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# Forecasting the Future Requirements of Customers for New Products

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## Abstract

This study focuses on finding a conceptual framework which can be used to predict the future customer requirements (CRs). of the target market segment for new product development. The lack of historical data is a problem for forecasting when it comes to new products, so existing forecasting methods are carefully examined. When developing new products, the first step is to understand the customer needs or requirements and their importance. Then, Kano Model is used to identify customer requirements' categories, to modify weights and predict the changes of states for each customer requirement. With the help of Markov Chain, the probability of states for each CR is predicted to generate four data points. At this point Grey Theory is a suitable tool, as it only requires four data points for a robust forecast. Grey Model (1,1) is applied to the data to predict the change in weight of CRs. To demonstrate the framework in work, a case study on notebooks has been realized. The framework is illustrated on an example new product.

**Keywords:** Customer Requirements, Kano Model, New Product Forecasting, Markov Chain, Grey Theory

**JEL Codes**: C53, M11, E37, O32

## 1. Introduction

The 20th century saw rapid change in the political, technical, and scientific environments and conditions, which has led to many structural differences in how businesses can operate today and make a profit. The concept of "mass production and standardization" emerged after the Industrial Revolution because of the availability of new machines with higher production capacities and the integration of energy sources into industry. Particularly after World War II, companies have achieved the freedom to conduct business abroad and compete for market share.

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Therefore, apart from niche markets, businesses in the production and service sectors competed on an equal footing to offer acceptable quality at the lowest prices possible, approaching the customer as a group rather than as an individual with a distinct mindset.

However, the individualism trend gained popularity in the 1970s, and customers started to demand and desire products tailored to their specific needs. Additionally, customer satisfaction has become a more important academic topic, especially in the field of marketing. The success of a product is thought to be determined by how much it satisfies customers; thus, "true quality" was defined as how much it satisfies the customer base (Akao, 1997). As a result of this shift, businesses have begun to invest in projects that measure and analyze the interests, motivations, and needs of their potential customers. Quality Function Deployment (QFD), which was created during this time and became essential to business management, served as a successful example (Akao, 1997).

With the development of the Internet, later WEB 2.0, e-marketing, and social media, the status quo in business has changed further significantly, and this change continues with each new technological development that is integrated into daily life and gained acceptance from large customer groups. Globalization enabled logistic chains to span almost the entire globe. Because of increased Internet usage, the cost of acquiring information has significantly decreased. Product life cycles have shrunk. Customers began to pay attention to innovative products.

These changes have made market competition extremely fierce, with market leaders able to differentiate themselves only through minor advantages. A high level of customer satisfaction with continuously improved products or service offerings is still a necessity to achieve greater business impact (Matzler & Hinterhuber, 1998; Bhattacharya, 2014). Now, to reach customers based on new and evolving preferences and behaviors, businesses must become more adaptable and agile in a world undergoing unprecedented change, particularly with the global Covid Pandemic. They must not only understand their customers' requirements but also anticipate future changes in their requirements for faster adaptation or a better chance of satisfying customers.

Although it is not frequently discussed in the literature, there is growing interest in the use of forecasting tools to anticipate future customer requirements. Research in this area primarily focuses on demand forecasting, adaptability and diffusion of new products, market penetration of new products, and high-detailed customer need analysis for new and existing products using QFD and/or Kano Model. The combination of structured customer requirements analysis with forecasting methodologies is rather limited, even though there are numerous diffusion models and time series forecasting techniques available for new products.

Time series analysis can be useful for products in well-established, stable markets. However, to preserve customer satisfaction when a new product is introduced to the extremely dynamic market, the specifications should not become out of date or less important, and the product should be in its most desirable and competitive state. Therefore, new frameworks are required to evaluate and forecast changes in customer requirements or their significance to customers/market for new products or those products with shorter life cycles.

Few studies that attempted to forecast the weight or importance of future customer requirements used rather simple methods such as Moving Average or Exponential Smoothing. Some other studies have used grey forecasting to make short-term forecasts, but they all used historical data to train their models.

Thus, there is a need for combining a forecast system that can detect the changes in customer requirements, interpolated from a QFD study or other analysis. There were some attempts to deal with this problem in literature such as; (H. H. Wu et al., 2005) have used GM (1,1) model to deal with this problem but that four periods of historical data was required. Wu and Shieh (2008) applied Markov Chain modeling to predict future weights of CRs however they classified the importance of CRs as High, Medium, and Low and attaining them weights of 5, 3 and 1 respectively.

This study aims to find a conceptual framework which can be used to predict the future customer requirements (CR) of the target market segment for new product development. With the combination of QFD methodology and Kano model, a detailed analysis about customer preferences is extracted. The change rate between Kano categories is calculated with Markov Chain matrix to produce input for GM (1,1) to forecast the weights of CRs.

## 2. Literature Review

The use of forecasting techniques to predict future customer needs is uncommon in the literature, but there is growing interest in this area. While diffusion models and forecasting with time series are abundant, the combination of QFD means and forecasting methods is somewhat limited.

### 2.1 Methods for Identifying Customer Requirements

Raharjo et al. (2010) carried out a time series analysis of historical data about customer needs from Kano questionnaires. Using compositional double exponential smoothing, the results for each Kano category, which are in percentage data form, are forecasted. Then, the importance rankings for customer needs are derived from Kano results and integrated into QFD model for better product success in market. Integration of Kano's Model into QFD to better identify Voice of Customer (VoC) is critical and is related to the topic of this study. The life cycle of attributes for CRs described by Kano is highly dynamic and the results from this study reflect this. According to this paper, application of multiple time series forecasting techniques doesn't only make QFD input more robust but also useful for implementing future strategies in the context of customer driven innovation.

Use of fuzzy logic for new product specification has also been applied in literature (Jeddi, 2016). Usually, the input variables in forecasting have been assumed to be numerical however this will not be the case for customer requirements. The authors suggest that incorporation of fuzzy set logic can be an answer to confront this question (Jeddi, 2016).

Kano Model can be also used to categorize different attributes. In an attempt to measure satisfaction among participants in university-industry cooperation efforts in Korea, a new index is calculated through Satisfaction and Dissatisfaction score of participants (Suh et al., 2019). Using the work of Sireli et al. (2007), a satisfaction index was calculated. Their aim was to find where the biggest improvement to satisfaction lies, therefore introduced an index called Potential Customer Satisfaction Index (PCSI). Using these two indexes and AHP method, they produced a matrix where cooperation areas lie and classified as "to be improved", "excellent", "care-free" and "surplus". The matrix will help to understand where effort must have been made to improve overall satisfaction and benefits of such cooperation.

There have been studies utilizing QFD for analyzing future and emerging trends in industries. A QFD framework was introduced by (Ju & Sohn, 2015) consisting of three hierarchical House of Quality stages which were based upon opinions of experts and patent analysis. Three stages are for megatrends, then future technology product and primary level of technology classification. This framework is suggested to be used for selecting which one to invest in and put R&D effort in from different promising technologies. It is exemplified by data from robotics industry; they came up with three different business model suggestions. The study mentions that better suited forecasting methods can be implemented (such as technology diffusion) within their framework as well.

### 2.2 Studies on Forecasting Customer Requirements

A paper has reviewed and developed a model of new service popularity (Vrdoljak et al., 2012). They have used Service Life Cycle growth models and Bass Model to predict how the new clip will gain popularity among viewers. They have used semantic similarity to gather input parameters to use in Bass Model to forecast growth. Certain new features of a product can be modeled with Diffusion Models if a similarity between historical product requirements can be established. This would, in return, make the forecast error smaller.

One of the applications of this combination has taken place in software industry (Purohit & Sharma, 2016). Their idea of forecasting customer requirements stemmed from the dynamic nature of customer requirements and the lag between QFD data collection phase and actual product launch. Thus, in today's rapid changing world, the actual product will not be able to satisfy customers; hence forecasting is a necessity for QFD (Purohit & Sharma, 2015). They have used data mining forecasting techniques in their process. The study constructed a framework for data management system, with the purpose of forecasting. While the main aim of this study is not to explain how this process would work but designing a software database and simplifying it; it is important because forecasting of customer requirements found out by QFD is described as critical.

Another paper, where data mining techniques have been used for QFD in order to predict future customer requirements (CR) for computer designers and manufacturers was published in Taiwan (Hsu et al., 2012). Based on a huge amount of data collected by a Taiwan manufacturer with sales questionnaires, time series-based data mining cycle techniques have been applied to predict future CRs. Having access to data of the last four periods, the weights of CRs, consequently engineering requirements (ER) are calculated. It has been suggested that this technique provides an effective procedure of identifying the trends of CRs and enhances customer relationship management in the computer marketplace (Hsu et al., 2012: 8).

Forecasting the future trends is also closely related to the purpose of this study. An example was found in cell phone industry, where the researchers have analyzed customer reviews on similar products on web and identified positive or negative trends (Tucker & Kim, 2011). Using the data that has emerged from their analysis; they stated that the positive trends, which means they are being demanded by users, correspond to "Attractive Quality" in Kano's Model. This information can help design engineers to enhance the new cell phone or the next version of the cellphone. Product features, which a negative trend has been found for, can be similarly eliminated, or substituted for the next period. The technique used here is called Holt-Winters exponential smoothing method and accuracy of the forecast is evaluated by Maximum Absolute Percent Error (MAPE). This study is important in that the input for forecasting obtained from publicly available customer review data and easy to collect.

Markov chain modeling and grey forecasting methods have also become a point of interest for analyzing and predicting customer requirements. Markov Chains are a specific type of stochastic models, in which the probability of a change happening depends upon the initial state of the model. They are used in a variety of fields; inventory management, predicting changes in market shares, stock prices, QFD projects, health services.

To describe the model further; we can assume a set of "$n$" states in $S = [s_1, s_2, s_{3,\dots}, s_n]$ and the process starts in a certain state at $t = 0$. The state, which the process starts, depends on the initial probabilities. When the transition probabilities are steady state or stationary, the Markov chain can be used to forecast future values. The probabilities of these state changes are called as 'transition probabilities', donated as $p_{12}, p_{11}, p_{13}$ and together they constitute square arrayed $P$ matrix.

An important function of Markov Chain Models is that; they can be used for obtaining probability results after "$n$" step transitions. To calculate the state probabilities, at the period "$n$", the following equation can be used.

$$Q * P^n \tag{1}$$

where $Q = [p_{(s_1)t=0}, p_{(s_2)t=0}, \dots, p_{(s_n)t=0}]$containing initial probabilities.

This feature of Markov Chain Modeling would be beneficial when forecasting the probabilities of the Kano categories that CRs belong to.

The use of Markov Chain is not limited to predicting the weight of customer trends in literature. In a later study, researchers applied Markov chain model to analyze the relationships between TMs and CRs from a probabilities point of view in case of incomplete information and data (Wu & Shieh, 2008). It is stated in another study that drawing of the relationship matrix between TMs and CRs is a vital part of each QFD practice since the final analysis and key decisions heavily depends on it (Wu & Shieh, 2006). When designing a House of Quality, this relationship usually takes the name of "the relationship between WHATs and HOWs"; WHATs refer to CRs and HOWs refer to TMs. This relation is assumed to be known by members of the team that is leading the QFD practice, usually a cross-functional team covering up different areas. However, in real life situations, the experience of the team may not be enough and/or due to limited information, it might be difficult to assess the relationship correctly. Thus, use of Markov Chains in this part of the QFD analysis, could approach it with a probabilities point of view (Wu & Shieh, 2008). The paper also makes an illustrative example of how their models work. For simplicity, the example only includes two CRs and one TM. After the assumption of the weights of relationship between CRs and TM, as strong, medium, and weak respectively, for the initial probability matrix; the probability matrix of the change of relationships from state to state is calculated. Calculation of the new weights after one, two and three transitions as well as steady state weights is done. The results are plotted on a graphic for each CR including after transition weights. Also, the output of the model could be used to monitor the importance trend of TMs and the model is flexible enough to update for whenever new data becomes available. The prioritization of TMs can be possible with this model for decision makers.

Grey Model is useful for problems where there is incomplete data, whether due to uncertainty or unavailability. Common usage areas are analysis of the relation between different systems, modeling, forecasting and decision-making problems.

The main contrast between traditional forecasting methods and forecasting with grey models is that grey model forecasting doesn't require large amounts of historical data. Actually, only four data points are needed to implement a grey model forecast (Deng, 1989). Grey Model is suitable for smaller amounts of data and this attribute of the model makes it a good candidate when dealing with processes such as new product forecasting when historical data is limited by definition (Wu et al., 2005). The model is given as follows.

$$x_{(0)}(k) + az_{(1)}(k) = b \tag{2}$$

The coefficients of $a$ and $b$; are called developing coefficient and grey input.

$$z_{(1)}(k) = ax_{(1)}(k) + (1 - \alpha)x_{(1)}(k-1) \tag{3}$$

$$x_{(1)}^{n} = \sum_{m=1}^{n} x_{(0)}^{m}$$

After calculation of coefficients, the forecast model GM (1,1) takes the form of

$$f_{(1)}(k) = \left(x_{(0)}(1) - \frac{b}{a}\right) e^{-a(k-1)} + \frac{b}{a} \tag{4}$$

In the equation above $k$ represents the forecast step, while $f_{(1)}(k)$ is the general solution for the grey equation. Calculation of $f_{(0)}(k)$, which will give the final forecasted values for periods.

$$f_{(0)}(k) = f_{(1)}(k) - f_{(1)}(k-1) \tag{5}$$

The resulting series is the forecasted values for given period; $k$.

Wu et al. (2005) proposed a model implementing GM (1, 1) method using the periodical QFD outputs, such as the weights of customer requirements; the relationship between CRs and technical measurements (TM), to forecast the weights of CRs for the 5th period based on the four data points observed historically. Forecast error percentage was low and organized graphics can be of help to monitor the changes. The relation of CRs with TMs could give companies a direction to check and plan which processes are important for customer satisfaction and how that can change in upcoming periods.

A Chinese study investigated the customer requirements analysis with two sub-sections; first clustering CRs with TMs, then implementing a trend analysis for CRs to see how their importance will change in future (Chen & Wang, 2008). They tested their method with data from an electrically powered bicycle manufacturer, as the demand for such bicycle had been growing and the company is eager to know

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future importance of bicycle features to help them with decision-making to implement feature in their new products. With historical data from the company for the last four periods, GM (1,1) forecasting method is applied to predict near future. The dynamic nature of CRs (and the related TMs) is noted by scholars and trends of each CR are plotted on a graphic to visualize the data. It has been suggested that this forecasting method will help company to satisfy or even exceed customer requirements, keeping their customers satisfied which will in turn increase the company's competitive power in marketplace.

## 3. Methodology

The most critical aspect of forecasting studies on new products is the lack of historical data on the product or service in question. The primary goal of this research is to develop a quantitative model that can predict the importance of customer requirements for new products as well as future trends. The proposed framework first prioritizes the customer requirements for a new product, and then forecasts the future importance weights of these requirements based on their initial values. The stages of the framework are shown in Figure 1. The following sections go into greater detail.

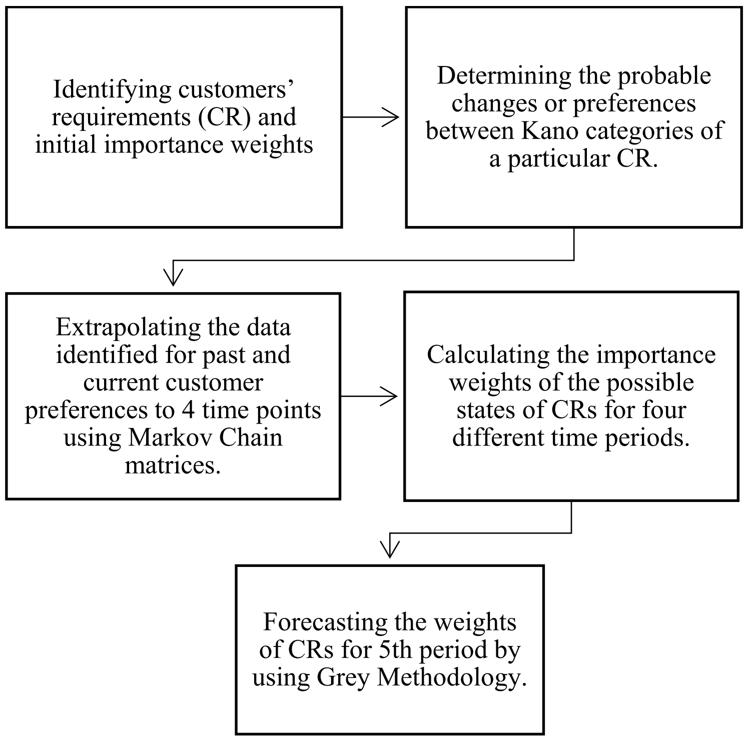


**Figure 1.** The stages of the proposed framework

### 3.1 Identifying Customers' Requirements and Initial Importance Weights

In the first part of the methodology, the QFD tools and Kano Survey will be used to collect customer related data. While QFD means are to be used for identification of CRs and the initial weights of them according to their importance to customers, determination of which Kano category each CR belongs will be determined by specially designed questionnaires (Kano Survey). The outputs from these models will be input to Markov chain matrices and later, to grey forecasting techniques. This stage includes the following operations:

- Identifying customer requirements for a new product by using QFD means.
- Calculating initial importance weights of the requirements of customers for a new product.
- Prioritizing the requirements of customers for a new product.

The initial determination of CRs is important which can be achieved by listening to "Voice of Customer". Suggested framework starts with identifying CRs with usual QFD practices, such as Gemba visit, focus groups, customer surveys or getting expert opinions and customer reviews.

After determining the CRs, the next step becomes finding out how important they are in the eyes of customers. Then initial raw weights of these CR's are asked to customer on a 1-9 Likert scale, which are averaged. This form is rather straightforward; asking customers how important it would be, if a product has certain features that can satisfy the CR. The scale used here, is a 9 point "Likert Scale" the same one used in Stehn and Bergström (2002). Integrated design and production of multistorey timber frame houses - Production effects caused by customer-oriented design ranging from "Not at all important" to "Extremely important". This is also advised by literature and used commonly in practice along with Kano questionnaire (Berger et al., 1993: 12).

### 3.2 Determining Probable Changes/ Preferences between Kano Categories

The second stage of this model aims at getting information about the variation in the level of importance customers attach between two time points for the same customer need. This observed variation will be used as basis for calculating the probabilities of transition from one category to another. Once the probabilities are obtained, they will be used as inputs onto the Markov chain matrices in the next stage. The following are the necessary calculations for generating these inputs.

- Adjusting of the initial weights of CRs by Kano categories they belong to via basic form.
- Determining the change between Kano categories of a particular CR by customers' last and current choice/point of view.
- Applying the frequency of the change of CRs in a Markov Chain Matrix to find out transition probability matrices.

The Kano Model classifies customer requirements under different categories according to how strong they are related to overall customer satisfaction. Kano in his paper (1984) argues that the impact of attributes on customer satisfaction can be greater or lesser depending on where they fall on the spectrum. There are four categories in this model so, a CR can fall under; Must be (expected by customers), One dimensional (linearly related to customer satisfaction), Attractive (is not expected by customers but has a high effect on satisfaction) and Indifferent (doesn't affect satisfaction). Identification of these categories is determined by the Kano Questionnaire. In the design of Kano questionnaires, participants are asked to evaluate their reaction given two situations (Table 1). The first form of the questions, called functional form, asks about the situation when a CR is met through the product. The second question, called dysfunctional form, asks about when the same CR is not provided or its absence (Berger et al., 1993: 7). The participants' answers are evaluated to the rules in "Evaluation Table" (Table 2), taken from (Matzler & Hinterhuber, 1998: 32).

**Table 1:** The Design Format of Kano Questionnaire

| ***Functional Form*** | |
|---|---|
| How would you feel if a laptop is easy to carry? | I would be delighted to find it that way |
| | I expect it to be that way |
| | I am neutral |
| | I would not like it that way but I can live with it that way |
| | It must not be that way |
| ***Dysfunctional Form*** | |
| How would you feel if a laptop is not easy to carry? | I would be delighted to find it that way |
| | I expect it to be that way |
| | I am neutral |
| | I would not like it that way but I can live with it that way |
| | It must not be that way |

**Table 2:** Evaluation Table

| Product requirement → / ↓ | | Dysfunctional form of the question | | | | |
|---|---|---|---|---|---|---|
| | | 1. I like it that way | 2. It must be that way | 3. I am neutral | 4. I can live with it that way | 5. I dislike it that way |
| Functional form of the question | 1. I like it that way | Q | A | A | A | O |
| | 2. It must be that way | R | I | I | I | M |
| | 3. I am neutral | R | I | I | I | M |
| | 4. I can live with it that way | R | I | I | I | M |
| | 5. I dislike it that way | R | R | R | R | Q |

**Source:** Matzler & Hinterhuber (1998: 32).

Customers last purchase preferences are also asked with the same questions; however, an explanation of situation is given as the headline information. The instructions are given as: "*Remember the last time you have purchased a new laptop or considered buying one. Please mark the appropriate option on the given scale for following items, as if the whole statement reads as "How would you feel if a laptop has an aesthetic appearance?"*. As an output of this part, two choices of customers can be inferred about that particular CR for each participant, a past and current one.

Classifying CRs into Kano categories is an attempt to get more information out of "voice of customer". In parallel to customer preferences, voice of customer also changes over time, especially the current situation of reduced time for new product introductions. New technologies are being adopted and getting acceptance by a broader user base (Xie et al., 2003). An attractive attribute at first launch, if successful, will be demanded more within time. Also, further down the production, costs are reduced so product price will become lower, making the attribute accessible to larger customer bases. A recent example is smart features in cell phones, at first, they were used and adopted rarely but today have become so mainstream that even elderly people must buy them even if they will not be able to take advantage of its full features. The change in state of a certain CR within time is possible for other categories as well.

In this study, Kano model and a modified Kano questionnaire will be used for gathering customer preferences data about product features. As implemented by two studies on this topic (Wu et al., 2005: 1244; Wu & Shieh, 2008: 640), modifying the questionnaire with asking customers about their last time purchases will be useful if an analogous or similar products already exist on the market.

Second part is where the forecasting the future needs of customers takes place. Since new products are considered in this study, it shouldn't be expected that there is historical data at hand to be relied upon. Therefore, more traditional quantitative methods such as simple moving average or exponential smoothing cannot be used. As mentioned, methods that don't require much data such as grey forecasting model or Markov chain probability models have been proposed in literature before. There has been an interest in this topic in literature recently however, a combination of such methods; namely Markov Chain Model and Grey Forecasting Method and a case study showing how it can work hasn't been done. This study differs from others as it shows fully integration of Markov Chain Modeling and Grey Forecasting in the context of analysis of future customer needs for enriching QFD practices.

### 3.3 Extrapolating Preferences Data to 4 Time Points using Markov Chain

Extrapolating the data identified for past and current customer preferences to 4 time points using Markov chain matrices, which refers to the the future possible states of customer requirements.

While Kano categories are descriptive, their integration into weight of CRs needs further work. In this stage, the purpose is to extend the data identified for two time points, i.e. kano category of customer requirements, to 4 time points using Markov chain matrices in order to forecast/predict how the states of customer requirements would change.

Tontini (2003) suggested using Satisfaction Index and Dissatisfaction Index to quantify the Kano questionnaires results as an adjustment factor. The results show that attractive attributes can be given more weight in the House of Quality. In a different fashion, the absence or poor quality of "Must-be" requirement will lead customer dissatisfaction, so it is also more important compared to where the CR is more likely to be classified as "Indifferent" category. The model suggested by Chuadra et al. (2011: 693) bases this effect of states on two indexes; the Satisfaction Index (SI) and Dissatisfaction Index (DI) and adjusts the weights according to Kano questionnaire results.

### 3.4 Calculating Importance Weights of the Possible States of CRs

This stage will calculate the importance weights of the possible states of customer requirements for four different time periods. It requires recalculating SI and DIs with data from 4 time points, finding adjusted importance weights of customer needs for 4 different time points. The adjustment factor that will be found in this stage is the maximum value of DI or SI for that particular CR, summed with 1. Then the raw weight is multiplied by this adjustment factor. This step is repeated for each data point in Markov Chain prediction for how the states would change. Then the whole process will be repeated for all other CRs.

The adjustment factor suggested by Tontini (2003) will be used to correct initial weights by the category probability each CR belongs to. These probabilities can change every period as mentioned, with changing customer opinions. Therefore, Kano questionnaire is implemented with a tweak in this study. Another set of question added which ask customers about their past choices as suggested by Wu and Shieh (2008). A "Transition probability matrix" (called P) can be created with results of customer past and current choices. The results for first point (i.e. customers' past choices) on the timeline constitute the initial probability vector of the Markov chain. The power of P matrix is taken to 3 steps to generate four different data points with different adjustment factors each step. Multiplication of these numbers newly generated adjustment factors with raw weights of CRs from "Self-Stated Importance" question would result in adjusted weight scores.

### 3.5 Forecasting the Weights of CRs for 5th Period Using Grey Model

The final stage will be run to find the future importance ratings of CRs.

With four different weights created by Markov chain matrices, then GM (1,1) forecasting method is applied to find future importance ratings of CRs. The weights of importance will be listed as original series, such as $x_{0(CR_n)}$ with four elements. "$CR_n$" specifies on which customer requirement the process has been done.

$$x_{0(CR_n)} = \left(w_{CR\_n}(1), w_{CR\_n}(2), w_{CR\_n}(3), w_{CR\_n}(4)\right) \tag{6}$$

Then, AGO (Accumulated Generating Operation) series of $x_{0(CR_n)}$ will be calculated. This series is named as "$x_{1(CR_n)}$". The relationship between these two series is given as;

$$x_1^n = \sum_{m=1}^{n} x_0^m \tag{7}$$

Thus turning $x_{1(CR_n)}$ into;

$$\begin{aligned} x_{1(CR_n)} = \Big(&w_{CR\_n}(1),\ w_{CR\_n}(1) \\ &+ w_{CR\_n}(2),\ w_{CR\_n}(1) + w_{CR\_n}(2) \\ &+ w_{CR\_n}(3),\ w_{CR\_n}(1) + w_{CR\_n}(2) \\ &+ w_{CR\_n}(3) + w_{CR\_n}(4)\Big) \end{aligned} \tag{8}$$

To whiten the series, $z_1$ series also needs to be calculated; as it represents the whitened values. The series is whitened to smooth the randomness of the original series and gain a clear rule (Slavek et al., 2015: 8225). The formula for $z_1$ , is given by Equation 4;

$$z_1(k) = ax_{(1)}(k) + (1-\alpha)x_{(1)}(k-1) \tag{9}$$

Here, $a$ value is taken as “0.5”, in accordance with the literature (Wu et al., 2004: 1243). $k$ represents the number of forecasting steps.

The original formula for $x_0$ series can be written as in GM (1,1) format;

$$x_0(k) + az_1(k) = b \tag{10}$$

This Equation 10 can be revised as Equation 11;

$$\begin{vmatrix} x_0(2) \\ x_0(3) \\ x_0(n) \end{vmatrix} = \begin{vmatrix} -z_1(2) & 1 \\ -z_1(3) & 1 \\ -z_1(n) & 1 \end{vmatrix} \quad \begin{vmatrix} a \\ b \end{vmatrix} \tag{11}$$

Then, vector $\begin{vmatrix} a \\ b \end{vmatrix}$ needs to be calculated. “$a$” is developing coefficient and “$b$” is grey input. By least square estimation, values for “$a$” and “$b$” is estimated from;

$$a = \frac{\sum_{k=2}^{n} z_1(k) \sum_{k=2}^{n} x_0(k) - (n-1)\sum_{k=2}^{n} z_1(k)x_0(k)}{(n-1)\sum_{k=2}^{n}[z_1(k)]^2 - [\sum_{k=2}^{n} z_1(k)]^2} \tag{12}$$

$$b = \frac{\sum_{k=2}^{n}[z_1(k)]^2 \sum_{k=2}^{n} x_0(k) - \sum_{k=2}^{n} z_1(k) \sum_{k=2}^{n} z_1(k)x_0(k)}{(n-1)\sum_{k=2}^{n}[z_1(k)]^2 - [\sum_{k=2}^{n} z_1(k)]^2} \tag{13}$$

Grey forecasted series is defined by $f_1$ and it is calculated as;

$$f_1(k) = \left(x_0(1) - \frac{b}{a}\right) e^{-a(k-1)} + \frac{b}{a} \tag{14}$$

This series is "grey" equivalent to $x_1$, which was AGO series of $x_0$. To find out the Grey forecast values for original series, IAGO series of $f_1$ needs to be calculated as given in the following Equation 15.

$$f_{(0)}(k) = f_{(1)}(k) - f_{(1)}(k-1) \tag{15}$$

The resulting series will consist of predicted values of weights of CRs.

## 4. Implementation

To demonstrate how the suggested framework works, a case study has been carried out for a hypothetical new product. A new product definition usually covers new to the world products, modified or improved products or even imitation products being new only the company (Ulrike, 2001: 170). In this study, for the sake of simplicity; an improved product category has been selected to analyze, instead of new to the world type of new product.

The sample product is chosen as a notebook modified with some innovative features compared to the existing products on the market. First, the CRs for notebooks have been identified based on previous QFD work on notebooks with innovative ideas as improved features added in. Once all CRs have been identified, a modified form of Kano questionnaire; with the addition being another added form, asking participants about their past choices; has been applied with "Self-Stated Importance" part as well. Each participant's survey has been analyzed individually. With the results of the questionnaire, the weight of CRs for current time and the change rates between Kano categories have been calculated. Also, to integrate Kano categories into CR weights, adjustment factor has been used. Incorporating these values into a transition probabilities matrix and initial probability vector, Markov Chain was taken to 3rd step. This gave CR weight results for four periods, with past choices serving as base, which are minimum required data points for Grey Forecasting Model. Then, the weights of CRs are forecasted with GM (1,1) method.

**Stage 1: Identifying Customers' Requirements and Initial Importance Weights**

Customer requirements can be determined by using several QFD means. Since it is the main purpose to determine the importance weights and future trends of customer requirements obtained through various methods, a sample product has been selected in this study and a list of customer requirements has been determined with the those determined in previous studies and the additions made with desk-research within the scope of this study. See other studies on how to identify true customer needs or requirements by using the powerful tools from QFD methodology (Özdağoğlu et al., 2018; Chin et al., 2019).

The product to implement the suggested framework is chosen as notebooks due to innovative features they tend to have and frequent model updates coming as new products. CRs for laptops are identified from three studies Wang (2008), Ko and Lo (2016), Chen and Huang (2015) with a couple of new features added in, frequently appearing in futuristic reviews on notebooks from tech magazines, totaling 24 CRs for notebooks. A summary of these studies is given in Table 1.

**Stage 2: Determining Probable Changes/ Preferences between Kano Categories**

This study made use of "Self-stated Importance Questionnaire", usually applied alongside basic form of Kano questionnaire. The participants are asked to evaluate the importance of a CR being present in a notebook, on a Likert Scale, from one to nine. Below is an example of how an item is asked with headline information of "*Assume that you are planning to buy a new laptop. Please rate the importance of following items based on your opinion*."

**Table 1:** Customer Requirements Identified from Other Studies

| *Application of green quality function deployment and fuzzy theory to the design of notebook computers (2016)* | *The synergy of QFD and TRIZ for solving EMC problems in electrical products – a case study for the Notebook PC (2015)* | *QFD optimization with Kano's Model (2008)* | *Quantification and integration of Kano's model into QFD for optimising product design (2014)* | *Customer Needs (This study)* |
|---|---|---|---|---|
| Design of appearance | | Stylish design | Stylish design | Aesthetic appereance |
| x | Fashion and exclusiveness | x | x | In line with latest trends |
| Convenient portability | Compact and easy to carry | Light and mobile | Mobility | Easy to carry |
| | | | | Smaller space allocation |
| Shock Absorbance | Damage resistant and low failure rate | x | x | Damage resistant |
| Display | Keyboard and screen are of the proper size and with | Large screen size | x | Cristal Clear View |
| x | Keyboard and screen are of the proper size and with | x | x | Comfortable to Use |
| x | x | Multimedia function | x | Compatible with different media types |
| x | Fast execution speed | x | x | Very fast execution |
| Operation time | Long battery life | | | Long operation time without charging |
| | | | | Low failure rate |
| Product not scratched easily | Damage resistant and low failure rate | x | x | Damage resistant* |
| Price | Continuously pursuing maximized | x | x | Inexpensive |
| Memory size | x | x | x | Very fast execution * |
| x | Fast execution speed | High computing speed | High computing speed | Very fast execution * |
| Hard drive space | x | Large storage | Large storage | Able to storage large size programs/data |
| Brand | Fashion and exclusiveness | x | x | x |
| Reputation (Brand image that has been established | x | x | x | Increases my reputation |
| Zero environmental pollution | x | x | x | Zero environmental pollution |
| Re-cycle for re-use | x | x | x | Re-cycle for re-use |
| x | Hazard free materials and operating process | x | x | Safe physical interaction |
| x | x | Wireless LAN | x | Connectivity to the different devices |
| x | x | Remote Control | x | Commandable without touching |
| x | x | Expandable device | x | Expandable storage capacity |
| x | Featuring wireless networking and powerful | High network performance | High network performance | Connectivity to the different devices* |
| x | Immediate mass production for market launch | x | x | x |
| x | x | Solid audio capability | Solid audio capability | Solid audio capability |
| x | x | Powerful graphics solution | Powerful graphics solution | Powerful graphics solution |
| x | x | x | x | Flexible (folding) display |
| x | x | x | x | Upgradable |

**Source:** Authors' original work

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Participants' answers to "Self-stated Importance Questionnaire" will be used for calculating raw importance weight for CRs. The average weight is found by the number of participants multiplied by each score category then divided by total participant number.

The questionnaire is formatted with Google Docs and distributed by e-mail. It was sent to people who are either business professionals or had professional experience before. This group was chosen as the most common laptop user, especially among the employees. Therefore, the developed product will especially represent the needs for this segment. Responses of 65 participants are examined individually. The raw weights of CRs are calculated according to "Self-stated Importance Questionnaire" results for each CR. Raw weights of CRs are normalized again for the data to be shown in percentages of total importance. Then, each CR has been given a ranking; "CR 9 – Very fast execution" came up as the most important CR, scoring a raw weight of "8.50" and accounting for %4.87 of total importance (Table 2).

**Stage 3: Extrapolating Preferences Data to 4 Time Points using Markov Chain**

After this step, answers to dysfunctional and functional questions are examined. Using Kano Evaluation Table, each CR has been assigned to Kano categories of Attractive (A), One Dimensional (O), Must be (M), Indifferent (I). After classification, percentages of each category have been found for each CR.

For example, CR 9 has been assigned to One Dimensional category, with percentages of each category "%23.08", "40.00", "12.31", "24.62", in A-O-M-I order. From these results, SI and DI indexes can finally be calculated. These indexes are calculated by equations below based on Tontini's (2003) work.

$$\mathrm{DI} = \frac{p_O + p_M}{p_A + p_O + p_M + p_i} \qquad \mathrm{SI} = \frac{p_A + p_O}{p_A + p_O + p_M + p_i} \tag{16}$$

Next step is to calculate adjustment factor, which is the maximum value of DI or SI for that CR, summed with 1. Then the raw weight is multiplied by this adjustment factor. This multiplied by raw weight gives the four different weights for CR22. The results are given in Table 3.

Table 4 shows how using Kano categories and adjustment factor can change importance ranking of CRs. The calculations are show for first period in this table. The results here imply that Adjustment factor has been effective in changing the importance ranking. CR 6 – Crystal Clear View has jumped from 6$^{th}$ to 2$^{nd}$; CR 12 – Inexpensive has gained the 3$^{rd}$ ranking. These demonstrate the need for adjustment of raw weights with Kano model.

**Table 2:** Initial Importance Weights of Customer Requirements

| CR List | Weight | Importance | Order |
|---|---|---|---|
| Aesthetic appereance | 6,59 | 3,78% | 19 |
| In line with latest trends | 6,80 | 3,90% | 18 |
| Easy to carry | 8,09 | 4,63% | 5 |
| Smaller space allocation | 7,20 | 4,12% | 15 |
| Damage resistant | 8,15 | 4,67% | 4 |
| Cristal Clear View | 8,02 | 4,60% | 6 |
| Comfortable to Use | 7,70 | 4,41% | 10 |
| Compatible with different media types | 7,02 | 4,02% | 16 |
| Very fast execution | 8,50 | 4,87% | 1 |
| Long operation time without charging | 8,28 | 4,75% | 2 |
| Low failure rate | 8,20 | 4,70% | 3 |
| Inexpensive | 7,65 | 4,39% | 12 |
| Able to storage large size programs/data | 7,35 | 4,21% | 13 |
| Increases my reputation | 5,89 | 3,38% | 22 |
| Zero environmental pollution | 6,33 | 3,63% | 20 |
| Re-cycle for re-use | 6,02 | 3,45% | 21 |
| Safe physical interaction | 7,70 | 4,41% | 10 |
| Connectivity to the different devices | 7,73 | 4,43% | 9 |
| Commandable without touching | 5,70 | 3,26% | 24 |
| Expandable storage capacity | 6,88 | 3,94% | 17 |
| Solid audio capability | 7,76 | 4,45% | 8 |
| Powerful graphics solution | 7,98 | 4,57% | 7 |
| Flexible (folding) display | 5,72 | 3,28% | 23 |
| Upgradable | 7,24 | 4,15% | 14 |

**Source:** Authors' calculations

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**Table 3**. Adjustment factor for each period and predicted weights of CR22

| Period | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| SI | 0,52 | 0,63 | 0,69 | 0,71 |
| DI | 0,43 | 0,48 | 0,56 | 0,63 |
| max(SI,DI) | 0,52 | 0,63 | 0,69 | 0,71 |
| **Adj. Factor** | **1,52** | **1,63** | **1,69** | **1,71** |
| Raw Weight | 7,98 | 7,98 | 7,98 | 7,98 |
| **Predicted Weights** | **12,13** | **13,01** | **13,49** | **13,65** |

**Source:** Authors' calculations

**Table 4:** Adjusted Weights and Rankings of CRs

| CR List | Weight | Importance | Order | Adj.Weight | Adj. Imp % | Adj. Order |
|---|---|---|---|---|---|---|
| Aesthetic appereance | 6,59 | 3,78% | **19** | 10,18 | 4,00% | **15** |
| In line with latest trends | 6,80 | 3,90% | **18** | 9,83 | 3,87% | **17** |
| Easy to carry | 8,09 | 4,63% | **5** | 11,90 | 4,68% | **7** |
| Smaller space allocation | 7,20 | 4,12% | **15** | 9,95 | 3,92% | **16** |
| Damage resistant | 8,15 | 4,67% | **4** | 12,15 | 4,78% | **5** |
| Cristal Clear View | 8,02 | 4,60% | **6** | 13,85 | 5,45% | **2** |
| Comfortable to Use | 7,70 | 4,41% | **10** | 11,19 | 4,40% | **11** |
| Compatible with different media types | 7,02 | 4,02% | **16** | 10,27 | 4,04% | **14** |
| Very fast execution | 8,50 | 4,87% | **1** | 13,86 | 5,45% | **1** |
| Long operation time without charging | 8,28 | 4,75% | **2** | 11,81 | 4,65% | **10** |
| Low failure rate | 8,20 | 4,70% | **3** | 12,96 | 5,10% | **4** |
| Inexpensive | 7,65 | 4,39% | **12** | 13,22 | 5,20% | **3** |
| Able to storage large size programs/data | 7,35 | 4,21% | **13** | 10,88 | 4,28% | **12** |
| Increases my reputation | 5,89 | 3,38% | **22** | 7,53 | 2,96% | **21** |
| Zero environmental pollution | 6,33 | 3,63% | **20** | 8,19 | 3,22% | **19** |
| Re-cycle for re-use | 6,02 | 3,45% | **21** | 7,69 | 3,03% | **20** |
| Safe physical interaction | 7,70 | 4,41% | **10** | 11,84 | 4,66% | **9** |
| Connectivity to the different devices | 7,73 | 4,43% | **9** | 10,50 | 4,13% | **13** |
| Commandable without touching | 5,70 | 3,26% | **24** | 7,20 | 2,83% | **22** |
| Expandable storage capacity | 6,88 | 3,94% | **17** | 8,85 | 3,48% | **18** |
| Solid audio capability | 7,76 | 4,45% | **8** | 11,87 | 4,67% | **8** |
| Powerful graphics solution | 7,98 | 4,57% | **7** | 12,12 | 4,77% | **6** |
| Flexible (folding) display | 5,72 | 3,28% | **23** | 7,02 | 2,76% | **23** |
| Upgradable | 7,24 | 4,15% | **14** | 9,38 | 3,69% | **17** |

**Source:** Authors' calculations

**Stage 4: Calculating Importance Weights of the Possible States of CRs**

Another piece of information needed for Markov Chain Matrix is also inferred by comparing participants' answers for their past and present choices. To build the transition probabilities matrix "P", changes of customers perception regarding CRs under which Kano category to be classified is needed. For each participant of the survey, both of their past "Kano choice" and present "Kano choice" is noted. An excel document is prepared for each CR. A 4*4 matrix table has been created. The rows represent their past choices and columns represent their current one. Here is the example table for CR 9. (Table 5).

**Table 5:** Changes in Customer Perception for CR 9

| CR 9 | *A* | *O* | *M* | *I* |
|---|---|---|---|---|
| ***A*** | 9 | 4 | 2 | |
| ***O*** | 1 | 22 | 3 | |
| ***M*** | | 1 | 7 | |
| ***I*** | 5 | 6 | 2 | 3 |

**Source:** Authors' calculations

To clarify how Table 6, number in the first row, first column (9) represents the number of participants, who classified CR 9 as Attractive in their past and current evaluation. Fourth row, first column number (5) represents the number of people who classified CR 9 in Indifferent category with their past choices but in their current evaluation changed it into Attractive.

These tables are constructed for each of the 24 CRs. They will serve to calculate transition probabilities. To get this, each section in the table is divided by the sum of the numbers in their respective rows. So for transition probabilities matrix ($P$), first row first column is calculated with 9/(9+4+2); resulting as "0.6". This represents the probability that for this CR, attractive selection will stay as attractive for the next period with a probability of "0.6". After the calculation for each section of the matrix; P is inferred for the targeted CR. $P_9$ is given below.

**Table 6:** Transition Probability Matrix for CR 9

| CR 9 | *A* | *O* | *M* | *I* |
|---|---|---|---|---|
| ***A*** | 0,600 | 0,267 | 0,133 | 0,000 |
| ***O*** | 0,038 | 0,846 | 0,115 | 0,000 |
| ***M*** | 0,000 | 0,125 | 0,875 | 0,000 |
| ***I*** | 0,313 | 0,375 | 0,125 | 0,188 |

**Source:** Authors' calculations

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To calculate the probabilities of the Kano category that a CR belongs to for each period/step of Markov Chain, we also need the Q vector, initial probabilities. These are inferred from customers' past choices. For Q vector, data in Table 5 is used again. The sum of the numbers in first column, divided by sum of the all numbers in the matrix (9+1+5)/(9+4+2+1+22+3+1+7+5+6+2+3) gives the initial probability that CR 9 falls under "Attractive" category. Same calculation method for column 2 represents "One Dimensional"; column 3 "Must be" and column 4 "Indifferent" category.

**Table 7:** Initial Probabilities for CR 9

| CR 9 | Initial Probabilities |
|---|---|
| *A* | 0,231 |
| *O* | 0,400 |
| *M* | 0,123 |
| *I* | 0,246 |

**Source:** Authors' calculations

After examination of Kano questionaries' results, for each CR, there are P matrix, Q vector, and raw weight at hand.

The results are analyzed for each participant for the calculation of the transition probability matrix. A Markov chain calculator designed for Excel has been used to calculate each step. Table 8 shows an example of how the results are displayed after Markov Chain modeling.

**Table 8.** The probabilities of CR22 being assigned each Kano category (A,O,M,I) for each period

| CR22 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| A | 0.148148 | 0.2436 | 0.26127 | 0.256817 |
| O | 0.37037 | 0.3899 | 0.431065 | 0.455998 |
| M | 0.055556 | 0.087 | 0.12599 | 0.169096 |
| I | 0.425926 | 0.2795 | 0.181675 | 0.118089 |

**Source:** Authors' calculations

These four predicted weights are used as input to GM (1,1) model. Calculations are done on Excel according to the formulas given in literature (Li and Li, 2016). Forecasted results for GM (1,1) are given below in Table 9.

**Table 9.** Forecast results for CR22 with GM (1,1)

| Period | GM 1,1 |
|---|---|
| 1 | 12.12 |
| 2 | 12.79 |
| 3 | 13.40 |
| 4 | 14.05 |
| 5 | 14.73 |
| 6 | 15.44 |
| 7 | 16.18 |
| 8 | 16.96 |

**Source:** Authors' calculations

**Stage 5: Forecasting the Weights of CRs for 5th Period by Using Grey Model**

After acquiring the much needed four data points, a forecast can be made with GM (1,1) model as explained in methodology. To facilitate the required calculations, the instructions given by Li & Li (2016: 89) are used in Microsoft Excel. Exactly all steps have been implemented to have a template to make the forecasting. According to Liu et al. (2014: 769), the suitability test for GM (1,1) to be built directly can be checked for $k > 3$, a criterion which all the input values for all twenty-four CRs satisfy the conditions for.

To further illustrate how GM (1,1) works, calculations for CR 9 is shown below. First, the predicted weights from the results of Markov Chain Modeling are taken as $x_0$ series. Then following steps, as explained above according to GM (1,1) equations, are carried out.

$$x_{0\ (CR\ 9)} = (13.86, 14.81, 15.44, 15.89) \tag{17}$$

$$x_{1\ (CR\ 9)} = (13.86, 28.67, 44.11, 60.00) \tag{18}$$

$$z_{1\ (CR\ 9)} = (22.06, 36.39, 52.05) \quad k \geq 2 \tag{19}$$

By solving the general GM (1,1) equation "$x_0(k) + az_1(k) = b$" with least square estimation method, values for $a$ and $b$ are obtained as "-0.06888" and "13.8556" respectively. The solution of $f_1(k)$ can be calculated as shown by the Equations 20, 21, 22 and 23.

$$f_1(k) = \left(x_0(1) - \frac{b}{a}\right) e^{-a(k-1)} + \frac{b}{a} \tag{20}$$

$$f_1(4) = \left(x_0(1) - \frac{13.8556}{0.06888}\right) e^{0.06888(4-1)} + \frac{13.8556}{0.06888} = 60.03 \tag{21}$$

$$f_1(3) = \left(x_0(1) - \frac{13.8556}{0.06888}\right) e^{0.06888(3-1)} + \frac{13.8556}{0.06888} = 43.57 \tag{22}$$

$$f_1(2) = \left(x_0(1) - \frac{13.8556}{0.06888}\right) e^{0.06888(2-1)} + \frac{13.8556}{0.06888} = 28.20 \tag{23}$$

To forecast the values for the original series, Equation 24 is used.

$$f_{(0)}(k) = f_{(1)}(k) - f_{(1)}(k-1) \tag{24}$$

$$f_{(0)}(4) = f_{(1)}(4) - f_{(1)}(3) = 16.46 \tag{25}$$

$$f_{(0)}(3) = f_{(1)}(3) - f_{(1)}(2) = 15.37 \tag{26}$$

$$f_{(0)}(2) = f_{(1)}(2) - f_{(1)}(1) = 14.34 \tag{27}$$

For CR 9, forecasted results until 8$^{th}$ can be seen in Table 10.

**Table 10:** Forecasted weights for CR 9

| Period | GM (1,1) |
|---|---|
| 1 | 13,86 |
| 2 | 14,34 |
| 3 | 15,37 |
| 4 | 16,46 |
| 5 | 17,64 |
| 6 | 18,89 |
| 7 | 20,24 |
| 8 | 21,69 |

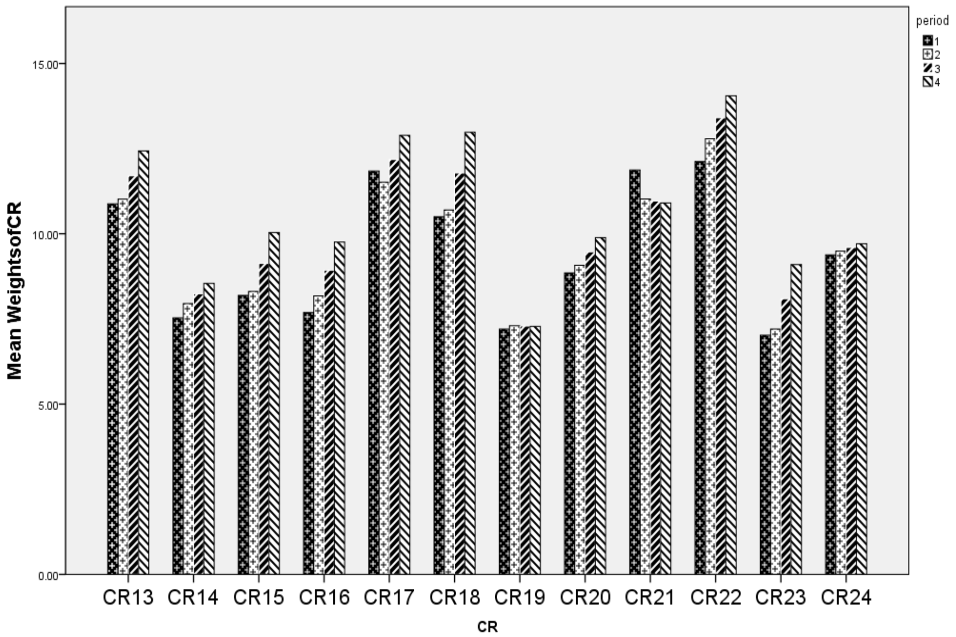
**Source:** Authors' calculations

Results indicate that with the GM (1,1) method, expected weights can exceed theoretical possible limit of 18 for long time periods. The raw weight scale is between 1 and 9. Adjustment factor changes between 1 and 2; as SI and DI can be 0-1 according to nature of the formulas. Therefore, results over 18 are unrealistic with given scales.

Given that GM (1,1) is more suitable for short term predictions (Liu et al., 2014: 770) when the $\alpha$ value is between 0.3 and 0.5 (taken as 0.5 in this study); a cut of point for forecasted periods needs to be set. In this study, it is set at 5th period as; there is no forecasted value that falls out of original scale until this point.

The forecasted change in the weight of CRs 13-24 can be seen in Figure 1 for four time periods.

**Figure 1.** Weights for CR 13-24




**Source:** Authors' estimates

It can be read from Figure 1, CR22 is an Indifferent attribute at first evaluation. However, after 3 periods, it has become a One-Dimensional attribute. This should be reflected in importance ratings, since One Dimensional attributes lead to better customer satisfaction. With the help of adjustment factor, GM (1,1) attains its final importance rating of "16.96". A comparison can be made between initial rankings for each CR and final one.

Table 11 shows the initial and forecasted importance weights of CRs along with the trend they show between first and final periods.

**Table 11.** Final Importance Ranking for 24 CRs

| CR List | Period 1 weights | Period 1 Order | Period 4 weights | Period 4 order | Trend |
|---|---|---|---|---|---|
| Aesthetic appereance | 10,18 | **15** | 10,90 | **15** | ↔ |
| In line with latest trends | 9,83 | **17** | 10,60 | **16** | ↓ |
| Easy to carry | 11,90 | **7** | 12,29 | **10** | ↓ |
| Smaller space allocation | 9,95 | **16** | 10,45 | **17** | ↓ |
| Damage resistant | 12,15 | **5** | 13,90 | **5** | ↔ |
| Cristal Clear View | 13,85 | **2** | 15,93 | **3** | ↓ |
| Comfortable to Use | 11,19 | **11** | 11,38 | **12** | ↓ |
| Compatible with different media types | 10,27 | **14** | 11,27 | **13** | ↑ |
| Very fast execution | 13,86 | **1** | 16,46 | **1** | ↔ |
| Long operation time without charging | 11,81 | **10** | 16,21 | **2** | ↑ |
| Low failure rate | 12,96 | **4** | 13,75 | **6** | ↓ |
| Inexpensive | 13,22 | **3** | 12,04 | **11** | ↓ |
| Able to storage large size programs/data | 10,88 | **12** | 12,43 | **9** | ↑ |
| Increases my reputation | 7,53 | **21** | 8,54 | **23** | ↓ |
| Zero environmental pollution | 8,19 | **19** | 10,04 | **18** | ↑ |
| Re-cycle for re-use | 7,69 | **20** | 9,76 | **20** | ↔ |
| Safe physical interaction | 11,84 | **9** | 12,89 | **8** | ↑ |
| Connectivity to the different devices | 10,50 | **13** | 12,98 | **7** | ↑ |
| Commandable without touching | 7,20 | **22** | 7,28 | **24** | ↓ |
| Expandable storage capacity | 8,85 | **18** | 9,88 | **19** | ↓ |
| Solid audio capability | 11,87 | **8** | 10,90 | **14** | ↓ |
| Powerful graphics solution | 12,12 | **6** | 14,05 | **4** | ↑ |
| Flexible (folding) display | 7,02 | **23** | 9,10 | **22** | ↑ |
| Upgradable | 9,38 | **17** | 9,71 | **21** | ↓ |

Comparing the rankings of the initial adjusted weights and the weights at the end of period four, the top three importance rankings have been changed. “CR

9 – Very fast execution" is still the most important attribute being at the first place; however, "CR 10 – Long operation time without charging" has taken the second place of "CR 6 – Crystal Clear View", which in turn fell to third place. "CR 12 – Inexpensive" has fallen to eleventh place, which shows that customers anticipate seeing price as less important in future when buying notebooks. However, a fast computer with a good bright screen with high definition that can last longer without charging is going to be desirable in market. It can be inferred that better specs for the main features of notebooks (screen, CPU, battery) will become more important and notebook producers may invest more R&D efforts into hardware rather than design characteristics. CRs related to design and trends, CRs related to new features such as flexible display or green CRs relating to environmental causes don't seem to be increasing in importance at least soon. Connectivity will also have an increasing trend. These results may stem from the characteristics of study's target group, working professionals. Different results can be expected if this questionnaire has been answered by a group of gamers or if this study was conducted in a society where environmental concerns are deemed more important, concerning green CRs.

## 5. Conclusion

This study developed a framework to forecast the weights of CRs for new products. With the integration of Kano model into QFD and a combination of GM and Markov Chain models, trends, and weights of each 24 CR are forecasted and compared. The change of Kano categories for CRs shows that importance ranking of these CRs will also change. The trends of CRs need to be better studied at design phase of product development.

From the results in Figure 1; the importance of CRs do really change with time. Our results indicate that both positive and negative trends can emerge within time. This is in line with previous literature that some features can become obsolete for customers (Löfgren et al., 2011: 242).

Table 11 shows the importance that this study has. There is a significant difference between both rankings, between initial phase and after fourth period. In fact, out of the listed 24 CRs, only four of them stayed in their previous order after forecasted values have been found out. Eight of the CRs has moved up in the ranking and surpassed other CRs in importance. Drastic change of CR 10 is eye catching. The prediction of such case would be important in the design phase of the new products.

It is proposed with this study that with the combination of QFD tools and Kano model, a detailed analysis about customer preferences can be extracted. The change rate between Kano categories is calculated with Markov Chain matrix to produce input for GM (1,1) to forecast the weights of CRs. Suggested qualitative method is the first in literature for laying out a framework for forecasting of customer requirements for new products, which tried to integrate Markov Chains and Kano Model categories together.

The framework proposed in this study is valuable to test in a better structured experiment. It contributes to the literature on Kano's Model and QFD; serves as an example to implement Markov Chains into Kano's model and shows that GM (1,1) can be used for predicting the weight of customer requirements. The initial results with limited data shows premise in the field as it can be valuable for companies due to its rather practical implementation.

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