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Use of Customer Data Analysis in Continuous Quality Improvement of Service Processes

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Abstract

Growth and importance of services are a natural response to wider forces that are creating change in our society. The paradigm shift we have been facing could be described as service revolution. With this paradigm shift, service quality is becoming a critical long-term competitive advantage which companies can obtain with logical and systematic use of statistical methods in continuous quality improvement of service processes, also taking into account recent fast developments of information and telecommunication technology. A so-called integral approach to the use of statistical methods in continuous quality improvement of service processes can be proposed as an alternative to well-known and practically widely applied partial approaches. Based on the possibility to identify individual customers and thus guarantee simultaneous availability of their demographic, socio-economic, transaction and survey data, its theoretical foundations are discussed in this paper along with basic challenges of its practical application.

1 Introduction

Companies in the most developed economies have been aware of the importance of product[2] and process quality for many decades due to theoretical and practical contributions of men who were nicknamed "quality gurus" both by the popular business press and in serious scientific publications. The most prominent among them are Deming, Juran, Crosby, Feigenbaum, Ishikawa and Taguchi (Peace, 1993; Drummond, 1994; Hagan, 1994; Cole and Mogab, 1995; Swift, 1995; Bisgaard, 1998; Easton and Jarrell, 2000).

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[2] Be it either a material good or service.

Service industries embraced the basic quality improvement ideas simultaneously with the manufacturing sector, yet neglected the use of statistical methods in quality improvement processes even more than their manufacturing counterparts. One of the reasons for such a state of affairs is given by differences in nature of services and manufactured goods. They have always been emphasised in the literature, especially with regard to measurability of service quality attributes and, consequently, characteristics of the measurement process. Therefore, the use of traditional (basic and extended) statistical quality control toolbox in quality improvement of service processes has usually a priori been limited to the most basic of tools (e.g., control charts).

This does not mean that complex statistical methods have not been used in the service sector. The toolbox developed by social sciences (containing e.g., exploratory and confirmatory factor analysis) has been proposed as the one to be of use in quality improvement of service processes by authors such as Parasuraman et al. (1985, 1988, 1994), Teas (1993, 1993a, 1994), Zeithaml et al. (1993), Cronin and Taylor (1992, 1994), Lytle et al. (1998), etc. For the better part, the toolbox consists of a series of instruments for measurement of perceived (subjective) service quality which, among other things, differ importantly with regard to applicable measurement scores. SERVQUAL as the most famous model (proposed by Parasuraman et al.) is based on comparisons of quality perceptions and expectations. SERVPERF by Cronin and Taylor is designed with a belief that performance perception scores alone give a good quality indication. Other authors (e.g., Carman, 1990) suggest a three component measurement model including perceptions, expectations and perceived importance ratings or weights of service attributes.

A survey of literature shows that traditional (basic and extended) statistical quality control toolbox is usually addressed in textbooks on production and operations management (e.g., Feigenbaum, 1991; Mitra, 1993; Noori and Radford, 1995; Martinich, 1997), dealing primarily with quality improvement of **manufactured goods**. On the other hand, the social sciences toolbox can be found in textbooks on service management and/or marketing (e.g., Zeithaml and Bitner, 1996; Kasper et al., 1999), dealing almost exclusively with quality improvement of **services**. As a consequence, two distinct partial approaches to the use of statistical methods in continuous quality improvement of service processes at the company level can be identified as shown in Figure 1. The **production function approach (PFA)** is relying on the use of traditional and extended statistical quality control toolbox. The **marketing function approach (MFA)** builds on the social sciences toolbox.

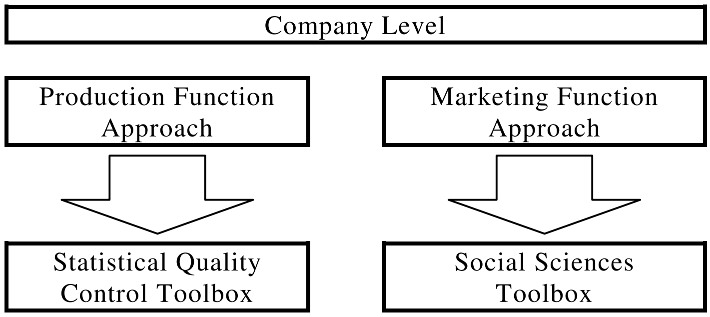

Figure 1: Partial approaches to the use of statistical methods in continuous quality improvement of service processes at the company level.

Apart from differences in statistical toolboxes used, the gap between the two approaches is further characterised by different metrics obtained and analysed. Easton (1995: 22) criticises service companies when he pointedly states:
"While many service companies collect the readily available quantifiable measures of their service processes, these metrics are often not direct measures of the key attributes of the service processes. As a result, many service companies have very few direct process measures - instead, they try to control their processes using customer feedback data. While customer satisfaction is clearly the goal, customer feedback generally cannot be used to effectively control processes because the cycle time for collecting such feedback is too slow and the relationship between the process parameters and the customer's perceptions is often obscure."

In other words, there exists a clear contradiction. Although time is of essence in quality improvement of service processes, a priori limitations have been set to the use of traditional statistical quality control toolbox (which is the trademark of the PFA) in the service sector. Results of customer surveys (which are the trademark of the MFA), on the other hand, are believed to be credible, although they are usually available too late and tend to be too unreliable3 to be of real value in continuous quality improvement of service processes.

Is it possible to change the service sector outlook on the use of statistical methods in continuous quality improvement of service processes? It is certainly possible to identify and/or hypothesise some **prerequisites for change**:

- In modern economies, the range of services is broader than ever. Using the process-focused classification scheme for services proposed by Silvestro et al. (1992: 73) it is possible to differentiate among professional services, mass services and service shops using the following six criteria: people versus equipment focus, level of customisation, extent of employee/customer contact, level of employee discretion, value added in back office versus front office, and product versus process focus. In this

[3] As Chidester (1995: 30) points out, one person's "good" might be either less or more than another's "fantastic".

paper, **mass services** are of special interest since they are characterised by many customer transactions involving limited contact time and relatively little customisation, while the offering is predominantly product-oriented with most value being added in the back office and little judgement applied by the front office staff. For a myriad of mass services facilitated by modern information and telecommunication technology (ITT; examples of services include ATM machines, Internet access, mobile phone services, etc.) their quality characteristics can be measured very accurately using the traditional basic statistical toolbox. In this framework, it can also be experimented with traditional extended statistical toolbox.

- Even if quality characteristics of services cannot be measured very accurately, rapid development of ITT makes it possible for companies to collect and store a wide array of **transaction data** (data on customer purchase and repurchase behaviour in terms of product types, volume, frequency, location, sales personnel, etc.). These data can be analysed by methods from the traditional statistical quality control toolbox and used as proxies for direct quality measures in continuous quality improvement of service processes.
- Transaction data analysis can be enhanced by survey data, taking advantage of the possibility to identify the transaction data source unambiguously (e.g. an individual consumer, a household, etc.) using various types of means. In the framework of this discussion, emphasis is given the use of either bar codes or chip technology in **smart customer cards**, issued in the framework of the so-called **loyalty programmes**[4]. Although these are designed primarily with establishment of **exit barriers** in mind, given the recent ITT development it could be argued that they have begun transcending their role as creators of exit barriers. Since the advent of the smart customer cards, they should be regarded primarily as facilitators of customer data collection. Rayner (1996: 3) agrees by emphasising that the major attraction of loyalty programmes lies in collection of data on customers and their purchasing patterns. She further points out that the means to identify customers opens new possibilities in customer data analysis.

From this exposition, the following **research proposition** can be derived: the means to identify customers in the framework of a loyalty programme opens new possibilities in application of statistical methods to continuous quality improvement of service processes. Simultaneous availability of survey and transaction data for identified customers is the basis for development of a so-

[4] **Loyalty programmes** should induce customers to remain loyal to the company in question over a longer time period, thus countering the influence of the **exit society** which lies in the freedom of choice among various providers of the same product (Irons, 1997a: 18). For a detailed discussion of loyalty programmes' characteristics see Ograjenšek (2002: 102-135).

called **integral approach** to the use of statistical methods in continuous quality improvement of service processes at the company level.

In the following discussion, the deductive (general - specific) research pattern is used to verify the stated research proposition. Firstly, challenges of customer data analysis are presented. Secondly, usefulness of loyalty-programme generated customer data is discussed with regard to development and implementation of an integral approach to continuous quality improvement of service processes. Finally, an overview of prerequisites and tools for practical implementation of the integral approach is given.

2 Challenges of customer data analysis

Customer data collected by companies can be divided into three groups:

- **demographic and socio-economic data** (e.g., gender, age, address, education, profession, income, ownership of real estate, etc.);
- **transaction data** (data on location of purchase and personnel involved, purchase frequency and volume, brand loyalty, complaints, returned products, etc.);
- **survey data** (evaluation of individual quality attributes, indication of brand preferences, etc.).

Characteristics of each customer data type are listed in Table 1.

Table 1: Types and characteristics of customer data: a comparison.

CRITERIA OF COMPARISON	DEMOGRAPHIC AND SOCIO-ECONOMIC DATA	TRANSACTION DATA	SURVEY DATA
Measurement scale level	Nominal-, ordinal-, interval- and ratio-scaled data	Mostly ratio-scaled data	Mostly interval-scaled data
Sources	Loyalty programme membership application forms (LP-MAF), customer surveys (CS)	(Electronic) points of sale (EPOS)	Customer surveys
Strengths	LP-MAF data very reliable when first collected and entered into a database; although less reliable, CS data useful when updating LP-MAF data	Objective, reliable and easy to collect in an existing EPOS network, give information on customers' actual behaviour	Give insight into customers' way of thinking and decision-making
Weaknesses	Reliability of LP-MAF data diminished with the passage of time (regular updating procedures necessary), CS data prone to survey errors	Abundance, which denies users simple ways of access and analysis	Subjective, prone to survey errors, infrequently collected, often incomparable over time due to changes in survey design
Cost	CS more costly to collect than LP-MAF data, LP-MAF data costly to (manually) enter and update	Data storage and database queries are major cost factors	Costly to collect and control for quality
Frequency of analysis	Always used in analysis of survey data, rarely used in analysis of transaction data	Regularly (monthly, quarterly ...) used in standard reports on performance	Annually or biannually, often even less frequently

The analysis of transaction data gives companies information on customers' actual behaviour (the "what"). The analysis of opinions and attitudes, on the other hand, gives them insight into customers' way of thinking and decision-making (the "why"). Transaction and survey data analysis can be further supplemented by inclusion of demographic and socio-economic data.

The wealth of customer data[5] demands of companies both mastering and taking advantage of the concept of **data warehouse**, defined by Inmon (1996: 33-37) as a subject-oriented, integrated, non-volatile and time-variant collection of data in support of management's decisions:

- as **subject-oriented**, it is organised around the applications of the company (e.g., product types or customer segments);
- as **integrated**, it is not affected by inconsistencies in encoding, attribute measurement, etc., at the operational level;
- as **non-volatile**, it remains unchanged (data manipulation takes place in the operational environment);
- as **time-variant**, it contains a sophisticated series of snapshots, taken at different moments in time (current value data are contained in operational databases).

The same author also states that there are **four different levels of detail** in the data warehouse: a current level of detail; an older level of detail (the bulk storage); a level of lightly summarised data; and a level of highly summarised data.

Data flow into the data warehouse from the **operational environment**. Usually a significant amount of data transformation occurs at the passage from the operational level to the data warehouse level. Once the data age, they pass from current to the older detail. As the data are summarised, they pass from current detail to the level of lightly summarised data. Finally, they are transferred from the level of lightly to the level of highly summarised data.

Important decisions that have to be made with regard to data stored in the data warehouse are **which data to store**, **for how long**, and **at what level of aggregation**:

- Companies can use Badiru's (1995: 154) data classification to make an easier decision about **which data to store**. Badiru differentiates among transient and recurring data. **Transient data** appear in the analytical process only once and are not needed again. Therefore, they should also not be permanently stored. **Recurring data**, on the other hand, are encountered frequently enough to necessitate storage on a permanent basis. The latter group of data may be further divided into:

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[5] Real-life data warehouses abroad usually contain data on several millions individual customers or households. In Slovenia, these numbers are reduced to several ten thousands of units. The problems, however, remain the same (the most frequently occurring one being the incompatibility of internal customer databases of demographic, socio-economic, transaction and survey data).

  - **static data** that retain their original values and parameters each time they are encountered in the analytical process (e.g., demographic data such as gender or year of birth);
  - **dynamic data** with the potential of taking on different values and parameters each time they are encountered in the analytical process (e.g., current age or length of membership in a loyalty programme).

- With regard to the **length of data storage**, sometimes (especially in case of financial records) legislative requirements have to be taken into account. From the viewpoint of the company, it only makes sense to store time series of those data that are regularly used in analytical procedures.
- As far as the **level of data aggregation** is concerned, companies have to base their decision upon the results of the cost-benefit analysis (taking into account cost of data storage at various levels of data aggregation, and potential benefits of future analyses). It has to be pointed out that there is nothing worse for a researcher than to find out that data from the past are aggregated at such levels that they cannot be used in analyses at hand.[6]

The most basic approach to explore customer data accumulated in the data warehouse is to use **classic statistical analysis** of either descriptive or inferential nature. This approach is extremely useful in the process of getting acquainted with basic characteristics of the observed population (in case of customers or customer segments the examples could be gender, age, or income structure). As such, it represents the starting point for explorations in unknown directions using quantitative tools that do not classify as statistical.

Frequently, the act of data exploration is referred to as **data mining**, which is most commonly defined as a set of activities used to find new, hidden or unexpected patterns in data. Using information contained within the data warehouse, data mining can often provide answers to questions that decision-makers had previously not thought to ask (Marakas, 1999: 356).

The term **knowledge discovery process** is usually used synonymously with the term data mining. In the literature it is regarded as a more descriptive term, which applies to all activities and processes associated with discovering useful knowledge from more or less aggregated data. According to Marakas (1999: 361-364) these activities and processes can be grouped into four major categories:

- **Classification**, including those activities and processes that are intended to discover rules which define whether an item belongs to a particular subset or class of data (e.g., which groups of customers are most likely to make a certain purchase in the next month).

[6] Two cases are probably similarly bad: finding out that data needed do not exist anymore, or finding them archived in such a way that they cannot be accessed without effort.

- **Association**, including those activities and processes that search for patterns with a high probability of repetition (e.g., if customers buy items A and B, what is the probability for their purchase of items C and D).[7]
- **Sequence**, including those activities and processes that are used to relate events in time (e.g., a sequence of purchase patterns that results in acquisition of a new car).
- **Cluster**, including those activities and processes that are used to group together a set of objects (e.g., customers) by virtue of their similarity or proximity to each other (e.g., what characterises customers who decided not to participate in a loyalty programme any longer).

When describing the activities and processes of knowledge discovery, Marakas focuses only on analysis per se. Other authors (e.g., Adriaans and Zantinge, 1996; or Han and Kamber, 2001), however, argue that the knowledge discovery process also includes data cleaning and integration, data selection and transformation prior to data mining, and additional two steps following data mining, namely pattern evaluation and knowledge presentation. All these steps are routinely part of what Bisgaard (2000) refers to as **scientific method**. Also, they are directly comparable to Bregar et al.'s (1999) **steps of** [statistical] **analysis**.

Which **data mining techniques** can be found in the literature? Marakas (1999: 364-365, 368) enumerates the following:

- **Statistical analysis.** The most mature of all data mining techniques, and the easiest to understand, it is nevertheless difficult to apply in conditions of non-linearity, multiple outliers, and non-numerical data typically found in a data warehouse environment.
- **Neural networks.** This technique is an attempt to mirror the way the human brain works in recognising patterns by developing mathematical structures with the ability to learn. It is the basis for development of non-linear predictive models that are capable of learning how different combinations of variables affect the data set. Technically speaking, the neural network is an interconnected assembly of simple processing elements (units or nodes), whose functionality is loosely based on the animal neuron. The processing ability of the network is stored in the interunit connection strengths (weights), obtained by a process of learning from a set of training patterns (Gurney, 1997: 1). A huge disadvantage of this technique is its "black box" character, making it impossible to formally test hypotheses.
- **Machine learning techniques such as genetic algorithms and fuzzy logic.** They possess the ability to derive meaning from complicated and imprecise data. In comparison to simple forms of regularities or dependencies treated by statistical methods, machine learning techniques can find more complex regularities or dependencies that include both numerical and logical

[7] As such, association is the basis for the analysis of cross-selling effects.

conditions and are far too complex to be observed by humans or discovered by means of conventional statistical analyses.

- **Decision trees.** This is a conceptually simple mathematical method of following the effect each event (or decision) has on successive events (or decisions).
- **Data visualisation.** This technique focuses on the process by which complex numerical data are converted into meaningful images by mapping physical properties to the data, and taking advantage of human visual systems in the process.

Further discussion of data mining techniques would go beyond the scope of this paper, since the focus here is on the use of statistical methods in continuous quality improvement of service processes. Their brief description, however, is necessary in order to determine the nature of relationship between statistical analysis and data mining. From the discussion above the notion that **data mining is a broader term than statistical analysis** could be derived. It has to be pointed out that the review of literature does not yield opposite views. Although Friedman (2001: 7) poses the question whether data mining should be part of statistics, he does not answer it satisfactorily. He merely notes that although some of the data mining techniques (e.g., pattern recognition and neural networks) have statistical roots, they have been largely ignored by statisticians. Table 2 is an overview of differences between statistical analysis and what could be named **non-statistical data mining techniques**.

Table 2: Comparison of statistical analysis and non-statistical data mining techniques.

COMPARISON CRITERIA	STATISTICAL ANALYSIS	NON-STATISTICAL DATA MINING TECHNIQUES
Focus	Knowledge verification (testing of well-formed hypotheses), level of significance given.	Knowledge discovery (digging without prior hypotheses), level of significance not given ("black box" techniques).
Size of data set	Up to several thousand units, limited number of attributes.	Several million units, several thousand different attributes.
Nature of data	Normally distributed, their structure should be well represented by linear models.	Conditions of non-linearity, multiple outliers, and non-numerical data can be dealt with.
Nature of models	Linear, seriously affected by a large number of outliers.	Non-linear, not affected by a large number of outliers.
Limitations of models	Depending on the model under consideration, usually non-linearity, multicollinearity, etc. The problem of missing values, errors and inconsistencies (data noise). Applicability of results (rules) to new data sets due to temporal and other constraints.	Accounting for the information, which is vital for decision-making processes, yet not included in the data warehouse. The problem of missing values, errors and inconsistencies (data noise). Applicability of results (rules) to new data sets due to temporal and other constraints.

One of the main differences between statistical and non-statistical data mining techniques is the emphasis on **mining without prior hypotheses** in case of non-statistical data mining techniques, which is far from principles of scientific research. Increasingly, more and more authors write in opposition of such a view. Rayner (1996: 4) is an example, stating that more and more practitioners agree how major data analyses must be justified on the basis of focused questions, the answers to which will lead to definite actions.[8]

It is difficult to predict whether a compromise between these two divergent points of view can be found. It could be argued that classic statistical analysis should be used in the early stages of the research to help formulate the focused questions, answered with the help of non-statistical data mining techniques. However, a certain degree of freedom is probably necessary in the process of applying non-statistical data mining techniques, helping researchers to clear their minds of preconceptions and stereotypes.

Nevertheless, the role of the scientific method and information technology is not to be underestimated either in the process of selecting the right customers and/or customer segments or in the process of serving them properly, thus supporting the following **goals of continuous quality improvement**:

- **maximisation of the customer lifetime value**, pursued through better customer segmentation and consequently better addressing the needs of identified customer segments[9];
- **faster and more problem-free unwinding of processes** achieved through shorter waiting lines, faster handling of complaints, etc.

Given the increasing availability of customer data, different types of models can be found to account for these goals. Cook et al. (1999) differentiate between customer and service provider models:

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[8] How rigorous should the testing of hypotheses be in the business setting is another issue for discussion. Targett (1983: 33-34) claims that managers rarely require a high degree of statistical rigour, since they have to react swiftly to patterns and irregularities emerging in [customer] data. When testing a hypothesis, they therefore rely on a wide range of methods, including qualitative ones.

[9] The **customer lifetime value** is defined as the value of a customer to the supplier over the entire period for which that customer is loyal to, or purchases from, the supplier (Rayner, 1996: 103; Hallowell and Schlesinger, 2000: 216). It can be calculated as the difference between the total volume of purchase and all applicable costs.

The concept of the customer lifecycle is not identical to **customer's life cycle**. The latter is characterised by events such as graduation, change of jobs, marriage, birth of the first child, divorce, retirement, major illness, etc. (Berry and Linoff, 2000: 79-80). Although not broadly advertised, milestones are often suggested by changes in customer demographic and socio-economic data (e.g. family name, address, income level) or transaction data (e.g. changed purchase patterns after childbirth).

- **Customer models** have a predominantly external focus, since they are used with the goal of maximising the customer lifetime value. They are divided into customer behaviour models and service quality impact models:
  - **Customer behaviour models** are either dynamic or stochastic models of customer retention. The former focus on the issue of customer loyalty and attempt to model it; the latter tend to examine customer behaviour during a single service encounter.
  - **Service quality impact models** examine the interaction between the customer and the service system. Attention is typically focused on the relationship between customer satisfaction and its impact on profitability. Two types of service quality impact models can be found in the literature; aggregate and disaggregate models. In case of the former, behaviour is aggregated across customers. The models then strive to decompose the positive impact of customer satisfaction into direct effects and indirect effects related to increased market share. In case of the latter, behaviour is treated at the individual level and the models attempt to project the financial impact of specific aspects of service.

- **Service provider** or **normative models** (much more frequently encountered in practice than customer models, although often in very simplified forms) have internal focus, since they strive to predict and evaluate the effects of alternative decisions on internal process flows. They are divided into marketing and operations models, which clearly signals their partiality:
  - **Normative marketing models** focus on the complaint management process, incentive systems for service providers, making of trade-offs between customer satisfaction and productivity in quality improvement processes, etc.
  - **Normative operations models** focus on queuing and scheduling (such aspects of service that have limited customer interaction or are applicable to both manufacturing and service). They tend to be industry-specific.

It has to be pointed out that several obstacles lie in the way of modelling on the basis of customer data. Added to the basic problem of data quality is the selection of sampling procedures, which would facilitate a selection of a representative sample of an ever growing customer population. Another huge problem are time restrictions imposed on model assumptions with rapidly changing population structure and characteristics. Last but not least, it is often a non-existent cooperation between businesspeople, IT experts and statisticians that effectively prevents any gains from customer data modelling and analysis.

3 Partial approaches versus an integral approach to continuous quality improvement of service processes

A detailed comparison of the **partial approaches** to the use of statistical methods in continuous quality improvement of service processes at the company level is necessary in order to determine their strengths and weaknesses more precisely. Selected comparison criteria are listed in Table 3.

Table 3: Partial approaches at the company level: comparison of characteristics.

CRITERIA OF COMPARISON	PRODUCTION FUNCTION APPROACH (PFA)	MARKETING FUNCTION APPROACH (MFA)
Theoretical background	Classic texts on statistical quality control	Texts on service management and marketing
Focus	Internal (back office - design and production - technical quality)	External (front office - delivery - perceived quality)
Standards	Objective (precisely determinable)	Subjective (customer expectations)
Statistical toolbox	Traditional SQC toolbox	Social sciences toolbox
Mode of application	Ex ante, real time and ex post	Ex ante and ex post
Goal of application	Design quality into products and processes in order to prevent negative service experiences	Use customer feedback to discover areas in need of quality improvement
Quality of tangible components	Measured directly with an array of different tools	Measured indirectly through customer observations
Quality of intangible components	Measured indirectly through expert observations	Measured indirectly through customer observations
Resulting measures	Direct process measures	Indirect customer perception measures
Time frame of measurement	Measures available very quickly	Measures available with considerable delay
Cost of measurement	Measures obtained at a low cost	Measures obtained at a high cost (due to survey design, implementation and evaluation)
Frequency of application	Very high (e.g., hourly, daily…)	Very low (e.g., annually or biannually)
Required level of employee quantitative literacy	Relatively low	Relatively high

In some cases it is extremely difficult to draw a clear line between characteristics of the production and marketing function approach. The internal and external area where quality is determined may be perceived as separate functions, yet they can hardly be separated in the service setting. Therefore, the entries in Table 3 should be understood as those **predominantly** characteristic for each approach. For example, PFA is characterised through its predominantly internal focus. However, some of its methods[10] (e.g., mystery shopping) can also be applied in the front office analysis. Also, not all MFA methods are so costly that companies could not afford to apply them more frequently than once or twice a year.

At the first glance, the comparison of both approaches shows that production function approach is clearly preferable to the marketing function approach in terms of cost, time frame, frequency of application and required level of employee quantitative literacy, to name just a few most important categories.

At the second glance, however, it could be argued that none of the approaches could completely replace the other. Haller (1998: 92-93) states that the best method to measure service quality does not exist. A variety of methods can be used to determine service quality, each based on a different understanding of the concept of quality, and therefore useful in different types of analyses. The same could also be claimed for both approaches.

As shown in Table 3, goals of PFA and MFA differ. Placed into the framework of continuous quality improvement, however, it could be stated that **when accounting for special and common causes of variation, the approaches complement each other**.

The idea to link these two complimentary approaches is supported by a number of authors (e.g., Collier, 1991; Brown and Bond, 1995; Kordupleski et al., 1995; Cook et al., 1999) although they do not indicate its operationalisation. Kordupleski et al. (1995: 85) come closest by saying: *"… there must be a link between customer needs and processes that can be directly managed. We should attempt to construct, for each customer need, an internal metric associated as closely as possible with that customer need. If we are successful, there should be a strong statistical relationship between the internal metric and the quality score for the corresponding customer need."*

Similar thinking is also the basis of an **integral approach** to the use of statistical methods in continuous quality improvement of service processes at the company level that can be developed in the framework of a loyalty programme. By linking demographic, socio-economic, transaction and survey data of identified customers, the following quality control and improvement goals can be achieved:

- **Transaction data** are available daily. Therefore, they should be analysed with the goal of fighting special causes of variation in service processes. These are due to acute or short-term influences which are normally not part of the process as it was designed or intended to operate (Beauregard et al., 1991: 15). Juran (1989: 28) refers to the process of finding and eliminating them as "fire-fighting", usually achieved with the statistical process control (SPC).

[10] For a detailed discussion of PFA and MFA methods see Ograjenšek (2002: 63-87).

- **Survey data** are available yearly or even less frequently. Therefore, they should be used as the basis for analysis of common causes of variation in service processes, also referred to as “historic” or “chronic” variation - the variation which seems to be built into the process (Beauregard et al., 1991: 15-16). This type of variation can be reduced by redesigning the service processes and thereby achieving quality improvement.
- **Demographic and socio-economic data** should be used as a link between transaction and survey data. Additionally, they should help companies characterise identified individual customers and/or customer segments.

A **hypothetical example** can be used to illustrate the basic idea of the integral approach: comments and criticisms with regard to service quality can be collected in a customer survey and used when designing or redesigning service processes. Customer reactions to changes in service design, on the other hand, can be monitored by means of real-time transaction data analysis, which, if deemed necessary, enables swift corrections. Therefore, transaction variables could also be referred to as **leading indicators**.

4 Instead of conclusion

A long-term cross-industrial empirical verification of the practical applicability of the integral approach to the use of statistical methods in continuous quality improvement of service processes at the company level as suggested in this paper remains one of the research challenges for the future. However, a preliminary study of links between transaction and survey variables on a sample of loyalty programme members of a well-known Slovene company in 2001 proved their existence and revealed **several problems**:

- Among the **problems of statistical-methodological nature** at least the following deserve special attention: complex database structure (which is due to huge numbers of units and attributes); distributions of variables which are far from normal; non-linear nature of links among transaction and survey variables; and bias introduced into models due to the fact that characteristics of loyalty programme members might importantly differ from characteristics of non-members. Existence of all but the last problem calls for the use of non-statistical data mining techniques. The last problem - possible differences in characteristics of loyalty programme members and non-members - should be accounted for both in analytical and decision-making processes. For example, knowing of the existence of differences it would be most unwise to use loyalty programme members as the focus or experimental group, especially if non-members represent the bulk of company’s customers.

- Among the **problems of practical nature** it has to be mentioned that we were not granted full and direct access to real-life customer data. Furthermore, a small sample size (only 1000 units) prevented us from experimenting with non-statistical data mining techniques (e.g., neural networks), which could have accounted for the non-linearity of discovered relationships between transaction and survey variables.

To conclude, preliminary research into the feasibility of the integral approach to the use of statistical methods in continuous quality improvement of service processes at the company level gave enough indications to justify further efforts in this area, provided that the role of customer loyalty programmes as facilitators of customer data collection will be further expanded in the future. With respect to this requirement, two different **possibilities** are discussed in the literature:

- People **most committed** to customer loyalty programmes see the use of customer data generated in their framework as the driving force of a genuinely customer-oriented business. Given the present technological developments, a complete redefinition of the retail process could take place in the not so distant future. Rayner (1996: 4) envisions systems more powerful than those currently available, communicating individually with millions of customers, capturing and directly satisfying their individual needs.
- People **most sceptical** about customer loyalty programmes predict a backlash against them, partly as a result of general disillusionment with their benefits, but mostly as an emotional reaction against the failure of automated processes to support personal relationships that some loyalty programmes appear to be offering (Rayner, 1996; Irons, 1997). Interestingly enough, the issue of customer privacy does not seem to be in the forefront of these discussions.

Whether or not customer loyalty programmes are going to stand the test of both ethical considerations and time, it has to be pointed out that they are definitely not the only means to collect data of identified entities (customers and households).

In other words, customer data analysis will probably continue to thrive - with or without customer loyalty programmes. As always, there will be the leaders who will have recognised its potential far in advance of everybody else, and there will be followers; some profiting from explorations of their predecessors, others finding it difficult to keep pace with rapid developments of information technology and analytical approaches. As the market has it, only the strongest will survive. Hopefully those, willing to use their knowledge and profits for benefit of all their stakeholders, not only a handful of privileged owners and executives.

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