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The Role of Consumer Behaviour Analytics in Product Pricing Strategy: A Systematic Review Trends and Challenges

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Abstract: In the fast-changing world of contemporary business, the intersection of consumer behaviour and pricing strategies has emerged as a critical area of focus for researchers and business organisations. The digital age has guided in a groundbreaking wealth of consumer data, enabling business institutions to gain deep insights into purchasing patterns preferences and decision-making processes. Simultaneously, the emergence of analytical tools, machine learning algorithms has empowered institutions to monitor these data and transforming the raw information into actionable intelligence that can inform dynamic and relevant pricing strategies.

This structured and systematic review aims to examine the current state of research on the role of consumer behaviour analytics in shaping the pricing strategies across various industries and in market research. By integrating findings from a diverse array of studies, this review seeks to identify prevalent trend, innovative approaches and challenges in the domain. Additionally, this review highlights the potential implications of combining consumer behaviour into pricing strategies for not only business organisations but also for the consumer welfare.

To conduct this review, we employed a meticulous and multi-faceted approach to review of literature and analysis. In this review initially an extensive search of peer-reviewed academic journals, industry reports and relevant conference proceedings published between 2012-2024, utilizing key databases such as Scopus, web of sciences and google scholar is used. The search strategy includes a detailed set of keywords and their combinations like “pricings models”, “consumer behaviour”, “dynamic pricing”. Following the initial search, we utilized a set of predefined set of inclusion and exclusion criteria to narrow down our selection, ensuring that the most relevant and high-quality research

Our analysis reveals several key findings that underscore the transformative impact of consumer behaviour analytics on pricing models. Firstly, there is a clear trend towards the adoption of dynamic pricing strategies that leverage real-time consumer data and market conditions, enabling businesses to optimize revenue and maintain competitiveness in volatile markets. Secondly, the integration of machine learning algorithms and artificial intelligence in pricing models has significantly enhanced the accuracy of demand forecasting and price optimization, leading to more nuanced and effective pricing decisions. Lastly, our review highlights the growing importance of ethical considerations and regulatory compliance in the application of consumer behaviour analytics to pricing strategies, particularly concerning issues of privacy, fairness, and transparency.

This systematic review illuminates the role of consumer mindset in shaping the pricing of a product. The role of consumer behaviour analytics in pricing models has become increasingly significant in recent years, driven by advancements in data collection technologies, analytical capabilities, and the growing recognition of the value of personalized marketing strategies.

Keywords: Consumer behaviour analytics, Dynamic pricing strategies, Price optimization, Demand forecasting, Data-driven pricing, Willingness-to-pay analysis Behavioural economics,

1.1. Background

The intersection of consumer behaviour and pricing of a product has evolved as a pivotal area of research in marketing sector and in business analytics. This multi-faced field integrates insights from data sciences, economics, marketing, sales and psychology to inform organisations in decision- making process. As market become more competitive, understanding the relationship between consumer and producer for setting a price has become paramount in practical application.

Consumer behaviour is a study of decision-making process by which individuals select, use, purchase and demand the goods and services which are then studied by the business organisations in deciding the price points for the consumers. The availability of vast consumer related data has significantly enhanced to process, capture and interpret the vast amount of consumer information, enabling more approaches to price optimization. There are various contemporary pricing models like dynamic pricing, subscription pricing, freemium pricing, usage-based pricing, value- based pricing, penetration pricing, price skimming, pay-what-you-want pricing, bundling pricing and geographic pricing. These pricing models incorporates behavioural economics principles, recognizing that consumer often deviate from the rational decision-making and fall prey to the allure of these pricing models. Prospect theory by Kahneman and Tversky 1979 and mental accounting by Thalet, 1985 have provided valuable insights into how consumer perceive and responds to different pricing strategies.

1.2 Different contemporary pricing models-

1.2.1 Dynamic Pricing

The dynamic pricing or real-time pricing or surge pricing model refers to the pricing strategy where the price of a product is adjusted to real time parameters such as present demand, supply and future scope. This concept has been utilized since decades but the roots of this can be traced back to industries lie airline travel and hospitality where prices are fluctuated very often due to various factors lie booking sessions, seasonality and occupancy rates. As technology continue to evolve, the future of dynamic pricing is likely to see integration with artificial intelligence and Internet of things devices, potentially revolutionizing business approaches in an increasingly digital and data-driven marketplace. Key component of dynamic pricing has demand-based pricing (Prices are adjusted according to changes in consumer demand, high demand decrease the price, low demand increase the price), Competitor based pricing (Price are influenced by competitor's strategy, ensuring their price are as low as possible to reduce profit shares of their competitors.), etc. In the dynamic pricing strategy business organizations utilize real time information on consumer behaviour, market conditions and with the predictive analysis future demand is forecast. This help in market segmentation allowing business organisation to tailor prices based on consumer preferences. And this can increase consumer satisfaction with product or service. There are several benefits of Dynamic pricing strategies which includes revenue optimisation, Inventory management, enhance competitive advantage, there are also some challenges with dynamic pricing strategy like Frequent price changes can lead to customer frustration and perceptions of unfairness, potentially impacting the revenue, developing and maintaining effective pricing algorithms can be highly resource-intensive, requires enhanced technology and expertise, In highly competitive markets, the effectiveness of dynamic pricing may diminish as more business organisations adopt similar strategies. The dynamic pricing model has significantly evolved in the current market situation due to technological advancement and machine learning which helps in accurate and efficient price adjustments in real time. E-commerce growth and consumer acceptance accustomed to fluctuating pricing in industries like travel, entertainment and fashion increased the trends of dynamic pricing strategies. Hence, Dynamic pricing is a powerful strategy which is contributing in shaping the industries according to current demand trends and consumer preferences.

1.2.2 Subscription Pricing

Subscription pricing is a model where consumer pays a recurring fee to access a particular product or service for fixed period of time. This pricing strategy has gained significant popularity across various industries like media, software, e-commerce and many more. As consumer behaviour evolves and technology enhances, the subscription- based pricing model reshapes the market dynamics. The subscription model is new trend but this concept is way old. It can be traced back to early magazine and newspaper models where readers paid on monthly basis to access the content. However, the digitalisation has transformed its landscape completely. With the rise of internet, business organisations have adopted subscription pricing strategy for digital goods and services and this increased revenue and customer loyalty. There are several key components of subscription-based pricing which includes flat-pricing strategy (A single fee for unlimited access), Tiered Pricing (Different levels of services at different price points), Usage-based pricing (Charges based on consumption) etc. The cost of acquiring subscribers can be high and for that effective marketing strategies are necessary. Retention is crucial, business organisations employ strategies like personalized content and customer engagement to minimize churn. There are many benefits of subscription-based pricing model like revenue predictions and financial forecasting becomes easy, the consumers tend to exhibit higher brand loyalty leading to long term consumer bond. With the help of subscription -based pricing valuable data on consumer preferences becomes easier to analyse and this helps in bringing more personalized experience to consumers. In subscription-based pricing model there are some challenges which organisations face including high churn rates and for that organisations must invest in retention strategies. Market saturation due to intense competition and offering differentiating content becomes critical. With numerous subscriptions available, consumers may feel overwhelmed, leading to potential cancellations and adding content regularly is pivotal. Beyond traditional industries like media and software new emerging industries like food delivery and fitness has also expanded their business on basis of subscription pricing. Nor only these many businesses are adopting hybrid pricing models that combine subscriptions with pay-per-use elements, offering greater flexibility to consumers.

1.2.3 Freemium Pricing

The freemium pricing is used to eliminate financial risk and commitment making it easier for the user to avail the services. This pricing strategy lower the risk of barriers to entry and encourages engagement. Consumers appreciate the control over their spending that usage-based pricing provides. This model aligns costs with actual usage, making it easier for users to manage their budgets. Initial levels of usage can set expectations for future consumption. Users might base their future patterns of usage on their initial experiences, affecting their satisfaction levels. Initial usage levels can set expectations for future consumption. Users might base their future usage patterns on their initial experiences, affecting their perceived value and satisfaction. A wide range of usage options can indulge users, leading to decision fatigue or suboptimal choices. Users might react more strongly to increases in usage costs than to decreases, due to the way gains and losses are perceived differently. This strategy can accelerate the rate at which new products or services are adopted, as the low price can entice early adopters and encourage word-of-mouth referrals. Initial low prices might influence long-term brand perception, and help the business organisations and entrepreneurs project their future revenue based on this usage.

1.2.4 Usage- Based Pricing

The user- based pricing is commonly known as user-centric pricing or customer-based pricing. It is a pricing strategy which related to dynamic pricing strategy that adjusts prices based on perceived value to the user rather than market competition. This model is particularly prevalent in industries such digital platforms. The user-based pricing model is related to many economic and psychological implications like Value perception, Willingness to Pay, Price discrimination, etc. In Value Perception the price a consumer is willing to pay is closely linked to the perceived value of the product or service. Business organisations employing this model often conduct market research to understand the value different segments of consumers place on their product or service. Willingness to Pay (WTP) is crucial for implementing a user-based pricing model. This involves assessing how much different users are willing to spend based on their needs, usage patterns and preferences. User-based pricing can be viewed as a form of price discrimination where firms charge different prices to different customers based on their individual characteristics or consumption behaviour. This approach can enhance consumer satisfaction and revenue when executed effectively. In the current modern digital economy, user-based pricing has gained popularity because of its Software as a Service (SaaS) Organisations like Adobe and Microsoft use user-centric pricing strategy. For example, Adobe offers different pricing tiers to its consumers for its creative cloud based on features. Even streaming service platforms such as Netflix and Spotify employ user-based pricing through personalized user centric model. They deep analyse the user behaviour and preferences to optimize pricing structures, offering family plans, student discounts, and personalized recommendations. Online retailers on e-commerce often use pricing algorithms that adjust prices based on user behaviour, purchasing history, and market demand. For instance, Amazon frequently alters prices based on individual user profiles and market competition. Benefits of User-Based Pricing are increased revenue by aligning prices with user willingness to pay, organisations can maximize revenue. This approach also allows to capture more consumer surplus which leads to enhanced profitability. Tailoring prices based on consumer preferences can lead to greater consumer satisfaction and loyalty, as consumers feel satisfaction for the expenditure they pay. There are some challenges too which comes with user centric pricing strategy like data privacy concerns, when user data is collected and analysed there is breach of privacy and to navigate that organisations must use General Data Protection Regulation (GDPR) to ensure transparency in their data usage practices. One leading challenge is complexity of implications, while developing a user-based pricing strategy it requires thorough analytics and market research, which can be resource-intensive and complex to execute. There is also risk of alienating consumers perceive pricing as unfair or discriminatory, it can lead to dissatisfaction and loss of confidence of user with the product or service and to overcome this business organisations must communicate their pricing strategies effectively to mitigate this risk as this cause direct impact on brand value. The user-centric pricing strategy is an evolution and it do affect the consumer behaviour. By focusing on consumer's perceived value, organisations can optimize their pricing structure. However, this strategy requires a conscious consideration of ethical, privacy and implementation challenges.

1.2.5 Value-Based Pricing

It is a pricing strategy that decides primarily based on the perceived value of a product or service to the consumer, rather than on the cost of production or competitive pricing. This approach is widely used across various industries, including consumer goods, and services, technology, fashion etc. allowing organisations to maximize profitability by aligning prices with customer expectations and perceptions of value. To understand value-pricing strategy there are several components like Customer Value Perception, it is the understanding that consumer derive value based on their needs, preferences and derive value based on their needs, preferences, and the benefits they perceive from a product or service. Organisations conduct and analyse market research to gauge how different features resonate with target audiences. Willingness to Pay (WTP) is also a core component of value-based pricing is determining the maximum price point which a consumer is willing to pay. This involves a detailed analysis, including user surveys and consumer behaviour data, to establish a price that reflects perceived value. Economic Value to the Customer (EVC) is a key concept and component in value pricing strategy and it quantifies the economic benefits a user gains from using a product compared to alternative products. In the current modern economy, value-based pricing has seen widespread implementations across many industries technology and electronics, luxury goods, capital goods, pharmaceuticals, consumer durable items and etc. Big companies like Apple and Salesforce utilize value-based pricing by highlighting unique features, quality, and brand prestige. Apple, for instance, prices its products based on the perceived value of design and user experience, often charging a premium compared to other alternative brands. Whereas Companies such as Coca-Cola and Procter employ value-based pricing strategies by emphasizing quality, brand loyalty, and emotional connections. These brands often justify higher prices by promoting their products' perceived superior value. In the healthcare sector, value-based pricing is increasingly very rapidly. Pharmaceutical companies assess the clinical benefits and improvements in patient outcomes their drugs provide and set prices accordingly. For example, new cancer therapies are priced based on their effectiveness compared to existing treatments. Big luxury brands on high scale leverage value-based pricing by cultivating exclusivity and a premium image. Pricing is often justified through brand heritage, vintage craftsmanship, and the overall consumer experience associated with the product. Benefits of value-based pricing includes maximized Profitability by aligning prices with perceived user value, businesses organisations can optimize revenue and enhance profit margins, capturing more consumer surplus, when consumers perceive they are receiving good value for their money, satisfaction increases, fostering loyalty and repeat purchases helping the brand to build a good reputation in the market. Value-based pricing strategy also helps in effective differentiation as value-based pricing allows to distinguish themselves from competitors by emphasizing unique value propositions and tailored offerings that meet specific user needs. Despite its multiple advantages, value-based pricing presents several challenges like accurately assessing user value requires extensive market research, data analysis, and ongoing consumer engagement, which can be resource-intensive and complex causing it difficult to implement. Risk of Misjudgement is also very high as user perceptions can lead to inappropriate pricing strategies. Brands must continually test and refine their pricing to align with actual customer value. It is potential for Price sensitivity, consumer perceive prices as disproportionately high compared to the value delivered, it can lead to dissatisfaction and potential loss of consumers. In highly competitive markets, differentiating based on value can be challenging. The value-based pricing model represents a strategic approach that prioritizes the consumer's perception of value in setting prices. By aligning prices with the benefits delivered to users, businesses organisations can enhance profitability while fostering customer satisfaction and brand loyalty increasing revenue. However, successful implementation requires a deep understanding of targeted consumer needs, effective market research, and agility in responding to changing market conditions. As the marketplace continues to evolve, organizations must gauge the complexities of value-based pricing strategies which are likely to gain a competitive advantage and drive its success in the wide market.

1.2.6 Penetration Pricing

Penetration pricing is a strategic approach used by business organisations to attract consumers to a new product or service by setting a low initial price to make market entry easy. This method aims to quickly gain market share and establish it in a competitive environment. As industries evolve and market dynamics tends to shift, penetration pricing continues to be relevant in various sectors. The concept of penetration pricing strategy emerged in the mid-20th century as businesses organisations found innovative ways to introduce new products. One of the earliest documented can be found by Procter & Gamble in the 1930s, when their company introduced a new line of detergents. By offering these products at a lower price than competitors, they rapidly gained profits and market share. The penetration pricing strategy gained attraction with the advent of consumer goods in post-world war II era, where business entrepreneurs sought to differentiate their offerings in a very crowded and tight marketplace. The economic conditions of that time were characterized by rising disposable income and increased consumer spending provided a ground for penetration pricing strategy. Penetration pricing model works on the principle of setting price lower initially compared to the existing market price. Introductory Offers are the key component of penetration pricing strategy. Temporary price reductions for new products to entice consumer is the mindset of the entrepreneurs or business organisations. Low-Cost Models are sub category of penetration pricing strategy, these are consistently low pricing strategies adopted by companies to maintain market presence. Bundled Pricing is also a part of penetration pricing strategy, offering multiple products at a reduced price to encourage bulk purchases.

1.2.7 Price Skimming

Price skimming is a pricing strategy that involves setting a high initial price for a new product or service and gradually lowering it as the product gets old over time. This approach is commonly associated with innovative products in various industries. The strategy originated in the 1980s, gaining traction as companies sought to maximize profits from early adopters willing to pay a premium for the latest innovations and products. Main reasons of adopting price skimming strategy is for targeting consumers willing to pay more initially, businesses can recover all the development costs quickly. It allows business organisations to segment the market based on consumers' willingness to pay, identifying different price-sensitive segments over time. It also helps in branding of the products. A high initial price can create a perception of quality and exclusivity, enhancing brand image. Early profits can also help in provide capital and funds for further research and development, facilitating innovation. Price skimming has many drawbacks as well which includes High prices can attract competitors, potentially leading to market saturation and driving prices down or loosing consumers also. Early adopters may feel alienated when prices drop, leading to dissatisfaction and brand loyalty issues. Changes in consumer preferences or economic conditions can affect the effectiveness of the strategy and eventually can affect market dynamcis. As prices decrease, managing inventory can become challenging, particularly if demand fluctuates. Price skimming is significant in industries characterized by rapid innovation and high development costs. It allows firms a strong market presence and finance ongoing research and marketing efforts. Additionally, it helps businesses adapt to changing market conditions by providing a framework for adjusting prices based on consumer behaviour and competition.

1.2.8 Pay-What-You-Want Pricing

Pay-What-You-Want Pricing strategy is a pricing is a flexible pricing strategy where consumers can choose the amount which they are willing to pay for a product or service. This model is often used in digital goods, art, food services, and charitable donations. It leverages consumer perception and behaviour, allowing them to determine the price based on their valuation of the product or service. This pricing strategy has many benefits which includes Increased Sales Volume: by removing fixed pricing strategy , businesses organisations can attract more consumers who might avoid the product by higher prices. Pay-What-You-Want can build a sense of community and loyalty as consumers feel empowered and valued, leading to a high repeat purchases. businesses organisations can gain valuable insights into consumer preferences and price sensitivity, informing future pricing strategies on basis of consume behaviour. This model can enhance brand perception, portraying the business as customer-centric and flexible, especially in industries like arts and non-profits. Not only this but elimination of price barriers as it allows access for lower-income consumers, expanding the potential customer base. This pricing strategy has some drawbacks also which can affect the organisation as Revenue Uncertainty, The unpredictable nature of consumer payment can lead to inconsistent revenue, making financial forecasting challenging. Some consumers may choose to pay very little or nothing, which can undermine the business's financial viability. Perceived Value Issues as the consumers pay less, they may perceive the product as having lower value, potentially harming the brand image. Operational Complexity can emerge as managing a PWYW system can be complicated, requiring careful monitoring and adjustments to ensure sustainability. Limited Application as this pricing strategy may not be suitable for all products or services, particularly where fixed costs are high. Pay-What-You-Want pricing strategy in today's modern day economy is very important as it aligns with the evolving consumers and their expectations for the transparency and fairness. It allows the business organisations to be more responsive to market demands and consumer sentiments. This pricing model can also generate goodwill and encourage the consumers to support the brands, especially in socially conscious markets. Additionally, PWYW can be used strategically during promotions or product launches to stimulate interest and gather data on consumer behaviour.

2. Consumer Behaviour Analytics

2.1 Definition and Types

2.1.1 Overview

The research of Reisch & Zhao (2017) showcased that, consumer behaviour analytics is a study of how organisations, groups, and individuals make decisions regarding using and purchasing products, experiences, and services. Analysis of patterns and decision, making processes, preferences, and consumer actions, organisations are able to gain valuable insights regarding what tends to motivate customer choices. The understanding allows organisations to customise their customer experiences, marketing strategies, and products for meeting the needs of the customers in a more effective manner. It ultimately leads to high customer satisfaction, brand loyalty, and could be seen in better sales.

According to Akter et al. (2019) consumer behaviour is impacted by a wide range of factors, such as – economic, cultural, social, and psychological factors. It is important to analyse these elements so that organisations are able to create customise marketing campaigns, look for areas for improvement, and also help in predicting trends. For achieving such insights, consumer behaviour analytics has been divided into two major types, which are – qualitative and quantitative analysis. Both the approaches provide unique perspective, and combining them can lead to a detailed understanding of how consumer behaviour works.

2.1.2 Qualitative Consumer Behaviour Analytics

In the views of Ramanathan et al. (2017) qualitative consumer behaviour analysis, emphasis upon understanding the subjective and deeper elements of customer experiences and motivation. The approach helps in exploring why the customers make certain decisions, and what psychological or emotional factors are involved in the same. It also takes into account how personal influences or culture can shape the behaviour of the customers. Qualitative analysis is dependent upon descriptive and rich information, that is usually collected from methods, such as case, studies, ethnography, focus groups, and interviews. One of the major advantages of quality analysis is the ability of understanding the reasons behind choices of the customers (Moinuddin et al., 2024). For example, focus group discussion can reveal how the customers are preferring a particular product because it is an alignment with their lifestyle, aspirations or personal values. This type of insight is difficult to capture only through quantitative metric. It is important to understand because powerful information could be gained for developing customer engagement strategies, products, and brand messaging. The common methods of qualitative consumer behaviour analysis are as follows:

Focus Groups: group discussions undertaken by a moderator helps and gathering collective insights from the participants, and reveal shared opinions or experiences (Muñoz-Leiva et al., 2012). For example, Sephora organised focus groups for collecting insights regarding customer experience and product preferences. It helps the organisation to improve upon the new product launches and develop effective marketing strategies.

Interviews: group or one on one interviews, enable researchers to explore customer behaviour, preferences, and thoughts by asking open ended questions in detail (Muñoz-Leiva et al., 2012). For example, Airbnb conducts in-depth interviews with guests and host for understanding preferences, motivation, and pain points, that allow them to improve user experience and mechanisms of trust.

Case Studies: detailed analysis of individual customer behaviours or experiences, they can provide insights regarding specific trends or scenarios.

Ethnography: observing customer and their behaviours in real time, settings can provide authentic perspective of how are the interacting with the services of products within daily lives.

However, Belk (2017) argued that qualitative analysis has multiple limitations because it is dependent upon subjective interpretation and small sample size. Due to this, might not be able to generate statistically significant outcomes or showcase the trends of broad population of customers. It is also resource intensive and time consuming, which makes it challenging to be applied on a larger scale.

2.1.3 Quantitative Consumer Behaviour Analytics

Vanhala et al. (2020) highlighted that, quantitative customer behaviour analysis revolves around numerical information for measuring customer behaviour and predicting the same. This approach involves data collection on a customer demographics, preferences, actions for identifying correlations and patterns. Quantitative analysis is undertaken with the help of statistical methods which makes it more scalable and objective as compared to quality approach. The data is typically gathered with the help of transaction, information, website, analytics, experiments, and customer surveys, that are then utilised with the help of statistical software and techniques. It helps the behavioural analyst to develop conclusions regarding customer behaviour.

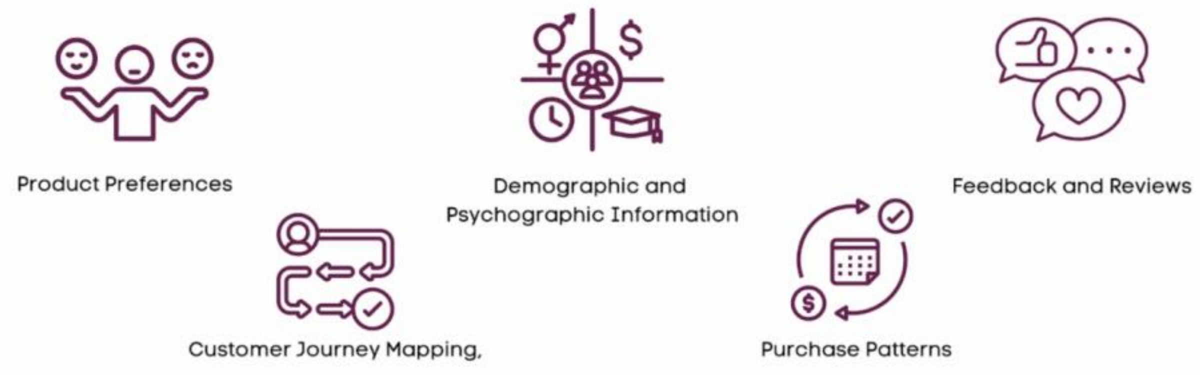

Figure 1: Information gained through Qualitative Customer Behaviour Analytics
(Source: Houseware, 2023)

Lutfi et al. (2023) contributed that the major advantage of making use of quantity analysis technique is the ability of providing measurable and concrete results that could be generalised across a large set of population. For instance, and organisation might conduct a survey of 1000 customers for determining which features of a product are found to be most important to them. The responses could then be statistical identified or analysed as well as decisions can be guided on marketing strategies or improvements. Quantity analysis is also preferred because of its capability. As digital technologies are rising, organisation now have access to volume of consumer information through sources like purchase, histories, website, analytics, and social media interactions (Lutfi et al., 2023). By making use of machine, learning algorithms and big data, organisations are able to uncover patterns and trends that are difficult to be detected in a manual manner. Common methods of quantitative customer behaviour analysis are as follows:

Purchase Data: analysing history of transaction for identifying patterns in customer loyalty, preferences, or spending (Silva et al., 2019). For example, Spotify evaluate a user, listening patterns, and preferences of songs for optimising recommendations and personalise playlist that adds to retention and user engagement for the brand.

Website Analytics: tracking interaction of the customers online, such as conversion rates, Time spent on pages, clicks, for measuring effectiveness and engagement.

Experiments: controlled studies that can manipulate the variables for testing their impact on behaviour of the customers (Holmlund et al., 2020). For instance, IKEA collect quantitative information on product interactions, sales, and foot traffic for optimising layouts of the store and positioning of products for maximum impact on sales.

Surveys: structured questionnaire that have been designed for gathering information on customer demographics, behaviours, and preferences.

However, Sturley et al. (2018) argued that, quantity analysis also has relevant restrictions and limitations. Even though it can provide valuable insights regarding how customer are doing, it does not have the depth for explaining why the customers are behaving in a particular manner. Apart from this, the emphasis on numerical data might not be able to consider cultural, psychological, emotional factors that can influence decisions of the customers.

2.2 Tools and Techniques

As per the views of Cherubino et al. (2019) in a rapidly evolving landscape of business, understanding the behaviour of customers has become highly critical for the organisations. Due to vast volume of information available and technological advancement within analytics, has enabled business to make use of a variety of techniques and tools for gaining deep inside regarding customer behaviours and preferences. These tools range between traditional methods such as a survey, to cutting technology such as Big Data analytics, and artificial intelligence.

2.2.1 Surveys

The paper of Srivastava & Gopalkrishnan (2015) highlighted that surveys are one of the most commonly used and oldest tools for understanding consumer behaviour analytics. Through distribution of questionnaires to the target audience, organisations can gather quantitative information on major metrics such as satisfaction, preferences, and inclination towards the brand. They can also be conducted through multiple channels like in person interviews, phone interview, or with the help of online forms. They are straightforward in terms of designing and implementing, because of which they are a popular choice for organisations of all sizes. They are able to take into account wide range of data points, ranging between basic demographic information to specific opinion of the customers regarding services or product (Sharma et al., 2014). Whenever they are conducted on a large scale, they can provide statistically significant insights regarding customer behaviour and preferences to the business. For instance, Starbucks understands the value of customer feedback through survey. Starbucks gathers and analysing information from its loyalty programs and survey in order to improve their menu and enhance experience of customer service.

On the other hand, Salehan & Kim (2016) contradicted that, despite of widespread uses, surveys are not always the best method. For instance, they can introduce response buyers. Within this, participants might not always be providing accurate or honest answers, especially, if they feel pressurised for responding in a socially acceptable manner. Apart from this, surveys are limited by the quality of the questions is selected in the same. If the questions are poorly designed, they can lead to misleading outcomes and close ended. Questions can also restrict the richness of the information, in which only surface level information could be gained. Moreover, surveys a time consuming, for the organisations as well as a respondent, and might not be able to capture the behaviour or sentiment shift of the customer in real time.

2.2.2 Big Data

Gandomi & Haider (2015) explained that, big data analytics has revolution is the ways in which organisations are looking forward to understand customer behaviour. Big data could be defined as vast volume of structured and structured information that is generated on a daily basis through multiple sources like website interactions, customer behaviour, online transactions, and social media platforms. Through analysis of this information, organisations are able to look for correlations, trends, and patterns that might be too complex to be detected through conventional methods. The major shrink of big data is present within its ability of providing real time insight regarding customer behaviour (Kambatla et al., 2014). For instance, retailers can track the Journey of the customers through social media activity, purchases, and online links. In this way, they can customise their marketing campaigns for responding to the emerging trends in the market. Big data also facilitates predictive analytics, by helping the organisation to anticipate future behaviour of the customers on the basis of their past pattern. For instance, Uber utilise big data for understanding behaviour of the rider. In this way, the entity is able to improve efficiency and optimise dynamic pricing model for user convenience and maximum revenue.

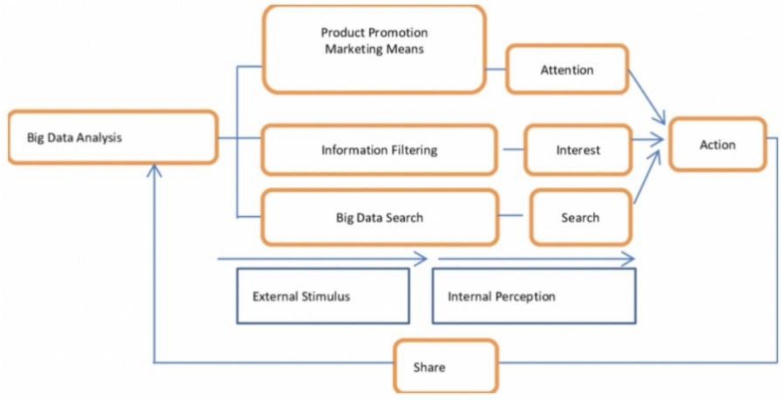

Figure 2: Big Data Mechanism for Analysing Consumer Behaviour
(Source: Zhang & Tan, 2020)

However, the findings of Provost & Fawcett (2013) argued that, even though big data has a considerable potential, it also has relevant challenges. For example, the vast volume of information that has to be processed, present a critical issue. Management and analysis of such data sets requires enormous, computational, expertise and power. Due to this, businesses have to make use of specialised tools such as Spark or Hadoop. Additionally, the risk of data overload is omni present. Without proper filtering of information, organisations can become overwhelmed by the volume of information available, that could lead to analysis paralysis. It is a situation in which too much data can restrict the effectiveness of outcome in terms of actionable insights. It is important to note that big data tends to emphasise upon the question of “what?”, instead of answering “why?” (Akter et al., 2016). That makes it difficult to understand the motivation behind different customer behaviour.

2.2.3 Artificial Intelligence

Bharadiya (2023) stated that, artificial intelligence has gained significant popularity as a tool for analysing customer information. AI powered analytics tools are able to automatically process large volumes of information, make predictions, and also uncovered patterns on the basis of algorithms of machine learning. AI could also be used alongside other tools such as predictive analytics and big data analytics for delivering more efficient and accurate results. One of the biggest advantages of using AI is the ability of being able to automate data analysis, which makes it more accurate and faster as compared to traditional methods. AI is also able to analyse and structured information, such as images, reviews, social media posts with the help of image recognition and natural level processing technique (Davenport, 2018). Due to this, it provides insights that traditional analytics methods might tend to miss. AI is also able to undertake personalisation by allowing organisations to customise marketing messages, provide product recommendations, and understand the individual customer experience on the basis of their unique patterns of behaviour. For example, Google makes use of AI algorithms for analysing customer behaviour. Due to this, organisation is able to predict the trend through machine learning models and also enhance add targeting.

On the contrary, Haleem et al. (2022) revealed that, use of AI within customer behaviour analytics has drawbacks, primarily because of cost. AI systems are expensive to develop, implement, and sustained. In the case of small and medium size organisations, this investment might not be feasible. Apart from this, AI systems required large volumes of information for training their algorithms, that could be a limitation for organisations that do not have access to resources of big data (Kietzmann et al., 2018). Additionally, there is a risk when artificial intelligence makes inaccurate predictions. If the data used for training is incomplete or biased in itself. Regarding data privacy, numerous ethical considerations are surrounding use of artificial intelligence that has to be addressed in order to make sure that customers do not feel alienated.

2.3 Data Sources

The paper of Wedel & Kannan (2016) showcased that, it is important to understand customer behaviour in order to remain competitive. For achieving the same, companies tend to be dependent upon wide range of data sources for gathering information about buying patterns, needs and preferences of the customers. The sources provide qualitative and quantitative information that helps in informing marketing strategies, customer engagement, and product development. However, businesses need to understand that each source of data has its own limitation and advantages, and it is upon the discretion of the organisation, which they are using, depending upon their needs.

2.3.1 Information about Transactions

According to Kwon et al. (2014) transactional data is one of the most commonly used sources of customer behaviour information. It is a type of data that is collected from customer, loyalty, programs, e-commerce platforms, and point of sales systems. Transactional information includes details regarding the purchases of the customers, such as – purchase date, payment method, price, and the product bought. The major strength of transactional information is present within precision and accuracy. It provides a clear record of the spending habits of the customers. In this way, organisations are able to measure the demand of products and services in a reliable manner (Xiang et al., 2015). It could also be utilised for identifying patterns within consumer behaviour over a period of time, such as effectiveness of sales, promotion, or trends of seasonal buying. For example, Amazon makes use of transaction information from its platform in order to analyse consumer behaviour patterns and purchasing habits. In this way, the company is able to optimise product offerings and make personalised recommendations.

However, Bello-Orgaz et al. (2016) argued that, even though transaction information is invaluable in tracking actual purchases of the customers, it is not able to convey the entire story. It exclusively emphasises upon "what?" factors of the customer behaviour regarding what was purchased, but it does not provide insight regarding "why?" was it purchased. It means that no explanation is provided regarding why a specific product is chosen by the customer, what factors impacted their decision, and whether or not their satisfied with the purchase.

2.3.2 Website Analytics

With reference to the findings of Wang et al. (2018) website analytics tools like Google analytics are widely utilised for tracking the behaviour of customers on digital platforms. These tools provide information on different metrics like rates of conversions, bounce rates, time spent on the site, and rate of page views. With reference to e-commerce organisations, web analytics is crucial source of information for understanding all the customers and interacting with online content, and where do they actually drop off in the process of buying. Website analytics are preferred by statisticians and other stakeholders because they provide deep inside regarding the online customer journey (Grover et al., 2018). By tracking activity of the users, business businesses are able to understand which pages are most engaging, what factors are contributing to the actual singles conversions, and how are the users navigating the site. These insights could be utilised for enhancing user experience, increasing sales, and optimising efforts of marketing. Website analytics are also able to provide real-time information, that helps organisations to weekly respond to the emerging issues or trends. For instance, Netflix utilise website analytics for tracking engagement of the customers, viewing patterns, and their preferences. Due to this, business has developed an overall model of user experience and content recommendations.

On the contrary, Mikalef et al. (2018) highlighted that, the volume of data collected through website and analytics is overwhelming for the organisations, particularly those that do not have relevant resources for managing or interpreting it effectively. Data dictation requires special skills such as understanding, metrics of session duration are bounce rates. They could be misleading if they are not contextualised in a proper manner. Apart from this, website analytics are only able to track behaviour on the website itself. It means that activity of customer outside the website across other digital platforms could not be tracked. Due to this, the overall Digital journey of the customer is presented to the business in a fragmented manner (Najafabadi et al., 2015). Lastly, concerns of privacy regarding third-party data usage and tracking cookies have led to development and enforcement of stricter regulations. Organisations have to follow regulations such as GDPR in a very strict manner that can restrict the granularity of the information that is available to the businesses themselves.

2.3.3 Data from Social Media Platforms

Kumar et al. (2016) affirmed that, social media platforms are now critical source of information regarding customer behaviour because they provide insights about emerging trends, brand engagement, public opinion.

Platforms such as Instagram, Facebook, and Twitter are able to generate vast volume of structured information in terms of user generated content, comments, shares, and likes on photos and reviews. The biggest advantages of utilising social media data is the ability of gaining real-time feedback on the behaviour and sentiment of the customers. By monitoring, interactions and conversations, organisations are able to quickly understand the reactions of public to the marketing campaigns, services, or product. Social media also facilitates deeper engagement with the customers, by providing opportunities for relationship, building and direct communication (Stephen, 2016). Tools of sentiment analysis, for instance, can enable companies to detect shift within public perception. It enables a timely intervention whenever a crisis or negative feedback restrict the positive opinion of the business. For example, Coca-Cola leverage, social media information for monitoring the consumer sentiment in real time basis. As an outcome of the same, the entity is able to adjust marketing strategies for brand loyalty and increased engagement.

On the other hand, Alalwan et al. (2017) highlighted that, even though immediate information could be gained from social media, it also generates a vast volume of noise of misleading and irrelevant information that can restrict understanding of meaningful insights. Extraction of actionable information from social media platforms is complex, and organisations have to make use of machine, learning tools, and natural language processing techniques for making sense of the structured information in form of images and text. Social media data is also not representative of all the customers, because it is inclined towards targeting younger demographics, and might not be able to capture the behaviour of less digitally active or older customers.

3. Future Directions and Emerging Trends

3.1 Emerging Trends in Pricing Strategies and Consumer Behaviour Analytics

In a contemporary marketplace that is rapidly evolving, pricing strategies are driven by customer behaviour analytics. Organisations make use of advance analytics and real information for customising pricing strategies for making sure that they are able to remain competitive, while maximising the profits (Rödiger & Hamm, 2015). The following trends are currently emerging in the market, and are able to reshape how the businesses tend to approach pricing and customer behaviour. They are discussed below:

Dynamic Pricing: companies such as Amazon are achieving success through dynamic pricing. It means that they adjust prices on a real time on the basis of competitors, demand, and supply. The strategy has been particularly successful for the organisation during sales events or peak shopping seasons (Victor et al., 2015). Through analysis of customer behaviour like purchase patterns and browsing history, Amazon personalise offers and prices for increasing rates of conversion.

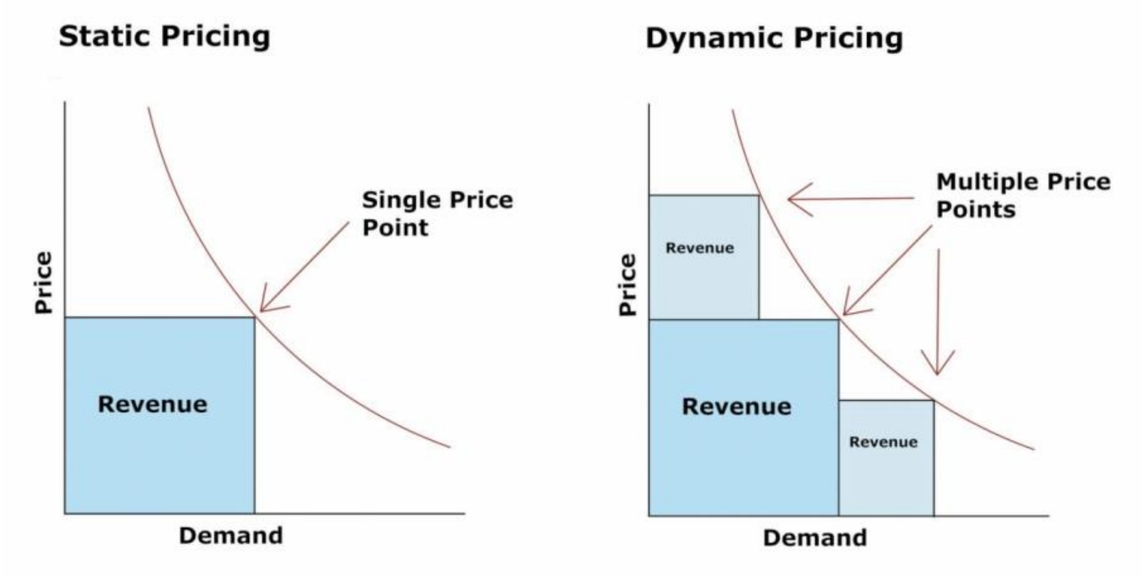

Figure 3: Dynamic Pricing vs Static Pricing
(Source: Paddle, 2022)

Subscription Pricing: brands such as Spotify Netflix have made a shift towards subscription-based models. These organisations use analytics of customer behaviour for predicting user patterns, increase retention, and optimise subscriptions (Victor et al., 2015). Data related to usage, frequency and content consumption allows organisations to create personalised offerings such as personalised content, recommendations of Netflix. It leads to improved customer loyalty and satisfaction for the businesses.

Price Customization: retailers such as Uber utilise machine, learning algorithms for offering a personalised pricing to the customers. For example, the search pricing of user, adjust the fares on the basis of a right demand, time of the day, and location. The data driven approach has been proved sometimes controversial for the entity, but has allowed it to maximise revenue by responding to the behaviour of the customer on a real time basis.

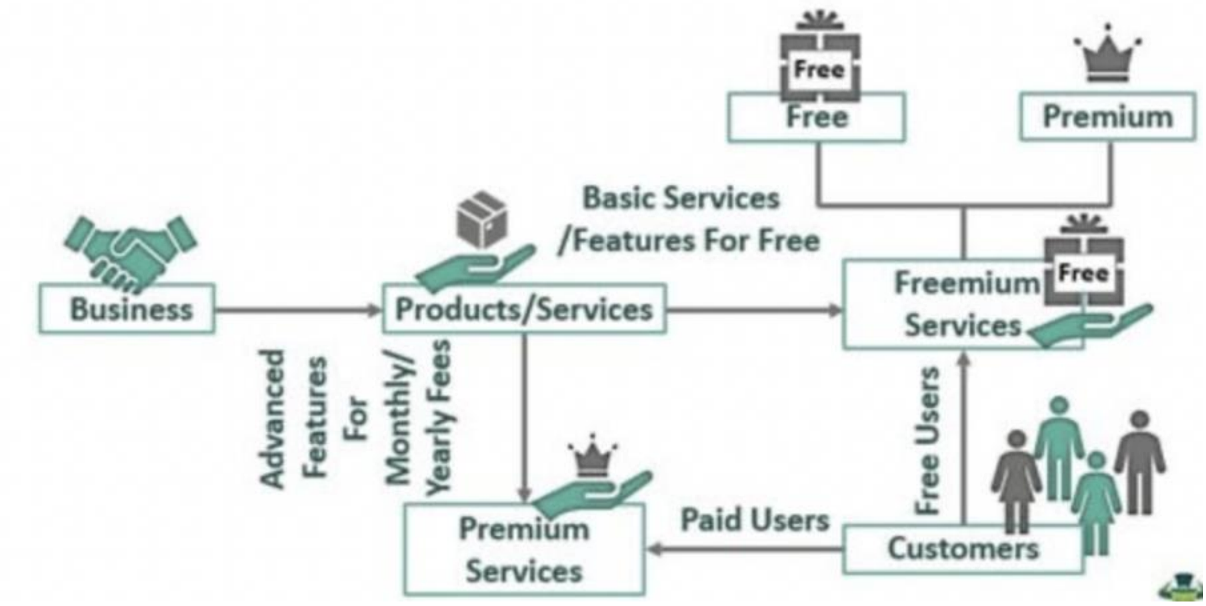

Figure 4: Concept of Freemium Pricing Model
(Source: Dheeraj, 2024)

Freemium Models: organisations such as LinkedIn and Drobox are utilising freemium pricing strategy, which is one of the most emerging trends in the domain of customer behaviour analytics. It means that the organisation provides basic services for free while encouraging the users to make upgrades to a subscription for accessing premium features (Nguyen et al., 2015). In identifying which users are likely to convert from free services to paid once, customer behaviour, data plays a major role. In this way, businesses are able to target them with customised incentives or promotions.

3.2 Potential Areas of Future Research

3.2.1 Identification of Gaps in the Current Research

Ethical Considerations in Data Collection: even though businesses are increasingly dependent on customer insights, research has not considered ethical challenges by data collection. Issues such as consent, management, data, security, and privacy concerns are critical, but not explored efficiently. Organisations like Google and Facebook are currently facing backlash because of unethical data practises. It has created a need for research that is able to establish ethical standards within customer behaviour analytics.

Behavioural insights about Up-and-coming Markets: recent research is heavily focused on customer behaviour and case studies from developed markets of Europe and the US. Due to this, it has neglected patterns and behaviours in the emerging economies like that of Brazil and India. For example, disruptive pricing strategies of Jio in India have transformed the consumption of mobile data patterns in the country. Yet, the customer behaviour research in such markets, has been found to be limited.

3.2.2 Suggested Areas for Future Investigation

Use of AI in Predictive Consumer Analytics: as artificial intelligence has been closely incorporated within consumer behaviour analysis, it is recommended that future researches. This should investigate how artificial intelligence can improve predictive analytics. For example, organisations such as Netflix are utilising artificial intelligence for predicting preferences of content, but more research is required for understanding, ethical concerns, biases, accuracy related to AI driven insights.

Privacy vs Personalization: it is important to establish balance between consumer privacy and personalisation, as a future area of research. As organisations such as Spotify and Amazon or emphasising on Personalized experience, future studies need to explore how much personalisation our customers will like to accept before privacy concerns are given more importance than trust and convenience. Both the organisations and customers are important stakeholders for understanding the relationship between privacy and personalisation, and implementing the same.

4.1 Summary of Key Findings

Throughout the review paper, multi dimensions of consumer behaviour analytics and their implications and pricing strategy have been explored. In an increasingly data driven and competitive market, the ability of analysing customer behaviour enables organisations to create more customised experience, make informed decisions, and optimise models of pricing. As an outcome of the same, multiple insights have emerged, that revealed the significance of customer behaviour analytics, and shaping effective pricing strategies for businesses from multiple industries.

The analysis of customer behaviour, both quantitative and qualitative, is a crucial factor in determining how the organisation should develop competitive pricing strategies. Through the collection of information and analysing how customers interact with products, businesses like Uber, Spotify, and Amazon, are able to dynamically manipulate their prices. They do so on the basis of customer preferences and real time demand. The ability of responding to changes in the customer behaviour allows the organisation to establish itself in competitive markets.

As data analytics have advanced, the pricing models also need to be adapted by the businesses. Strategies like freemium pricing, subscription models, dynamic pricing, are becoming increasingly prevalent across industries. Organisations such as Spotify, Netflix, and dropbox are prime examples of the same. These models have valuable businesses to improve their pricing for matching what the customers are willing to pay, maximise long-term profitability, also increase retention. By analysis of customer data, businesses are not only attracting more customer, but also extracting better monetary value from their customer base over a period of time.

The findings have also revealed that incorporation of machine learning and AI within customer behaviour. Analytics has opened new possibilities for prediction of customer actions and optimisation of pricing strategies. Google and Netflix are making use of artificial intelligence for predicting future customer behaviour on the basis of past information. In this way, they have been able to enhance precision of pricing adjustment and also provide Personalized recommendations. AI driven analytics have allowed organisations to fulfil the trends, respond with agility, and future behaviour, particularly when they are functioning in highly dynamic markets.

Despite of the advantages of customer behaviour, analytics, ethical concerns regarding constant management and data privacy or a significant challenge. As the business is collect, vast volume of personal data for developing pricing strategies, it is important to make sure that data is utilised in a responsible and ethical manner. Recent controversy involve organisations like Google and Facebook that revealed the potential for miss use of customer information. It has also raised questions regarding how the need for privacy concerns will be managed alongside gaining information of consumer insights. The gap present in ethical research reveals the significance of developing frameworks and standards for guiding the businesses within their data usage.

Additionally, as the customers are becoming aware of social issues and environmental problems, sustainability is also a major factor in shaping behaviour of the customers. For example, Patagonia has successfully synchronised its pricing strategies with the customer demand for ethical and sustainable products. However, research present on how sustainability impact long-term customer behaviour is still restricted. It provides a fertile area for future investigation for the interested researchers. As organisations are increasingly making use of sustainable practises, it is important to understand how to incorporate such values within pricing strategies for building trust and maintaining customer loyalty.

4.2 Significance of Consumer Behaviour Analytics in Shaping Pricing Strategies

Customer behaviour analytics is not only a tool for understanding what the customers are looking forward to, but is also important and developing pricing strategies that are resonating with the needs of the target audience. In consumer decision making process, pricing plays one of the most critical role, and directly impacts competitiveness and profitability of the organisation. By making use of customer behaviour, analytics, organisations can develop pricing models that are reflective of the real time conditions in the market, for optimising revenue and synchronising customer expectations with the business. The significance of customer behaviour analytics in developing pricing strategies is discussed as follows:

Pricing and personalisation: one of the most important advantages of customer behaviour analytics is the ability of driving personalisation. In the current market, customers look for personalised experiences, and it could also be applied to pricing. In pricing, personalisation can take multiple forms such as pricing on the basis of shopping, history of the customer, loyalty, programs, and personalised discount. For example, Nike makes use of data from Nike plus loyalty programs for offering personalised pricing and promotions. It drives repeated purchases and enhances customer satisfaction. The ability of personalising pricing on the basis of individual customer behaviour helps the organisation to increase rates of conversion, improve overall satisfaction, and also retain customers.

Real-Time and Dynamic Pricing: as customer behaviour is becoming more difficult and volatile to predict, dynamic pricing could be applied. This adjust the prices on the basis of competition, demand, and other major factors. Consumer behaviour analytics enables businesses to collect and analyse real-time information, so that prices could be adjusted in a dynamic manner. For instance, search pricing model of Uber is based on real time data, which make sure that prices are reflecting the current conditions in the market.

Addressing price sensitivity: customer behaviour analytics can also help organisations to deal with price sensitivity. It refers to how the changes in prices can impact demand of customers. Through analysis of past pattern and identifying purchase data, organisations can determine the optimal point of price that can maximise sale, retain customers, and not sacrifice profitability. For example, Walmart utilises data analytics for understanding the price sensitivity of the customers. In this way, it provides competitive pricing on its products while maintaining healthy margin of profit.

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