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Game theory modelling of retail marketing discount strategies

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Purpose

The use of game theory combined with Monte Carlo simulation modelling to support the analysis of different retail marketing strategies, in particular the use of payoff matrices for modelling the likely outcomes from different retail marketing strategies.

Design/methodology/approach

Theoretical research was utilised to develop a practical approach for applying game theory to retail marketing strategies via payoff matrices combined with Monte Carlo simulation modelling.

Findings

Game theory combined with Monte Carlo simulation modelling can provide a formal approach to understanding consumer decision making in a retail environment, which can support the development of retail marketing strategies.

Research limitations/implications

Game theory combined with Monte Carlo simulation modelling can support the modelling of the interaction between retail marketing actions and consumer responses in a practical formal probabilistic manner, which can inform marketing strategies used by retail companies in a practical manner**.**

Practical implications

Game theory combined with Monte Carlo simulation modelling can provide a formalised mechanism for examining how consumers may respond to different retail marketing strategies.

Originality/value

The originality of this research is the practical application of game theory to retail marketing, in particular the use of payoff matrices combined with Monte Carlo simulation modelling to examine likely consumer behaviour in response to different retail marketing approaches.

Keywords: Retail marketing, game theory, modelling

1. Introduction

Yi and Yoo (2011) commented that consumers are exposed to a flood of frequent sales promotion practices such as everyday low price, seasonal price off, special price discount, free gift, buy one get one free, and other promotions in their daily lives. Iranmanesh et al (2017) stated that perceived savings positively affect consumers' intention to purchase products with regard to volume discounts. Scriven et al (2017) commented that the tendency for consumers to buy on promotion relates mostly to how much promotion is available in a given category of product. The extent of promotion can be so high that as many as half of all brand buyers buy the brand solely when it is on promotion.

In this paper, we examine how game theory, a branch of decision mathematics, can be applied to retail marketing management in a practical manner that can be applied in professional practice. The modelling approach involved obtaining lower boundary values and upper boundary values to form a confidence interval. By confidence interval in this context is meant the range of values that a marketing professional might subjectively assign to a particular measure of a given variable used for marketing based upon experience, or the confidence interval of a given variable that might result from a sample marketing survey. Ghadge et al (2013) stated the benefits of combining game theory and simulation modelling in the field of supply chain management. The modelling approach then used this information to model the likely distribution of values using Monte Carlo simulation (Narayanan, 2013). This simulation approach can be applied to the payoff matrix, in order to determine the likelihood of profitable outcomes from multi-buy discounting at a particular level. This approach enables the marketing professional to simulate consumer responses to different potential discount factors using game theory, based upon previous experience or samples of market survey data.

In particular, we examine how payoff matrices combined with Monte Carlo simulation modelling can be used to analyse the likely outcomes resulting from different retail marketing strategies. In a simplified scenario, involving one retailer and a consumer, payoff matrices visually represents the consumer purchasing decision making process in a two dimensional grid structure. One axis or dimension of a payoff matrix can represent the retail company's actions and the other the consumer response. In actual commercial practice, this might not be a constant sum game in that any gains made by one party are at the expense of the other. A retailer strategy might be to increase the number of consumers so that any discounts offered are more than offset by the increase in sales and so lead to a greater profit for the retailer and reduced costs for the consumer (Anderson, 2011). The cells within the payoff matrix represent the purchasing outcomes reached depending on which decisions were made by the retailer and the consumer.

The rationale for applying game theory to retail marketing strategy management is that it can provide an approach to modelling, describing and documenting the likely outcomes from different retail marketing strategies. Game theory can provide a more formalised mechanism for examining how consumers may respond to different retail marketing strategies. This provides a basis for a more formalised analysis of likely outcomes from different retail marketing strategies in a practical manner that can be applied in professional practice. In addition, the use of confidence intervals and Monte Carlo simulation modelling to simulate the likely consumer actions in response to different discounting factors can avoid many of the problems inherent in simply reporting the statistical significance of a test statistic that might be used for marketing modelling. A confidence interval focuses on what the effect is, rather than what it is not. If the lower bound of the confidence interval exceeds the value predicted by the null hypothesis (e.g. a correlation exceeds 0.0) it can be concluded with a specified level of certainty that the effect is real (i.e. exists in the population) (Newton and Rudestam, 1999). Confidence intervals applied in the game theory simulation of consumer actions in response to different discounting factors can aid in modelling and understating the effects of different discounting approaches.

The research described in this paper concerns the use of game theory in the specific area of retail marketing discounting, and in particular, limited research in terms of actual practical application in professional marketing practice. The originality of this research is the practical application of game theory to retail marketing, in particular the use of payoff matrices combined with simulation modelling to examine likely consumer behaviour in response to different retail marketing approaches.

2. Literature review

2.1 Game theory

Game theory can be considered to have as its origins the publication of Augustin Cournot’s Researches into the Mathematical Principles of the Theory of Wealth (Cournot, 1897). This attempted to explain the underlying rules governing the behaviour of duopolies (where only two sellers exist in one market, although, in practice, the term is also used where two companies have dominant control over a market). Research into game theory initially evolved as a branch of economics (Von Neumann and Morgenstern, 1944). Game theory concerns the mathematical study of the decision making process (Davis, 1983) and can model how individuals may behave in specific circumstances that resemble simple types of games, allowing an examination of the relationships between decisions and outcomes.

Game theory includes the concept of utility, which concerns a mathematical measure of player satisfaction (Von Neumann and Morgenstern, 1944). In games that involve a deterministic function between decision and outcome, there can be a utility value assigned to the outcome of each decision. A Nash equilibrium (Nash, 1951) concerns a situation when the game players cannot improve their payoff by independently changing their strategy. This means that it is the best strategy assuming the other game player has chosen a strategy and will not change it (Goldfarb et al, 2012). The Nash equilibrium will be reached when the best rewards are obtained after the game occurs (Neslin and Greenhalgh, 1983; Sanchez-Torres et al, 2018).

The saddle point property is a game theory concept that concerns the choices of game players that lead to the same result (Von Neumann and Morgenstern, 1944; Ngendakuriyo and Taboubi, 2017). A payoff matrix (Dahlstrom et al, 2014) visually represents the decision making process involved in a game in a grid structure. One axis of the payoff matrix represents one player's decision. The other axis of the payoff matrix represents the other player's decision. The cells within the payoff matrix represent the outcomes reached depending on which decisions were made by the players concerned. For a general two-player zero-sum game, for a saddle point to exist, the payoff matrix would need to include an element that is both a minimum of its row and a maximum of its column (Jadlovska and Hrubina, 2011).

2.2 Retail marketing strategy modelling

Marketing science combines a variety of academic fields such as economics, statistics, econometrics and psychology (Hsu et al, 2012; Weber et al, 2018). However, typically, empirical examination of the impact of marketing science on actual commercial practice is somewhat rare (Roberts et al, 2014). Pricing is that element of a firm's marketing mix that focuses on generating value to the company in the form of revenues (Venkatesh, 2010). Retail marketing approaches such as multi-buy offers may be used in response to similar approaches by competitor retailers (Patterson et al, 2011), to address reducing sales volumes, or reducing profits, or to potentially expand the customer base (Maxwell et al, 2012). Traditionally, sales promotions are regarded as a technique that brings about direct sales increases (Yi and Yoo, 2011). Cain (2014) commented that incremental sales volume is essentially short run in nature, capturing the period-to-period sales variation driven by temporary selling price, multi-buy promotions and off- and online media activity. These can be converted into incremental revenues or profits, and benchmarked against costs to calculate return on investment for to each element of the marketing mix. Philander (2016) commented that in order to de-seasonalize demand and to stimulate short-term sales, companies may frequently use undifferentiated marketing tools such as price discounts and other promotions.

Chen et al (2012) stated there can be a tendency among consumers to neglect base values when processing percentage change information when evaluating economically equivalent offers presented in percentage terms, such as bonus packs and price discounts. Liu and Chou (2015) argued that a free gift promotion typically lowers consumers' willingness to pay for the target product compared with a price bundle promotion.

Retail marketing approaches such as multi-buy offers may be undertaken locally, regionally, nationally or even internationally. Typically, a pilot approach in a local area may be useful to assess the potential of the approach before moving on to larger scale implementation (Palazon and Delgado-Ballester, 2009; Pratten, 2006). Typically, the modelling of marketing approaches such as multi-buy offers and analysis of their potential and actual effectiveness would be undertaken by marketing analysts, managers or directors (Gamliel and Herstein, 2011). Balachande and Ghosh (2013) commented that the act of multi-buying can significantly reduce churn (the consumer’s subsequent decision to terminate their relationship with the company) even though customers who are more predisposed to multi-buy have an inherently higher predisposition to churn.

If consumers are exposed to continuous sales promotions, such promotions should be regarded as more than just a tool for sales increases. As marketers may spend a considerable amount of funds on sales promotions, it is important to understand the effects of such sales promotions (Yi and Yoo, 2011). Thomadsen et al (2012) commented that marketers need to learn about individual consumers in order to better price-discriminate. In terms of mathematical modelling, companies routinely use customers' purchase-history data to better understand and learn about customers' preferences and use this information to optimize future prices.

Confidence intervals (Cheema et al, 2012) can provide assessments of the range of values that a marketing professional might subjectively assign to a particular measure of a given variable used for marketing modelling. This might be based upon experience, or estimates might be made of the range of likely values of a given variable from sample marketing survey data using the sample mean and sample standard deviation. However, Brenner, et al (1996) commented that judgements of confidence and estimates of relative frequency can be practically indistinguishable. Furthermore, Kahneman, and Tversky (1996) stated that judgments of frequency (and not only subjective probabilities) can be susceptible to large and systematic biases. This is important for marketing strategy development in that marketing professionals need to be careful with regard to selecting appropriate samples of marketing survey data, and appreciating that there will always be variability within and between samples.

2.3 Game theory for retail marketing

Game theory can be used to examine the relationships between decisions and outcomes in the process of playing a game. Sanchez-Torres et al (2018) examined the use of game theory for email marketing strategies. The interactivity between actions and outcomes can be used to model consumer behaviour (Kim et al 2014). A game theory view of retail consumer behaviour can involve viewing consumer purchases as a series of strategic decisions made by the consumer (Jiang, and Srinivasan, 2016). However, theoretical predictions can be sensitive to the details of the modelling assumptions, that can make general predictions elusive. A trade-off exists between the generality of modelling assumptions and the usefulness of the resulting insights in answering questions in a specific organisational situation (Thomadsen et al, 2012).

Bronnenberg et al (2008) commented that despite the growing amount of empirical literature concerning dynamic consumer behaviour, little research has been undertaken with regard to the implications of choice dynamics for marketing decision-makers. The incorporation of game theory into marketing models has the potential to enrich the scope of marketing modelling (Mudambi, 1996). For example, the use of temporary discounts to control the evolution in the distribution of consumers' willingness-to-pay and to price-discriminate over time. Game theory can be used to analyse the actions and outcomes of consumers in terms of the likelihood of being willing to pay for a given product when different temporary discounts are applied. By analysing the consumer actions and outcomes over a set of different temporary discounts, models of likely consumer responses to different discounting approaches can be developed. Doherty and Delener (2001) stated the need for multiple marketing strategies and approaches for estimating the likelihood of their success.

Game theory can be used to analyse the likely outcomes resulting from different retail marketing strategies adopted by an organisation. However, as Anderson (2011) stated, the most basic game theory concepts, such as the zero-sum game, which describes conditions in which each gain by one player produces an equal and corresponding loss for the other may have limited applicability to marketing. This is because marketing can produce dividends for both players when the right message reaches the right audience at the right time. Meyer et al (2010) stated that greater convergence of game theoretic modelling and behavioural research in marketing would lead to new insights for both fields.

3. Research methodology

The research reported in this paper involved a multi-disciplinary literature review concerning game theory mathematical modelling, simulation modelling of marketing approaches, and marketing strategies used within the retail sector. Theoretical research was utilised to develop a practical approach for applying game theory to retail marketing strategies via payoff matrices combined with simulation modelling. Payoff matrices combined with Monte Carlo simulation modelling can provide a method of formal probabilistic mathematical modelling of the likely outcomes in terms of consumer responses (or opponent player game moves) to retailer actions (or player game moves). A confidence interval represents the probable minimum value and maximum value in the population of interest. The confidence interval concerns the likelihood, expressed as a percentage, of the average value of a variable being between a lower boundary and upper boundary value. Thomadsen (2012) commented that a key ingredient of any game-theoretic model is the information each of the game players possesses (these can be termed games of imperfect or incomplete information). In a market setting, the consumer typically needs to assess the pricing of a product before purchase.

A key question associated with the use of payoff matrices in game theory is how are the payoffs determined. In this paper, we describe a methodology based on established practices within (PERT) Program Evaluation and Review Technique (used in Critical Path Analysis). The approach requires that marketing staff be able to provide maximum and minimum values for each payoff. Monte Carlo simulation is then employed to simulate payoff tables that are then solved in the usual way, obtaining mixed strategies. A mixed strategy is a probability distribution over the set of actions that a player might make. The method is repeated many times in order to provide probability distributions for each player's overall optimal strategies. Finally these distributions are then used to assess how robust the strategies are and so give an estimate of the risk associated with the game situation.

The game theoretic approach combined with simulation modelling of retail marketing approaches described in this paper is demonstrated by modelling the game play resulting from the pricing level used in a multi-buy sales offer by a retailer and the cumulative responses from a set of consumers. This approach offers a rigorous probabilistic modelling technique that is able to be applied in professional commercial practice. This is an important area of research since game theory can support the modelling of the interaction between retail marketing actions and consumer responses in a formal probabilistic and practical manner, which can inform marketing strategies used by retail companies.

4. Research Results

4.1 Game theory for retail marketing

4.1.1 Game theory concept of utility for retail marketing

The game theory concept of utility (a mathematical measure of player satisfaction) can be incorporated into the analysis of retail marketing strategies by considering consumer satisfaction (Carter and Curry, 2010). This can be conceptualised as relating to there being an appropriate variety of purchasing options for the consumer, and whether the consumer feels that they have 'won' in some manner with regard to a given purchase in a multi-buy sales offer or similar situation. However, statements of consumer satisfaction after a purchase might be a rather rough guide to actual utility since consumers might forget what other options were available, and might post-justify their behaviour.

4.1.2 Game theory concept of the saddle point property for retail marketing

The game theory concept of the saddle point property concerns the choices of game players that lead to the same result (Von Neumann and Morgenstern, 1944). A saddle point in retail marketing activities can be conceptualised as an equilibrium in discounting and consumer purchasing (Anderson, 2010). For the retailer, this concerns what can be termed a minimax strategy, with the solution being the saddle point (Ormerod, 2010). From the retailer viewpoint, the retailer is minimizing the maximum amount that can be lost through discounting. For the consumer the minimax strategy concerns maximising the amount that can be gained from the minimum amount of purchases of discounted items. However, not all marketing discounting situations may have saddle points, since consumers may not respond to particular discounting approaches.

4.1.3 Payoff matrices for retail marketing

A payoff matrix is a visual representation of all the possible outcomes that can occur when two individuals make a strategic decision. One axis of the payoff matrix can represent the consumer's decision. The other axis of the payoff matrix can represent the strategy adopted by the retail company. The cells within payoff matrix can represent the outcomes that depend upon the consumer and retail company player decisions.

Payoff matrices might initially be developed by marketing staff in terms of initial estimates values. However, it would be more practicable to develop confidence intervals based upon sampling from consumer surveys using the sample mean and sample standard deviation, in order to attempt to ensure that the payoff matrices represent a statistically representative assessment of likely consumer purchase outcomes. Dyner and Franco (2004) commented upon the typical quantity and quality of the information that is available in marketing decision-making processes.

		Consumer	
		Multi-buy purchase	Single purchase
Retail company	Low pricing	(profit p_1, saving s_1)	(profit p_2, saving s_2)
	High pricing	(profit p_3, saving s_3)	(profit p_4, saving s_4)

Table 1. Multi-buy payoff matrix.

Table 1. shows a simplified payoff matrix representing the outcomes from a multi-buy offer by a retail company for a single consumer transaction. The retail company makes a move in the purchasing game equating to a particular marketing strategy (low or high pricing of multi-buy goods), which relates to a profit p_n. The consumer makes a move in the purchasing game equating to multi-buy purchase or single purchase, which relates to a saving s_n.

The typical dominant game strategies (strategies that always provides greater utility (greater worth) to a player, no matter what the other player's strategy), might be that the retail company would chose to always set the pricing of multi-buy goods to maximise overall profits, and that the customer would choose the multi-buy option in order to maximise savings (assuming that the consumer might require or have use for multiple items, which would depend upon the type of product).

It would be assumed that if there is a dominant strategy, then the player would choose that strategy. A dominant strategy is a best response to every strategy of the other player. In the example above, the two strategies available are S1 – "Low pricing of multi-buy goods" and S2 – "High pricing of multi-buy goods". The retail company might choose the "High pricing of multi-buy goods" strategy (S2) over the "Low pricing of multi-buy goods" strategy (S1). This decision might arise if the confidence interval based upon analysis of sample data from market research surveys indicated that it would be likely that there would be sufficient numbers of sales within the confidence interval at a high multi-buy price to increase profits overall compared to the single purchase price. If the confidence intervals based upon market research surveys indicated that this might be unlikely, then the strategy chosen might be the low pricing of multi-buy goods, to provide sufficient numbers of sales at a low multi-buy price to increase profits overall compared to the single purchase price.

However, in actual retail marketing practice, the consumer purchasing game may not be a constant (or zero) sum game in the sense that any gains made by the consumer are at the expense of the retailer. A retailer marketing strategy might be to increase the number of consumers so that multi-buy discounts offered are more than offset by the increase in consumer sales that would lead to a greater profit for the retailer and reduced costs for the consumer (Anderson, 2011).

		Competitor retail company	
Retail company		Low pricing	High pricing
	Low pricing	(profit p_1, competitor profit c_1)	(profit p_2, competitor profit c_2)
	High pricing	(profit p_3, competitor profit c_3)	(profit p_4, competitor profit c_4)

Table 2. Competitor payoff matrix.

Table 2 shows a simplified payoff matrix representing the outcomes from multi-buy offers made by a retail company and a competitor retail company. The retail company makes a move in the purchasing game equating to a particular marketing strategy (low or high pricing of multi-buy goods). The competitor retail company makes similar moves in the purchasing game equating to a change in marketing strategy (low or high pricing of multi-buy goods). In simple game theory terms, it would appear that the retail company could only "win" (in terms of making more profit than a competitor, or increasing market share compared to a competitor) when the multi-buy pricing is set higher than that of the competitor retail company. This simplification, however, does not take branding, or other marketing issues into consideration.

However, in actual practice retail marketing is somewhat more complex that a simple two-player game of retailer versus a single consumer, or a retailer versus a competitor retailer. In order to model the complexity inherent in retail marketing in actual practice, the payoff matrix concept needs to be viewed in a higher dimension. Thus, we need to view the payoff matrix as a 'cumulative' representation of a three dimensional matrix that incorporates simulation of repeated game play by a large number of consumers (Ormerod, 2010), and utilise confidence intervals in order to model the likely ranges of outcomes.

The modelling approach used involves obtaining lower boundary and upper boundary values for variables of interest either from marketing professionals of from market surveys. This information is then used to model the likely distribution of values using Monte Carlo simulation. This simulation approach can be applied to the payoff matrix, in order to determine the likelihood of profitable outcomes from multi-buy discount at a particular level.

Let the standard retail profit on a given item be x and let the discount applied to each multi-buy item be d. Therefore, the multi-buy profit per item will be $x – d$. If market research has indicated that the confidence interval of m_l to m_u items of the given product are typically purchased each day, then, there will be values, n_l and n_u, where:

$$(n_l + m_l)(x – d) > m_l x$$

$$(n_u + m_u)(x – d) > m_u x$$

In other words, based upon the confidence interval of m_l to m_u items of the given product being typically purchased each day the overall profit made from selling $n_l + m_l$ items at a multi-buy discount will be greater than the profit made from selling m_l items at full price. The overall profit made from selling $n_u + m_u$ items at a multi-buy discount will be greater than the profit made from selling m_u items at full price. There will be a range of values n_l to n_u from the simulation modelling which will determine if an overall profit is made based upon the estimate of typical number of the given product sold per day. In game theory terms, this is when the retail company wins over a set of consumers, or wins over a competitor retail company.

As an example, if one cotton T-shirt sold for £10, a retailer might wish to simulate the likely outcomes of offering a discount of 10%, 15% or 20% if two cotton T-shirts were purchased. Monte Carlo simulation was used to simulate cases of consumer decisions based upon the different discount levels and anticipated sales levels to examine the potential resultant profits. Thus, for example if there was a £4 profit on a £10 T-shirt, then a 10% discount on the purchase of two T-shirts (2 for £18) would result in £3 profit per T-shirt.

If market research indicated that the confidence interval of the number of items of the given product typically purchased each day was within a lower boundary of 100 to an upper boundary 120, and the standard profit on the full price item is £4, and the multi-buy discount is £1, then

$(n_l + m_l)(4 - 1) > m_l(4)$ and $(n_u + m_u)(4 - 1) > m_u(4)$

$(n_l + 100)(4 - 1) > 100(4)$ and $(n_u + 120)(4 - 1) > 120(4)$

when n_l is greater than 33, i.e. when 33 additional items per day are purchased at the discounted price compared to the expected number of items purchased, and when n_h is greater than 40. Thus, the confidence interval of the additional number of items to be sold necessary to increase overall profits would be 33 to 40.

	Cumulative consumer set confidence interval $n_l + m_l$ to $n_u + m_u$		
Retail company		Multi-buy purchase	Single purchase
	Low pricing	(profit p_{1i}, saving s_{1i})	(profit p_{2i}, saving s_{2i})
	High pricing	(profit p_{3i}, saving s_{3i})	(profit p_{4i}, saving s_{4i})

Table 3. Cumulative payoff matrix.

Table 3. shows a simple example payoff matrix representing the cumulative outcomes from a series of consumer transactions based upon Monte Carlo simulation modelling where i represents the values in the confidence interval range from the lower boundary (l) to the upper boundary (u). If n_l to n_u represents the confidence interval of the number of additional transactions required to increase overall profit based upon simulation of sales of the lower pricing of multi-buy goods, then the retail company “wins” in these instances (and would also “win” if there were sufficient numbers of transactions at the higher pricing of multi-buy goods).

Monte Carlo simulation of consumer decisions (whether single or multi-buy purchase) was applied to sales volumes of 100, 120, 130, 140 and 150 per day representing potential increases in sales due to discounting. The Monte Carlo simulation involved using random numbers to generate different proportions of consumers choosing the multi-buy option. This was then repeated for discount levels of 15% and 20% in order to examine potential profits. In this manner, simulation of differing anticipated sales volumes, and proportions of consumers opting for the multi-buy discount for different discount levels can inform marketing staff of the likely outcomes in terms of profits for different discounting strategies.

The approach involves marketing staff providing two values for each payoff (a maximum and a minimum). Monte Carlo simulation is then employed to simulate payoff tables, as per the examples above, which are then solved in the usual way, obtaining mixed strategies. The method is repeated numerous times in order to provide probability distributions for each player's overall optimal strategies. Finally these distributions are then used to assess how robust the strategies are and so give an estimate of the risk associated with the game situation.

Using market research from representative groups of potential consumers, the likelihood of consumers making a multi-buy decision at a low multi-buy pricing and a higher multi-buy pricing could be examined. If the samples were reasonably representative, then, if an estimate of the confidence interval of the size of the typical consumer base were available, it would be possible (using the proportions choosing the multi-buy options from the sample), to estimate the likely actual numbers of multi-buy customers. From this, the range of potential profits from adopting the multi-pricing strategies could be estimated. If the outcomes from the simulations are robust, that is that the likelihood of profitable outcomes appears more likely than not, then a multi-buy discount strategy might be justifiable.

In game theory terms of Nash equilibria (Nash, 1951), the best strategy of consumers might be to adopt the multi-buy move in response to both the low and high multi-buy pricing moves by the retailer. In which case, for the retailer, the best strategy would be the high multi-buy pricing.

The consumer would typically always choose the "Low pricing of multi-buy goods" for this example, if available (although this may not always be available). However, not all purchasing decisions can be predicted in this manner, since there may be no dominant strategies. When none of the players in a game has a dominant strategy, we should expect players to use strategies that are the best responses to each other. If a retail company chooses a strategy S and a set of consumers chooses a strategy T. We say that this pair of strategies (S, T) is a Nash equilibrium if S is a best response to T, and T is a best response to S. However, there will be marketing approaches that may have no Nash equilibria at all. For such marketing approaches, we can make predictions about consumers' behaviour by enlarging the set of strategies to include the possibility of randomisation.

Initially, a payoff matrix and the confidence intervals could be estimated by marketing staff. However, statistical analysis of data from sample consumer groups (e.g. by region or by product category) could be used to determine more reliable confidence intervals and probabilities. This can inform the overall retail marketing strategy by providing probability estimates of likely outcomes from consumer purchasing decisions, based upon different marketing approaches.

5. Conclusion

In this paper, we have demonstrated how game theory combined with Monte Carlo simulation modelling can be applied to retail marketing activities. Game theory combined with Monte Carlo simulation modelling can provide a formal approach to understanding consumer decision making in a retail environment, which can support the development of retail marketing strategies. Game theory combined with Monte Carlo simulation modelling can support the modelling of the interaction between retail marketing actions and consumer responses in a practical formal probabilistic manner, which can inform marketing strategies used by retail companies in a practical manner.

Payoff matrices combined with Monte Carlo simulation modelling can be used to model the probabilities of consumer actions in response to retail marketing approaches. The game theory concept of utility (a measure of game player satisfaction) can be modelled by considering consumer satisfaction. This can be viewed as there being an appropriate variety of purchasing options for the consumer, and whether the consumer feels that they have 'won' in some manner with regard to a given purchase for example with regard to a multi-buy sales offer. If a retail company chooses a particular strategy and a set of consumers chooses a given strategy, then this pair of strategies would be a Nash equilibrium if they are a best response to each other. However, there will be marketing approaches that may have no Nash equilibria at all.

Monte Carlo simulation of consumer decisions (whether single or multi-buy purchase) can be used to model different sales volumes representing potential increases in sales due to different levels of discounting. The Monte Carlo simulation involves using random numbers to generate different proportions of consumers choosing the multi-buy option. The approach involves marketing staff providing two values for each payoff (a maximum and a minimum). Monte Carlo simulation is then employed to simulate payoff tables. The method is repeated numerous times in order to provide probability distributions for each player's overall optimal strategies. These distributions are then used to assess how robust the strategies are and so give an estimate of the risk associated with different levels of multi-buy discounting.

The originality of the research reported in this paper is a formalised, statistical and scientific approach to the practical application of game theory to retail marketing strategy development, in particular the use of payoff matrices combined with Monte Carlo simulation modelling to model likely consumer behaviour in response to different marketing discount approaches.

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