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Trend Modelling as a Support of Managerial Decision-Making Process in Relation to Customers

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The issue of managerial decision-making in relation to customers plays a significant role in any enterprise. Managerial decisions are often based on input information that is difficult to quantify. Therefore, common statistical methods cannot be easily used. A trend is the least informative quantifier. The goal of the paper is to present a new formal tool of the managerial decision-making process based on the trend model. This tool is demonstrated using the following variables: word of mouth, electronic word of mouth, brand trust, consumer experience and consumer price perception. These variables were chosen from scientific papers that confirmed a relationship among them. A trend analysis of the model involves assessing the relevant group of particular situations. The model's predictions can be described as a sequence of these scenarios. The findings show that the trend model is a powerful and suitable tool in the managerial decision-making process.

Keywords: *Trend Modelling; Decision-Making Process; Brand Trust; Brand Love; Word of Mouth; Price Perception; Consumer Experience.*

Introduction

In the 21st century, it is crucial for enterprises to effectively manage decision-making processes in relation to their customers. It is evident that these processes require not only ICT system support but also appropriate methods and knowledge. The spectrum of knowledge contains data of a diverse nature. There are two main types of knowledge.

First, it is explicit knowledge having an exact representation, e.g. the laws of physics, numerically expressed characteristics, precisely defined concepts, phenomena precisely described by equations, data obtained by experimental measurements, statistical analyses, data based on inaccurately described phenomena, data burdened by the element of uncertainty, randomness, or ambiguity. This data bring accurate/certain knowledge (Nonaka, 2008).

Second, it is tacit knowledge that for various reasons does not or cannot have such representation. It is of various types. For example, heuristics (data obtained from experience), engineering intuition, expert knowledge, etc. This data brings inaccurate/uncertain knowledge (Wethyavivorn & Teerajetgul, 2020). The description of every real phenomenon contains a vague knowledge of the phenomenon (Xue & Deng, 2021). In this sense, it refers to the vagueness as an objectively existing phenomenon. Uncertainty is a phenomenon whose character is given by elements of inaccuracy, vagueness, and randomness. All forms of human behavior consist of the implementation of various decisions, taking into account uncertainty. (Zellner *et al.,* 2021). Questionnaire surveys are a common data collection technique in business decision-making process. The results obtained are mostly categorical in nature. The analysis of categorical data allows to determine the dependencies between the observed traits based on the frequencies of individual variants of the traits. However, this dependence cannot be understood in the sense of functional dependence, therefore, it is difficult to create a mathematical model (Agresti, 2018; Magidson, 1982). Trend modelling allows the creation of mathematical models even for categorical data. Introducing this new tool and creation of the trend model for strategic is the goal of the study. The resulting model advantage is the simple formulation, modification and interpretation of the results to support the strategic.decision-making over an extended period. decision-making of the firm. In this paper, a created model works with corporate decision variables that are long-term in nature. These are particularly brand trust, brand love, price perception, consumer experience and WOM. The strategic significance eWOM is constantly increasing for marketing specialists and entrepreneurs. They are compelled to comprehend its effects on employee turnover and other essential measurements (Kumar *et al.,* 2016). The companies have to work on improving these variables on a long-term and continuous basis. The individual areas belong to the highest level of managerial decision-making and belong to the strategic field of decision-making. The model supported by the transitional graph is, therefore, useful to define strategic objectives and future scenarios how to reach them.

The majority of businesses have to face the fact that the rapid development of their ICT infrastructure does not always align with their overall company strategy and objectives (Gudanescu *et al.,* 2010). The entire ICT sector's quick and unregulated growth has a substantial impact on this tendency. This makes implementing ICT systems in any organization a very difficult, multidisciplinary undertaking that necessitates careful adaption of installed ICT tools in accordance with the business strategy (Marchand *et al.,* 2002). Relationship marketing and customer relationship management, also known as CRM, have developed quickly as a result of efforts to better understand client requirements

(Payne & Frow, 2005). CRM is a huge asset for businesses looking to boost their competitiveness. CRM focuses on external factors, namely those relating to customers. But it's also essential to have a strong internal focus on the processes for developing solutions (Tuli *et al.,* 2007). Managers have to understand customers of their enterprise really well and create effective offers and solutions on the basis of customer expectations, needs, characteristics, etc.(Dibb & Simkin, 1996). Customers prefer a great variability of products as they can better choose a product matching their requirements. However, each market segment should be financially attractive to yield growth in sales and profit (McDonald & Dunbar, 2004). On the one hand, managers of each enterprise have to make important decisions on a daily basis in order to satisfy the requirements of their customers. On the other hand, managers have to make decisions in such a way as to achieve their strategic objectives while using limited resources.

Nowadays managers can use different forms of media for the communication with consumers. It is necessary to apply relevant marketing tools to assure efficient communication with individual target groups. CRM facilitate the enhancement of consumer service thanks to storing relevant information and data (Xu *et al.,* 2002). CRM platforms allow marketers to identify the most significant online media based on the consumers` needs and preferences. Moreover, the efficient use of CRM system allows enterprises to increase their turnover and profits (Yapanto, 2021). Furthermore, CRM systems significantly simplify marketing processes both within the company and in its communication with external stakeholders. These platforms allow marketing experts to improve the efficiency through varios digital media. Crucial types of digital marketing encompass influencer marketing, SEM, SEA, SEO, mobile applications, content and evangelism marketing. The last form of marketing play a significant role in communication with prospect customers and loyal consumers. It is an advanced sort of WoM where consumers recommend goods of the enterprise on free-of-charge bases. These consumers trust strongly in a quality of selected products and services and are willing to persuade the other prospect customers to purchase and use them (Pornsrimate, & Khamwon, 2020).

Word of Mouth

In traditional literature WoM was established for a long time, see e.g. (de Matos & Rossi, 2008; Duhan *et al.,* 1997. Word of mouth means an oral communication between a sender and receiver. The sender has to think about the kind of information they want to send to a receiver to get an appropriate reply.

The message of communication includes service, goods or brand. The message carries a clear commercial purpose. (Harrison-Walker, 2001). Hence, customer regard word-of-mouth credibility more highly than they do business commercials (Herr *et al.,* 1991). Word of mouth is seen as a non-commercial information source which hugely affects the formation of consumer opinions and purchasing intentions (Hennig-Thurau *et al.,* 2004).

Users who obtain information from online discussions show greater interest in product-related themes compared to those who rely on business commercials and marketing sources (Bickart & Schindler, 2001). A commercial message conveys some kind of advantage, motivation and stimuluses why consumers ought to do some type of conversion such as purchase of a product. The message's appeal could be classified into two categories:

1. Rational appeal - attracting consumers by the benefits of the present product's attributes.
2. Emotional appeal – eliciting consumers` positive or negative emotions to increase purchase willingness (Kotler & Keller, 2015).

It is significant to emphasize that the long-term relationship with promotion activities influence the approach of customers and lead to WOM. The WOM is not only a powerful tool in traditional marketing communication but in it electronic form (eWOM) is considered to be more efficient and beneficial (Alavijeh *et al.,* 2018).

(eWOM) has the potential to significantly influence consumer brand perception and approach more than any other kind of message (Godes & Mayzlin, 2004). The motivation of consumers to use eWOM is increasing due to the high transparency of this source. Consequently, they can also exert greater influence over product and service quality, as well as pricing, based on consumer requirements (Park & Kim, 2008). Enterprises ought to strive to have as many loyal customers as possible because the loyalty has a beneficial impact on WOM (Alguacil *et al.,* 2018).

The strategic importance of eWOM is constantly increasing for marketing experts and outsources. They face the challenge of comprehending its effects on employee turnover and other crucial KPIs (Kumar *et al.,* 2016). EWoM as the channel of marketing exchange of information was extended at the expense of traditional word of mouth during the last decade. This phenomenon arises due to the rapid expansion of the internet and social networks, which create information-rich environments. Customers have a chance to express their opinions and experience publicly. They can also complain about insufficient services or poor quality products. Negative word of mouth can reach a widespread audience (Beneke *et al.,* 2015). Widely used social media platforms like Facebook and Twitter serve as popular channels where customers can express their opinions and grievances (Gregoire *et al.,* 2009).

This study empirically examines if and why consumers' intent to spread unfavorable information about the manufacturer may grow when third parties indicate how unsustainable luxury fashion products are in comparison to mass-market fashion products..

Non-positive worth of mouth warrants specific regard because of its strong impact on customer perception (Amatulli *et al.*, 2020; Herr *et al.,* 1991). Unfavorable WoM holds more sway, attracts greater focus, and reaches a wider audience compared to positive WoM. (Lau & Ng, 2001).

The negative impact has been described in the online environment as well (Verhagen *et al.,* 2013). Generally, users engage in eWOM messaging primarily due to their need for social interaction, commercial motivations, and empathy for others (Hennig-Thurau *et al.,* 2004). Unfavourable eWOM from dissatisfied consumers can impact the perceptions of online users, posing a threat to a company's brand (Shang *et al.,* 2006). The motivations behind positive and negative eWOM differ: Users participate in positive eWOM due to their involvement with the goods, while negative eWOM is driven by curiosity, motivation for slandering and looking for relevant information (Amblee & Bui, 2008).

Consumers would like to get news concerning goods to lower the level of uncertainty and risk. If they come across negative comments such as complaints it will have a bad effect on the enterprise`s reputation. Unfavorable reviews create mistrust in the brand and also trigger negative perceptions about the brand's image. A pessimistic user outlook might be seen as the overall assessment of the brand approach (Wang, 2010).

Outcomes of research indicate that the readiness to engage in negative eWOM significantly shapes brand approaches. A decline in goods quality directly affects brand attitudes adversely. Brand approach is intricately linked with concepts such as brand love and trust (Wu & Wang, 2011).

Price Perception

Consumer price perception can be explained as the understood worth of an individual product of service in consumer`s head. The price of a commodity is the significant factor according to which the consumer decides when buying goods (Liu & Lee, 2016). When setting the price, it is possible to treat each customer individually and the ideal price level is determined according to their expectations (Mance *et al.,* 2029). This could be a rather theoretical alternative because the costs associated with such approach could be too high. The process of evaluating commodities during their purchasing decisions, consumers rely on reference prices as their expectations for pricing (Wang *et al.,* 2018). In situations where the actual price falls below the reference price, customers perceive it as a gain. Conversely, they perceive a loss when the current price surpasses the reference price (Zhang *et al.,* 2014). Consumers' perceptions of a particular price have a significant impact on their decision to buy and their level of satisfaction. It demonstrates how a consumer's judgment regarding the fairness of product and service pricing is significantly shaped by their voting behavior. The price has an influence on customer loyalty as well (Michael, 2010). When pricing a product based on the customer's perceived ideal price level, it is important for the marketer to consider several important factors such as the type of market, the uniqueness and product value, seasonal aspect, the size of the market (region), product availability or utility. However, the business must set the price so that it is perceived as fair by the customer. Failure to do so may result in customer dissatisfaction and reduced loyalty to the retailer, brand or product. This will ultimately lead to a change in the user´s behaviour and they will decide to purchase a product from a competitor.

There have been developed methodologies and methods for figuring out a product's best market pricing (Duffett *et al*., 2018; Schuller *et al*., 2018). Reference pricing is related to value-based pricing. This approach seeks to determine the price based on the value that the product or service provides to the user. This approach seeks to set the price according to the value the product or service brings to the customer. The advantage of this approach is that it takes into account the value customers attach to the product. This approach leads to sellers not unnecessarily overpricing their products as this could lead to customer churn (Hinterhuber, 2004).

Brand Trust and Brand Love

Brand view is defined as users' overall assessment of a brand. It involves their judgment of whether the brand is good or bad, forming their view toward the brand based on this assessment. (Low & Lamb, 2000; Wilkie, 1994). Some studies consider brand attitude as a one-dimensional model (Beneke *et al*., 2015). However, a one-dimensional model is able to describe brand attitude only with limitations as it offers only limited clarity into how customers judge brands applying various criteria. Therefore, researchers recognise three elements for an insight: Cognition, affection and conation (Beneke *et al.*, 2015; Schiffman, 2015). It is feasible to interpret cognition as brand trust, affection as brand sentiment, and conation as the intention to make a purchase by the user (Beneke *et al*., 2015; Wu & Wang, 2011).

Several models of brands were developed. The linkage between consumer and brand is really significant in these models (Esch *et al.,* 2006). Brand trust is often combined with expectations, reliability of brand, willingness to reduce the uncertainty or risk and consumer experience. Consumers have some expectations in terms of the product and service quality provided by enterprises. (Munuera-Aleman *et al.,* 2003) associate brand with the emotion of customer security. Users evaluate the brand positively based on knowledge and experience of if it is responsible and reliable for them and vice versa. Consumer trust of a brand will decrease in the case of negative reference. Negative word-of-mouth and electronic word-of-mouth can have adverse effects on consumers, leading them to develop a negative attitude towards brands. Negative WOM and eWOM will have a negative impact on consumers and they will start to develop a negative attitude towards brands (Wang, 2010). In this context it is necessary to convince consumers of the good quality and high value of a brand so that they believe they will have a positive experience. These aspects are connected with the customer satisfaction. The customer satisfaction is connected with consumer loyalty (Ahmed *et al.,* 2020).

In theory, brand love is associated with interpersonal love from psychology (Sternberg, 1986). Fournier (1998) emphasizes that love is one of the core elements of a consumer's relationship to a brand. The relationship could be strengthened by the positive experience of the consumer. The consumer is the cornerstone of brand theory. Park & Kim (2008) focused their work on consumers' devotion to brands. Similarly Escalas & Bettman (2003) connect brand love with self-brand attitude. Batra et al. (2012) constructed a model that contains the following main factors: passion-driven behaviour, self-brand integration and positive emotional connection. Brand love is closely associated with a lasting connection, the expectation of distress upon separation, the overall equilibrium of attitudes, and a sense of certainty and confidence. Some articles also indicate that customers can develop a sense of affection for their brand (de Matos & Rossi, 2008). There are many factors that are connected with brand love such as product characteristics, brand quality, consumer loyalty etc. (Carroll & Ahuvia, 2006). However, the term "brand love" is already firmly entrenched in brand theory (Batra *et al.,* 2012).

This paper follows the Carroll and Ahuvia (2006) model and predominately the results of the Karjaluoto et al. (2016) paper. Those authors proved the positive effect of brand love on WoM and eWoM, the positive effect of brand trust on brand love and that consumer experience and consumer price perception strengthens the positive linkage between brand love and worth of mouth.

Brand love, brand trust, price perception, customer experience and word of mouth are subjective and vague in nature, which is why it is very difficult to quantify them. Common statistical methods are less suitable in this case. Trend modelling thus is an appropriate and efficient tool.

Materials and Methods

Deep knowledge items are the fundamental concepts that are considered as the foundation of a theory. These concepts are often referred to as laws or principles that reflect undisputed elements of the corresponding theory.

Real problems are not just based on equation type knowledge also known as deep knowledge. They are usually based on non-equation type knowledge, is often found in the simplified description of the socio-economic-technical system under study. Such knowledge is obtained by non-numerical heuristics, qualitative interpretation of experiments, engineering intuition, etc. These are usually expressed verbally using natural language and are also considered shallow knowledge in the above sense. It is clear that a qualitative model, any quantitative knowledge can be transformed into qualitative knowledge through a process called degradation. (Alonso-Fernandez *et al.*, 2019)

Verbal descriptions of shallow knowledge items can be described by pairwise trends such as decreasing, constant, and increasing (Doubravsky & Dohnal, 2018; Yan *et al.,* 2013). These relations are used to represent the relationship between two trends. For example, if marketing-related investments increase, then business profits increase. Pairwise trend relations are used to represent the relationship between these two trends in a graphical format. The strength of the relationship between trends can be determined using the graph and can be used to predict future trends (Doubravsky *et al.,* 2020). Typical examples of pairwise trend relations are given in Figure 1.

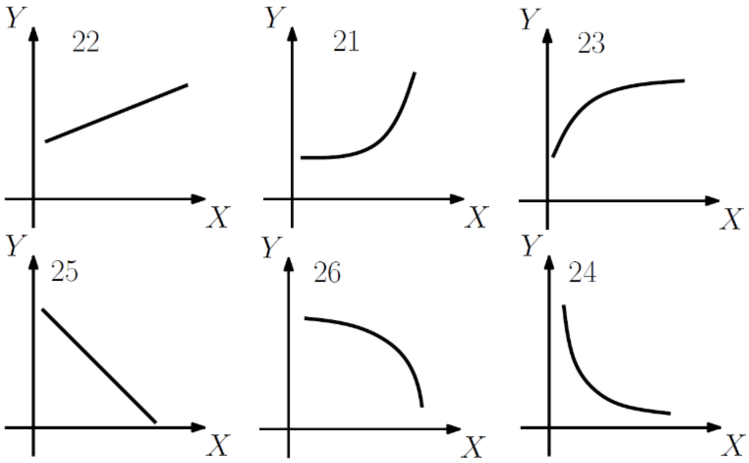

Figure 1. Trend relations (Dohnal, 1991)

For pairwise relationships (see Figure 1), there is no numerical quantification of the relationship between the variables *X, Y*. For example, relation No. 23 indicates that if the variable *X* grows, then the variable *Y* grows and the growth rate decreases.

The numbers 21, 22, 23, 24, 25, and 26 are just pairwise relationship labels for the first quadrant (Dohnal, 1991).

It has proved necessary to have an effective calculus for dealing with both quantitative and qualitative knowledge in order to find a model that as a whole is of the nature of a so-called trend model. The basic definitions that are relevant follow.

Trend Analysis

The process of creating trend models using trend analysis is called trend modelling. Four qualitative values, see Table 1, are considered in the trend analysis of trend model M (1), (Vicha & Dohnal, 2008).

$$\mathrm{M}(X_1, X_2, \dots, X_n) \tag{1}$$

Table 1

Qualitative Values

Values:	Positive	Zero	Negative	irrelevant for solving problem
Trend:	Increasing	Constant	Decreasing	Any direction
Symbol:	+	0	−	*

The trend model M (1) is specified when behaviour of all variables X_i is given by the triplet

$$(X_i, \mathrm{D}X_i, \mathrm{DD}X_i),\ i = 1, 2,\ldots, n \tag{2}$$

where X is the degradation of $x(t)$, DX is the degradation of $x'(t)$ and DDX is the degradation of $x''(t)$, resulting in the appropriate sign. (Doubravsky *et al.,* 2020).

For example, the triplet is (+, −, −), shortly (+ − −). This triplet can be interpreted so that the X variable is positive, decreases (DX = −)and the decline rate increases (DDX = (−).

Suppose that the trend model M is given by a set of differential equations, (Vicha & Dohnal, 2008). By substituting (2) into the equations describing the trend model M, it can be determined whether there is no conflict with the meaning of any of these equations, then is called a scenario (Doubravsky & Dohnal, 2018; Doubravsky *et al.,* 2020).

The set S(n, m) of scenarios is called the solution of the trend model M.

$$\mathrm{S}(n,m) = \left\{\left((X_1, \mathrm{D}X_1, \mathrm{DD}X_1), \ldots, (X_n, \mathrm{D}X_n, \mathrm{DD}X_\mathrm{n})\right)_j\right\} \tag{3}$$

where $j = 1,2,\ldots,m$.

The trend model, studied in this paper, is based on w pairwise relations, as seen in Figure 1:

$$P_r(X_i, X_j), r = 1,2, \ldots, w. \tag{4}$$

By substituting (2) into the relations describing the trend model, it can be determined whether there is no conflict with the meaning of any of these relations. The result is a set of scenarios (Dohnal & Doubravsky, 2015; Doubravský, 2019; Doubravsky & Dohnal, 2018).

For example, the following three-dimensional scenario, $n = 3$,

X_1	X_2	X_3
(+ − −)	(+ − 0)	(+ + +)

indicates that X_1 decreases and the decline rate increases, X_2 decreases and the decline rate is constant, X_3 grows and the growth rate increases.

Higher derivations are neglected in most practical examples because of the difficulty of interpretation. (Bredeweg *et al.,* 2016).

Suppose that the trend model M is given by pairwise relations 22 and 26, see (5).

	Shape	X	Y
1	26 (see Figure 1) X_1	X_2	
2	22 (see Figure 1) X_3	X_2	

(5)

Then the solution of this model is in Table 2.

Table 2

Scenarios

	X_1	X_2	X_3
1	+ − −	+ + +	+ + +
2	+ − −	+ + 0	+ + 0
3	+ − +	+ + −	+ + −
4	+ − 0	+ + −	+ + −
5	+ − −	+ + −	+ + −
6	+ 0 −	+ 0 +	+ 0 +
7	+ 0 0	+ 0 0	+ 0 0
8	+ 0 +	+ 0 −	+ 0 −
9	+ + −	+ − +	+ − +
10	+ + −	+ − 0	+ − 0
11	+ + +	+ − −	+ − −
12	+ + 0	+ − −	+ − −
13	+ + −	+ − −	+ − −

If we are not able to decide between the concrete of trend shape of relations, see Figure 1. Two simple macroinstructions M_+ and M_- can be used (Doubravsky *et al.*, 2020):

The macroinstruction M_+ X_i X_j means: if X_i increases, X_j increases too;
The macroinstruction M_- X_i X_j means: if X_i increases, X_j decreases. (6)

The macroinstruction M_+ corresponds to the relations 21, 22, 23, see Figure 1. The macroinstruction M_- corresponds to the relations 24, 25, 26, see Figure 1.

Transition Graph

The set of scenarios contains a finite number of scenarios that can be understood as states of the analyzed system formulated by the qualitative model M. Systems can move from one state to another over time; in this case we speak of dynamic system behavior. The dynamic behaviour of a system formulated using a qualitative model can be represented by a transition graph.

The transition graph H = (S, T) is an oriented graph, where S is the set of scenarios and T are ordered pairs of scenarios. The elements of the set E are called transitions (Doubravsky *et al.,* 2020).

$$\mathrm{H} = (\mathrm{S}, \mathrm{T}) \tag{7}$$

Thus, we can say that the transition graph defines an ordering relation on the set of scenarios that allows to identify the mutual transitions between the scenarios.

The set of all possible transitions between scenarios for positive nature of observed variables is given in Table 3 (Dohnal, 1991).

Table 3

A list of all one-Dimensional Transitions

	From	To	Or	Or	Or	Or	Or	Or
1	+ + +	+ + 0						
2	+ + 0	+ + −	+ + +					
3	+ + −	+ 0 0	+ 0 −	+ + 0				
4	+ 0 +	+ + +						

	From	To	Or	Or	Or	Or	Or	Or
5	+ 0 0	+ − −	+ + +					
6	+ 0 −	+ − −						
7	+ − +	+ − 0	+ 0 0	+ 0 +	0 0 +	0 − +	0 − 0	0 0 0
8	+ − 0	+ − −	0 − 0	+ − +				
9	+ − −	0 − 0	+ − 0	0 − −				

The sixth row of Table 3 shows that scenario (+, 0, −) can only transition to scenario (+, −, −).

Figure 2 represents the transition graph H of the trend model M (5).

Using the transition graph, the scenarios can then be arranged according to their temporal sequence and the behaviour of the system under analysis can be predicted based on this arrangement.

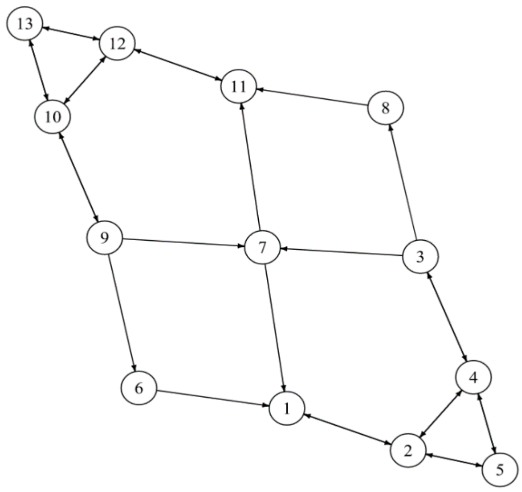

Figure 2. The Transition Graph of the Trend Model M (5)

Trend Reconstruction

Suppose that a set of possible scenarios is S_M and the whole set of scenarios S is not known:

$$S \supseteq S_M \tag{8}$$

The set S is the solution of a trend model M (2):

$$M \rightarrow S_M \tag{9}$$

A trend reconstruction is the opposite process of trend analysis (7). Then the set of S_M serves as the basis for the reconstruction of the trend model M_S (Doubravsky *et al.,* 2020).

$$S_M \rightarrow M_S \tag{10}$$

If we are looking for a solution of the reconstructed model M_S, we get a set of scenarios S_{MS}

$$M_S \rightarrow S_{MS} \tag{11}$$

For this set,

$$S_{MS} \supseteq S_M \tag{12}$$

In the following, only linear reconstruction is used in the paper because nonlinear reconstruction requires enormous computer time (Dincbas et al., 1990; Harrington & Salibián-Barrera, 2010; Singhi et al., 1996).

Two operations are defined for these values – the sum with the + sign and the product with the • sign, which are naturally derived from the sum and product operations of real numbers as given in Table 4 and Table 5 (Dohnal, 1991). In doing so, the result (*) is interpreted to mean that the latter can be (+), (−), (0) due to the indistinguishability of the magnitudes of the qualitative values.

Table 4

Qualitative Sum

+	(+)	(0)	(−)
(+)	(+)	(+)	(*)
(0)	(+)	(0)	(−)
(−)	(*)	(−)	(−)

Table 5

Qualitative Product

•	(+)	(0)	(−)
(+)	(+)	(0)	(−)
(0)	(0)	(0)	(0)
(−)	(−)	(0)	(+)

The basic and crude method of solving the trend model is to create all possible triplets for each variable that satisfy the equations of the model with respect to qualitative sum and product. Thus, solving the trend model is a combinatorial problem.

For example, let us consider variables X_1 and X_2. The set S_M of solutions consists of two scenarios, see Table 6.

Table 6

Available Scenarios

	X_1	X_2
1	−	+
2	+	−

For each scenario in Table 6, the relevant equations are determined using the qualitative sum and product.(Dohnal & Doubravsky, 2015; Doubravsky *et al.,* 2020).

Table 7

Equations of the First Scenario, see Table 6

	The equation of the first scenario	***The equation of the second scenario***
1	$(+)X_1 + (+)X_2 = (*)$	$(+)X_1 + (+)X_2 = (*)$
2	$(+)X_1 + (0)X_2 = (-)$	$(+)X_1 + (0)X_2 = (+)$
3	$(0)X_1 + (+)X_2 = (+)$	$(0)X_1 + (+)X_2 = (-)$

The scenarios in Table 6 satisfy the first equation in Table 7, which is therefore a reconstruction of the trend model M.

Trend Decision-Making

Let's assume there are two independent variables, X_1, X_2 and an objective functions Q. The goal is to maximize the objective function, such as profit.

$$DQ = + \tag{13}$$

Supposed that a solution of trend model is the set of three scenarios S(n = 3, m = 3). For greater clarity, the scenarios will be written in tabular form.

Table 8

Independent Variables and Objective Function

Scenario	X_1	X_2	Q
1	+ + +	+ + +	+ − −
2	+ + −	+ − −	+ + +
3	+ − −	+ − +	+ − +

Therefore, the first scenario is incorrect as the objective function Q declines if variables X_1 and X_2 follow the trend pattern given in (13).

The variables in set X can be categorized into three subsets for optimization purposes:

$$X = \{X_1, X_2, \ldots, X_n\} = O \cup N \cup Q. \tag{14}$$

Any decision-making will rely on a n-dimensional model M. A set X of n variables is a union (14) of Controllable variables O, Non-controllable variables N and the single Goal variable Q.

The model M can be written as follows.

$$M = f(X) = f(O, N, Q) \tag{15}$$

In this paper, we only consider controllable variables. Model M then is.

$$M = f(O). \tag{16}$$

The other types of variables can be easy incorporated into the model M by pair-wise relations.

Case study and Discussion

This paper follows the (Carroll & Ahuvia, 2006) model and predominately the outcome of Karjaluoto et al. (2016) paper. They demonstrated the positive impact of brand love on word-of-mouth and eWOM. Additionally, they highlighted the positive influence of brand trust on brand love and found that consumer experience and perception of pricing enhance the positive relationship between brand love and WOM. The results come from the the online survey conducted by Karjaluoto et al. (2016) in Finland. These results were presented in their research paper. Sampling method was used for this survey. A total of 342 respondents took part in the survey of which 59 % were females and 41 % males. The survey involving 342 participants was conducted, with 59 % being females and 41 % males. The respondents' ages varied from 15 to 66+ years. The authors utilized a five-point Likert-type scale and conducted both exploratory and confirmatory factor analyses to obtain the results. Hypotheses were tested with SmartPLS 3.

The qualitative model, given in Karjaluoto et al. (2016) contains the following variables:

- *BT*-Brand trust
- *BL*-Brand love
- *EX*-Customer Experience
- *PR*-Consumer price perception
- *WOM*-Word of mouth
- *eWOM*-Electronic word of mouth

The following trend model M (Table 9) relies on pairwise trend relations (4).

Table 9

Equation-Less Trend Model

	X	**Y**	**Shape, see Figure 1 and (6)**
1	BT	BL	M+
2	BL	WOM	M+
3	BL	eWOM	M+
4	EX	WOM	M+
5	PR	WOM	M−
6	WOM	eWOM	21

The solution of the trend model, as indicated in Table 9, consists of a set of 7 scenarios outlined in Table 10. In this context, only the positive variables are taken into account, meaning that all triplets follow the general format of (+, evaluate, evaluate). For instance, any Consumer price (PR) is inherently positive.

Table 10

Scenarios of the Trend Model in Table 9

	BT	BL	WOM	eWOM	EX	PR
1	+ + +	+ + +	+ + +	+ + +	+ + +	+ − −
2	+ + −	+ + −	+ + −	+ + −	+ + −	+ − +
3	+ 0 +	+ 0 +	+ 0 −	+ 0 +	+ 0 +	+ 0 −
4	+ 0 0	+ 0 0	+ 0 0	+ 0 0	+ 0 0	+ 0 0
5	+ 0 −	+ 0 −	+ 0 −	+ 0 −	+ 0 −	+ 0 +
6	+ − +	+ − +	+ − +	+ − +	+ − +	+ + −
7	+ − −	+ − −	+ − −	+ − −	+ − −	+ + +

The transformation table (Table 3) can be utilized to create a comprehensive list of all potential transitions among the seven scenarios. The transitional graph G_M (Figure 3) has 8 transitions. The nodes in the graph are scenarios S (Table 9) and the transitions between the scenarios are represented by oriented arcs.

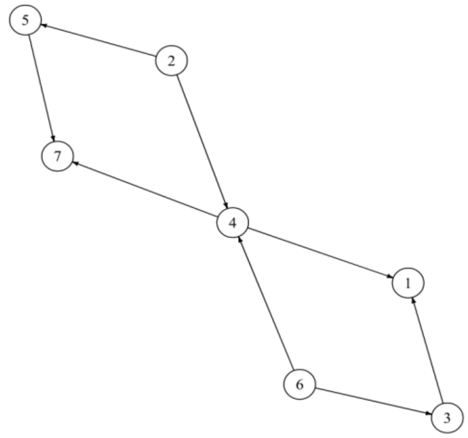

Figure 3. Transitional Graph G_M

For instance, an enterprise is in the situation described in scenario 4 (Table 9). Management of the enterprise is willing to establish an upward trend of brand trust, brand love, *WOM*, *eWOM* to reach scenario 2 (Table 9).

Figure 3 shows there is no path to get from Node 4 to Node 2. This can be caused by the pairwise relationships (Table 8) being derived from the results of the survey for a sample of customers (Karjaluoto *et al.,* 2016). These pairwise relations are not required to encompass all relationships among observed variables. Hence, trend reconstruction is employed subsequently.

From scenarios S_{ML} (Table 10) the following trend model M_{SL} (a set of 7 linear equations) is reconstructed.

Table 11

Set of 7 Linear Equations

	BT	*BL*	*WOM*	*eWOM*	*EX*	*PR*	Right side
1	+ 0 0	− 0 0	− 0 0	− 0 0	− 0 0	− 0 0	0
2	0 + +	+ − −	− − −	− − −	− − −	− + +	0
3	0 0 0	0 + +	+ − −	− − −	− − −	− + +	0
4	0 0 0	0 0 0	0 + +	+ − −	− − −	− + +	0
5	0 0 0	0 0 0	0 0 0	0 + +	+ − −	− + +	0
6	0 0 0	0 0 0	0 0 0	0 0 0	0 + +	0 + +	0
7	+ 0 0	+ 0 0	+ 0 0	+ 0 0	+ 0 0	0 0 0	+

For instance, equation number 5 in model M_{SL} (Table 11) represents the following linear equation:

$$\mathrm{D}eWOM + \mathrm{DD}eWOM + EX - \mathrm{D}EX - \mathrm{DD}EX - PR + \mathrm{D}PR + \mathrm{DD}PR = 0 \tag{17}$$

The trend model comprises seven linear differential equations, as outlined in Table 11. The trend analysis of the reconstructed model MSL is presented through the set SML, consisting of nine scenarios as detailed in Table 12.

Table 12

Scenarios S_{ML} of the Trend Model M_{SL}

	BT	*BL*	*WOM*	*eWOM*	*EX*	*PR*
1	+ + +	+ + +	+ + +	+ + +	+ + +	+ − −
2	+ + −	+ + −	+ + −	+ + −	+ + −	+ − +
3	+ 0 +	+ 0 +	+ 0 −	+ 0 +	+ 0 +	+ 0 −
4	+ 0 0	+ 0 0	+ 0 0	+ 0 0	+ 0 0	+ 0 0
5	+ 0 −	+ 0 −	+ 0 −	+ 0 −	+ 0 −	+ 0 +
6	+ − +	+ − +	+ − +	+ − +	+ − +	+ + −
7	+ − −	+ − −	+ − −	+ − −	+ − −	+ + +
8	+ + 0	+ + 0	+ + 0	+ + 0	+ + 0	+ − 0
9	+ − 0	+ − 0	+ − 0	+ − 0	+ − 0	+ + 0

The set S_{ML}, see Table 12, contains 2 additional scenarios, Nos. 8 and 9.

The trend results are not limited to the set of scenarios SML. It is simple to create transitions among these scenarios based on the transitions in Table 3. The transitional graph G_{ML} has 16 transitions (Figure 4).

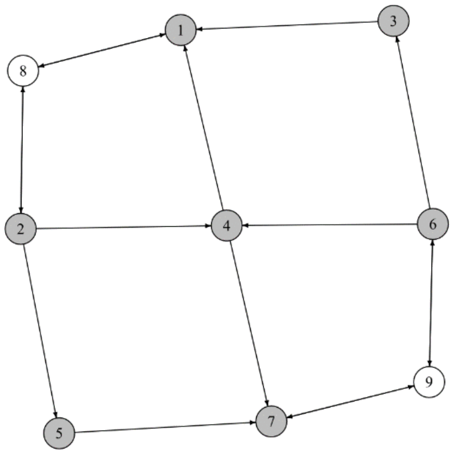

Figure 4. Transitional Graph G_{ML} Based on the set of Scenarios in Table 12

In the graph, the dark nodes symbolize the scenarios outlined in Table 10. The transitional graph GM is a subset of the transitional graph GML (Figure 4). Nodes in GM correspond to scenarios S from Table 12, and the directed arcs depict transitions between these scenarios. Figure 4 displays all conceivable directed paths, each describing a trend for either a forecast or a historical context. The transitional graph in the equation-free trend model M from Table 8 encompasses all potential future and past behaviours. Hence, making a forecast is akin to choosing a specific path through the transitional graph G_{ML}.

Conclusion

From a managerial perspective, it is crucial to elucidate the logic that company should adhere to. For instance, if the enterprise finds itself in the situation outlined in Scenario 4 (Table 12). Management of the enterprise is willing to establish an upward trend of brand trust, brand love, *WOM* and *eWOM* in order to reach Scenario 2 (Table 12). However, this goal also involves a reasonable reduction in price and strengthening of positive consumer experience. The transitional graph G_{ML} shows how to reach Scenario/Node 2. Actually, there are two paths that the management can follow. The shorter path starts in Node 4 and goes through Node 1 and Node 8 and finishes in Node 2. It is possible to argue that management could be satisfied with the trends of individual variables described in Scenario 1 (Table 2). Nevertheless, there is the problem with the variable - consumer price perception *PR* as consumers have to perceive that the price is decreasing substantially. It means that the price level of a product would be significantly reduced by the management so that consumers could be satisfied with this reduction. This situation can cause financial problems for the enterprise because the amount of the product margin would not have to ensure sufficient profit. That is why the management prefers Scenario 2 where the price level of the product is declining at an ever slower pace. The longer path starts also in Node 4 and goes through Nodes 7, 9, 6, 3, 8 and finishes in Node 2. This path is less suitable from a managerial perspective as the enterprise would have to go through more scenarios, which would mean a higher use of corporate resources and time.

This case study shows that there are two possible paths to reaching the requested scenario. If the management of a company is striving to increase brand trust, brand love, word of mouth and electronic word of mouth it is necessary to increase consumer experience and decrease consumer price perception simultaneously. The companies have to work on improving used variables on a long-term and continuous basis. The individual areas belong to the highest level of managerial decision-making and are strategic in nature,

The reality in the majority of enterprises is that quick development of their ICT infrastructure does not necessarily reflect the business strategy and main goals (Gudanescu *et al.,* 2010). The model supported by transitional graph is therefore useful to define strategic objectives and future scenarios how to reach them. The trend modelling should be implemented specifically in a customer relationship management module within an enterprise information system. Managers of each enterprise have to make important decisions in order to satisfy the requirements of their customers and need to use information company system on a daily basis. On the other, managers have to make decisions in such a way as to achieve their strategic objectives while using limited resources. The created model is the appropriate solution for strategic decision-making process.

Trend reconstruction serves as the inverse process to trend analysis. Although there are no universal algorithms for nonlinear trend reconstruction, reconstructing a set of linear differential equations from a set of scenarios addresses a wide range of managerial decision tasks. If the linear model derived from reconstruction is not approved by managers, no applicable model can be developed. Trend analysis and, consequently, the trend model provide a partial solution. The trend model requires minimal information since it solely relies on trends and can readily integrate various vague heuristics provided by experts.

Complex decision-making is related mainly to soft sciences such as management and marketing. The process is complex and lacks information. Traditional numerical analysis often results in oversimplified and/or highly specific quantitative models A lack of information is the main reason. The trend modelling proposed allows us to integrate difficult-to-measure factors easily, such as brand love, customer perception or WOM into decision-making models. Continued advancements in trend modelling lead to increased accuracy in the results.

A limit can be seen in the fact that the results are in trends and lack numerical evaluation. However, numerical input variables are often difficult to quantify because the results of questionnaire surveys are influenced by consumer feelings and perceptions. Therefore, trend modelling was used as the most suitable tool. Limits of this model are associated with the limited validity of the data from which this study drew. Therefore, future research should be aimed at gathering more data from various economic sectors. It would also be beneficial to focus on the differences between the segments within the same industry. It would be beneficial to find out if there are other variables that should be involved into the proposed model. Trend modelling allows us to add easily additional variables to this model. Managers can thus simulate the influence of other variables such as customer satisfaction, etc.

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