Improving Quality of B2B Customer Satisfaction Using Innovative Predictive Model

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ABSTRACT

Purpose: This paper presents a predictive model for strategic management of B2B customer satisfaction, designed for Quality 5.0 challenges and situations with limited data.

Methodology/Approach: A two-phase methodology was used. In the first phase, the methodology identifies key quality factors using focus groups and online surveys. In the second phase, a trend model is derived from a numerical correlation matrix that describes all past and possible future states of the system.

Findings: The results show two main strategies (dynamic and conservative) for transitioning from declining satisfaction to growth. It was found that this goal can be achieved by managing fully controllable factors such as website navigation, information complexity, and graphic design quality.

Research Limitations/Implications: By focusing on qualitative scenarios, the model is effective in environments with insufficient data and opens up possibilities for future expansion with fuzzy logic.

Originality/Value of Paper: The presented model is an innovative formal tool that complements existing quantitative methods in areas where data is lacking. Its value lies in its function as a strategic management simulator that converts qualitative descriptions of trends into structured action scenarios, thereby strengthening managerial decision-making in the context of Quality 5.0.

Category: Research paper

Keywords: quality; correlation matrix; predictive model; B2B customer satisfaction; decision-making

Research Areas: Quality by Innovation; Strategic Quality Management.

1 INTRODUCTION

Customer satisfaction measurements are unique and complex due to their multidisciplinary nature, e.g. feelings, moods, experiences, rumours, etc. The main problem is vague and uncertain input data which makes it difficult to develop applicable models for forecasting and decision-making. This is the main reason the trend description of a correlation matrix is used in this paper.

The transformation of the traditional behaviour of market entities and the increasing level of complexity in their relationships are the key drivers in multiple industrial sectors (Solomon, 2014). Enterprises are forced to react to this transformation and change their business strategies and scenarios. Communication technologies play a key role in this transformation and have an impact on relationships among buyers, sellers and the market (Di Fatta et al., 2016; Caputo and Walletzký, 2017).

The internet, web presentation and social media have spread quickly and the use of digital communication has increased rapidly. The relationships between buyers and suppliers are changing, and new communication modes help managers to satisfy buyer needs and develop a competitive advantage (Murphy & Sashi, 2018).

Competitive advantage was, for a long time, primarily based on technological products connected with the ability to develop and produce. Thus, capital, raw materials, production capacity and capabilities or human resources were scarce (Kellen & Wolf, 2003). This situation has changed quickly because of the turbulent character of markets, and a new scarcity can be seen in superior customer knowledge and the ability to offer solutions (Biggemann et at., 2013). Efforts towards customer requirement knowledge led to the rapid development of relationship marketing and customer relationship management or CRM (Payne & Frow, 2005). CRM is a great help to companies in increasing their business competitiveness. This is still true in some sectors, but the situation has changed dramatically in the majority of the markets within the past few decades due to the globalisation of the international business environment. Increased competitiveness caused a greater focus on orientation towards customers, customer requirements and their loyalty (Franceschini et al, 2015).

Customer loyalty is closely connected with marketing communication and customer satisfaction (Dimyati, 2015). Satisfaction appears most commonly in the context of customer stakeholders (Kotler & Armstrong, 2016). Halimi and Chavosh (2011) emphasise that there is a close link between customer satisfaction and marketing communication in B2B markets. Several articles revealed that a higher level of customer satisfaction ultimately leads to higher customer loyalty, word of mouth recommendations and references on the internet (Yoo et al., 2015; Guo et al., 2009). Social media and Web 2.0 intensified the use of digital communication between sellers and buyers (Murphy & Sashi, 2018). Seller organisations are forced to improve their online communication channels to share significant information such as delivery time or product specification (Joshi & Roh, 2009). Higher competition in markets compels enterprises to use differentiating strategies for the purpose of attracting and retaining consumers. For instance, customization of products belongs to differentiating strategies (Beatty et al., 2015; Tam & Ho, 2005). Nowadays, a lot of enterprises display their products on webpages and customers are able to configure these products according to their wishes and needs. Enterprises are striving to improve their webpages to communicate with their customers more efficiently. Moreover, by improving enterprise webpages can persuade multiple potential customers to make their first purchase.

A range of established methods exists for measuring and analysing customer satisfaction, including statistically rigorous and validated approaches. These tools have been successfully applied in many service and consumer contexts. However, their direct application in specialised B2B environments is sometimes constrained by the characteristics of the market, such as smaller customer bases, infrequent transactions, and the limited availability of continuous feedback data. As Gounaris (2024) points out, B2B relationships are shaped by longer interaction cycles, relational dependencies, and contextual variables that require more tailored measurement frameworks, which are not always supported by conventional models. Moreover, while many approaches can identify factors influencing satisfaction, they often provide limited guidance on the sequencing and timing of improvement actions when managers must operate under uncertainty. In the context of B2B digital platforms, empirical research linking specific technical and operational website attributes to measurable customer satisfaction outcomes is relatively scarce. Hasler et al. (2022) confirm that attributes extensively examined in B2C settings—such as navigation, content quality, and operational integration—manifest differently in B2B contexts, and that integrated causal models remain underdeveloped. This research gap motivates the present study, which applies a correlation-matrix-based approach combined with trend modelling to generate actionable improvement scenarios under conditions of limited and fragmented data.

2 THEORETICAL FRAMEWORK

2.1 Customer satisfaction

The notion of customer satisfaction in connection to marketing appeared in scientific studies in the 1960s (Keith, 1960). In the 1970s, 1980s and 1990s an increasing number of studies dealt with this subject. In the early 1990s, Peterson and Wilson (1992) estimated that the number of articles dealing with this subject exceeded 15,000. At the beginning of the new millennium, Parker and Mathews' article of 2001 could be considered revolutionary. These authors drew attention to the fact that the expression of satisfaction may have a different meaning depending on the purpose of its use. In the marketing field, Parker and Mathews refer to two approaches to the definition of customer satisfaction. The first premise leads to a definition where satisfaction is understood as a result of consumption. Under the second premise, satisfaction is understood as a process.

Customer satisfaction (CS) is not just a by-product of business operations; it is a pivotal performance metric with far-reaching implications. Satisfied customers contribute to enhanced firm value. For example, Seok et al. (2024) found that high levels of customer satisfaction mediate the positive effects of Environmental, Social, and Governance (ESG) performance on firm value. Similarly, in the digital era, marketing analytics are most effective when they directly or indirectly enhance customer satisfaction. Companies that utilise marketing data to boost agility, such as rapidly responding to consumer demands, see significant improvements in satisfaction and, in turn, performance outcomes (Agag et al., 2024). This relationship is also echoed in the context of digital transformation. Digitalisation enables real-time data analysis, personalised offerings, and seamless service delivery, all of which elevate satisfaction and enhance business competitiveness (Brunner et al., 2025). One of the most consistent findings across the literature is that customer satisfaction serves as a mediator between various organisational factors and customer loyalty. Gazi et al. (2024) highlight how organisational commitment, knowledge management, and CRM strategies influence customer loyalty indirectly through satisfaction. Their structural model shows that satisfaction forms a crucial bridge between what organisations offer and how customers respond in terms of loyalty. This mediating role was also confirmed in the tourism and retail sectors. In these industries, factors like brand image or CRM strategies do not lead directly to loyalty unless they first elevate satisfaction levels (Tahir et al., 2024). Businesses must first win customers emotionally and experientially before expecting long-term commitments such as repeat purchases or advocacy.

Customer satisfaction is also a key driver of customer retention. Satisfied customers are significantly less likely to switch to competitors and are more likely to maintain long-term relationships with companies. Gazi et al. (2024) note that profitability and loyalty, both indicators of retention, are directly and indirectly influenced by satisfaction levels. Research on service quality further supports this, showing that when companies meet or exceed expectations, customers are more likely to stay, building a perception of reliability and trust. For example, banks that implemented green banking initiatives observed that environmentally conscious services, such as digital banking and green loans, increased satisfaction. This reduced the likelihood of customer switching, underscoring the strategic importance of satisfaction in sectors where loyalty is crucial (Mir et al., 2025). There is a strong relationship between service quality and customer satisfaction. Improvements in service dimensions like responsiveness, reliability, and assurance directly enhance satisfaction. This is evident across industries, including retail and telecommunications, where quality service delivery fosters emotional satisfaction and customer advocacy (Gazi et al., 2024). A longitudinal study also showed that firms prioritizing data-driven service improvements, such as predictive analytics, consistently recorded higher satisfaction scores over time (Agag et al., 2024).

Brand image significantly influences customer satisfaction by shaping perceptions and expectations. Tahir et al. (2024) affirm that a positive brand image leads to higher satisfaction and stronger customer loyalty. When consumers feel aligned with a brand's values and experience consistent service, they are more likely to express satisfaction with their interactions. Moreover, the moderating role of brand image enhances the impact of customer relationship management (CRM) strategies. A strong, trustworthy brand supports satisfaction gains, while a weak brand may reduce the effectiveness of even well-structured CRM efforts (Gazi et al., 2024).

2.2 Customer satisfaction measurement

There are several methods used to measure customer satisfaction. Identification and consequent prioritisation of customer requirements are part of various customer satisfaction models. Kano et al. (1984) worked with essential, one-dimensional and attractive requirements for products. While essential and one-dimensional requirements are primarily connected with the core and total product, attractive requirements go towards the augmented product. A more complex approach combining customer requirement identification, prioritisation and product development can be seen in Total Quality Management (TQM) models (Akao, 2004).

One of the most well-known concepts of satisfaction measurement is the service-quality method referred to as SERVQUAL (Parasuraman, Zeithaml, & Berry, 1988). Cronin and Taylor (1992) wanted to offer an alternative to SERVQUAL. These authors designed a service-performance method dubbed SERVPERF, which is based on the measurement of performance (Performance level). In their paper, Cronin and Taylor announced that they had managed to reduce the number of items used to measure the quality of services by 50% to 22, as opposed to the 44 used by the SERVQUAL method. Abdullah (2006) modified SEFVPERF into a higher education performance method (HEdPERF). In this paper, the author concluded that it is important to modify SERFPERF according to the industry. Several authors have focused their research on the importance of the determination of individual factors within satisfaction measurement (Gruber et al., 2010; Douglas et al., 2008).

For measuring customer satisfaction several methods have been created by professional authors. Table 1 presents some of the most well-known concepts.

Table 1 – Concepts for measuring the quality of products and services

Model	Author	Description
Technical-functional model	Grönroos (1993)	This model focuses on three dimensions of quality: technical quality, functional quality and quality of image.
SERVQUAL	Parasurman, Zeithaml and Berry (1988)	This method is a multidimensional research instrument which is used to measure service quality by capturing respondents' expectations and perceptions within the five dimensions. This method uses the questionnaire technique with the questionnaire containing the following five dimensions: Tangibility,

Model	Author	Description
		reliability, responsiveness, assurance and empathy. Each dimension includes relevant questions. There are 44 questions in total which are organised into matched pairs of items - 22 expectation items and 22 perception items.
SERVPERF method	Cronin and Taylor (1992)	An alternative SERVPERF method, which is based on measurement of performance.
Sequential Incident Technique (SIT) method	Stauss and Weinlich (1997)	This method is based on phase-oriented research of customer perception. The customer evaluates his positive, negative or neutral relationship to the particular service. The SIT method is based on the Critical Incident Method (CIT).
PCP model of attributes	Philip and Hazlett (1997)	This model has a hierarchical structure based on three basic attributes. These involve crucial, main and secondary characteristics.
Internal model of quality of services	Frost and Kumar (2000)	This is a model of quality of services based on the concept of gaps in the SERVQUAL method. In this case, the evaluators are employees.
Concept of forward and backward gaps	Sahay, Seth, Deshmukh and Vrat (2006)	This is a theoretical framework for the method of measuring the quality of services in supply chains.
SERVQUAL method	Hu, Lee and Yen (2010)	The modification of the SERVQUAL method for measuring patients' satisfaction with the quality of services in hospitals.
BSQ Index	Firdaus, Suhaimi, Saban and Hamali (2011)	The index for measuring the quality of services in the banking sector. In their research, the authors identified 29 factors relevant to this area.
E-Service Quality (ESQ)	Ighomereho et al., 2022)	E-Service Quality (ESQ) framework extends traditional service quality models (like SERVQUAL) to the digital environment, addressing how customers evaluate the quality of online services and e-commerce experiences. It emphasises dimensions such as website design, ease of navigation, security, personalisation, and fulfilment. The goal is to help online businesses assess and improve the digital touchpoints that shape customer satisfaction and loyalty.
Qualitative-Cost Prediction Model	Siwiec et al., (2022)	This predictive model integrates product/service quality parameters with cost considerations to forecast customer satisfaction levels. It accounts for technical features, usability, aesthetics, and their weighted importance to the target customer segment. By linking qualitative and cost aspects, it supports decision-making for product design, pricing strategies, and quality management to better align with customer expectations.
AI/NLP Feedback Analysis Model	Tian et al. (2024)	This model leverages artificial intelligence and natural language processing (NLP) to automatically extract sentiment, themes, and actionable insights from large volumes of open-ended customer feedback. Unlike traditional surveys, it processes text data at scale and in real-time, enabling organisations to detect trends, predict satisfaction levels, and identify areas for service innovation more efficiently.

Expectations, perception and customer loyalty are cornerstones of the customer satisfaction measurement methods. Predominately, customer loyalty in a B2B market has great importance (Askariazad & Babakhani, 2015). Customer loyalty is considered to be a constant stream of revenue for enterprises in B2B markets as customers remain with producers and reject competitors (Rust et al., 2000). Concerning the nature of large orders in a B2B market, there are high profits for those producers that are successful in increasing and maintaining loyal customers (Rauyruen and Miller, 2007). In B2B markets, relationships between producers (suppliers) and customers are crucial. Orders from several large customers often account for a substantial share of manufacturers' and suppliers' turnover. Apart from financial targets, it is essential to create and take care of long-term relationships with customers and to maintain loyal customers in B2B markets (Gounaris, 2005).

From the marketing management point of view, it is significant for manufacturing enterprises and suppliers of products and services to properly understand the nature of their customers in order to work out enduring relationships and to support customer loyalty (Askariazad & Babakhani, 2015).

Trust variability has to be taken into account in B2B markets as well as customer expectations, perception and loyalty. Trust is emphasised in relationship literature to be significant in providing a better explanation of customer loyalty (Ulaga & Eggert, 2006; Gil-Saura et al., 2009; Suh & Houston, 2010). It is difficult to measure customer satisfaction because it is based on expectations, perception and other intangible aspects (Stefano, 2015). Customer loyalty, expectations and perceptions are hard to determine due to the complexity of human behaviour (Daniel & Berinyuy, 2010.

2.3 Website Quality Evaluation

Website evaluation has evolved significantly as digital presence becomes central to organisational success. The assessment of website quality generally revolves around usability, accessibility, content quality, interactivity, and overall user experience. Morales Vargas et al. (2022) argue that despite an abundance of digital platforms, specific and standardised methods for assessing website reliability and ethical attributes remain underdeveloped. Most studies rely on expert-based heuristic inspections, though user-based studies are increasingly advocated for more authentic insights. A user-centred approach helps evaluate the practical and emotional experience users derive from website interaction. This encompasses both functional aspects (such as navigation and loading speed) and hedonic dimensions like creativity and aesthetic appeal (Zeng et al., 2012). A comprehensive evaluation model must balance these aspects to reflect both user satisfaction and brand performance. Various frameworks exist to assess web pages, from heuristic checklists to data-driven decision models. Ayani et al. (2020) provide a critical review of health website evaluations, highlighting the insufficiency of conventional methods to capture domain-specific needs. Their findings stress the need for robust, context-sensitive evaluation frameworks that can incorporate automatic tools and support transparent web ranking systems.

For more commercial applications, Akincilar and Dagdeviren (2014) proposed a hybrid multi-criteria decision-making model combining AHP and PROMETHEE to evaluate hotel websites. Their model integrates multiple attributes — such as accessibility, aesthetics, information accuracy, and booking convenience — and weighs them based on importance. This systematic approach is adaptable across industries, suggesting its utility for B2B applications. While functionality remains foundational, creativity increasingly influences user engagement and perceived website quality. Zeng et al. (2012) highlight that websites must not only perform well technically but also captivate users emotionally through unique design and storytelling. Creativity enhances user attention, memory, and loyalty, all of which are critical for commercial success. In this regard, Morales-Vargas et al. (2022) recommend expanding evaluation protocols to include trust-building elements such as content reliability, transparency, and ethical standards. Especially in digital journalism and content-heavy sites, credibility and editorial rigour play a central role in quality perception.

Public-sector website evaluations introduce another lens for the delivery of public value. Karkin and Janssen (2014) emphasise the importance of public values such as transparency, participation, and responsiveness. They found that Turkish municipal websites, while strong on usability and categorisation, underperformed on dialogue and responsiveness, indicating the need for citizen-centric design and evaluation. These findings support a broader call for evaluation models that align technical performance with ethical and societal expectations, a principle just as relevant in commercial and B2B domains. Business-to-Business (B2B) websites pose distinct evaluation challenges. In B2B, websites are not just sales platforms but critical tools for relationship management, information exchange, and brand representation. Mudambi and Aggarwal (2003) argue that industrial distributors must leverage websites not only for transactions but also to deliver strategic value in areas like customer relationship management (CRM), operations, and knowledge sharing. Unlike B2C, where visual appeal and speed dominate, B2B website quality is more closely tied to credibility, integration with backend systems (like ERP), and the ability to support complex decision-making processes. Quality indicators include customisation, data accuracy, product configurability, and post-sale support infrastructure. Furthermore, usability remains vital in B2B but with a different lens: clarity in technical documentation, seamless access to specifications, and robust search functionalities are more valued than flashy interfaces. Maguire (2023) highlights that effective B2B sites should support both intuitive navigation and deep task completion capabilities while balancing usability with core business goals. Website quality is multidimensional, requiring organisations to consider a spectrum of indicators ranging from accessibility and performance to trust and creativity. In the B2B sector, where decision-makers rely on websites for critical procurement and information tasks, these evaluations must go deeper. The ideal B2B website is transparent, functionally robust, responsive, and aligned with user intent, providing both information and relational value.

3 METHODOLOGY

3.1 Trend Modelling – Natural Languages

Natural Languages (NL) can be seen as important tools if unique and difficult to observe or measure customer satisfaction is studied (Harrison, Roggero, & Zavattaro, 2019). Natural languages are widely used in communicating expertise, both in oral instruction and written texts (Schmidt & Wetter, 1998).

Real, complex decision-making models are often interrelated mixtures of verbal or graphical descriptions based on NL and some sub-models based on classical methods of operational research or mathematics and similar formal tools. Modern linguistics has undergone substantial development in recent times. Flexible incorporation of methodologies from formal logic and the mathematical sciences is the reason (Nefdt, 2016).

If the complexity of the task studied increases, then the extent of NL-based descriptions increases and the extent of mathematical tools, e.g. sets of differential equations, decreases. This is caused by the very nature of human reasoning, which is close to qualitative reasoning based on qualitative analysis.

Qualitative analysis can be very useful if further conventional statistical analysis is not feasible or interesting. Objective and subjective knowledge must be synthesised to gain the obvious benefits of objective precision and semi-subjective common-sense abilities.

Objective knowledge items are usually suitable for mathematical treatment, such as mathematical models with sets of differential equations and statistical models where original data sets are available, or no original data sets are available, or there is partial data set availability (Pee & Chua, 2016; Schneider et at, 2018; Watson, 1994).

Subjective knowledge items are based on NL. These relationships are either direct or indirect. Moreover, the relationship can be either quantitative or qualitative, as can the models. For example, statistical time series (quantitative) versus causal models (qualitative), as discussed in Bolger & Wright (2017):

- experience,
- analogy,
- feelings.

NL processing algorithms can teach computers to use NLs like human experts if some specific tasks are performed, e.g. information searching (Monchaux et al., 2015), language translation (Deng & Liu, 2018). Complex models based on NL closely depend on input information or knowledge items. (Caines, Hoffmann, & Kambourov, 2017). Because some of these items cannot be used flexibly for reasoning.

Therefore, in this paper the trend model is presented to transfer some elements of NL based data into such a form which can be integrated into human common-sense reasoning.

Some knowledge items related to decision-making tasks are often available as verbal descriptions or statements based on trends – increasing, constant and decreasing. These trends are the least information intensive quantifiers. If trends are not available or observable then nothing can be measured with all the obvious negative consequences related to strategic management (Marmer & Slade, 2018; Mousavi & Gigerenzer, 2014).

From a practical point of view, the trend is a statement, e.g.

S1: The better the website experience (*WE*), the more satisfied (*CS*) a customer is, (Plantinga, Scholtens, & van Duuren, 2015).

The trend represents a pair-wise proportionality or relation P between variables X and Y.

$$P(X_i, X_j), i \neq j. \quad (1)$$

Two types of pair-wise relations are considered in this paper, e.g.:

An increase in (X) has SUPporting effects on (Y) and vice versa
An increase in (X) has REDucing effects on (Y) and vice versa (2)

The following computer instructions are used to develop a trend model based on pair-wise proportionalities (1) and (2):

SUP X Y,
RED X Y, see (2). (3)

For example, the statement S1 is represented by the following instruction (4):

SUP *WE CS*. (4)

Graphical examples of pair-wise trend relations P (1) are given in Figure 1. The identification numbers are given in this picture.

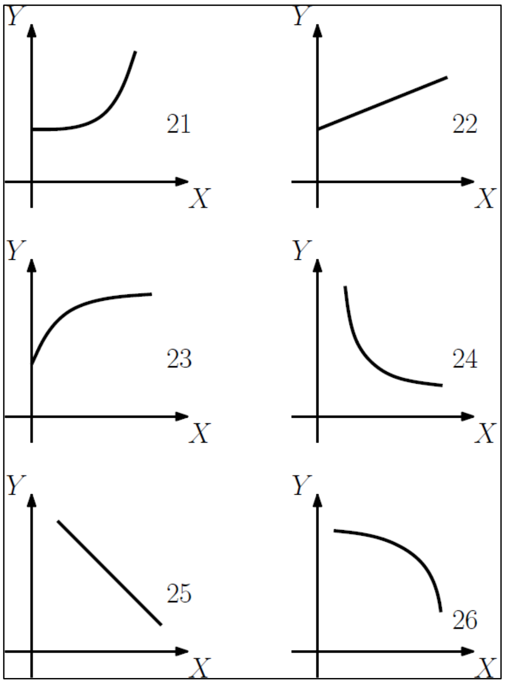

Figure 1 – Examples of trend pair-wise relations

All pair-wise relations P*(X, Y)* in Figure 1 are trend relations. It means that nothing is quantitatively, e.g. numerically known. For example, the relation 21, Figure 1, indicates that:

- The variables *X* and *Y* take positive values.
- The relation is increasing; the first derivative d(*Y*)/d(*X*) is positive.
- The graph is convex, so $d^2(Y)/d(X)^2$ is positive (growth rate is increasing).
- If $X = 0$, then *Y* is positive.

As seen in Figure 1, relations 21, 22 and 23 are relations with a supporting effect, while relations 24, 25 and 26 are relations with a reducing effect, see (2).

The trend model **M** is a description of the system being examined, which is based on trends and four qualitative values, see:

Table 2 –Values and trends

Symbol	Value	Trend
+	Positive	Increasing
0	Zero	Constant
-	Negative	Decreasing

The *n* dimensional trend model **M** is represented by *w* pair-wise relations P (1).

$$M(\boldsymbol{X}) = (P_1(X_i, X_j), P_2(X_i, X_j), \dots, P_w(X_i, X_j)), \text{ where } i, j = 1, 2, \dots, n, i \neq j. \quad (5)$$

Its solution, which is called the trend analysis, is a set **S** containing m scenarios of n triplets which satisfy the model **M** (all pair-wise). Each element/scenario of this set is written

$$[(X_1, DX_1, DDX_1), (X_2, DX_2, DDX_2), \dots, (X_n, DX_n, DDX_n)] \tag{6}$$

where,

- n is the scenario dimensionality,
- DX_i and DDX_i is the first and second time trend derivatives of the i-th variable.

The third trend, derivative DDDX and higher derivatives can be used. However, they are rarely known and difficult to interpret, and therefore, they are ignored in this paper.

Each triplet represents some trend of variable X_i. For example, a triplet (X, DX, DDX) may be (+, +, +). This triplet can be interpreted as follows: the variable X is a positive (X = +), increasing over time (DX = +), and the growth accelerates (DDX = +).

3.2 Trend Interpretation of the Correlation Matrix

Different types of correlation matrices exist (Bun et al., 2017, Frigessi et al., 2011). They are frequently used (Paul & Aue, 2014) and are therefore well-known (Shevlyakov & Oja, 2016).

It is possible to generate a trend model based on the first trend derivatives if a deterministic correlation matrix C is given, see (3). A correlation matrix C($n \times n$) can be degraded to a trend model as follows:

$$\begin{aligned} &If\ c_{i,j} > 0\ then\ SUP\ X_i\ X_j, \\ &If\ c_{i,j} < 0\ then\ RED\ X_i\ X_j \end{aligned} \tag{7}$$

where $c_{i,j}$ is the correlation coefficient between variables X_i and X_j.

3.3 Trend Model Consistency

The statistical nature of the classical numerical correlation matrix can cause problems if a trend correlation matrix is used (7). Roughly speaking, the correlation matrix is (nearly always) statistically inconsistent. The deterministic interpretation (7) can generate trend models which have no solution.

A trivial brute-force or exhaustive search can be used to solve simple trend models. For example, the following simple example,

$$\begin{aligned} &SUP\ X\ Y, \\ &RED\ X\ Z, \\ &SUP\ Y\ Z, \end{aligned} \tag{8}$$

provides just the steady state solution:

Table 3 –The steady state solution of the model (8)

	X	*Y*	*Z*
1	(+, 0, *)	(+, 0, *)	(+, 0, *)

There is just one scenario, as seen in Table 3. This scenario has all three values, DX, DY, and DZ, equal to zero. This is a clear indication that the model is restrictive and no dynamic behaviour is possible because the second derivative is irrelevant (symbol *). However, if the very nature of variables X, Y, Z indicates that there are dynamic scenarios, then the model (8) is over-restrictive.

A model (8) rectification is to remove one or more statements or relations. If the last statement (8) is removed, then the following three scenarios are obtained:

Table 4 – The solution of the model (8) without the third relation

	X	*Y*	*Z*
1	(+, +, *)	(+, +, *)	(+, –, *)
2	(+, 0, *)	(+, 0, *)	(+, 0, *)
3	(+, –, *)	(+, –, *)	(+, +, *)

If the second statement of the model (8) is removed, then the modified model gives the following set of scenarios.

Table 5 – The solution of the model (8) without the second relation

	X	*Y*	*Z*
1	(+, +, *)	(+, +, *)	(+, +, *)
2	(+, 0, *)	(+, 0, *)	(+, 0, *)
3	(+, –, *)	(+, –, *)	(+, –, *)

Each modification has a different set of scenarios (see Table 4 and Table 5).

Some models are not restrictive. The following model,

$$\begin{aligned} &RED\ X\ Y, \\ &SUP\ Y\ Z, \\ &RED\ X\ Z, \end{aligned} \tag{9}$$

provides the set of the following three scenarios:

Table 6 – The solution of the model (9)

	X	*Y*	*Z*
1	(+, +, *)	(+, –, *)	(+, –, *)
2	(+, 0, *)	(+, 0, *)	(+, 0, *)
3	(+, –, *)	(+, +, *)	(+, +, *)

A trend model **M** has w pair-wise relations (1). The model (9) has three relations, w = 3. The model **M** is a restrictive trend model **MR** if it has the steady state scenario as its only solution (see e.g. (8) and Table 3).

A modification of a trend model **MR** = ($P_1,\dots, P_w$) to eliminate restrictiveness (relations) by removing $w - v$ relations

$$MR = (P_1, \dots, P_w) \rightarrow \boldsymbol{MN} = (PN_1, \dots, PN_v);\ w > v. \tag{10}$$

The modification (10) is not unique. Therefore, restrictiveness elimination is an optimisation problem. There are different elimination goals E, e.g.

E1*:* Minimum number of removed relations $w - v$.

*E*2*:* Min $\Sigma|c_{i,j}|$; $c_{i,j} \in$ R where R is the set of removed pair-wise trend relations of the model M to satisfy the modification (10).

The goal *E*2 eliminates such pair-wise relations, which have low values of the corresponding correlation coefficients c.

However, potential users of the **MR** model usually have their own elimination preferences and eliminate relations using their common sense reasoning. While users often rely on their common sense when removing restrictive relationships, this process can lead to subjectivity. To increase the objectivity and robustness of the model, especially in situations where deterministic interpretations generate models without solutions, we recommend using structured expert assessment techniques. For example, the Delphi method can be used to systematically collect and refine expert opinions on the relevance of specific relationships. Alternatively, structured workshops with multiple experts in the field can facilitate collaboration and transparent discussion, allowing for collective verification of removed links. Such approaches help calibrate and verify the practical relevance of removed links, thereby strengthening the reliability of generated scenarios in real-world applications.

3.4 Transitional Graph

A classical correlation matrix represents relationships between observed variables for a specific moment. However, when an enterprise strives to make decisions to influence customer satisfaction, it is necessary to know the relationship between the variables observed and customer satisfaction.

For this purpose, econometrics can be used. But for a great number of the observed variables, there are many problems in meeting basic conditions, such as the homoscedasticity, autocorrelation, etc. (Chen, Gao, Li, & Lin, 2015; Gujarati & Porter, 2009; Varian, 2014).

Because trend modelling is only based on trends and not concrete numbers, this approach offers an elegant way to avoid these restrictions.

The set **S** (6) contains all scenarios which meet each pair-wise relations of the trend model M (5). Scenario transitions can be generated using the transformation table (see Table 7) from this set of scenarios; the result is a transition graph H.

Table 7 – A complete set of one-dimensional transitions

	From	To	Or	Or	Or	Or	Or	Or
1	(+, +, +)	(+, +, 0)						
2	(+, +, 0)	(+, +, +)	(+, +, –)					
3	(+, +, –)	(+, +, 0)	(+, 0, –)	(+, 0, 0)				
4	(+, 0, +)	(+, +, +)						
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)				
10	(0, +, +)	(+, +, 0)	(+, +, –)	(+, +, +)				
11	(0, +, 0)	(+, +, 0)	(+, +, –)	(+, +, +)				
12	(0, +, –)	(+, +, –)						
13	(0, 0, +)	(+, +, +)						
14	(0, 0, 0)	(+, +, +)	(–, –, –)					
15	(0, 0, –)	(–, –, –)						
16	(0, –, +)	(–, –, +)						
17	(0, –, 0)	(–, –, 0)	(–, –, +)	(–, –, –)				
18	(0, –, –)	(–, –, 0)	(–, –, +)	(–, – ,–)				
19	(–, +, +)	(–, +, 0)	(0, +, +)	(0, +, 0)				
20	(–, +, 0)	(–, +, –)	(–, +, +)	(0, +, 0)				
21	(–, +, –)	(–, +, 0)	(–, 0, –)	(–, 0, 0)	(0, +, –)	(0, 0, –)	(0, 0, 0)	(0, +, 0)
22	(–, 0, +)	(–, +, +)						
23	(–, 0, 0)	(–, +, +)	(–, –, –)					
24	(–, 0, –)	(–, –, –)						
25	(–, –, +)	(–, –, 0)	(–, 0, +)	(–, 0, 0)				
26	(–, –, 0)	(–, –, –)	(–, –, +)					
27	(–, –, –)	(–, –, 0)						

For example, the second line of Table 7 indicates that it is possible to transfer the triplet (+, +, 0) into the triplet (+, +, +) or (+, +, –).

The transformation table can be appropriately modified as needed to solve problems. However, the transformations shown in this table are based on the basic properties of the elementary functions of mathematical analysis. And so they are accepted by a wide range of experts.

The transitional graph H is the directed graph. Its nodes are the scenarios S and T ⊆ (S × S) is the set of the ordered pairs (the transitions based on Table 7):

$$H = (S, T). \tag{11}$$

The transitional graph H represents all possible future times relating to the scenario (Dohnal & Doubravsky, 2015; Doubravsky & Dohnal, 2018).

It can be said that the transition graph defines the arrangement relation of the S set, which enables the identification of mutual transitions between individual scenarios. Thus, using the transition graph, scenarios can be arranged according to their time sequence. On the basis of this arrangement, the behaviour of the system expressed by the trend model can be predicted.

The use of the approach can be shown in the example of a well-known damped oscillation (Dohnal & Doubravsky, 2015).

*Table 8 – The **S** set of scenarios*

Scenario	(*X*, *DX*, *DDX*)
1	(0, 0, 0)
2	(+, –, 0)
3	(–, +, 0)
4	(+, 0, −)
5	(+, –, −)
6	(–, 0, +)
7	(–, +, +)
8	(0, +, –)
9	(+, +, –)
10	(–, +, –)
11	(0, –, +)
12	(+, –, +)
13	(–, –, +)

Table 8 shows the result of the trend analysis of damped oscillation. There are 13 scenarios. Table 7 enables the identification of mutual transitions between these scenarios. Graphical representation of these transitions is the transitional graph H in Figure 2.

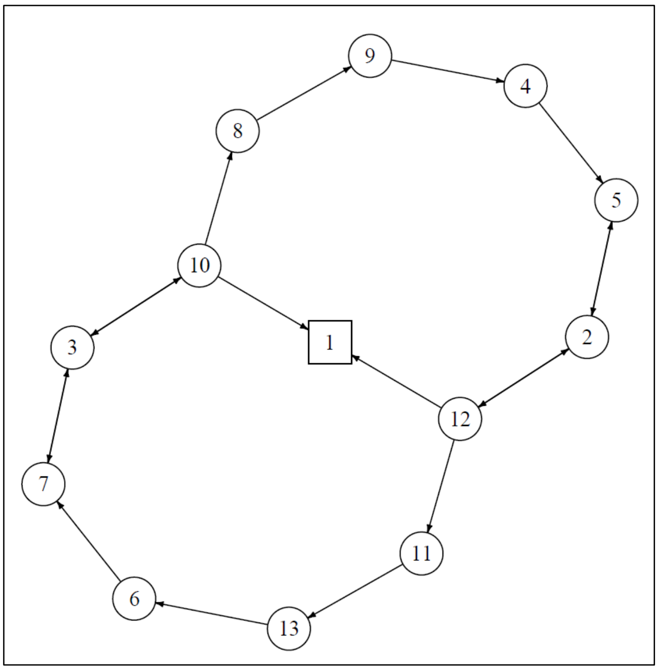

Figure 2 – The transitional graph H

The node's number represents the scenario's number, see Figure 2 and Table 8. There are only edges entering node 1. Thus, if the system goes into node 1, it will remain in it, and therefore node 1 represents a steady state.

It can be seen from Figure 2 that 4 → 5 → 2 → 12 → 11 → 13 → 6 → 7 → 3 → 10 → 8 → 9 → 4 is a closed sequence beginning and ending in node 4. Except for node 1, there are closed sequences for the remaining nodes of the transition graph.

For the transitions 4 → 5 → 2 →… the scenarios are (+, 0, –) → (+, –, –) → (+, –, +) →…

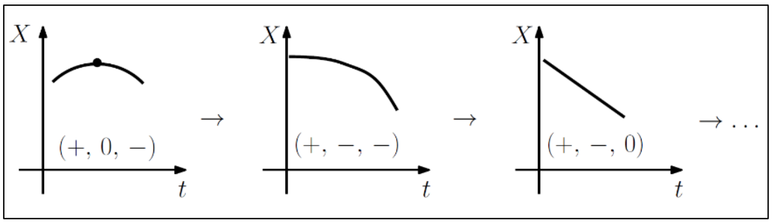

Figure 3 – The pair-wise relations

Each scenario can be graphically interpreted using pair-wise relations (see Figure 1), where instead of the X variable, the time *t* is used. Their pair-wise relations are in Figure 3. The trend function of the *X* variable is given in Figure 4.

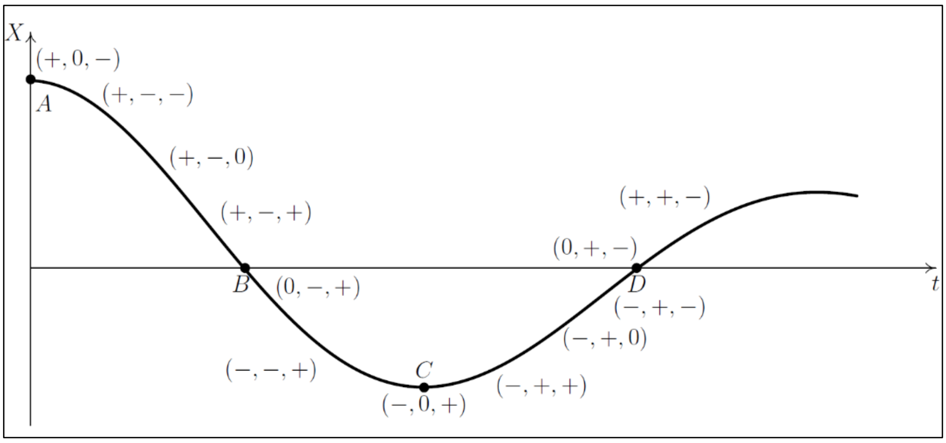

Figure 4 – Trend function of a damped oscillation

A simple common sense analysis of the damped oscillator in classical mechanics indicates that a spring which is currently moving upwards must stop first and then it can move downwards, etc.

3.5 Uncertainty of Qualitative Forecasts

The set of observed variables,

$$X_1, X_2, \dots, X_n \tag{12}$$

is chosen as relevant. It means forecasts will be based on an n-dimensional model. A set X of model **M**'s variables is a union of fully controlled or decision variables D, Goals variables G and not fully controlled variables O:

$$X = D \cup O \cup G \tag{13}$$

where,

$$\begin{gathered} D \cap O = \emptyset, \\ D \cap G = \emptyset \end{gathered} \tag{14}$$

and,

$$\begin{aligned} D &= (D_1, \dots, D_v) = (X_1, \dots, X_v), \\ G &= (G_1, \dots, G_t) = (X_{v+1}, \dots, X_{v+t}), \\ O &= (O_1, \dots, O_w) = (X_{v+t+1}, \dots, X_{v+t+w}). \end{aligned}$$

In this case, the total number of variables equals,

$$n = v + t + w. \tag{15}$$

The O set of variables is not under the complete control of a decision maker. If a decision maker is a company manager or a government, then the O set is different. This is the first reason why future behaviours depend heavily on interpretations of the set of X variables. The second reason is the model under study itself. An n-dimensional model **M** used to forecast is a set of equations or pair-wise relations P (1).

4 CASE STUDY

The proposed method was applied to customers and prospective customers of an enterprise specializing in drive technology for industrial automation in the Czech B2B market. To ensure statistical robustness and representativeness, a quota sampling approach was employed. Quotas were defined across three main variables: industry sector, enterprise size, and respondent profile, with an additional classification of customer relationship status (current vs. prospective). Four key industry sectors were targeted, representing the company's core and adjacent markets: automotive, machinery, electronics, and logistics & warehousing automation. Enterprise size was defined by number of employees, following adapted thresholds for industrial B2B markets:

Small: 1–49 employees, Medium: 50–249 employees Large: 250+ employees Respondents were selected from two main professional profiles. The first group were marketing and sales managers that are directly involved in client acquisition, brand positioning, and digital communication. The second group were technical and procurement managers that are key influencers or decision-makers in supplier selection and technical evaluation.

A total of 226 respondents completed the main survey. The sample size was determined using a finite population correction based on an estimated total population of N = 500 eligible enterprises, in order to achieve a margin of error of approximately ±5 % at a 95 % confidence level for proportion estimates. This approach ensures sufficient statistical precision for B2B customer satisfaction studies. The sample composition intentionally included more small and medium enterprises, reflecting their greater prevalence in the company's customer base and the importance of their feedback for digital marketing strategy.

The research was conducted in two stages. Stage 1 consisted of five focus groups (n = 30) to identify relevant factors for webpage quality evaluation. Factor saturation was reached by the third group. Stage 2 was the main quantitative survey, administered online, where respondents rated their satisfaction with the production enterprise's webpages using the factors identified in Stage 1.

Table 9 – Distribution of respondents

Industry	**Enterprise Size**	**Marketing Sales**	**Technical Procurement**	**Customers**	**Prospects**	**Total**
Automotive	Small (1–49)	12	6	13	5	18
	Medium (50–249)	15	7	14	8	22
	Large (250+)	10	5	11	4	15
Machinery	Small (1–49)	13	5	12	6	18
	Medium (50–249)	14	6	13	7	20
	Large (250+)	9	4	8	5	13
Electronics	Small (1–49)	11	6	10	7	17
	Medium (50–249)	14	6	13	7	20
	Large (250+)	9	4	8	5	13
Logistics & Warehousing	Small (1–49)	12	5	11	6	17
	Medium (50–249)	15	7	14	8	22
	Large (250+)	9	4	8	5	13
Total		153	65	145	73	226

The allocation of respondents in the final sample reflects the actual market structure of the industrial automation sector, where small and medium-sized enterprises (SMEs) represent the majority of potential customers. According to Eurostat and industry-specific market analyses, SMEs account for more than 90 % of enterprises in manufacturing and logistics-related sectors, and they are often the most active users of supplier webpages for information gathering and procurement decision support. By intentionally assigning higher quotas to small (1–49 employees) and medium-sized (50–249 employees) companies, the study enhances external validity and ensures that the findings are generalizable to the dominant market segment. At the same time, the inclusion of large enterprises (250+ employees) preserves the representativeness of high-value accounts with complex procurement processes. The balance between customers and prospective customers supports comparative analysis of satisfaction levels, providing actionable insights for both customer retention and acquisition strategies.

The observed variables listed in Table 10 were identified during the qualitative phase of the study, which consisted of four focus groups with participants representing the industry. These groups helped define key dimensions of customer satisfaction with the company's website, including both general evaluation constructs and specific functional attributes. Subsequently, in phase 2, these identified factors were incorporated into the main quantitative online survey. Respondents rated their satisfaction with the manufacturing company's website based on these factors using a 0–10 scale. The responses from this survey were then used to calculate Pearson's correlation coefficients between all pairs of identified variables, resulting in the numerical correlation matrix C shown in Table 11. This matrix represents the empirical relationships between customer satisfaction (G) and various website attributes (D1–D9, O1–O5).

Table 10 – Observed variables

Description	**Type of a variable, see (13)**
Customer satisfaction	G
First impression of the website	D1
Website navigation	D2
Basic product sorting function	D3
Ease of configuration of the final product	D4
Generator of final product documentation including drawing	O1 (dependent on external suppliers)
Product information complexity	D5
Picture, documentation and drawing quality	D6
Functionality and appearance of the documentation browser, including 3D drawings	O2 (dependent on external suppliers)
E-shop communication to the customers	D7
Reaction rate of the e-shop to customer requirements	D8
Transportation selection, including custom procedures if needed	O3 (dependent on external suppliers)
Payment method selection	O4 (dependent on external suppliers)
Overall product price level	D9
Delivery time	O5 (dependent on external suppliers)

Table 11 – The correlation matrix

	D1	D2	D3	D4	O1	D5	D6	O2	D7	D8	O3	O4	D9	O5
G	0.037	–0.080	0.164	0.317	0.021	–0.024	–0.009	0.012	0.166	0.197	0.243	0.103	0.217	0.134

The trend model **M** is based on using of RED, SUP relations (3) generated using the numerical correlation matrix C, see (Cuervo-Cazurra, Nieto, & Rodríguez, 2018), for 13 variables, see Table 10 and Table 11, and a set of pair-wise relations P formalized by (7).

Table 12 – The trend model M

Relation No.	Type of relation, see (7)	Variable *X*	Variable *Y*, see (3)
1	SUP	G	D1
2	RED	G	D2
3	SUP	G	D3
4	SUP	G	D4
5	SUP	G	O1
6	RED	G	D5
7	RED	G	D6
8	SUP	G	O2
9	SUP	G	D7
10	SUP	G	D8
11	SUP	G	O3
12	SUP	G	O4
13	SUP	G	D9
14	SUP	G	O5

The solution of the model **M** (Table 12) is the **S** set containing nine scenarios. Because the questionnaire survey used a scale of 0–10, all variables are positive, it means that all triplets have the following general form (+, D*X*, DD*X*), (see Table 13).

*Table 13 – Scenarios of the model **M** (Table 12)*

	G	D1	D2	D3	D4	O1	D5	D6	O2	D7	D8	O3	O4	D9	O5
1	(+,+,+)	(+,+,+)	(+,–,–)	(+,+,+)	(+,+,+)	(+,+,+)	(+,–,–)	(+,–,–)	(+,+,+)	(+,+,+)	(+,+,+)	(+,+,+)	(+,+,+)	(+,+,+)	(+,+,+)
2	(+,+,0)	(+,+,0)	(+,–,0)	(+,+,0)	(+,+,0)	(+,+,0)	(+,–,0)	(+,–,0)	(+,+,0)	(+,+,0)	(+,+,0)	(+,+,0)	(+,+,0)	(+,+,0)	(+,+,0)
3	(+,+,–)	(+,+,–)	(+,–,+)	(+,+,–)	(+,+,–)	(+,+,–)	(+,–,+)	(+,–,+)	(+,+,–)	(+,+,–)	(+,+,–)	(+,+,–)	(+,+,–)	(+,+,–)	(+,+,–)
4	(+,0,+)	(+,0,+)	(+,0,–)	(+,0,+)	(+,0,+)	(+,0,+)	(+,0,–)	(+,0,–)	(+,0,+)	(+,0,+)	(+,0,+)	(+,0,+)	(+,0,+)	(+,0,+)	(+,0,+)
5	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,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	(+,–,+)	(+,–,+)	(+,+,–)	(+,–,+)	(+,–,+)	(+,–,+)	(+,+,–)	(+,+,–)	(+,–,+)	(+,–,+)	(+,–,+)	(+,–,+)	(+,–,+)	(+,–,+)	(+,–,+)
8	(+,–,0)	(+,–,0)	(+,+,0)	(+,–,0)	(+,–,0)	(+,–,0)	(+,+,0)	(+,+,0)	(+,–,0)	(+,–,0)	(+,–,0)	(+,–,0)	(+,–,0)	(+,–,0)	(+,–,0)
9	(+,–,–)	(+,–,–)	(+,+,+)	(+,–,–)	(+,–,–)	(+,–,–)	(+,+,+)	(+,+,+)	(+,–,–)	(+,–,–)	(+,–,–)	(+,–,–)	(+,–,–)	(+,–,–)	(+,–,–)

It is relatively easy to generate the list of all possible transitions among nine scenarios (see Table 13), using the transformation table (see Table 7). There are 16 transitions among the set of nine scenarios. The corresponding transitions graph H is given in Figure 5.

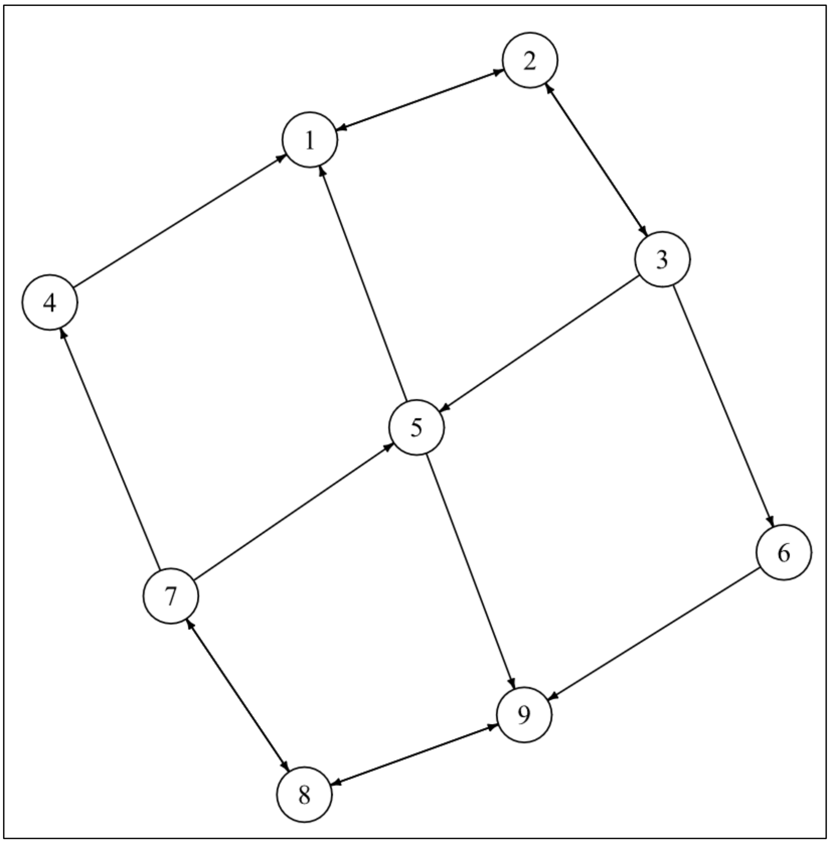

Figure 5 – Transitional graph H based on the set of scenarios in Table 13

Figure 5 shows that the nodes are the scenarios of the set **S** (see Table 13) and oriented arcs are the transitions between these scenarios. Figure 5 gives all possible oriented paths. Any path is a trend description of a forecast or a history. It means that the transitional graph H represents all possible past or future behaviours of the trend model **M** (see Table 12). Any forecast is identical to a choice of a path through the transitional graph H.

Let us consider customer satisfaction (G) is the goal variable and, for example, scenario 8 represents the current situation. Table 10 shows G has the triplet (+, –, 0), it means that customer satisfaction decreases. The management requirement is to increase customer satisfaction. For example, to get to node 1 where G has the triplet (+, +, +); (see Table 13).

Knowledge of scenarios (see Table 13) and transitional graphs (see Figure 5) enables the identification of ways to increase customer satisfaction. Each way is identical to a simple path or paths through the transitional graph H.

Each transition is associated with a change of variables (see Table 10). For example, there is the transition from node 5 to node 9 (see Figure 5). Table 14 shows all factors must change.

Table 14 – Scenarios 5 and 9 (see Table 13)

	G	D1	D2	D3	D4	O1	D5	D6	O2	D7	D8	O3	O4	D9	O5
5	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)	(+,0,0)
9	(+,–,–)	(+,–,–)	(+,+,+)	(+,–,–)	(+,–,–)	(+,–,–)	(+,+,+)	(+,+,+)	(+,–,–)	(+,–,–)	(+,–,–)	(+,–,–)	(+,–,–)	(+,–,–)	(+,–,–)

Thus, each simple path in the graph represents how to set fully controlled factors to achieve a customer satisfaction increase.

There are many algorithms for identifying all simple paths between two nodes in the directed graph. The Depth First Search (DFS) algorithm is used in this paper. For further details of DFS, see Cormen (2009).

There are two paths between node 8 and node 1:

$8 \rightarrow 7 \rightarrow 4 \rightarrow 1$,

$8 \rightarrow 7 \rightarrow 5 \rightarrow 1$.

For example, the path of $8 \rightarrow 7 \rightarrow 4 \rightarrow 1$ shows the goal variable (G – customer satisfaction) must go through nodes 8, 7, 4 and 1 (see Figure 5). It means G must go through this sequence of states (+, –, 0) → (+, –, +) → (+, 0, +) → (+, +, +). A graphical representation of this sequence follows.

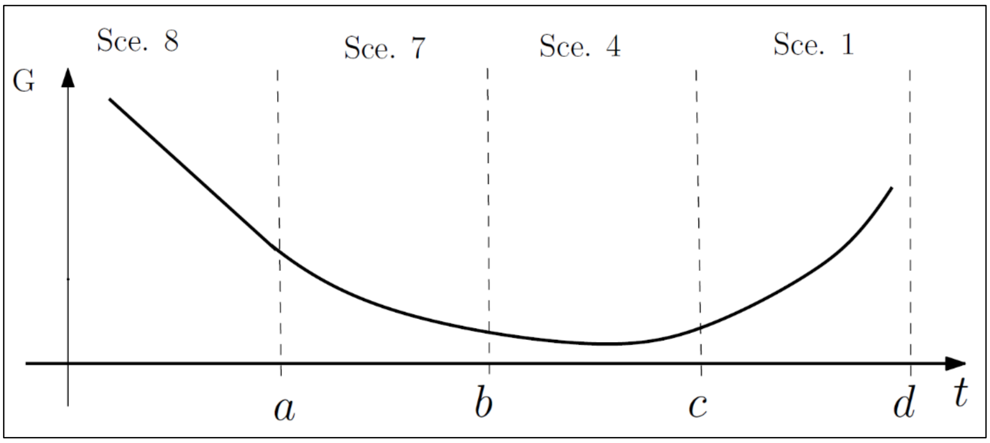

Figure 6 – Trend function of G

Figure 6 does not represent a conventional graph; it is a trend graph. It means that the only restrictions are the inequalities 0 < a < b < c < d. Numerical values of intervals, e.g. (*a*, *d*), are irrelevant. Thus, Figure 6 represents the possible future states of G (customer satisfaction). Similarly, possible states of the factors are illustrated in Figure 7.

Knowledge of the trend functions enables us to get an idea of the relationship between variables. Thus, management has in its hands a means of responding to changes in not fully controlled factors in order to achieve the desired level of the goal variable using changes of fully controlled factors.

For example, G (customer satisfaction) decreases so in order to slow down this decline, G must move to a state represented by scenario 7 (see Figure 6). If the factors O1, O2, O3, O4 and O5 (not fully controlled) decline, Figure 7 (Scenario 7) shows the fully controlled factors D1, D3, D4, D7, D8 and D9 must be declining too and the fully controlled factors D2, D5 and D6 must increase. In our particular case, this means that a company has to improve the web presentation to make it more user-friendly, increase the complexity of product information presented and improve the graphical output quality of the product documentation, including the photos, pictures and drawings. Further recommendations can be formulated analogously to Scenarios 1 and 4.

5 DISCUSSION

5.1 Theoretical contribution and contextualization

This study presents a new formal tool that responds to a specific challenge in the field of customer satisfaction management in B2B markets: a chronic lack of data for robust quantitative analysis. While established models such as SERVQUAL or SEM-based methods are undoubtedly valuable, their applicability is conditional on the availability of large amounts of data, which is often not realistic in a B2B environment. Our approach, based on trend descriptions, therefore does not compete with these methods, but rather provides a complementary solution for data-limited situations. In this way, we contribute to the theoretical debate by linking the principles of systems thinking and qualitative modelling with an issue that has so far been viewed primarily from a quantitative perspective. This approach is particularly relevant in the context of Quality 5.0, which emphasises improving and expanding human capabilities with advanced technologies, ensuring that human operators are an integral part of quality management systems and processes. By transforming qualitative trend descriptions and elements of natural language (NL) data into a structured set of actionable scenarios, our model effectively enhances human decision-making and strategic planning. It empowers managers to interpret complex relationships and make more informed decisions even under data scarcity, thereby elevating their effectiveness within quality management frameworks in the digital age."

5.2 Interpretation of key findings from the case study

The specific application and benefits of the model are demonstrated by the results of a case study. Figures 6, 7, and 8 offer a detailed view of how the target variable G (customer satisfaction) can evolve from a situation of gradual decline to sustained and accelerating improvement.

Figure 5 outlines two alternative development paths from the current state (Scenario 8) to the desired final state (Scenario 1). The first path, 8 → 7 → 4 → 1, represents a more dynamic recovery, while the second, 8 → 7 → 5 → 1, includes a stabilization phase, see Table 12. These two options provide management with a strategic choice: either strive for rapid improvement with higher risk, or take a more conservative approach and consolidate gains gradually.

The first route, 8 → 7 → 4 → 1 (Figure 6), represents a more dynamic recovery path. From the starting point, G (customer satisfaction) moves into Scenario 7, where the decline begins to slow (+, −, +), indicating a deceleration of the downward trend. This is followed by Scenario 4, in which satisfaction levels stabilise but are already building momentum toward positive growth (+, 0, +). The final shift to Scenario 1 brings G into full acceleration, with both the level and rate of satisfaction increasing. The second route, 8 → 7 → 5 → 1, begins in the same way but then passes through Scenario 5, where satisfaction is held steady (+, 0, 0) for a period before it transitions directly into accelerating growth in Scenario 1. This suggests a conscious decision to consolidate gains and ensure stability before committing to broader improvement efforts.

Figure 7 provides insight into how each observed factor changes along the faster path (8 → 7 → 4 → 1). At the initial point in Scenario 8, most factors including D1 (first impression), D3 (basic product sorting), D4 (ease of configuration), D7 (e-shop communication), D8 (reaction rate), D9 (overall product price level), and the externally influenced O1 (generator of final product documentation), O3 (transport selection and customs), O4 (payment method selection), and O5 (delivery time) are in decline at a constant rate. Three factors, however, already show positive momentum: D2 (website navigation), D6 (picture, documentation, and drawing quality), and O2 (documentation browser including 3D), which are improving and contributing to user experience enhancements despite the overall downward trend in satisfaction. In Scenario 7, the slowing decline in G is driven by continuing these targeted improvements in navigation, visual quality, and documentation browsing while allowing other variables to temporarily decline as resources are redirected. Scenario 4 then marks a turning point where most factors level out, creating the conditions for simultaneous improvement across the board. By Scenario 1, nearly all variables are on an upward trajectory, although the initial leader navigation, visual quality, and documentation browsing naturally begin to taper due to diminishing returns once their main deficiencies have been addressed.

Figure 8 illustrates the more conservative path (8 → 7 → 5 → 1), where Scenario 5 acts as a stabilisation phase. Here, all variables, including G (customer satisfaction), hold steady, neither increasing nor decreasing. This pause allows the organisation to reinforce earlier gains, particularly in attributes heavily influenced by external providers, such as O1 (generator of final product documentation), O3 (transport selection including customs procedures), O4 (payment method selection), and O5 (delivery time), ensuring that operational dependencies are managed before resuming broader improvements. The transition from Scenario 5 to Scenario 1 then results in a simultaneous lift in most variables, leading to accelerating G (customer satisfaction). As in the faster path, improvements in D2 (website navigation), D6 (picture, documentation, and drawing quality), and O2 (documentation browser including 3D) eventually slow, but they provide a strong foundation for the wider gains seen at the end state.

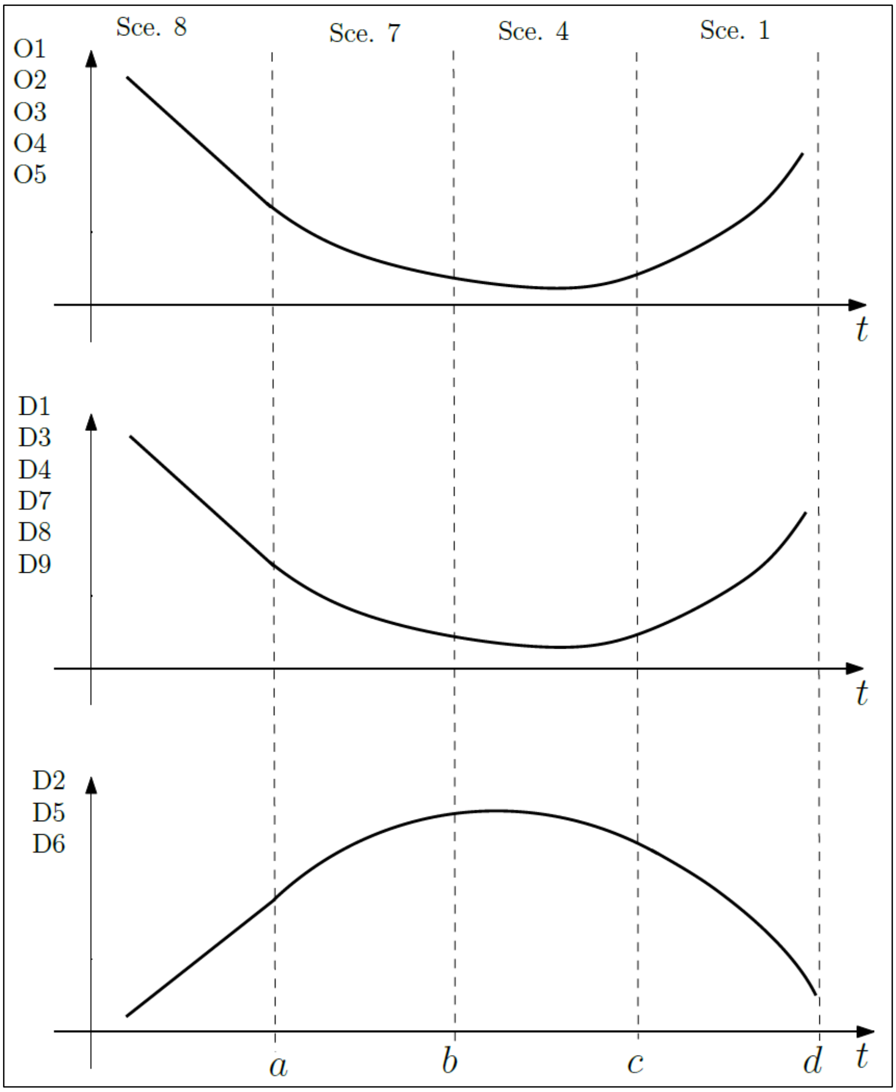

Figure 7 – Trend functions of the factors

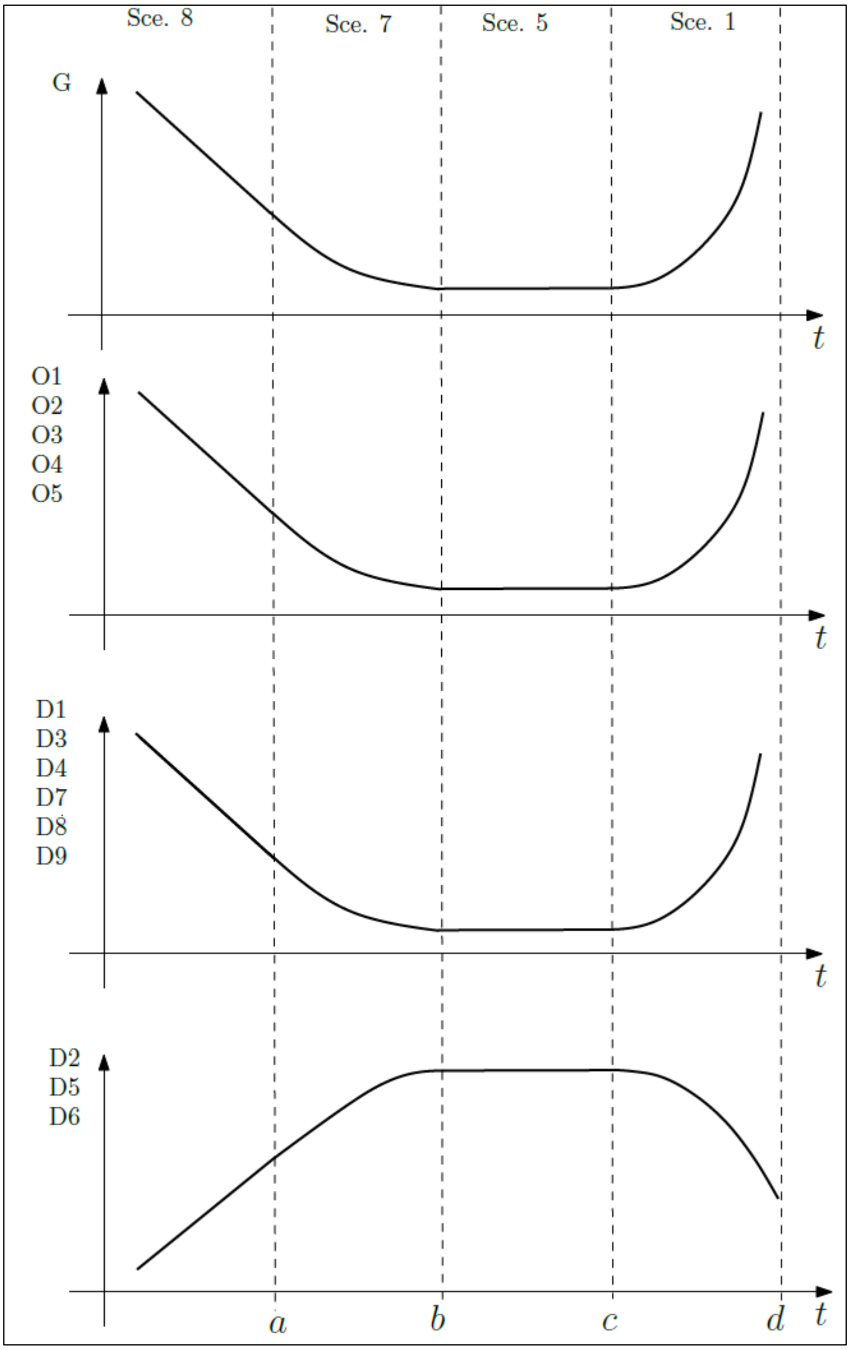

Figure 8 – Trend functions of the observed variables

5.3 Management implications and practical applicability

From a practical point of view, the benefits of our model go beyond mere prediction. Its greatest strength lies in its use as a simulator for strategic decision-making. By generating all possible scenarios and visualising specific paths (as shown in Figure 7 or Figure 8), the model effectively supports the decision-making process. Managers can use these outputs to set priorities for their activities. Instead of relying on intuition, they can allocate resources to those factors that the model has identified as key to initiating positive change (e.g., improving website quality before investing in other areas). This makes the model a tool for more informed and targeted management, leading to improved customer satisfaction.

5.4 Conclusion

This article presented a new predictive model for managing customer satisfaction in the B2B sector, which is specifically designed to function in environments with limited data. The main benefit is a formal tool that generates all possible scenarios for future development based on qualitative trend descriptions, enabling managers to better navigate complex issues and make more informed decisions. The model serves as a support for strategic planning, helps identify critical factors affecting satisfaction, and allows for the prioritisation of activities leading to its improvement. Although the model has certain limitations, it offers a promising and practical approach for companies facing uncertainty and a lack of data, and opens up new possibilities for further research in this area.

However, it is necessary to acknowledge the limitations of our approach, which also open the door to future research. First, the model is qualitative in nature, and its results depend heavily on the accuracy and completeness of the input correlation matrix compiled by experts. The subjectivity of this step represents a potential bias. Second, our model does not generate probabilities for individual scenarios, but only shows their possibility. These limitations directly suggest the direction of future research. It would be beneficial to explore the integration of fuzzy logic into the model, which would allow us to work with vague terms such as "slight improvement" or "significant deterioration" and thus better capture the nuances of managerial judgment. Furthermore, it would be crucial to conduct a longitudinal case study where the model's predictions over time would be compared with actual measured customer satisfaction, which would serve as a form of validation. Finally, verifying the applicability of the model in other B2B sectors, such as professional services or industrial manufacturing, would confirm its robustness and broader applicability.

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CONFLICTS OF INTEREST

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