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Analysis of different implementations of bigdata techniques in consumer behaviour

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Abstract. As a matter of fact, consumer behaviour analysis plays a key role in sales strategy designs in recent years. Thanks to the rapid development of data analysis techniques as well as machine learning schemes, it is available to analyse the data collected in daily life to realize the consumer behaviour analysis (e.g., prediction, judgement). With this in mind, this study will select some of the specific cases with different models to discuss the implementation way. According to the analysis, the performances for the different models in different situations are discussed. At the same time, the current limitations for different applications as well as analysis pattern are clarified as well as evaluated based on the analysis. In the meantime, the prospects for the further study are demonstrated. Overall, these results shed light on guiding further exploration of implementation the big data analysis techniques as well as machine learning scenarios in consumer behaviour.

Keywords: Bigdata Analysis, machine learning, consumer behaviour.

1. Introduction

Over the past several decades, the study of consumer Behaviour has undergone considerable change. Originating in the late 1950s, the field shifted from primarily practitioner-focused, descriptive studies to a more theoretical and academically rigorous approach. While initially seen as an extension of economics, the discipline expanded to include insights from psychology, sociology, anthropology, and statistics. Such expansion emphasized the importance of not only understanding the strategies adopted by marketers but also the perspectives and motivations of the consumers themselves.

Today's consumer behaviour research integrates theories and methodologies from various social sciences. This interdisciplinarity, combined with the ever-evolving nature of real-world consumer Behaviours, has led to debates concerning the true essence of the field. One prominent perspective sees consumer Behaviour as the study of how individuals engage in buying, using, and disposing of goods and services in the marketplace. Although the present review does not offer an exhaustive history, it touches upon some key themes in the evolution of the field. It emphasizes that despite the changes over the decades, certain fundamental questions remain. The article delves into the most appropriate theoretical and methodological approaches for this research domain [1]. Another area of focus within consumer Behaviour is the study of attribution, which seeks to understand how individuals assign causes to events and outcomes. Approximately a decade ago, Mizerski, Golden, and Kernan delineated four key attribution theories and conducted a review of consumer Behaviour research from 1971 to 1978.

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Despite attribution theory's enduring prominence in social psychology, its impact on consumer Behaviour research appears to have waned somewhat.

This is surprising given the importance of understanding how consumers perceive cause-and-effect relationships. For example, consumers might buy pain relievers because they believe these products relieve pain, or they might believe that certain athletic shoes enhance performance. This article's primary objective is to emphasize the importance of attribution theory in the realm of consumer Behaviour and to provide an overview of research conducted subsequent to Mizerski et al. Importantly, many recent studies delve into aspects that were not examined in the earlier review, placing a strong emphasis on the fundamental principles of attribution theory. This review seeks to consolidate these studies, highlighting key areas of interest. Additionally, it provides a deeper dive into specific areas of attribution research for those who want a more comprehensive understanding [2]. At its core, consumer Behaviour involves the decisions and actions associated with choosing, purchasing, and utilizing products and services. The process often starts with consumers recognizing a need, assessing potential products based on perceived value, and then making a purchase decision after considering their budget and current market prices. Various external factors, i.e., social, cultural, personal, and psychological – also play a pivotal role in influencing these decisions [3]. The study of consumer Behaviour has garnered significant attention from researchers in social sciences, especially over the past fifty years, as indicated by MacInnis and Folkes. Numerous scholars have explored this domain deeply, leading to a rich body of work. As societal, technological, and economic landscapes change, so do consumer Behaviours, necessitating shifts in research focuses and methodologies. Periodic evaluations, like the one proposed by Williams and Plouffe, are essential to chart the field's progress.

By employing content analysis, researchers can systematically assess various communication forms to gain insights into prevailing themes, identify gaps, and set future directions. Examining articles from renowned journals offers a glimpse into the current trends and concerns in the field. Comprehensive reviews such as this also allow scholars to see the broader context rather than focusing solely on individual elements. Given the rapid advancements in the consumer Behaviour domain, there is an urgent need for a current and comprehensive review. This article seeks to address this gap, presenting an analysis of consumer Behaviour research trends over the past 12 years, based on a thorough examination of articles from five major journals [4]. Within the realm of consumer Behaviour, one delves into the decision-making processes that consumers undertake when it comes to the acquisition, utilization, and disposal of various commodities, services, and concepts. This exploration draws its roots from Jacoby's work in the mid-1970s. The focus of this review is on research conducted between 1993 and 1996, with particular attention given to articles published in esteemed journals like the Journal of Consumer Research, Journal of Marketing, and select others. Although space constraints limit the number of works discussed here, it's worth noting that many insightful papers from the Association for Consumer Research's annual proceedings are commendable [5].

2. Recent progress

Based on Big Data Analysis, the AISAS Model Framework offers an innovative approach to understanding consumer Behaviour in today's digital age. Introduced by the Dentsu Company, the AISAS model is especially relevant for dissecting consumer decision-making in the networked economy. This model outlines five sequential steps that consumers typically follow: Action, Interest, Search, another Action, and Share. While it builds upon the conventional AIDMA framework, the AISAS model distinguishes itself by emphasizing the two network-centric stages of 'search' and 'share'. This not only underscores the pivotal role of searching and sharing in today's online world but also shifts away from a one-sided communication approach to a more interactive consumer experience, showcasing the profound impact of the internet on daily lives and purchasing habits [6].

Consumer Behaviour is influenced by two main categories: external stimulants and internal perceptions. External elements like product promotion, marketing strategies, pricing, sales numbers, brand reputation, and user reviews, play a significant role in shaping a consumer's internal understanding and value assessment, thereby swaying their buying choices. The power of big data analysis is its ability

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to turn intricate, vast, low-density data into valuable commercial insights. This analytical process equips businesses to tap into genuine consumer needs, devise precise marketing tactics, and carve a competitive edge. Moreover, big data outcomes refine these external influencers, steering consumers toward the best choices for maximum benefit.[7]

Figure 1. Comparison of the two framework [8].

Merging the AISAS model with big data analysis, this study crafts a framework to illustrate the profound influence of big data on consumer Behaviours. As shown in Fig. 1, big data's effect on external variables offers stimuli via product promotions, marketing techniques, information filtering, and data searching. These, in turn, affect attention, interest, and search Behaviours, altering internal perceptions and culminating in purchasing decisions.[8] Post-purchase, sharing experiences becomes a crucial information source for subsequent big data evaluations, creating a cyclic effect on consumer choices.

The advent of the Big Data era is often linked to the point when storing data became cheaper than discarding it. The marketing realm has witnessed an influx of diverse data sets, primarily because interactions with consumers are now predominantly online, through social media and mobile platforms, making it easier to record every action. This transformation has made consumers continuous producers of both well-organized transactional data and the more contemporary unstructured Behavioural data. Big Data is usually characterized by three key attributes: volume (referring to the data's size), velocity (indicating the rapid pace at which data is being generated), and variety (encompassing diverse data formats and types). Unlike traditional statistical data, these sets often include non-numeric outputs like words, images, or videos. The lure of Big Data for marketers lies in its potential to guide marketing decisions and shape campaigns more effectively. It's argued that the rise of Big Data analytics has revamped modern marketing practices. For instance, a 2013 survey by eMarketer revealed that 85% of senior marketers in the U.S. believed that Big Data provided insights into over half of their marketing initiatives concerning consumer Behaviour. While we'll delve deeper into the utilities of Big Data later, it's noteworthy to mention that a significant portion of Big Data stems directly from consumer Behaviour, especially on social media platforms, making it invaluable for marketers and consumer Behaviour researchers alike [9].

An investigation employed sentiment analysis to sift through extensive data, aiming to gauge the implications and worth of online consumer feedback [10]. This deep dive into research showcased the significant role of sentiments in determining the effectiveness of these reviews. It was observed that titles exuding positive emotions and content with a neutral tone attracted more readers, gaining a reputation for being valuable. However, overly emotional content in reviews seemed to deter readers. Interestingly, comprehensive, and well-structured reviews were found to resonate more with readers, marking them as particularly useful. These findings offer a roadmap for e-commerce platforms looking to harness automation for sorting and ranking consumer feedback. Ultimately, the research underlined

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the direct relationship between the depth and consistency of reviews and their popularity and relevance. This highlights the pivotal role of analyzing big data in gaining insights into consumer Behaviour [11].

3. Basic descriptions

Previously, several big data analysis methods emerge [12]:

- Digital Footprint Analysis. Companies can glean insights into consumer Behaviour and preferences by scrutinizing the digital trails consumers leave in their everyday activities.
- Physical Retail Behaviour Analysis. While not exclusively a "big data" approach, it closely mirrors online user Behaviour analysis. It encompasses observations of which products customers engage with, the duration of their decision-making process, and more.
- Mouse-Tracking Analysis. To understand how users navigate and engage with content, companies deploy mouse-tracking tools, shedding light on user decision-making on websites or online platforms.
- Analysis of Customer Forums, Product Feedback, and Social Media Posts. Such platforms effectively serve as organic "focus groups." Companies harness them to gather and assess feedback on their offerings, tapping into real-time and genuine opinions.

With the strides made in data-related technology, i.e., spanning collection, storage, and analysis, companies can now extract significant insights about a vast array of consumers from the digital imprints they cast in their daily lives. Notably, analysing actions in a physical retail setting mirrors that of studying Behaviour online. For instance, the tools range from observing interactions with products to using mouse-tracking utilities for a more profound understanding of decision-making processes [12]. Additionally, leveraging customer forums, product reviews, and social media yields access to expansive, organic 'focus groups' often with minimal or no financial outlay [13].

This segment delves into the primary sources of big data within the retail sphere, highlighting the capacity to harness robust insights across five unique dimensions: consumers, product dynamics, temporal patterns, geographical nuances, and varied channels, further elaborated in Fig. 2. Generally, "big data" conjures visions of vast datasets. Modern tracking tools have transitioned businesses from broad data evaluations, typical during times of limited data (as mentioned by Dekimpe and Hanssens), to now zeroing in on detailed, person-centric analyses. This shift enables more precise audience targeting (as emphasized by Rossi, McCulloch, and Allenby). One could argue that a primary business goal is to broaden data reach via customer acquisition, effectively increasing unique IDs and amplifying transactional values on an individual basis. In the retail context, it's crucial to consistently monitor changing customer patterns and cohesively tie transactions over periods. Loyalty programs emerge as the most prevalent approach for such monitoring. Nevertheless, methods like tracking credit card usage, identifying IP addresses, and monitoring user account logins are also highly conspicuous. It's not just about data volume; companies are now equipped with an intricate suite of data attributes. This covers a wide range, from CRM data connections, demographic details from payment systems, feedback via email surveys, to in-store visit tracking. Merging insights from social channels and a myriad of user-generated content further amplifies and enriches the understanding of consumers [14].

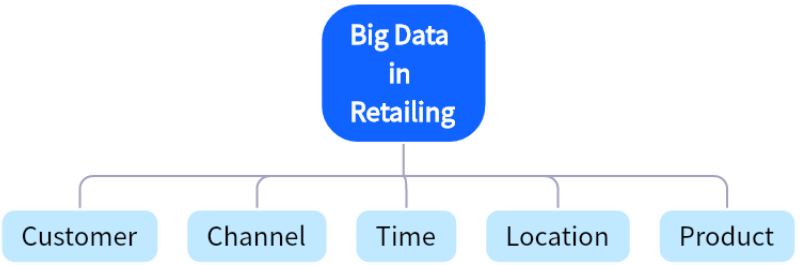

Figure 2. Bigdata in retailing [14].

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4. Application

Big data has drastically transformed the landscape of consumer Behaviour research by offering tools and techniques to analyse complex patterns and predict future Behaviours. Here are three key instances where big data analysis plays a critical role in comprehending consumer Behaviour:

As for personalized Marketing and Recommendations, with the proliferation of online shopping and digital media, businesses are keen to provide a tailored shopping experience for their consumers. The data from consumers' online activities, like browsing history, past purchases, and search queries, is vast and unstructured. Personalized recommendation systems utilize collaborative filtering and content-based filtering. Collaborative filtering anticipates a user's preferences by considering the choices of users with similar tastes, whereas content-based filtering suggests items by analysing the characteristics of the items and a user's profile. Personalized marketing results in higher customer engagement, increased sales, and improved customer retention. Building on consumer Behaviour patterns, the method underscores the idea that when consumers buy a certain product, they are likely to show interest in related items. This observation led to the analysis of each item's purchase history, revealing items that are often bought in tandem. Establishing this relational database facilitates swift recommendation generation, primarily using cross-referencing techniques. In essence, by understanding a consumer's present selections and past purchases, the system zeroes in on complementary items, removes any previously recognized or bought products, and showcases the new suggestions to the user.

In comparison to the conventional user-focused recommendation models, this novel strategy boasts several distinct advantages. Foremost among these is the approach's computational efficiency: the bulk of the processing work, which involves creating the product relationship database, is done offline. Thus, real-time recommendations are streamlined, relying mostly on quick database lookups. The strength of these recommendations, given a substantial data backing, can rival even the most recent algorithmic innovations. Remarkably, the method is adept at serving a wide user demographic and an extensive product array without diluting the quality of the recommendations. Furthermore, the system's agility shines through when new user preferences emerge, allowing for instantaneous adaptation. A standout feature of these recommendations is their intuitive nature, with suggestions that mirror or extend users' purchasing patterns [15].

Fast-forward to 2003, and this item-centric recommendation method, also known as item-based collaborative filtering, was deeply embedded across Amazon's digital ecosystem, shaping multiple facets of the user shopping journey from homepage layout to search outputs and even checkout prompts. As a result of this bespoke strategy, Amazon metamorphosed into a uniquely personalized shopping destination for each of its users [16]. Yet, the influence of this method wasn't restricted to Amazon alone. Many digital giants, like YouTube, as well as various online commerce sectors adopted and benefited from this approach. Illustrating its impact, data from a Microsoft Research study highlighted that a dominant slice of Amazon's web traffic and the lion's share of Netflix's viewership could be attributed to these algorithmic recommendations. Taking stock of its significance, Netflix quantified the annual worth of its recommendation ecosystem at a staggering sum, exceeding US$1 billion [17]. Tracing back to its origins, when Amazon's inventory was predominantly books, this recommendation mechanism has been a silent observer and active participant in the retailer's metamorphosis into an all-encompassing e-commerce titan. As Amazon's product assortment grew and diversified, there was an intrinsic need for the recommendation system to continually evolve, ensuring its ongoing relevance and sophistication.

In the realm of recommendation systems, there exists a noteworthy challenge: how to generate meaningful suggestions when there's a dearth of user interaction data. This sparse data makes it taxing to anticipate preferences, especially when compared to active users. Bridging this void, innovative solutions in the form of intelligent gift finders have come to the fore. These tools make informed suggestions by tapping into diverse criteria like age, gender, lifestyle, and individual characteristics [18]. The tech industry has taken note, with e-commerce juggernauts like Yahoo Shopping and Ebay.com integrating these cutting-edge gift finders. However, the journey is far from complete. There's a vast expanse of uncharted territory in this domain, awaiting exploration. Recognizing the commercial promise these tools hold, further research and development in this sector could reshape the e-commerce

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paradigm. On the technological frontier, deep learning is spearheading a transformative shift in the recommendation arena, unlocking newfound avenues to elevate metrics such as Recall and Precision. Modern systems, fortified by deep learning, are setting new benchmarks, outclassing their traditional counterparts with commendable recommendation quality. Their advanced capabilities enable them to unravel complex user and product interactions and craft sophisticated data representations across various layers. Augmenting their potency, these systems are adept at assimilating a spectrum of data from textual context to visual cues, weaving them into a cohesive recommendation narrative [19].

For sentiment analysis for product reviews, in today's digital landscape, customers frequently express their experiences and viewpoints regarding products and services on social media and various online platforms. Analysing these reviews can provide insights into consumer sentiment and areas of improvement. Sentiment analysis, also known as opinion mining, employs techniques from Natural Language Processing (NLP), text analytics, and computational linguistics to detect and extract subjective content from the source text. Machine learning models like Naïve Bayes, SVM, and deep learning models (e.g., LSTM) are commonly used. Companies can adjust their strategies based on real-time feedback, leading to better products and more satisfied customers. Building systems adept at handling subjective content presents distinct hurdles. Taking the development of an app focusing on searching for reviews or opinions, the significance of such an application can't be understated, be it for filtering blog content [20] or other broader search categories mentioned earlier. Here's a breakdown of the challenges this endeavour could entail:

- If incorporated into a universal search platform, there's a need to ascertain if users are indeed seeking subjective data. Identifying these search queries might sometimes be straightforward, with terms like "review" or "opinion". Alternatively, a user-controlled “checkbox” can be provided for direct input. However, categorizing these queries can be complex, as evident from the 2005 KDD Cup challenge [21].
- Alongside recognizing pertinent documents for opinion-based inquiries, another task is to pinpoint documents or segments containing reviews or opinionated content. While platforms like Epinions.com and Amazon.com structure their reviews in predictable formats, blogs present a more diverse landscape. Blogs, which often delve into subjects beyond products, offer a diverse range of content and style, complicating the search process.
- After sourcing relevant documents, gauging the sentiment or pinpointing specific opinions becomes the next challenge. Some platforms, like Yahoo! Movies, simplify this by having structured reviews, but unstructured texts present multiple complexities, especially when considering the attribution of quotes.
- Lastly, a system must efficiently summarize and present the extracted sentiment. This could involve:
  - Consolidating ratings from diverse scales (e.g., stars versus letter grades).
  - Prioritizing certain opinions.
  - Highlighting areas of agreement and disagreement.
  - Recognizing clusters of opinion groups.
  - Valuing the credibility of opinion sources.
  - It's worth noting that visual representation might sometimes be more fitting than text summaries, diverging from the usual topic-focused document summaries [22].

Xu and Liao employed a sophisticated two-tier CRF model to identify comparative relations, taking advantage of intricate dependencies between relations, entities, and words, along with flexible inter-relation dynamics. Their objective was to craft a visual model that pulls out and illustrates comparative relations from customer feedback. They applied this model to mobile customer reviews sourced from various platforms like amazon.com, epinions.com, blogs, SNS, and emails [23]. The visual representation of their findings, known as comparative relation maps, was intended to aid enterprise risk management decisions. The data suggests that their approach outperforms alternative methods, making their comparative relation map a promising tool for guiding enterprise decision-making [24]. Several systems collate opinions on specific features of competing products, offering users a comparative

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perspective on advantages and disadvantages [25]. Nevertheless, these systems largely tap into broad user sentiments, potentially skewing when gathering data on rivals or pinpointing operational vulnerabilities. In contrast, the research delves into gleaning comparative insights directly from product reviews. Such comparative feedback more accurately mirrors customer inclinations towards competing products, thus enhancing competitor intelligence and bolstering enterprise risk management [26].

For predicting consumer churn, customer retention is pivotal for businesses. By predicting which customers are likely to churn (or leave), businesses can devise strategies to retain them. Churn prediction models are built on historical data using features like purchase frequency, customer complaints, and service usage patterns. Algorithms like logistic regression, decision trees, and neural networks are applied to predict churn probability. Early identification of potential churners allows businesses to offer targeted promotions, improving customer loyalty and reducing acquisition costs. Churn analysis, which predicts potential customer departure, delves into data patterns using varied data mining methods. To address the issue of churn, various approaches have been investigated, including methods such as Hybrid firefly-based classification, Decision tree, Bayesian techniques, and others. Hybrid models, merging two distinct methods, have shown efficiency, especially in managing vast datasets from the telecom sector [27]. This study primarily focuses on forecasting customer churn, identifying essential factors, and utilizing data mining methods to design and evaluate the effectiveness of a hybrid predictive model. The suggested model aims to forecast a user's likelihood to churn and surpasses traditional predictive methods, such as surveys [28].

5. Conclusion

As strides into the era of information, the power of big data analysis in consumer behaviour is undeniable. From predicting purchasing patterns to personalizing customer experiences, big data promises a revolution in the way businesses engage with consumers. However, like all technologies, it is not without its limitations. Firstly, the quality of insights is only as good as the data. Data inaccuracies or biases can skew results, leading to misguided strategies. For instance, if the data collected predominantly reflects urban consumers, it might not provide accurate insights into rural consumer behaviour. Privacy concerns also loom large. With more data being collected than ever before, concerns over data breaches, misuse, and unauthorized sharing have amplified. Consumers are becoming increasingly wary of how their data is used and shared, leading to potential resistance in data collection.

Another significant limitation is the interpretability of data. While advanced algorithms can sift through vast amounts of data, deciphering meaningful patterns requires a human touch. Misinterpretation or overreliance on automated insights can lead to erroneous conclusions. Moreover, the rapid evolution of consumer behaviour poses a challenge. What was relevant a year ago might not hold true today, rendering some data obsolete. This transient nature of consumer preferences means that businesses need to continually adapt, sometimes making long-term predictions based on big data precarious. Furthermore, there’s the risk of over-reliance on quantitative data. While numbers can provide a broad overview, they often miss the nuances, emotions, and motivations that qualitative research can offer. A holistic understanding of consumers cannot be achieved by big data alone.

As one gazes ahead, the horizon for big data analysis in consumer Behaviour is teeming with promise, assuming one can tackle the limitations mentioned earlier. One of the highly anticipated developments is the fusion of Artificial Intelligence (AI) and Machine Learning (ML) with the vast realm of big data. This convergence will allow for more accurate predictive modelling, enabling businesses to pre-empt consumer needs and tailor their offerings accordingly. As these models become more sophisticated, their predictive accuracy is set to improve. Another promising development is the blending of quantitative and qualitative data analysis. Future tools might be capable of not just analysing numbers but also emotions, sentiments, and motivations. This would bridge the gap between raw data and a deeper understanding of consumer Behaviour. Moreover, as concerns over privacy grow, one can expect more stringent data protection regulations to come into play. This would not only protect consumers but also push businesses to be more transparent and ethical in their data practices. As a result, there might emerge a stronger bond of trust between consumers and businesses. In addition, the rise of decentralized data

storage solutions, like blockchain, could revolutionize how consumer data is stored and shared, providing a secure and transparent method that might alleviate many existing concerns. Lastly, as businesses become more aware of the limitations and pitfalls of big data, there will likely be a move towards more hybrid models of data analysis. This would involve combining the computational power of big data with the human touch of traditional research methodologies.

In conclusion, while big data analysis in consumer Behaviour has its limitations, its future looks promising. By marrying technology with ethical practices and human intuition, the next wave of data-driven consumer insights is poised to be even more impactful and insightful. As long as businesses remain adaptive, transparent, and responsive to both technological advancements and consumer concerns, big data will undoubtedly continue to shape the landscape of consumer Behaviour analysis in unprecedented ways. To sum up, big data analysis in consumer Behaviour, while powerful, faces challenges like data inaccuracies and privacy concerns, but its integration with AI and a focus on ethics and qualitative insights promise a transformative future in understanding consumers.

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