix, which are product, price, promotion, place, people, process, and physical evidence were used to analyse these applications. They explained in detail how machine learning tools and technologies (i.e., supervised learning algorithms and unsupervised learning algorithms) can be used to support the various stages of the marketing mix. Their research concluded that marketing is not a one-size-fits-all analytical solution, which is neither desirable nor likely to be effective, but includes various subdomains with diverse data and analytics requirements (e.g., advertising, promotions, product development, and branding) and that analysts must, therefore, have a thorough understanding of marketing modeling approaches to forecast marketing response, marketing-mix optimisation, and personalisation.

In addition, Miles (2014) explored the use of marketing analytics in predicting customer behaviour patterns, particularly focusing on Small Business Enterprises (SMEs). The study found that marketing behaviour analysis can forecast client behavioural patterns. It further shed light on the need for redefining the use of marketing analytics as a measurement tool for examining customer behaviour.

Kennedy, Kunkel, and Funk (2021) compared linear regression and Support Vector Machine (SVM) techniques for measuring social media engagement effectiveness. For each social media post, a linear and SVM model were created and trained to predict the total interactions. The SVM model had lower error in predicting Total Interactions compared to the linear model. They highlighted the benefits of predictive modelling, demonstrating that SVM provides more accurate

marketing measurement compared to linear regression but fails to account for the complex, non-linear, and contextual nature of social media engagement. In general, the SVM provided a more accurate marketing measurement of non-linear and contextual model compared to linear regression. However, Kennedy, Kunkel and Funk (2021) recognised that the approaches failed to account for the complex, non-linear and contextual nature of social media engagement.

The results from these techniques can be used to develop and support public policy. Grubmüller, Götsch, and Krieger (2013) outlined the benefits of integrating social media analytics with public policy for future-oriented decision-making. They stressed the importance of training public administrators in diversity awareness and social media literacy. Understanding how to interpret social media responses within its various categories is essentially important to the strategic development of any organisation. El-Taliawi, Goyal, and Howlett (2021) examined the prevalence of big data analytics in public policy research and teaching. They found that selected institutions in few countries have adapted big data and analytic techniques in public policy, emphasising the need for more attention in this integration. El-Taliawi, Goyal, and Howlett's (2021) examination of 75 universities who were engaged in public policy research revealed that only 59 institutions offered a degree or programme in public policy, and only 30% of them included big data analytics courses. The spread of big data analytics in public policy pedagogy varies greatly by region as well; although big data is covered in 50% of programmes in North America, only 18% or fewer of programs in Europe and other parts of the world offer big data-related courses. This is a concerning trend that indicates that the promise of big data may not be realised in the future for policy research and application. Therefore, big data's ability to drastically alter public policy remains unrealised.

Methodology

The methodology used in the article "The Future of Marketing Analytics and Public Policy" by Davis, Grewal, and Hamilton (2021) involves a comprehensive review and synthesis of existing literature in the fields of marketing analytics and public policy. **Figure 1** presents a clear definition of the schematic areas that affect both marketing analytics and public policy.

The authors examined current trends, developments, and challenges in combining marketing analytics and public policy to provide insights into future directions and potential implications for both academia and practice. Through a systematic analysis of scholarly articles, industry reports, and case studies, the authors identified key themes, emerging technologies, and opportunities for leveraging marketing analytics in the realm of public policy. This qualitative approach allows them to offer valuable insights and recommendations for policymakers, researchers, and practitioners interested in harnessing the power of marketing analytics to address societal challenges and promote public welfare.

Figure 1

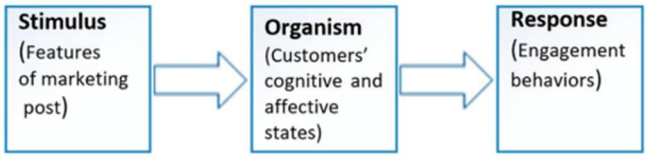
Six main areas of importance for marketing analytics and public policy

Source: Davis, B., Grewal, D., and Hamilton, S. (2021)

Dai and Wang (2021) used the SOR theoretical framework as seen in **Figure 2**.

Figure 2

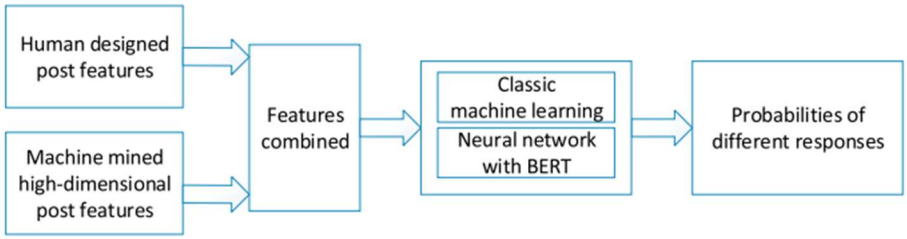
SOR Theoretical Framework



Source: Dai, Y., & Wang, T. (2021)

The methodology used by Dai and Wang (2021) involved the collection of data on customer engagement behaviour in response to marketing posts posted on social media, for example, Facebook. Classic machine learning algorithms and neural network (BERT) were used to analyse the data and predict customer engagement behaviour. Human-designed independent variables and marketing posts texts were used as predictors to test whether prediction performance can be improved. As seen in **Figure 3** it was concluded that the best performance occurred with the combination of human-designed features with the marketing post texts as predictors. Using human-designed variables and marketing posts separately generated poorer results.

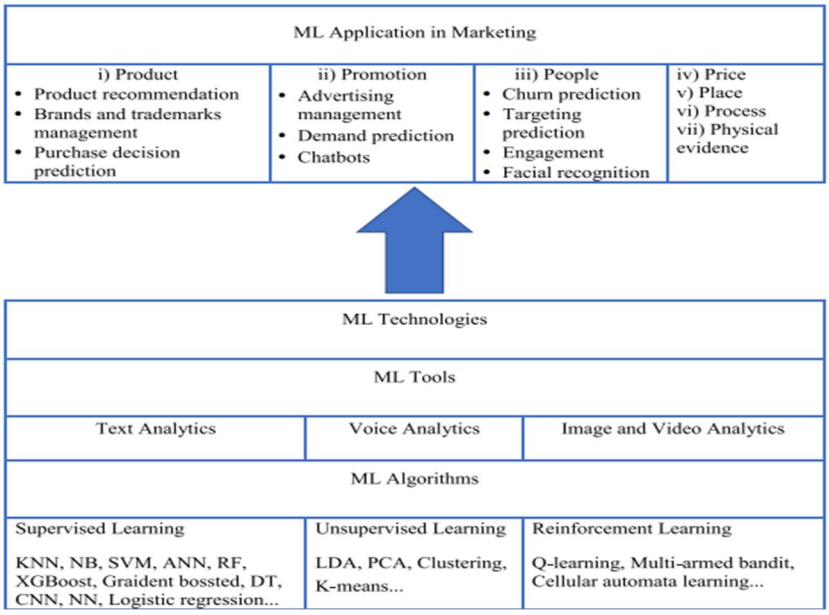
Figure 1
Methodology for Experiments



Source: Dai, Y., & Wang, T. (2021)

Kennedy, Kunkel, and Funk (2021) used a Support Vector Machine (SVM) and a linear model that was developed and trained to predict the Total Interactions for each post. Results showed how it can be used to leverage post characteristics to forecast post success and contextualize existing post metrics. Ngai and Wu (2022) conducted a literature review on Machine Learning (ML) applications in marketing. The review was used to build a 2-layer conceptual framework that shows the marketing mix and ML can be applied to support the development of major marketing applications as seen in **Figure 4**.

Figure 2
Conceptual Framework ForML Application in Marketing

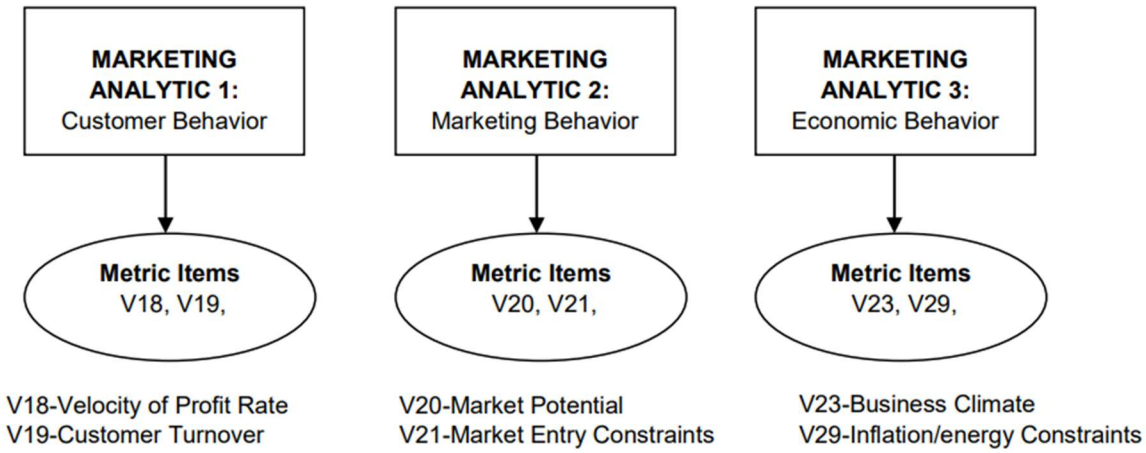


Source: Ngai & Wu (2022)

The upper section illustrates the application of ML in marketing, focusing on the 7Ps marketing mix: product (including product recommendations, brand management, and purchase prediction), promotion (covering advertising management, demand forecasting, and chatbots), people (encompassing churn prediction, targeting, engagement, and facial recognition), price, place, process, and physical evidence. Meanwhile, the lower section portrays ML technologies, which include various tools such as text analytics, voice analytics, and image and video analytics, as well as algorithms like supervised learning, unsupervised learning, and reinforcement learning.

A study done by Miles (2014) aimed to assess whether marketing analytics could serve as a predictor of customer behavioural patterns, focusing specifically on small business enterprises (SMEs). Three main constructs of marketing analytics—customer behaviour analytics, marketing behaviour analytics, and economic behaviour analytics—were examined within this context as illustrated in **Figure 5**.

Figure 3
Constructs of Marketing Analytics



Source: Miles (2014)

Initially, conceptual models were developed to scrutinise and evaluate customer behaviour patterns in the dataset, a crucial step for establishing the validity of the three constructs concerning customer behaviour in SMEs. Results showed that distinct behavioural and social resources of customers were challenging to identify. The discriminant analysis revealed that only marketing behaviour analytics exhibited moderate significance, as measured by Wilks' lambda statistics. Pearson correlation analysis was then conducted to test hypotheses and investigate inter-correlations within marketing analytics variables. The findings suggested a need for further research to refine analytics, as the results yielded limited insights into predicting customer behaviour patterns.

These findings have two key implications: firstly, they offered insights into customer behaviour within business enterprises, indicating that marketing analytics can moderately predict such behaviour. Secondly, they underscored the importance of refining marketing analytics as measurement tools for examining customer behaviour, emphasising the need for additional research in this area. In conclusion, this research contributes to the development of a theory of marketing analytics for measuring customer behaviour and enhancing the understanding of its potential benefits. While the results did not fully meet expectations, Miles (2014) marked a starting point for leveraging analytics to measure customers' behaviour in firms, highlighting avenues for further investigation in the realm of marketing analytics.

Performance Review

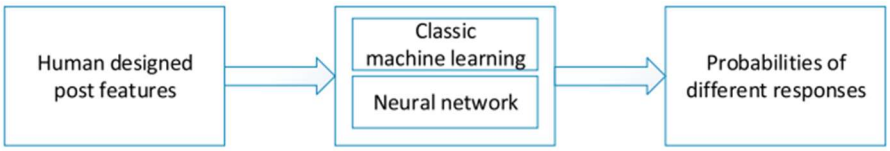
Governments should incorporate social media and mobile techniques into their e-services portfolio, as highlighted by the World Bank (2012) study on "Information and Communications for Development." This is primarily because social media can result in higher participation rates than traditional e-government applications. Grubmüller, Götsch, and Krieger (2013) highlighted that evidence-based policy making is most successful when public administrators rely on diverse information portfolios. The researchers claim that governments can profit from integrating publicly available, user-generated data using the approach of social media analytics (SMA), given the increasing significance of social media in the previous ten years. At the time of this publication, Grubmüller, Götsch, and Krieger (2013) referenced the United Nations E-Government Survey (2012) that discovered governments in 123 developing and wealthy countries currently use the internet to get public input.

In research done by Davis, Grewal, and Hamilton (2021), one focal analytical methodology that can lend support to the design of public policy is social media analytics. Social media analytics is the process of analysing data from social media platforms (such as Facebook, Instagram, Pinterest, YouTube, WhatsApp, TikTok, and Weixin/WeChat) in order to derive insights for marketing. While researchers have used social media analytics to gain insights into general marketing (Grewal et al., 2020; Ordenes et al., 2019), they have also raised concerns about important public policy issues, such as attempts to use social media for political purposes and the need to comprehend the role of content provided and created by bots, as well as privacy risks. Social media analytics offers an effective method to comprehend how actual customers react to products and brands' social media presence online. Research done by Rossi et al. (2001), where they reviewed behaviours by 620,000 followers and 475,000 engagements of a gambling site, showed that 41,000 U.K. adolescents have gambling accounts, and this produced changes in public policy recommendations.

Similarly, using a sample of 54,464 tweets, Crow et al. (2021) investigated the social media pages of the Republican and Democratic Parties in the United States for their article "Power and the Tweet: How Viral Messaging Conveys Political Advantage". Tweets from the Republican Party were more likely to be retweeted, presumably because they primarily employ judgmental language (e.g., stressing consideration of alternatives over action). Additionally, these authors offer suggestions to decision-makers regarding how best to facilitate and promote policy discussions.

Selecting the right social media marketing techniques is crucial for encouraging various sorts of client interaction. Using the S-O-R method, Dai and Wang (2021) conducted three groups of experiments and compared results. The intent was to determine which stimuli induce or activate customers' cognitive and affective states that lead to different behaviour responses. In each test, results from classic machine learning and neural network models were compared. Three classic machine learning algorithms, Logistic Regression, Random Forest Classifier and LGBM Classifier, were used, along with the neural network models constructed by the Keras framework.

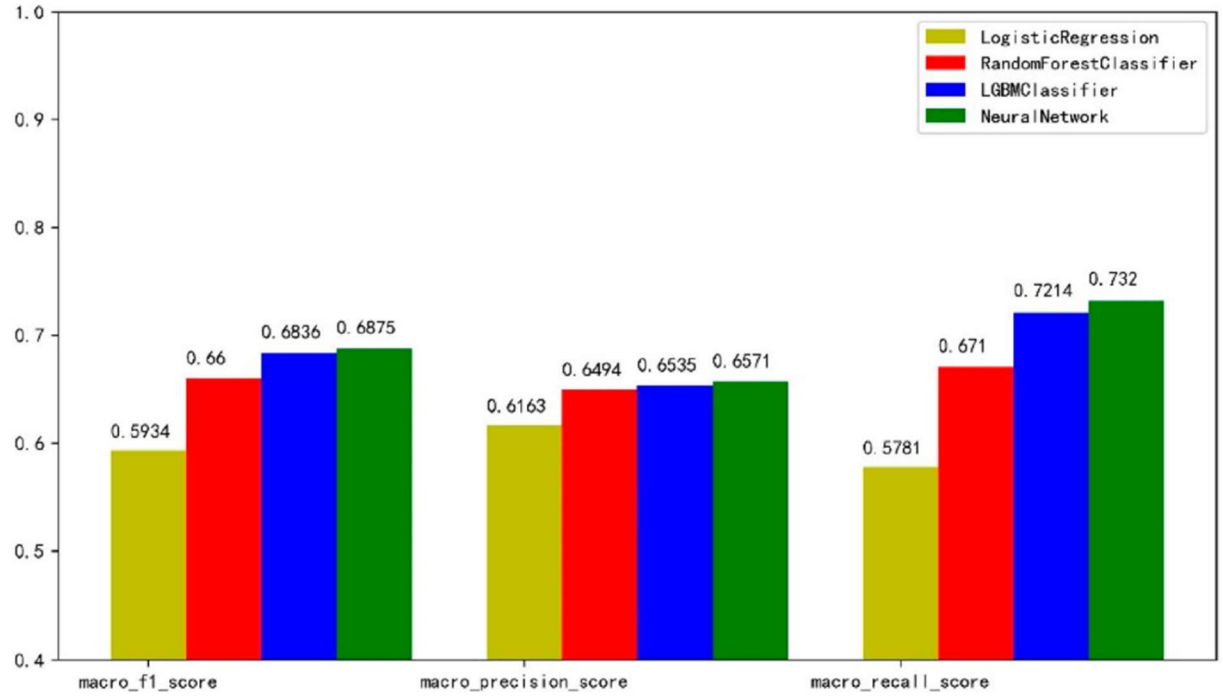
Figure 4
First Experiment Process



Source: Dai, Y., & Wang, T. (2021)

In the first experiment, twenty-two (22) human-designed independent variables were used as predictors to test whether human recognised patterns could predict the choices of customer engagement behaviours. The process is shown in **Figure 6**. The neural network model gets better results than the classic machine learning models as seen in **Figure 7**. It also shows that good performance can be achieved by using only human-designed variables, which means we as humans have identified many features in the posts which can be used to differentiate customer engagement behaviour choices.

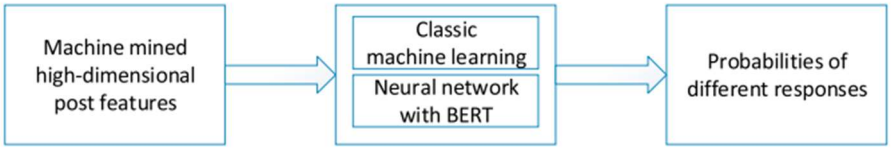
Figure 5
Results of First Experiment



Source: Dai, Y., & Wang, T. (2021)

In the second experiment, only marketing posts were used as predictors to test whether machines can mine some regular patterns from history data to predict the results with good performance. After the training process, the neural network model used has better performance than the classic machine learning models. The process used is shown in **Figure 8**.

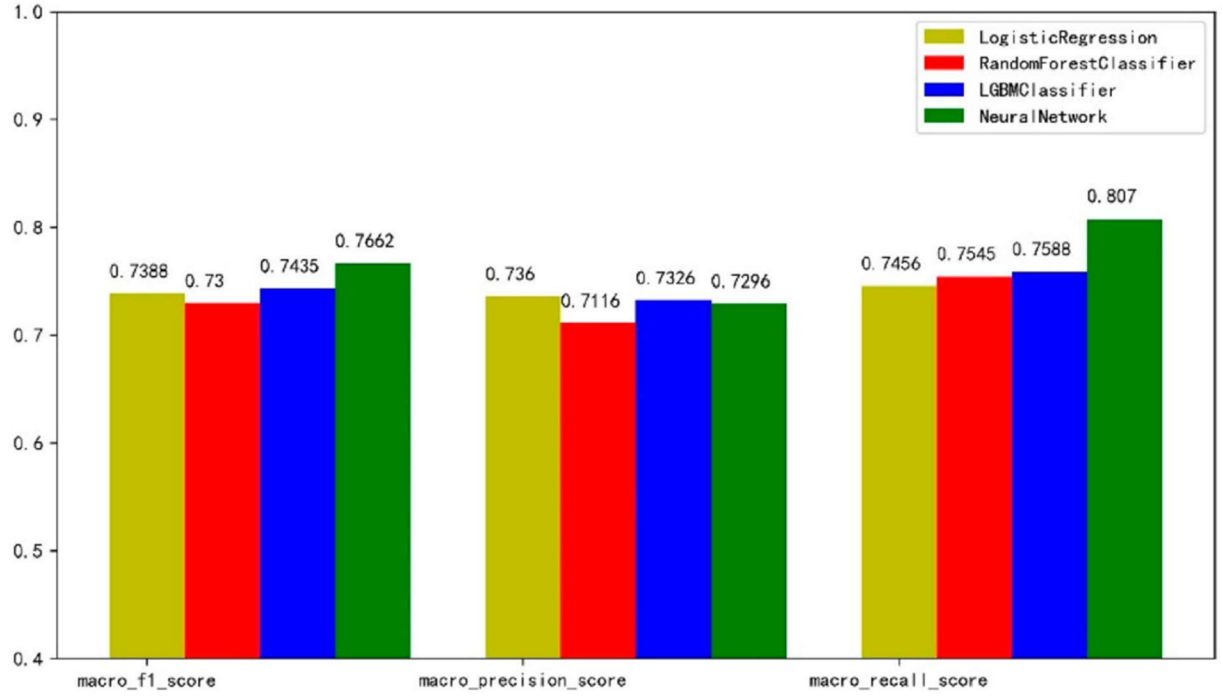
Figure 6
Second Experiment Process



Source: Dai, Y., & Wang, T. (2021)

Results of performance for the second experiment are shown in **Figure 9**.

Figure 7
Second Experiment Process

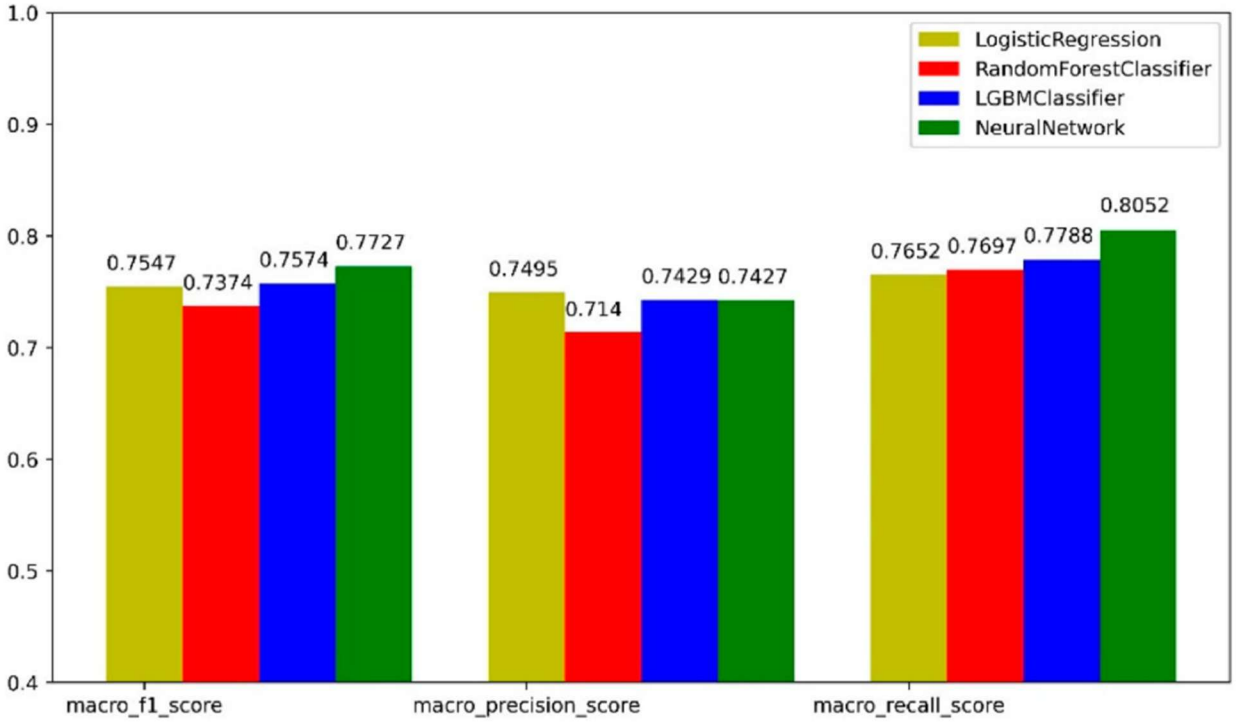


Source: Dai, Y., & Wang, T. (2021)

In the third experiment, both the marketing post texts and human-designed independent variables were used as predictors to test whether such a way could help to improve the prediction performance. The process is imaged in **Figure 3**.

After the training process, the results received on the test set show that the neural network model performs the best in **macro_f1_score** and **macro_recall_score**, and the **Logistic Regression** model (classic machine learning algorithm) got the best result in **macro_precision_score** as presented in **Figure 8**.

Figure 8
Results of Third Experiment



Source: Dai, Y., & Wang, T. (2021)

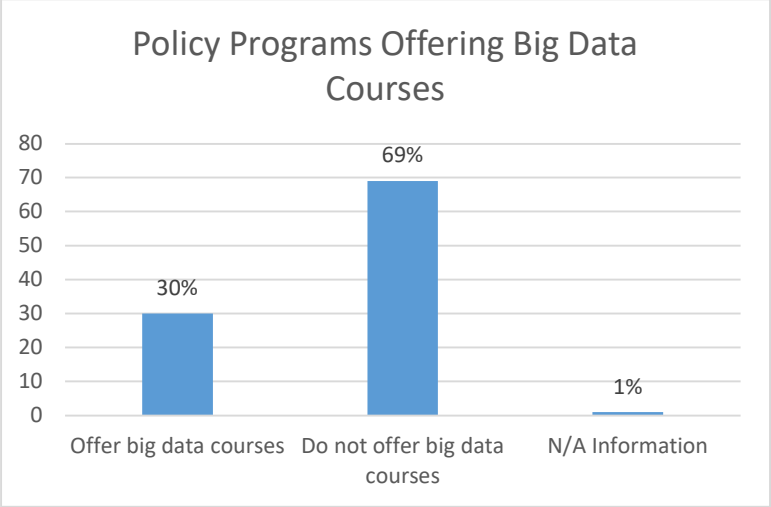
It was concluded that the best performance is achieved by incorporating human-designed features with the marketing post texts as predictors, using both classic machine learning and neural network models.

Discussion

The reviewed articles presented a wealth of knowledge on their given research. However, there is little to no knowledge of any existing dataset that can be referenced in relation to marketing analytics and public policy. Though attempts were made to highlight the topics involved and its relationship, only few experiments can be identified. Research done by Dai and Wang (2021) presented evidence of predictors that were used to determine the features that can be used to create marketing posts. However, only results of the experiments were mentioned. No mention was made to results being used to affect the creation of public policy.

While big data analytics has made significant inroads into various social science disciplines, including public administration, its integration into policy analysis lags behind. El-Taliawi, Goyal, and Howlett (2021) conducted a survey of 59 university websites, focusing on programs, courses, and specializations related to public policy and public affairs that incorporate big data analytics. Their findings revealed that only 30% of these programmes offered courses in big data analytics, while 69% did not include such offerings in their degree programmes, as outlined in **Figure 11**. Furthermore, in their examination of patterns and trends in big data analytics for public policy research, El-Taliawi, Goyal, and Howlett (2021) identified over 1500 publications. However, the majority of these publications consisted of literature reviews lacking sample datasets or detailed experimentation.

Figure 9
Policy Program Offering Big Data Courses



Source: Taliawi, Goyal, & Howlett (2021)

The rise of big data presents both challenges and opportunities for governance and policymaking. From the standpoint of policy sciences, it offers new avenues for public policy research and practice. Whether exploring the policy process or conducting policy analysis, integrating big data analysis alongside conventional methods like polling, surveying, cost-benefit analysis, econometric evaluation, and content analysis can enhance the effectiveness and depth of research in public policy domains.

In the Caribbean, a single ministry can be tasked with overseeing multiple local resources, which can be challenging to manage. For example, in Trinidad and Tobago, the Ministry of Public Utilities handles the management of water resources, electricity, postal services, waste disposal, and meteorological services. The Ministry of Social Development and Family Services is

responsible for social welfare services, national family services, disability affairs, social displacement, division of ageing, and HIV/AIDS coordination. The Ministry of Trade and Industry oversees trade policy development and implementation, investment promotion, industrial development, export promotion, business facilitation, consumer protection, standards and quality control, and intellectual property rights. Despite the adoption of programmes that would alleviate or lessen any challenges experienced by consumers of these services, there would be varying and opposing views from the members of the public on how these services are managed.

These state agencies are very dependent on policy development and adherence for the administration of these services offered to citizens. Trinidad and Tobago is poised to be a leading example in the era of Digital Transformation for Small Island Developing States (SIDS) in the Caribbean Region. By leveraging marketing analytics, Trinidad and Tobago can create data-driven policies that address the unique challenges of being part of the SIDS, leading to improved public services, economic resilience, and overall sustainable development. It can further lend support to social welfare development, environmental sustainability, improved disaster preparedness and response, consumer protection and market regulation, education and workforce development, innovation and entrepreneurship, and total governance and accountability.

Conclusion and Recommendations

An examination of the literature reveals limited evidence of analytics being effectively applied as a foundation for public policy. Bridging this gap requires identifying practical steps to integrate data-driven approaches into policy development and implementation.

This research proposes the application of marketing analytics to public policy development that would improve the perception of consumers towards governmental agencies and the services provided. Utilising predictive analysis and machine learning techniques to identify current factors influencing consumer behaviour towards ministerial agencies has the potential to enhance consumer engagement and foster positive behavioural outcomes in response to the services provided. Drawing on the Stimulus-Organism-Response theory, this research aims to conceptualise marketing strategies and guidelines that can effectively stimulate and activate consumers' cognitive and affective states, thereby promoting favourable behavioural responses.

Rising consumer concerns point to the need for targeted marketing interventions. Despite the potential of marketing analytics to influence public policy, there is limited research on its application to state-managed services. The study aims to bridge the gap by merging marketing analytics with public policy to address negative consumer perceptions. By using predictive analysis and machine learning, it seeks to identify factors affecting consumer behaviour and improve engagement with public services.

Integrating big data analytics into public policy education and promoting interdisciplinary research can strengthen the analytical capacity of the public sector. Applying behavioural frameworks like the S-O-R model can enhance citizen engagement and satisfaction, as this framework seeks to analyse how stimuli, such as online reviews, impact consumer behaviour, and guide policy improvements.

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