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An Intelligence-Based Model for Supplier Selection Integrating Data Envelopment Analysis and Support Vector Machine

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Abstract

The importance of supplier selection is nowadays highlighted more than ever as companies have realized that efficient supplier selection can significantly improve the performance of their supply chain. In this paper, an integrated model that applies Data Envelopment Analysis (DEA) and Support Vector Machine (SVM) is developed to select efficient suppliers based on their predicted efficiency scores. In the first step, fuzzy linguistic variables are changed to crisp data as initial dataset for DEA. Actual efficiency scores are then calculated for each Decision Making Unit (DMU) using CCR-DEA model. Afterwards, suppliers' performance-related data are used for training SVM-DEA model. A numerical example representing an actual case is provided to indicate the applicability of the model.

Keywords

Supplier selection, support vector machine, data envelopment analysis, supplier efficiency, artificial intelligence.

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Introduction

One of the main objectives of Supply Chain Management (SCM) is to organize and coordinate flow of raw materials and components from different suppliers to manufacturers, aiming at manufacturing the products that meet customers' expectations (Pagell & Wu, 2017; Fallahpour et al., 2017a; Fallahpour et al., 2017b; Panda et al., 2017). Effective SCM strategies can be established by implementing responsible and efficient purchasing and supply rules. A preliminary step in this regard would be to ensure that suppliers are successfully selected (Kumar et al., 2017; Panda et al., 2017). This process is named as Supplier Selection Process (SSP). An appropriate SSP is important for designing and operating SCMs efficiently. A proper SSP may lead to a long-term and close relationship between a purchaser and supplier, which might ensure a successful SCM (Kazemi et al., 2015a; Liu et al., 2018; de Boer & de Boer, 2017). This highlights the fact that in today's competitive market, suppliers have an invaluable influence on the success of manufacturing industries (GüNeri et al., 2011; Kazemi et al., 2014; Gupta & Barua, 2017; Luthra et al., 2017). In order to handle a SSP, decision-makers should employ an appropriate approach and proper criteria for the problem. SSP is known as a typical multi-criteria decision making process, which consists of multiple factors, parameters and conflicting criteria. A widespread interest from both academics and practitioners has recently been given to the SSP (Karsak & Dursun, 2016; Montanari et al., 2017; Zimmer et al., 2016; Keshavarz Ghorabaee et al., 2017; Wetzstein et al., 2016).

Over the years, several methods have been proposed which are summarized in seven main categories as mathematical programming, multiple attribute decision making, fuzzy set theory, intelligent approaches, statistical or probabilistic methodologies, hybrid approaches and other exciting methods (Vahdani et al., 2012). Each category possesses its own specific merits and demerits. The inability of traditional methods to produce a realistic solution in SSP has become a critical concern for managers and experts. As a superior alternative approach, Multi Criteria Decision Makings (MCDMs) are simple methods, although highly dependent on human judgments (PrasannaVenkatesan & Goh, 2016). Mathematical programming encounters significant problems when considering qualitative factors and requires arbitrary aspiration levels (Modak et al., 2016b; Modak et al., 2016a). In addition, it cannot accommodate subjective attributes. Most of the other categories do not consider the interactions among the various factors and also cannot effectively realize risk and uncertainty in determining the supplier's performance (Önüt et al., 2009; He et al., 2017).

Fuzzy set theory, as one of the most widely used techniques for modelling uncertainty, is recognized as an appropriate tool that can simplify decision making process (Shekarian et al., 2017; Kazemi et al., 2016a). Fuzzy set theory has been integrated into various MCDM models to furnish the possibility of describing uncertainty quantitatively (Kazemi et al., 2016b; Chou & Chen, 2017; Kazemi et al., 2015b; Shekarian et al., 2014; Ehsani et al., 2017; De & Mahata, 2017).

On the other hand, it can be seen that DEA, as a non-parametric approach, has been utilized to assess the suppliers' efficiency and ranking (Ignatius et al., 2016). Although DEA determines the efficiency of suppliers, it assumes that collected data accurately reflects all relevant input and output variables that describe the evaluation process. In practice, this is a restrictive assumption given that gathering complete information of all relevant inputs and outputs may not be feasible. Moreover, implementing DEA for large dataset with many inputs and outputs needs huge computer resources in terms of memory and CPU time (Emrouznejad & Shale, 2009; Fallahpour et al., 2016). In order to overcome the mentioned problems, researchers have established integrated models.

In order to overcome the mentioned problems derived from DEA, researchers tried to combine DEA with Artificial Intelligence (AI) to predict the efficiency score and to take the advantages of the strengths of various methods, or complement their weaknesses (Misiunas et al., 2016; Vlahogianni et al., 2016; Modhej et al., 2017; Saberi et al., 2016). AI based models, including artificial and fuzzy neural networks, have widely been utilized in the field of supplier selection (Fallahpour et al., 2017a; Fallahpour et al., 2017b; Kuo et al., 2010). In addition, AI based models have some priorities over other approaches as, for example, they do not need a complicated decision making process. This type of models can tackle complexity and uncertainty of decision making process better since in comparison with MCDM methods, they do not require experts' opinions. The AI methods provide the actual trade-off based on the learning from the experts or cases in the past (Fallahpour et al., 2016).

Despite knowing the merits of integrated algorithm, shortcomings among existing researches make it reasonable to create a selection model based on an intelligent approach in a fuzzy environment. All in all, in this study, an integrated DEA-SVM (Support Vector Machine) model is presented to identify the best supplier for textile mills. To the best of our knowledge, there is not any study that analyzed SSP by using jointly DEA and SVM approaches in textile industry. Hence, this study presents an integrated DEA and AI approaches to demonstrate the advantages of using both DEA and AI approaches in combination. The reminder of the paper is as follows: The second section includes the literature review. Third section will explain the methodology and the proposed model. In Section 4, the implementation of the model, results and discussion are interpreted. Finally, the conclusion is presented in Section 5.

Literature Review

Academic societies and research groups believe that integrated or hybrid supplier selection structures enhance the synergy of the study and improve efficiency of the extracted results (Fallahpour et al., 2017b). Demirtas and Üstün (2008) introduced an integrated multi-objective decision process that used analytical network process to rank suppliers considering tangible and intangible variables. They also developed a Multi-Objective Mixed Integer Linear Programming (MOMILP) to allocate the optimum order quantities to the selected suppliers. Liao and Kao (2011) addressed an integrated Fuzzy

Technique Approach for Order Preference by Similarity to Ideal Solution (F-TOPSIS) and Multi-Choice Goal Programming (MCGP) to solve SSP.

Mokhtari et al. (2013) used fuzzy Delphi, fuzzy Analytical Hierarchy Process (AHP) and fuzzy VIKOR in the supplier selection process in textile industry. The authors aimed to model a highly reliable and acceptable standard for supplier selection in textile mills. Fuzzy Delphi was exploited to derive five essential criteria, while fuzzy AHP and VIKOR were used to weight those criteria and select the best suppliers, respectively. Integration of fuzzy logic and TOPSIS again appeared in Yayla et al. (2012), where the authors selected the appropriate supplier in the garment industry.

Non-parametric approaches like DEA are more flexible and do not assume any functional form. In common, traditional approaches for estimating empirical production functions aimed at measuring the technical efficiency can be divided in two types. Stochastic frontier analysis imposes a parametric model whose parameters can be adjusted through the empirical dataset. This approach draws up a linear piecewise convex production frontier through the efficient decision-making units (DMU) (Santin, 2008). DEA technique aids decision makers in grouping alternatives into efficient and inefficient ones (Wu, 2009). Some researchers have pointed out some close connections between DEA and MCDM (Amin et al., 2006; Azadeh et al., 2008; Tavana et al., 2016b; Mousavi-Nasab & Sotoudeh-Anvari, 2017). Some of them have focused on the similarity between the notion of efficiency in DEA and MCDM, although practically the two approaches are different in measuring efficiency (Opricovic, 2016; Yousefi & Hadi-Vencheh, 2016; Verma & Puri, 2017). In DEA, the efficient frontier is built as the envelope of all the decision-making units included in the sample. Efficiency is measured in relative terms by comparing each unit with the others in the same sample (Ghasemi et al., 2015). But, in MCDM, efficiency is measured in absolute terms. In a MCDM problem, the decision-maker faces a number of constraints which determine the feasible set. Therefore, by exploring the feasible set it is possible to determine what solutions are efficient without any comparison across DMUs (Andre et al., 2010). The usefulness of DEA has been shown in supplier selection area. For instance, Mohammady Garfamy (2006) conducted a DEA approach for supplier selection. Azadeh et al. (2016) developed an integrated approach based on experimental design and computer simulation for supplier selection. The authors applied DEA to assess suppliers based on different criteria in a closed loop supply chain. Recently, there has been an exponential growth in the number of publications related to theory and applications of DEA, and it has attracted supply chain investigators in supplier evaluation and selection programs. Emrouznejad and Yang (2018) presented a comprehensive review on the application of DEA to different fields.

Although DEA has been applied in several studies including supplier selection, there are still some drawbacks which make it infeasible to apply it in some cases. DEA assumes that the collected data accurately reflect all the relevant input and output variables which describe the evaluation process. In practice, this is a restrictive assumption (Oum et al., 2013). However, in DEA the number of inputs and outputs included in the model defines the number of constraints. As the number of constraints increases, the efficiency scores of Decision Making Units (DMUs) will also increase and more suppliers tend to lie on or to be close to the frontier (Hanafizadeh et al., 2014). In order to overcome the limitations associated with homogeneity and accuracy of the assumptions of DEA, AI techniques were introduced recently to assist in estimating the efficiency frontiers for decision makers. It has been demonstrated that AI techniques can assist model developers in finding data envelopes, which are based on the entire dataset rather than on some extreme data points from which uncertain information has been lost (Kanal & Lemmer, 2014).

One of the popular areas of research in supplier selection has been to integrate Artificial Intelligence (AI)-based models and MCDM models in different areas of SSPs. GüNeri et al. (2011) proposed a predictive ANFIS-based model for both criteria selection and performance evaluation of supplier, and proposed the applicability of their model in textile industry. Vahdani et al. (2012) a linear neuro-fuzzy model for supplier assessment in cosmetic industry. The models was developed and implemented in two different stages: Selecting appropriate criteria for assessing the suppliers and then evaluating performance of suppliers using the developed model. Fallahpour et al. (2016) integrated the so called Kourosh and Arash Method (KAM), DEA and Genetic Programming (GP) for a green supplier selection.

Model and Methodology

In the following, the developed model for supplier selection using DEA-SVM will be presented, including three steps. In the first step, by using GMIR method, linguistic variables are changed to crisp data as initial dataset for DEA. In the second step, DEA will be used to classify suppliers into efficient and inefficient groups based on the computed efficiency scores. In the last step, SVM will be applied as a classification or regression module, which presents supplier performance-related information to train AI model and employ the trained predictor to new suppliers. In Step 3, the objective is to address the classification or the regression problem, which involves the development of a relationship between the classes and the criteria. To establish such a functional relationship, it is necessary that the prediction error between the priori efficiency and predicted efficiency values is minimized. In the following sub-sections, three main elements of the developed model will be discussed in detail.

Fuzzy Set Theory

In the real world, there are many qualitative criteria for evaluating suppliers' performance, which usually rely on subjectivity, ambiguity and vagueness. In other words, exact data are insufficient for supplier selection. Fuzzy Set Theory (FST) was introduced by Zadeh (1965) and is a useful approach for measuring qualitative and vague concepts. In this paper, triangular fuzzy numbers were exploited to evaluate the suppliers' performance.

A fuzzy set is defined by means of its membership function $f_{A(x)}$ shown in Figure 1 and based on the following definitions.

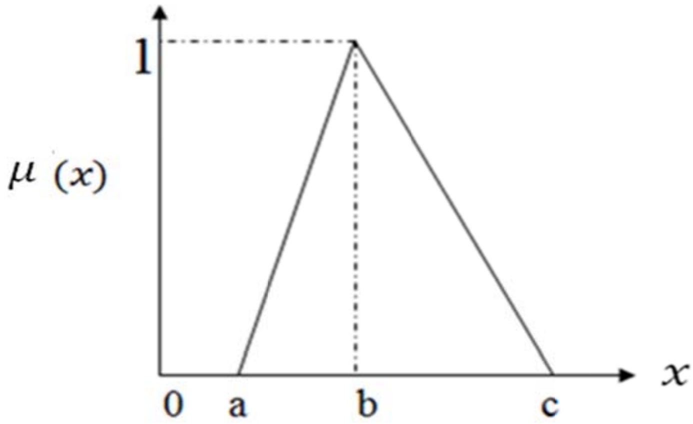

Figure 1. Triangular fuzzy number

Definition 1. Assume $\widetilde{A}$ is a fuzzy set in a universe of discourse X and membership function $\mu_{\widetilde{A}}(x)$ describes it .This function is related to each element x, where x belongs to the interval [0, 1]. The function value $\mu_{\widetilde{A}}(x)$ is termed as the degree of membership of x in $\widetilde{A}$ (Kazemi et al., 2010).

Definition 2. The fuzzy set $\widetilde{A}$ is both normal and convex. By normality, it is meant that:

$$\exists x \in X, \quad \mu_{\widetilde{A}}(X) = 1 \tag{1}$$

And by convex, it is meant that:

$$\forall x_1 \in X, \ \forall x_2 \in X, \ \forall \alpha \in [0, 1],$$

$$\mu_{\widetilde{A}}(\alpha x_1 + (1-\alpha)x_2) \geq mi(\mu_{\widetilde{A}}(x_1), \mu_{\widetilde{A}}(x_2)) \tag{2}$$

Definition 3. $\widetilde{A}$ is defined to be a triangular fuzzy number represented by a triplet (a,b,c), where, $a < b < c$. Its membership function is defined as:

$$\begin{cases} 0, & x < a \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ \dfrac{c-x}{c-b}, & b \leq x \leq c \\ 0, & x > c \end{cases} \tag{3}$$

Fuzzy Scale for Measuring the Importance of Each Criterion

Efficiency is typically calculated by optimizing output over input, which implies that for increasing the efficiency, either the output should increase or the input should decrease (Ozcan, 2008). Table 1 is used for weighting the inputs and outputs. In order to evaluate supplier's performance, decision-makers (experts) assign a linguistic value to each criterion of the suppliers based on their judgment, varying from Very Low (VL) to Very High (VH). Since in DEA (or any model), the outputs affect the efficiency directly, the fuzzy linguistic numbers are assigned to the outputs. On the other hand, the inputs affect the efficiency inversely; therefore, the fuzzy numbers can still be considered from VL to VH, provided that they are assigned a reversed value, that is, (7, 9, 10) and (0, 1, 3) respectively. It should also be noticed that the specific scales for the linguistic judgments depend on the real application systems and the domain of experts' opinions.

Table 1. Fuzzy Linguistic Variables

Linguistic values	Outputs	Inputs
Very low (VL)	(0, 1, 3)	(7, 9, 10)
Low (L)	(1, 3, 5)	(5, 7, 9)
Medium (M)	(3, 5, 7)	(3, 5, 7)
High (H)	(5, 7, 9)	(1, 3, 5)
Very high (VH)	(7, 9, 10)	(0, 1, 3)

DEA

DEA, developed by Charnes et al. (1978), is a mathematical programming approach for evaluating the relative efficiency of homogenous decision-making units with multiple inputs and outputs. DEA is a non-parametric method that calculates efficiency without introducing specific weights for inputs and outputs or specifying a production function. Also, DEA is a leading method for performance analysis in many areas, because it provides a better way to organize and analyze data. It allows efficiency to change over time and requires no prior specification of the best practice frontier. DEA can be used to measure efficiency analysis of alternative suppliers. In supplier selection area, suppliers are assessed on benefit criteria (outputs) and cost criteria (inputs). The efficiency of a supplier is defined as the ratio of the weighted sum of its outputs to the weighted sum of its inputs. In practice there are n suppliers indexed by j, and $j = 1,2,3,...,n$ to be evaluated. The jth supplier (denoted as s_j) has m different inputs (x_{ij}) and s different outputs (y_{rj}). Let the observed input and output vectors of s_j be $X_j = (x_{1j}, x_{2j}, ..., x_{mj})^T \succ 0 \;\; j = 1,2,...,n$ and $Y_j = (y_{1j}, y_{2j}, ..., y_{sj})^T \succ 0 \;\; j = 1,2,...,n$ respectively. Therefore, the relative efficiency of s_j is calculated as:

$$s_j = \frac{\sum_{r=1}^{s} u_r y_{kj}}{\sum_{i=1}^{m} v_i x_{ij}} = \frac{U^T Y_j}{V^T X_j}, \;\; j = 1,2,...,n \tag{4}$$

Where $V = (v_1, v_2, ..., v_m)^T$ and $U = (u_1, u_2, ..., u_s)^T$ are input and output vectors, respectively. The Charnes Cooper Rhodes (CCR)-DEA model can be written as:

$$minimize \qquad \theta - \varepsilon\left(\sum_{i=1}^{m} s_{i^-} + \sum_{r=1}^{s} s_{r^+}\right)$$

subject to

$$0 = \theta x_{i0} - \sum_{j=1}^{n} x_{ij}\lambda_j + s_{i^-} \quad i = 1,2,....,m \quad and \quad y_{r0} = \sum_{j=1}^{n} y_{ij}\lambda_j - s_r^{\,r} \tag{5}$$

$$r = 1,2,...,s \, and \quad 0 \le s_i^-, s_r^+, \lambda_j \;\; \forall i, j, r$$

The CCR model assumes Constant Returns to Scale (CRS) for the inputs and outputs. To take into account Variable Returns to Scale (VRS), a model introduced by Banker et al. (1984), with the abbreviation name (BCC-DEA) is utilized. The BCC model aids in determining the efficiency scale of a set of units (which is a technically efficient unit for the VRS model). The BCC-DEA model evaluates whether increasing, constant, or decreasing returns to scale would boost the observed efficiency. In the case of CRS, the output changes proportionately to input, as it also does in the CCR-DEA model. In the case of CRS, a change in the input leads to a disproportional change in the output (da Silva et al., 2017). The efficiency of a specific DMU can be evaluated by BCC model of DEA which is as follows (Banker et al., 2016; da Silva et al., 2017):

$$minimize \qquad \theta_0 - \varepsilon\left(\sum_{i=1}^{m} s_{i^-} + \sum_{r=1}^{s} s_{r^+}\right)$$

subject to

$$\theta_0 x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_{i^-} \quad i = 1,2,....,m \quad and \quad y_{r0} = \sum_{j=1}^{n} y_{ij}\lambda_j - s_{r^+} \tag{6}$$

$$r = 1,2,...,s \quad and \quad 1 = \sum_{j=1}^{n} \lambda_j \quad and \quad 0 \le s_{i^-}, s_{r^+}, \lambda_j \quad \forall i, j, r$$

SVM

SVMs are a group of supervised learning methodologies that can be employed for classification or regression. SVMs illustrate an extension to non-linear models of the generalized portrait algorithm developed by Vapnik in 1995. The SVM algorithm is based on the statistical learning theory and the Vapnik-Chervonenkis dimension introduced by Vladmir and Alexey Chervonenkis (Nurwaha & Wang, 2011). A SVM performs classification by constructing an N-dimension hyper-plane that optimally separates data into two categories.

SVM models are closely related to neural networks. Using a kernel function, SVM is an alternative training method for polynomial, radial basis function and multi-layer perceptron classifiers in which the weights of the network are obtained by solving a quadratic programming problem with linear constraints, rather than by solving a non-convex, unconstrained minimization problem as in standard NN training (Lee & To, 2010).

The optimal plane classifier uses only dot products between vectors in input space. So, the goal of SVM modeling is to find the optimal hyper-plane that separates clusters of vector in such a way that cases with one category of the target variable are on one side of the plane and cases with the other category are on the other side of the plane (Rejani & Selvi, 2009). The vectors near the hyper-plane are the support vectors. The hyper-plane can be constructed by solving a convex optimization problem that minimizes a quadratic function under linear inequality constraints. The optimization problem employed to get the optimal hyper-plane and the decision function used for the actual classification of vectors can be expressed in dual form which depends only on dot products between vectors. The dual representation of the decision function is:

$$f(X) = sgn\left[\sum_{i=1}^{l} Y_i \alpha_i \prec X.X_{i\succ} + b\right] \tag{7}$$

Where $\alpha_i \in R$ is a real-valued variable that can be considered as a measure of how much information all value X_i has. Thus, for vectors that do not lie on the margin, this value will be zero. The optimal hyper-plane classifier uses only dot products vectors in input space. In feature space, this will be translated to $\prec \phi(X), \succ \phi(X)$. A kernel function $K(X, X')$, which gives two vectors in input and returns the dot product of their images in feature space, is given by:

$$K(X, X') = \prec \phi(X), \phi(X') \succ \tag{8}$$

With the help of the decision function for the optimal hyper-plane classifier in dual form and applying the mapping ϕ to each vector, we get:

$$f(x) = sgn\left[\sum_{i=1}^{l} Y_i \alpha_i \prec \phi(X).\phi(X_i) \succ + b\right] \tag{9}$$

We will use kernels which will give a non-linear decision function of the form:

$$f(X) = sgn\left[\sum_{i=1}^{l} Y_i \alpha_i K(X, X_i) + b\right] \tag{10}$$

The SVM algorithm is based on statistical learning theory, which is practical since it reduces optimization problem with a unique solution. A generalization to regression that is having $y \in R$ can be given. In this case, the algorithm tries to build a linear function in the feature space such that the training point lies at a distance of $\varepsilon \succ 0$. Similar to the pattern-recognition case, this can be written as a quadratic programming problem in terms of kernels. The kernel approach is employed to address the curse of dimensionality. The support vector regression solution, using an ε insensitive loss function, is given by:

$$maxW(\alpha,\alpha^*)max\sum_{i=1}^{l}\alpha_i^*(y_i-\varepsilon)-\alpha_i(y_i+\varepsilon)-1/2\sum_{i=1}^{l}\sum_{j=1}^{l}(\alpha_i^*-\alpha_i)(\alpha_j^*-\alpha_j)K(X_i,X_j) \quad (11)$$

With constraints: $0 \le \alpha_i, \alpha_i^* \ge C, i = 1,....,l.$ α_i *and* α_i^* are the Lagrange multipliers.

$$\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)=0 \quad (12)$$

The regression equation is given by:

$$f(X)=\sum_{SVs}\alpha_i^- -\alpha_l^-)K(X,X_i)+b^- \quad (13)$$

where

$$\prec w^-, X \succ = \sum_{i=1}^{l}(\alpha_i-\alpha_i^*)K(X,X_i) \quad (14)$$

and

$$b^- = 1/2\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)K(X_i,X_r)+K(X_i,X_s) \quad (15)$$

The equality constraint may be dropped if the kernel contains a bias term, b being accommodated with the kernel functions; in that case, the regression function is given by:

$$f(X)=\sum_{i=1}^{l}(\alpha_i^- -\alpha_i^{*-})K(X,X_i) \quad (16)$$

The quadratic loss function produces a solution which is equivalent to a ridge regression, zero order. Regularization parameter is $\lambda = 1/2C$ where λ and C are optimization parameters (Ghosh & Chatterjee, 2010). Kernel functions can have various forms such as polynomial, Gaussian radial basis, exponential radial basis which have the following forms (Geng et al., 2016):

$$Polynomial\ kernel:\ K(x,z) = \langle x,z \rangle^p \tag{17}$$

$$Gaussian\ radial\ basis\ kernel:\ K(x,z) = e^{\left[-\frac{|x-z|^2}{2\sigma^2}\right]} \tag{18}$$

$$Exponential\ radial\ basis\ kernel:\ K(x,z) = e^{\left[-\frac{|x-z|}{2\sigma^2}\right]} \tag{19}$$

Where p in equation specifies the degree of polynomial kernel and σ indicates the width of the kernels.

The Developed Integrated DEA-SVM Model under Fuzzy Environment

Figure 2 depicts the conceptual model for supplier selection using DEA and SVM. The hybrid model can function as both classification and regression models, including three modules. In Module 1, by using GMIR method, linguistic variables are changed to crisp data as initial dataset for DEA. Module 2 uses DEA and sorts suppliers into efficient and inefficient groups based on the computed efficiency scores. Module 3 is a classification or regression module based on the AI-based models and presents the supplier performance-related information to train the AI model and employs the trained predictor on new suppliers. In Module 3, the objective is to address the classification or the regression problem, which involves the development of a relationship between the classes and the criteria. To establish such a functional relationship, it is necessary that the prediction error between the previous efficiency and predicted efficiency values is minimized.

Results and Discussion

Data collection and DEA Inputs–Outputs

Data used in this study have been collected from a spinning and weaving factory located in Iran. Production of this company is cotton and cotton-polyester blended spun yarn. This firm has more than 600 employees and a monthly production capacity of 150,000 kilograms of yarn and 120,000 meters of woven fabric, respectively. Commercial manager was selected as the expert to consult about the suppliers' performance and criteria for supplier selection. The selected expert has a PhD degree in fiber spinning, and totally has more than 15 years of experience in the textile industry.

The first step in the assessment of the suppliers' performance involves defining the evaluation criteria. In this study, based on the literature and the expert's opinion, six criteria were selected and applied to the garment company. The criteria were Quality of the Material (QM), Cost (C), Delivery (D), Service (S), Flexibility (F) and Customer satisfaction (Cs). In terms of DEA, S, D and QM are outputs and C, F and Cs are inputs. Table 2 defines each criterion. The expert was asked to deliver his judgment related to all the suppliers' criteria using fuzzy linguistic variables, due to imperfect information and uncertainty affecting the assessment. His evaluation over the selected criteria in linguistic preferences is shown in Table 3.

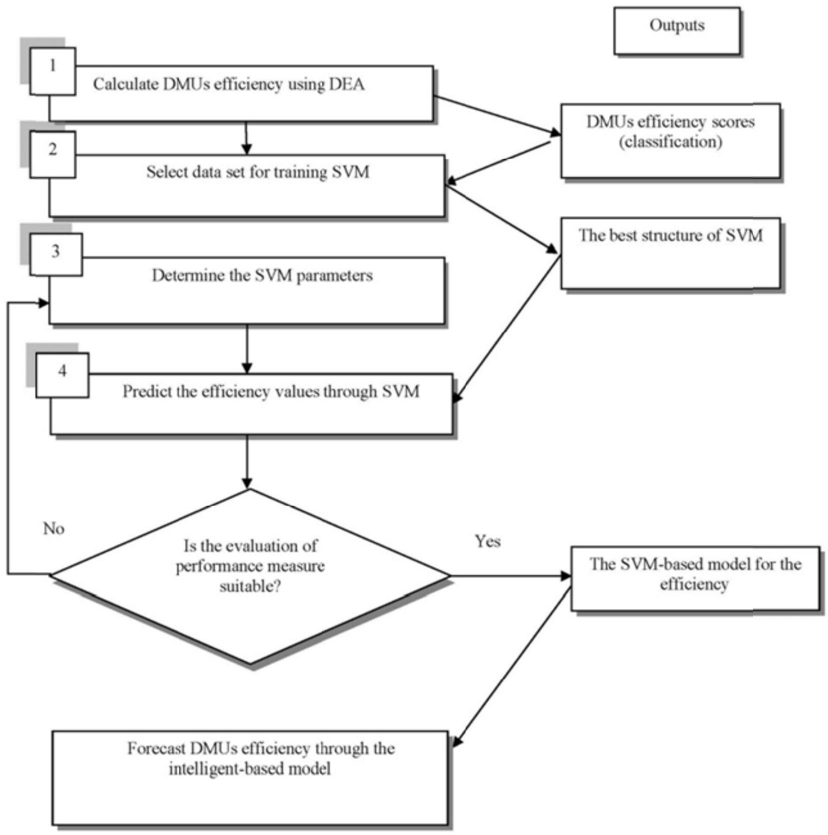

Figure 2. The hybrid model for supplier selection

Table 2. Selection Criteria for Evaluating the Suppliers' Performance (Çelebi & Bayraktar, 2008; Lima et al., 2013; Mukherjee, 2016)

Criteria	Definition
Quality of Material (QM)	The ability of supplied materials to meet or exceed purchasers' expectations. In order to evaluate this criterion, quality certification and standards are very important. This attribute has positive impact on the suppliers' efficiency: with QM increasing, the suppliers' efficiency increases too.
Service (S)	This refers to the after sales responsibility borne by the supplier and the motivation to share skills for problem solving. It also looks at the efficiency of scheduling and ability to handle changing orders. This attribute affects directly the supplier's efficiency.
Delivery (D)	This looks at the on-time delivery. As the performance against this criterion increases, supplier's profile is better.
Flexibility (F)	This factor shows the level of the flexibility of supplier in supplying material, price of the supplied material, etc.
Cost (C)	This covers the final cost of the goods purchased, the ordering cost (the cost of preparing a purchase order and cost of receiving the goods ordered) and the transportation cost. A supplier is termed as "more efficient" if its total cost is lower than that of the competing suppliers.
Customer satisfaction (Cs)	The level of satisfaction of the customer.

Table 3. Assessment Result of Suppliers with Respect to the Defined Criteria

Criteria	Input for DEA model				Output for DEA model		
Supplier	Material quality	Transportation cost	Material price	Delivery time	Flexibility	Satisfaction	Revenue
S1	(7,9,10)	(5,7,9)	(5,7,9)	(1,3,5)	(1,3,5)	(5,7,9)	(3,5,7)
S2	(1,3,5)	(7,9,10)	(3,5,7)	(7,9,10)	(7,9,10)	(3,5,7)	(3,5,7)
S3	(5,7,9)	(5,7,9)	(1,3,5)	(1,3,5)	(5,7,9)	(5,7,9)	(5,7,9)
S4	(5,7,9)	(1,3,5)	(5,7,9)	(5,7,9)	(5,7,9)	(3,5,7)	(3,5,7)
S5	(3,5,7)	(7,9,10)	(5,7,9)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)
S6	(0,1,3)	(5,7,9)	(3,5,7)	(7,9,10)	(7,9,10)	(5,7,9)	(3,5,7)
S7	(0,1,3)	(5,7,9)	(1,3,5)	(7,9,10)	(5,7,9)	(7,9,10)	(5,7,9)
S8	(0,1,3)	(5,7,9)	(1,3,5)	(7,9,10)	(7,9,10)	(5,7,9)	(7,9,10)
S9	(3,5,7)	(5,7,9)	(3,5,7)	(1,3,5)	(3,5,7)	(7,9,10)	(7,9,10)
S10	(0,1,3)	(0,1,3)	(3,5,7)	(7,9,10)	(3,5,7)	(5,7,9)	(1,3,5)
S11	(3,5,7)	(5,7,9)	(1,3,5)	(7,9,10)	(7,9,10)	(3,5,7)	(3,5,7)
S12	(3,5,7)	(7,9,10)	(3,5,7)	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,10)
S13	(5,7,9)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)
S14	(0,1,3)	(5,7,9)	(3,5,7)	(1,3,5)	(3,5,7)	(7,9,10)	(5,7,9)
S15	(3,5,7)	(7,9,10)	(7,9,10)	(5,7,9)	(5,7,9)	(7,9,10)	(7,9,10)
S16	(5,7,9)	(7,9,10)	(1,3,5)	(5,7,9)	(3,5,7)	(5,7,9)	(7,9,10)
S17	(1,3,5)	(5,7,9)	(7,9,10)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)
S18	(1,3,5)	(5,7,9)	(7,9,10)	(3,5,7)	(3,5,7)	(7,9,10)	(3,5,7)
S19	(5,7,9)	(0,1,3)	(3,5,7)	(1,3,5)	(0,1,3)	(1,3,5)	(1,3,5)
S20	(3,5,7)	(3,5,7)	(7,9,10)	(3,5,7)	(7,9,10)	(7,9,10)	(5,7,9)
S21	(3,5,7)	(7,9,10)	(3,5,7)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)
S22	(1,3,5)	(5,7,9)	(7,9,10)	(3,5,7)	(7,9,10)	(5,7,9)	(3,5,7)
S23	(3,5,7)	(0,1,3)	(7,9,10)	(0,1,3)	(1,3,5)	(5,7,9)	(1,3,5)
S24	(7,9,10)	(5,7,9)	(3,5,7)	(7,9,10)	(1,3,5)	(5,7,9)	(7,9,10)
S25	(5,7,9)	(1,3,5)	(3,5,7)	(3,5,7)	(3,5,7)	(7,9,10)	(5,7,9)
S26	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)
S27	(7,9,10)	(0,1,3)	(7,9,10)	(7,9,10)	(3,5,7)	(7,9,10)	(3,5,7)
S28	(7,9,10)	(3,5,7)	(5,7,9)	(3,5,7)	(7,9,10)	(3,5,7)	(7,9,10)

Criteria	Input for DEA model			Output for DEA model			
Supplier	Material quality	Transportation cost	Material price	Delivery time	Flexibility	Satisfaction	Revenue
S29	(5,7,9)	(3,5,7)	(1,3,5)	(7,9,10)	(5,7,9)	(5,7,9)	(7,9,10)
S30	(7,9,10)	(3,5,7)	(5,7,9)	(1,3,5)	(7,9,10)	(3,5,7)	(5,7,9)
S31	(5,7,9)	(5,7,9)	(1,3,5)	(0,1,3)	(5,7,9)	(1,3,5)	(3,5,7)
S32	(1,3,5)	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,10)	(5,7,9)	(3,5,7)
S33	(3,5,7)	(3,5,7)	(1,3,5)	(1,3,5)	(3,5,7)	(5,7,9)	(7,9,10)
S34	(7,9,10)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)	(5,7,9)
S35	(5,7,9)	(0,1,3)	(5,7,9)	(7,9,10)	(7,9,10)	(5,7,9)	(7,9,10)
S36	(1,3,5)	(7,9,10)	(1,3,5)	(5,7,9)	(5,7,9)	(7,9,10)	(1,3,5)
S37	(5,7,9)	(5,7,9)	(1,3,5)	(3,5,7)	(5,7,9)	(5,7,9)	(7,9,10)
S38	(1,3,5)	(7,9,10)	(5,7,9)	(5,7,9)	(7,9,10)	(7,9,10)	(3,5,7)
S39	(3,5,7)	(7,9,10)	(7,9,10)	(5,7,9)	(7,9,10)	(5,7,9)	(7,9,10)
S40	(5,7,9)	(5,7,9)	(7,9,10)	(1,3,5)	(5,7,9)	(5,7,9)	(5,7,9)
S41	(1,3,5)	(7,9,10)	(5,7,9)	(3,5,7)	(1,3,5)	(5,7,9)	(5,7,9)
S42	(0,1,3)	(3,5,7)	(7,9,10)	(1,3,5)	(7,9,10)	(7,9,10)	(1,3,5)
S43	(0,1,3)	(7,9,10)	(7,9,10)	(1,3,5)	(7,9,10)	(5,7,9)	(5,7,9)
S44	(7,9,10)	(3,5,7)	(5,7,9)	(5,7,9)	(1,3,5)	(5,7,9)	(5,7,9)
S45	(5,7,9)	(7,9,10)	(1,3,5)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)
S46	(5,7,9)	(7,9,10)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(3,5,7)
S47	(7,9,10)	(5,7,9)	(7,9,10)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)
S48	(7,9,10)	(3,5,7)	(5,7,9)	(7,9,10)	(0,1,3)	(7,9,10)	(7,9,10)

In supplier selection problems, all criteria are evaluated by linguistic judgements received from experts. However, it is easier for decision experts to use crisp values instead of fuzzy ones. After receiving the expert's opinion in terms of linguistic variables for each criterion, the fuzzy numbers were converted into crisp values through a defuzzification rule as Table 4 shows. In this work, defuzzification is applied with GMIR of the triangular fuzzy numbers, introduced by Chen and Hsieh (1999) for three input and four output criteria. Chen and Hsieh (1999) proved that GMIR of triangular fuzzy numbers $\widehat{A}(a_1,a_2,a_3)$ becomes (Chen & Hsieh, 1999):

$$\partial\widehat{\mathrm{A}} = \frac{(\mathrm{a} + 4\mathrm{b} + \mathrm{c})}{6} \tag{20}$$

Thereafter, expert's judgment is arranged based on Table 4 and crisp values were used for DEA efficiency measurement. The linguistic variables in Table 4 were also used for the importance of each criterion and their relevant triangular fuzzy numbers.

Table 4. Linguistic Variables for the Importance Weight of Each Criterion and Their Relevant Fuzzy Numbers and Crisp Values (Awasthi & Kannan, 2016)

Linguistic variables	Triangular fuzzy numbers	Crisp values
Very Bad	(0,1,3)	1.167
Bad	(1,3,5)	3.000
Fair	(3,5,7)	5.000
Good	(5,7,9)	7.000
Very Good	(7,9,10)	8.333

Calculating Suppliers' Efficiency

In the CCR model, each DMU designs its own optimal weights and achieves its best efficiency (Zuo & Guan, 2017; Kwon, 2017; Paradi et al., 2018; Hosseinzadeh-Bandbafha et al., 2018). In DEA, CCR model is believed to be more powerful than BCC model (Sarkar & Sarkar, 2017; Liu & Lim, 2017; Azadi et al., 2017; Yoon et al., 2017; Jauhar & Pant, 2017). In this paper, efficiency scores of the suppliers were calculated according to CCR-DEA model using LINGO (13.0 X64) software. Table 5 shows efficiency scores calculated for the suppliers. It is necessary to note that the efficiency scores of only 12 suppliers are provided in the table due to space limitation.

Table 5. Efficiency Score Calculated by CCR-DEA for Each Supplier

Supplier	CCR-DEA	Supplier	CCR-DEA	Supplier	CCR-DEA	Supplier	CCR-DEA
S1	0.784	S13	0.975	S25	0.734	S37	0.884
S2	0.984	S14	1.000	S26	0.611	S38	0.575
S3	0.588	S15	0.671	S27	0.953	S39	0.865
S4	0.788	S16	0.938	S28	0.881	S40	0.537
S5	0.734	S17	0.911	S29	0.842	S41	0.739
S6	0.444	S18	0.868	S30	0.709	S42	0.778
S7	0.857	S19	0.976	S31	0.769	S43	0.937
S8	0.794	S20	1.000	S32	0.619	S44	0.691
S9	0.846	S21	0.941	S33	0.800	S45	1.000
S10	0.810	S22	0.822	S34	0.565	S46	0.774
S11	0.956	S23	1.000	S35	0.810	S47	0.850
S12	0.933	S24	0.867	S36	0.703	S48	0.913

Estimating the Suppliers' Efficiency

At this stage, the crisp values of the determined criteria (obtained from Table 4) and the efficiency scores related to the efficiency (Table 5) are considered as independent and dependent variables, respectively, for estimating the suppliers' efficiency using SVM. To develop the intelligent-based model, 75% of the dataset is selected for training the SVM-model and the remaining 25% of the dataset is used for testing the model (Mousavi et al., 2014; Tavana et al., 2016a; Armaghaniet al., 2017a; Shirazi & Mohammadi, 2017; Karkevandi-Talkhooncheh et al., 2017). There is no exact rule to find the best structure for the AI-based models, and this is always a trial and error process (Sgurev et al., 2017; Armaghani et al., 2017b; Zhou & Yao, 2017; Yu et al., 2017; Kaboli et al., 2016 ; Raut et al., 2017; Raut et al., 2017). To find the best SVM model, different structures are examined, specified in Table 6. In case of SVM model, all the Radial Basis Function (RBF), polynomial, sigmoid and linear kernel functions were used to map the data (Xu et al., 2016; Wan et al., 2016; Cao & Zhang, 2016). The penalty term (C) and regularization factor (γ) are optimized on trial and error basis (Vahdani et al., 2016; Pan et al., 2017). For developing the SVM model, the DTREG software is used. It is worth noting that the average statistical metrics namely Mean Absolute Error (MAE), Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are employed to evaluate the accuracy of the proposed model. These metrics are defined by:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|P_i - \hat{P_i}\right| \qquad MSE = \frac{1}{N}\sum^{N}(P_i - \hat{P_i})^2 \qquad RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - \hat{P_i})^2} \tag{21}$$

The mean square errors of testing and training data were measured by presenting them to the trained network. Then, the average of these statistical merits of testing subsets was considered to compare the models. Table 6 shows the results of training processes for the optimal developed model.

Table 6. Performance and Characteristics of SVM-DEA with the Best Architecture on Training and Testing Data

Model	(C and γ)	Training function	Training data			Testing data		
			MAE	MSE	RMSE	MAE	MSE	RMSE
SVM-DEA	(12670,0.026)	sigmoid	0.037	0.003	0.060	0.051	0.004	0.068
	(12670,0)	linear	0.13	0.013	0.001	0.074	0.062	0.250
	(11026,0.0421)	Polynomial	0.010	0.009	0.098	0.046	0.006	0.080
	(10489,0.0749)	RBF	0.104	0.018	0.137	0.461	0.36	0.190

As can be seen, the SVM model with polynomial training function and C=11026 and γ=0.0421 is the best model in both training and testing. Figure 3 (a and b) shows the accuracy of the model in comparison with the real efficiency.

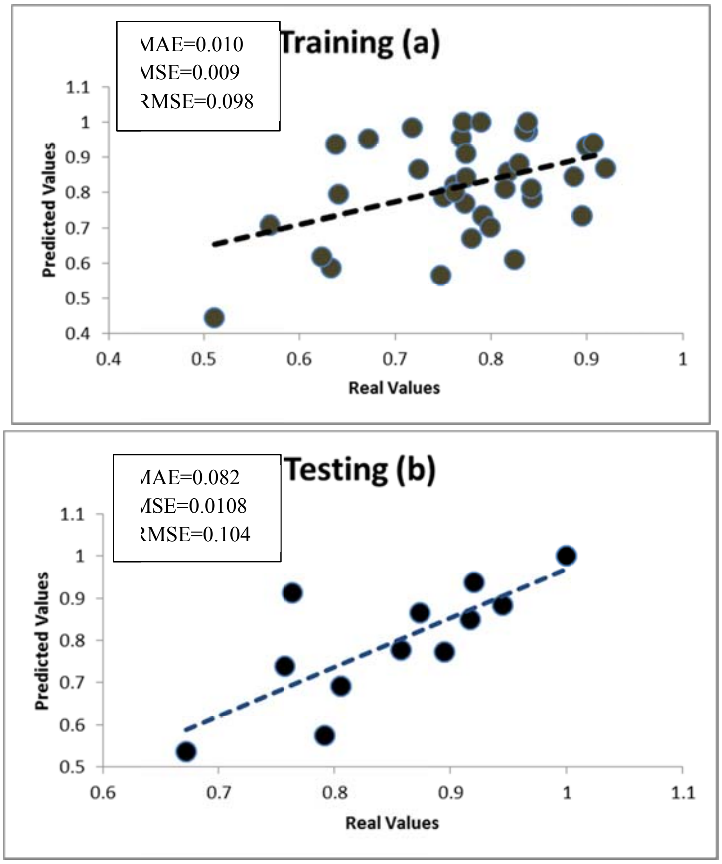

Figure 3. The training and testing results

Furthermore, the obtained results of average MSE, RMSE and MAE of six subsets of testing data are provided in Table 7. As it can be seen from the table, the performance of SVM-DEA model is satisfactory.

Table 7. Performance of SVM-DEA Architecture with the Best Architecture on Training and Testing Datasets

Data set	SVM-DEA model					
	Training data			Testing data		
	MSE	RMSE	MAE	MSE	RMSE	MAE
1	0.017	0.132	0.100	0.001	0.037	0.030
2	0.012	0.108	0.078	0.034	0.185	0.160
3	0.091	0.124	0.091	0.102	0.015	0.123
4	0.012	0.110	0.084	0.031	0.177	0.137
5	0.017	0.132	0.099	0.031	0.177	0.137
6	0.012	0.113	0.084	0.001	0.037	0.302
Ave	0.027	0.120	0.089	0.033	0.105	0.148

Conclusion

In this study, a new integrated model was developed to help in selecting efficient suppliers in textile industry by using DEA and SVM as an AI-based methodology. This model can function as both a classification model and a regression model. To make the decision making process more easier, linguistic scores received from experts were transformed to crisp values by using the GMIR method of the triangular fuzzy numbers. Then, an efficiency score (CCR-DEA) was calculated for each decision making unit using DEA, which performed as a new output for AI-based model. Then, SVM was utilized to execute decision making process for supply chain as a powerful and accurate tool in estimation function. Finally, the developed model was applied for estimating the suppliers' efficiency. The finding illustrates that the developed DEA-SVM is a robust and powerful tool for predicting the efficiency of suppliers, and can be used as a tool for supplier selection process.

There are several opportunities to extend this study in the future. The emphasize of the recent studies has been on sustainable SSP using economic, environmental and social attributes (Malviya & Kant, 2015; Dubey et al., 2017; Johnsen et al., 2017). So, using sustainability criteria is recommended for suppliers' performance evaluation and selection, which can be considered as an immediate extension of this study. Another room for future research that would be of interest is using other AI-based techniques such as Simulated Annealing, Gene Expression Programming, and ANFIS, allowing to compare the result of other methods with the ones of this study. Furthermore, future studies can take into account the relationships among criteria and develop the current models based on the interdependencies among the criteria.

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Predictors of PGSI: A Study of Pakistan Stock Exchange

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Abstract

This study used PGSI to measure the motives of online stock exchange gamblers according to their responses about their online gambling. The main aim of the current study is to holistically explore the impact of motivational factors that motivate more usage of online gambling in Pakistan and behavioral factors that investigate the level of implementation of responsible gambling practices on PGSI in Pakistan's online stock exchange gamblers. We collected data through questionnaires and for analysis we used SEM, multiple regression and multinomial logistic regression. Results indicated that motivational factors that significantly impact PGSI are excitement, financial motivation, escape and relaxation and in terms of responsible gambling practices, game design and transparent terms and conditions are the key elements of behavioral factors while self-exclusion and self-help (SE and SH) are not considered as significant factors.

Keywords

Factor analysis, regression, gambling

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Introduction

Gambling is the betting of cash or something of significant worth and "Gambling can be defined as placing something of value at risk in the hope of gaining something of greater value" (Potenza, Fiellin, Heninger, Rounsavila, & Mazure, 2002). According to Jassinove (1996), gambling is "any risky behavior, based on a combination of skill or chance, or both, in which something of value can be won or lost". "Gambling problems have been increased day by day by the accessibility and availability of opportunity of gambling regardless of the fact that the effect is moderated by means of different factors" (Reith, 2012). Teenagers and adolescents are influenced to gamble for various reasons like excitement, amusement, entertainment, accomplishing and learning and also, extreme cognitive bias, risk and upper stages of anxiety and stress. Individuals who bet without a doubt do as such for an assortment of reasons including incentive and the trust of winning cash. According to Smith, Battersby, Harvey, Pols, Baigent, and Oakes (2011), depression, relation, family conflict and financial strain are the reasons why gambling becomes problematic for people. It is critical to investigate the motives why individuals bet? The two main purposes of this research are, first, **H1:** There is a positive and significant relationship between behavioral factors and problem gambling severity index, second, **H2:** There is a positive and significant relationship between motivational factors and problem gambling severity index.

Motivational factors are the factors which urge us to bet, differentiate what sorts of betting people take part in and decide the sum they will play and wager. Motivation is a mixture of intrinsic and extrinsic factors which start directly and offer power to behavior (Clarke, 2004). Internal (intrinsic) inspiration depends on requirements, perceptions and feelings whereas external (extrinsic) inspiration for the most part originates from the cultural, social and environmental factors (Reeve, 2009). This research takes three motivational factors including excitements, financial motivation, escape and relaxation. Excitements and escape and relaxation are among internal motivational factors that urge the gamblers to behave whether gambling relieves gamblers' boredom or is a source of relaxation, and financial motivation is included in external motivational factors that peruse whether gambling is a source to win money or to earn money. The PGSI is a curtailed version of the first apparatus called the Canadian Problem Gambling Index, comprising of nine items instead of thirty one. Customers can utilize it as a self-evaluation apparatus, or one can utilize it as a major aspect of his screening procedure. PGSI containing nine items with a four-point Likert scale is utilized to measure the problem gambling severity. The index score and order are 0=never, 1=sometime, 2 =most of the time, 3 = almost always .On the basis of gamblers' responses, the scores are attained in the subsequent arrangements of 0=non-problem group; score of 1 or 2=low problem group; score of 3 to 7=moderate problem group and score of 8 or more=problem group.

Behavioral finance provides us with a clarification why individuals make irrational financial decisions. Behavioral finance is a moderately new field that tries to consolidate behavioral and intellectual mental hypotheses with ordinary financial aspects. This research covers three behavioral factors SE and SH, transparent term and condition, and game design .SE and SH or voluntary exclusion "usually refers to a policy enacted by some governments and/or individual casinos as a way of addressing the issue of problem gambling" and transparent term and condition refers to a method, action or procedure that needs concealed motivation condition and conforms to the exposure prerequisites or straightforwardness in word and aim. Game design "is the art of applying design and aesthetics to create a game for entertainment or for educational, exercise, or experimental purposes". (Blaszczynski & Nower ,2002)

The purpose of this research is to inspect the tendencies of financial decision making and spending behavior in different parts of individuals' finance that are connected with different data handling styles and to analyze the relationship among elements that encourage more use of web betting among online stock exchange gamblers in Pakistan. The target of this study is to enlighten the psychological mental process that may account for people's propensity to take part in betting exercises, and furthermore to investigate more information about online gambling in Pakistan that how many people are involved in online gambling and to evaluate the motives regarding dependable gambling practices, behavioral components (Blaszczynski, Steel & McConaghy ,1997). This study tries to cover up the gap and observe the irrational financial decision of Pakistan stock exchange gamblers.

In previous studies, financial factors were recognized as one motive, but in our study financial motives are treated as far as to win money or to earn money. This reaction has course of action proposals as there may be a necessity for healthy signage. According to Baker and Kim (1971), "item response theory analysis of the problem gambling severity index" is a worldview for the outline examination and scoring of tests, polls, and comparable instruments measuring capacities, attitudes or different factors. It is a hypothesis of testing in view of the relationship between individual's exhibitions on a test item and the test takers' levels of execution on a general measure of the capacity that item was intended to gauge. A few diverse factual models are utilized to address to both the test item and test taker attributes.

The Theory of Reasoned Action (TRA) which is presented by Terry, Gallois, and Mccamish (1977) shows that before acting specific behavior, individuals should study the behavior consequences. Therefore intention is considered a fundamental component in measuring change in behaviors. as indicated by icekajzen , "Intention changes by the thinking style of individuals together with the individual's impression of the way their general public sees a similar behavior weather it is positive or negatives"(Boyce, Wood & Powdthavee, 2013). Accordingly, individual mentality and social intention are fundamental to the execution of a behavior and thusly, behavioral change.

Yet there is a gap in the relationship of PGSI with motivational factors and behavioral factors and that should be investigated (Mulkeen, Abdou, & Parke, 2016). This research has been both concrete and hypothetically important, because the results of this research are very practical for stock exchange gamblers. It gives you information regarding the relationship between PGSI and motivational factors, and the relationship between PGSI and behavioral factors.

Review of Relevant Literature

Within this section, we evaluate the relevant literature in the concept of predictors of PGSI including motivational factors, behavioral factors and personality traits. As said above, the two main purposes of this research are, first, to explore the relationship among motivational factors and problem gambling severity index that motivates more usage of online gambling in Pakistan, second, to investigate the relationship of behavioral factors and PGSI that investigates the level of implementation of responsible gambling practices (PGSI) in Pakistan.

According to Mulkeen et al. (2016), this research utilizes PGSI to decide the contrasts in UK web players' answers to their thought processes in betting on the web. It likewise assesses their perspectives identifying with mindful betting practices and behavioral elements. A three-phase examination covering Structural Equation Modeling (SEM), numerous relapse, and multinomial strategic relapse is utilized. The primary research tool is a web-based questionnaire. Our discoveries for the inspiration components climax that the maximum vast elements which players observe are escape and unwinding, monetary inspiration, and status rivalry. As far as a player sees in connection to capable betting practices and behavioral components, both self-rejection and self-improvement, and amusement configuration are distinguished as the main variables. Different variables, for example, proactive capable betting, straightforward terms and conditions, and utilization of player's data are not recognized as critical components by players. This investigation likewise recommends that the monetary rationale to bet ought to be separated into the accompanying sub-intentions: to win cash and to gain pay. Our principle arrangement suggestion incorporates the requirement for a more straightforward framework that spots accentuation on substantial or auditable methods for exhibiting moral duties, and to determine ranges of change.

Numerous hypotheses and research articles throw light on the significance of personality traits and its impact on problem gambling severity index, yet, there is a black box in the relationship of problem gambling and personality traits in Pakistan stock exchange gamblers and there should be more investigations (Callan, Ellard, Shead, & Hodgins, 2008). Our research objective is to explore the differences between individuals and non-problem gambling with high, moderate, low and other severe problem gambling in Pakistan stocks exchange. According to Wittek et al. (2016), gambling problem exists in high level among men, and those people who are living alone, who are unemployed, who are uneducated and their results demonstrate that non-problem gambling exists with high scores of neuroticism and low scores of agreeableness and conscientiousness. While numerous researchers recommend that there is a satisfactory level of consistency inside PGSI scores then a player's inspiration to bet (Rick, 1998; Gujarati, 2003).

Betting, including obsessive betting and issue betting, has got expanded consideration from clinicians and analysts in the course of recent decades, since betting open doors has extended the world over. Betting disarranges influence 0.2–5.3% of grown-ups around the world, despite the fact that estimation and pervasiveness differ as indicated by the screening instruments and strategies utilized, and accessibility and availability of betting open doors. A few particular treatment approaches have been positively assessed, for example, intellectual behavioral and brief treatment models and pharmacological medications. Albeit promising, family treatment and support from Gamblers Anonymous program are less well exactly bolstered. Betting scatters are very comorbid with other emotional well-being and substance utilize clutters, and a further comprehension is required of both the causes and treatment ramifications of this issue. This article audits definition causes and connected elements with substance manhandle, screening and conclusion, and treatment approaches (Habil, 2012).

In another study, Abdi (2014) conducted a survey that is a book audit in which the writer investigated betting inspirations and the effect of betting on personal satisfaction of the bettors and families, groups and social orders of the speculators. In the audit, the creator tended to social parts like social esteems and cultural assimilation impact on teenagers and youthful grown-up bettors to start and upkeep betting and issue betting. In the survey, the specialist likewise tended to believe that teenagers and youthful grown-ups are persuaded to bet for different reasons like diversion, fervor, entertainment, learning and fulfilling, and furthermore, genuine subjective inclination, chance inclined states of mind, and more elevated amounts of stress and uneasiness. Additional investigation showed that there is a sexual orientation distinction on what arouse speculators to start and keep up betting and issue betting. At last, regarding the effect of betting on the personal satisfaction and general well-being position, it is perceived that betting yields both potential costs (like an extensive variety of challenges on the people, families, and groups either in a roundabout way or straightforwardly, additional contrary outcomes of betting like issue) and advantages (like feeling of connectedness and socialization through optional relaxation time amusement, upgrading the wage of the people, fortifying memory, adapting methodologies and so on) that influence all parts of the group, including well-being and financial measurements.

The point of the present examination was to enhance the shortcomings of the three-dimensional gambling motives questionnaire and to look at the psychometric properties and variable structure of the Gambling Motives Questionnaire-Revised. The gambling motives questionnaire was distributed to an example of 418 speculators (92% men, mean age 19.5 years). Members finished the gambling motives questionnaire and an extra item tapping boredom, and in addition an assortment of measures of betting conduct and betting issues as the foundation measures. Results demonstrated that the Gambling Motives Questionnaire-Revised is better spoken to as a four element structure tapping the following four betting thought process components: Upgrade, adapting, social, and self-delight, $\Delta\chi 2$ $\Delta(df) = 24.76$ (prob=0.001). Expelling two problematic items from the Gambling Motives Survey and including an extra item tapping boredom likewise enhanced the fit of the Gambling Motives Questionnaire-Revised. The subscales improvement, social, and adapting were all important indicators of a variety of betting practices (prob=0.05), while upgrade, adapting, and self-satisfaction anticipated the recurrence of betting practices (prob=0.01). Adapting and self-satisfaction anticipated loss of control (prob=0.01), though self-satisfaction anticipated betting issues (prob=0.001). The Gambling Motives Questionnaire-Revised comprising of the four measurements upgrade thought processes, social intentions, adapting thought processes and self-delight intentions, is a dependable and substantial instrument to measuring betting thought processes (Myrseth, 2016).

The following paper tells us about the current flow about SEM (Structural Equation Model) and fit indices. The paper exhibits a choice of fit indices that are broadly viewed as the most useful files accessible to scientists. And laying out each of these records, rules are displayed on their utilization. The paper additionally gives revealing procedures of these files and finishes up with a talk on the eventual fate of fit indices (Hooper, 2008).

Methodology

In this research, we used convenient sampling techniques because it is difficult to collect data from all stock exchange gamblers by two Pakistani agencies (AKD securities and Zafar securities) or other gamblers who are conveniently available by other sources and generalized it on all the population and distributed questionnaires by conducting a survey in companies or businesses and searched for stock exchange gamblers. So our target population is Pakistan’s stock exchange gamblers. A similar study has been conducted in UK on internet gambling, but this research wants to check the impact of motivational and behavior factors on PGSI (Mulkeen, Abdou, & Parke, 2016). Since it is a wider research topic we chose this population.

So, we extended our data analysis into broad stages. We started with the collection of relevant data through questionnaires. The questionnaire holds 33 questions containing both open and close question (no more material is given related to behavioral and motivational components in open questions) and was classified into four areas. First, it was intended to acquire the assent from gamblers and gather data on their behaviors including which type of games they want to play and how frequently they play. The questionnaire based on PGSI containing nine items with four-point Likert scale were utilized to measure the problem gambling severity index score and ordering of 0=never, 1=sometime, 2=most of the times, 3=almost always. On the basis of gamblers' responses, the scores are attained in the subsequent arrangements of 0=non-problem group, score of 1 or 2 =low problem group, score of 3 to 7 =moderate problem group, and score of 8 or more = problem group.

Second area concentrates on gamblers' perception that encourages them to play. These incorporate variables such as financial motivation, escape and relaxation and excitements. Third area builds up player's mentalities towards 16 responsible betting practices on dependable betting practices and behavioral components utilizing a seven-point Likert scale with 1=strongly disagree to 7=strongly agree. These reports identify transparent terms and conditions, SE and SH, and game design in research. The last part of the survey deals with demographic data including age, gender, qualification, experience and designation. It ought to be stressed that PGSI is resolved utilizing set up measures while rest of the questions incorporated into our poll are created particularly for this review. For data analysis, we used SPSS21 software (statistical package for social sciences) and applied a multiple regression to check the impact of motivational factors and behavioral factors on PGSI. Since the variable which is not measured directly while based on some items for this purposes, we need a latent variable to calculate factor analysis. Our dependent variable is a categorical variable, which is why we applied multiple logistic regression and used STATA for structure equation model to check motivational factors and behavioral factors. Cronbach's alpha is calculated to check the reliability of scale items. Moreover, Cronbach's alpha is ascertained for both phases accomplishing 0.716 and 0.967 for motivational and behavioral elements correspondingly.

Too many difficulties have been confronted during collection of data. Some respondents responded quickly and some took a lot of time .In average, 10 respondents responded in ten days and collection of data was completed within six months and some respondents refused to give us their personal information that is why convenient sampling will be used .That is the reason from 412 respondents, 300 gave back the polls. There were 412 questionnaires distributed to Pakistan's stock exchange gamblers out of which 300 were reliable (72.81% response rate), and the final samples for females are 103 (35%), for males are 197 (66%), their average age lies between 28-36 years old, and the frequency of the game is 4 intervals a week. Repliers are arranged regarding the PGSI problem as 21(7%) no problem gambling group, 45(15%) low problem gambling group, 169(57%) moderate problem gambling group, 65(21%) high problem gambling group. we used three stages for data analysis.

First Stage: SEM (Structural Equation Modeling)

It is a multivariate technique that is used for measuring the relationship among observed and latent variables and is used to find out the error in the model and also to measure the complicated and structural model relationship (Hair Jr, Barry, & Kr, 2017). The aim of this model is to measure the quality of instruments and to check the internal consistency, reliability and validity. In PLS-SEM, we used partial least square techniques. These incorporate the composite reliability and construct validity and it means how much an instrument measures the construct. Construct validity is further divided into two types, they are convergent validity and discriminant validity. Convergent validity attempts to measure the correlations between theoretically similar measures and discriminant validity means the construct that should not be the same as other related constructs and we used AVE that tells us about the variance of items which is measured by any latent variable to assess both types of validity. According to Kock (2015), if AVE > 0.05, then convergent validity is acceptable and discriminant validity is acceptable when the square root of AVE is greater than the correlation of inter construct.

Reliability refers to "a statistical measure of how reproducible the survey instruments are". It is determined by ascertaining Cronbach's alpha that is generated through the scale of different items, and also Composite Reliability (CR) is calculated which tells about the error and validity of the construct.

Second Stage: Multiple Regressions

In multiple regressions, we used PGSI scores as predictor variables and motivational factors and behavioral factors as criterion variables by using results of SEM.

Regression 1:

$$\mathrm{PGSI} = \alpha + \mathrm{E}\beta_1 + \mathrm{RE}\beta_2 + \mathrm{FM}\beta_3 + \mathrm{e_i}$$

In Regression 1, we used PGSI scores as predictors and results of SEM of motivational factors as criterion variables where α refers to intercept which calculates the mean of the replies when dependent variables are 0 (zero); β delta tells us about the change in predictors when there is one unit

Change in independent variables: PGSI stands for problem gambling severity index and E denotes excitements, RE shows escape and relaxation, and FM represents for financial motivation and e signifies error term in the model.

Regression 2:

$$\mathrm{PGSI} = \alpha + \mathrm{TTC}\beta_1 + \mathrm{SESH}\beta_2 + \mathrm{GD}\beta_3 + \mathrm{e_i}$$

In Regression 2, we used PGSI scores as predictors and results of SEM of behavioral factors as criterion variables where α refers to intercept which calculates the mean of the replies when dependent variables are 0 (zero); β delta tells us about the change in predictors when one unit changes in independent variables, PGSI stands for problem gambling severity index, TTC denotes transparent term and condition, SESH represents SE and SH, GD shows game design, and e signifies error term in the model.

Third Stage: Multinomial Logistic Regression

We used multinomial logistic regression when the predictor variables are nominal. We took PGSI categories as predictor variables and made a two multinomial logistic regression for both motivational factors and behavioral factors.

MR1:

$$\mathrm{Log}\left(\frac{\mathrm{p}}{1-\mathrm{p}}\right) = \alpha + \beta_1\mathrm{E} + \beta_2\mathrm{RE} + \beta_3\mathrm{FM} + \varepsilon_\mathrm{i}$$

In Regression 1, we used PGSI categories as predictors and results of SEM of motivational factors as criterion variables where α refers to intercept which calculates the mean of the replies when dependent variables are 0 (zero), β delta tells us about the change in predictors when one unit changes in independent variables, PGSI stands for problem gambling severity index and E denotes excitements, RE shows escape and relaxation, and FM represents financial motivation, and e signifies error term in the model.

MR2:

$$\mathrm{Log}\left(\frac{\mathrm{p}}{1-\mathrm{p}}\right) = \alpha + \beta_1\mathrm{TTC} + \beta_2\mathrm{SESH} + \beta_3\mathrm{GD} + \varepsilon_\mathrm{i}$$

In this regression, we used PGSI categories as predictors and results of SEM of behavioral factors as criterion variables where α refers to intercept which calculates the mean of the replies when dependent variables are 0 (zero); β delta tells us about the change in predictors when one unit changes in independent variables, PGSI stands for problem gambling severity index, TTC denotes transparent term and condition, SESH represents SE and SH, GD shows game design and e signifies error term in the model.

Reliability of the instruments. “Reliability quality has been essential for any researcher (Shook, Ketchen, Hult, & Kacmar, 2004), as per the respondents must ensure that they had given genuine data about the investigation. The reliability quality has been attained to gauge the consistency. It is not a statistical test while it has been a reliability quality procedure. The ideal estimation of Cronbach’s alpha is "1" as portrayed by Sekaran (2003). Along these lines, the reliability quality of the instruments was registered from SPSS (Statistical Packages for Social Science) programming. The outcomes of reliability quality test has been given below.

Table 1 explains the ratability and validity and it is found that AVEs are showing convergent validity and the square roots of AVEs are larger than the inter construct of the model that shows there is discriminant validity and the model is reliable. Table 2 displays the ratability and validity and it is found that AVEs signify convergent validity and the square roots of AVEs are larger than the inter concept of the model that shows the existence of discriminant validity, and the model is reliable because Cronbach's alpha standards are 0.915 and the AVEs and CR values are 0.605 and 0.914.

Table 1. The Dimension Model of the Player's Motivational Factors (SEM1).

Constructs	Indicators	Loading	AVE	α	CR
Excitement	Is exciting for me	-0.88	0.73	0.61	0.84
	relieves boredom for me	-0.82			
Escape and relaxation	To relax	-0.72	0.53	0.6	0.7
	To vent animosity in a socially adequate manner	-0.61			
	To take my brain off different things	-0.84			
Financial motivation	Is a source to win money for me	-0.84	0.71	0.92	0.95
	Is a source to earn income for me	-0.85			
Problem gambling severity index	Convenience	0.72	0.64	0.93	0.94
	Confidentiality and secrecy	0.81			
	Accessibility of higher jackpots	0.85			
	Accessibility of well odds	0.88			
	Quicker games	0.86			
	The detail that you are not playing through real cash or e cash	0.79			
	The detail that you can play a number of games at a time	0.81			
	The detail it's not as thrilling by way of land gambling	0.71			
	The accessibility of improved tools to the relief that you gamble safer	0.67			

Table 2 . The Measurement Model of Responsible Gambling Practices and Behaviors SEM_2

Constructs	Indicators	Loadings	Ave	α	CR
Transparent terms and conditions	Terms and conditions for rewards are unmistakably conveyed	0.66	0.60	0.91	0.91
	Terms and situations for plusses are fair	0.73			
	gambling websites are open and true	0.82			
	Terms and conditions are essential to confirm players do not misuse the system	0.73			
	Online arbitrary number producers are used to define the game's result	0.81			
	Terms and conditions for plusses are deceiving	0.88			
	gambling software is rational	0.77			
SE & SH	Self-exclusion is fruitless as players can merely select to play at alternative site	0.83	0.66	0.95	0.90
	It is casual to get round the self-avoidance plot for any site	0.69			
	Fundamental for all sites to co-work to have a far reaching 'self-avoidance' framework	0.75			
	betting sites must deliver material about gambling problem	0.89			
	gambling sites should deliver material on someplace to get help	0.86			
Game design	Play times for version of an amusement ought to be precisely the same as the genuine version	0.88	0.705	0.92	0.92
	Betting administrators should not configure recreations utilizing addictive qualities	0.79			
	The primary need for client benefit is to keep consumer glad to continue spending	0.62			
	Having point by point data on my gaming and wagering decisions is valuable	0.93			
	Betting administrators should NOT be considered responsible to controllers	0.92			
Problem gambling severity index	Availability	0.72	0.64	0.93	0.94
	Confidentiality and secrecy	0.81			
	Accessibility of advanced jackpots	0.85			
	Accessibility of well chances	0.88			
	Quicker games	0.86			
	The way that you are not playing with genuine money but rather e-money	0.79			
	The reality you can play in excess of one amusement at any given moment	0.81			
	The reality it's not as energizing as land based betting	0.71			
	The accessibility of better instruments to enable you to bet more securely	0.67			
	Advancements	0.83			

Results and Discussion

We used three types of analyses of multiple regression, SEM and multinomial logistic regression to identify behavioral factors and motivational factors. The Problem Gambling Severity Index (PGSI) is employed as a dependent variable for analysis, and the purpose for applying three types of analysis is that a phase result is utilized as a contribution for the following phase. For instance, the results of our first phase, to be specific, SEM results are utilized as contributions for the second phase modeling that is multiple regression. This conforms reliability in this method and has the ability to interface fundamental attributes of our unpredictable modeling through one another. The third type of analysis, multinomial logistic regression, tells us about the relations between the gambling groups.

The verified conclusion of this study has yielded the reliable connection between variables. The objective of this research is to inspect the tendencies of financial decision making and spending behavior of individuals' finance and to check the relationship among elements that encourage more use of web betting among online stock exchange gamblers in Pakistan. The target of this study is to enlighten the psychological mental process that may account for people's propensity to take part in betting exercises and furthermore to investigate more information about online gambling in Pakistan that how many people are involved in online gambling and to evaluate the motives regarding dependable gambling practices, behavioral components according to their personality. Data were analyzed through SPSS by using the following techniques: Regression (simple and multiple) factor analysis, SEM, multinomial logistic regression.

Do Motivational Factors Affect PGSI That Motivates More Usage of Online Gambling in Pakistan?

In this hypothesis, three motivational factor estimation, financial motivation and escape and relaxation are taken into account, all these three factors are reliable and the value lies between (0.53-0.73). According to the Shook, Ketchen, Hult, and Kacmar (2004), respondents must make sure that they have provided true information about the study. The reliability has been referred to measure the consistency. The ideal estimation of Cronbach's alpha is "1" as depicted by Sekaran (2003).

Result of multiple regressions shows that models are significant with 99% (pb0.000) confidence level and their R^2 value is 0.732. Escape and relaxation and financial motivation are positively linked with PGSI representing that the greater the scores are, the more essential escape and relaxation and financial motive are. While excitement has a negative relationship with PGSI which represents the greater the scores are, the less essential excitement is as a motivational factor. Moreover, escape and relaxation and finance are the key motivational factors that urge a player to gamble. Results show all the variables are highly significant.

Factors analysis results indicate that all the questions which are related to each item are acceptable because the correlation matrix in Appendix 1 for motivational factors shows no value is more than 0.5 which indicates the acceptable level of multicolinearity, and thus explains discussing the factors independently (Alm, 1998; Gujarati, 2003).

Multinomial logistic regression results indicate moderate problem gambling is more liable and gambling classification is more disposed to be inspired by financial motivation as compared to other categories. Financial motivation is considered as the core motive for Pakistan's stock exchange gamblers and escape and relaxation are considered as less motivational as compared to others categories.

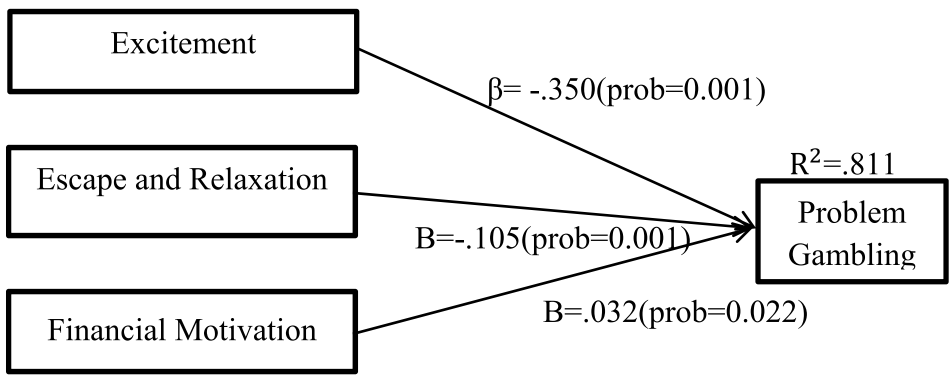
What Is the Effect of Behavioral Factors on Problem Gambling Severity Index?

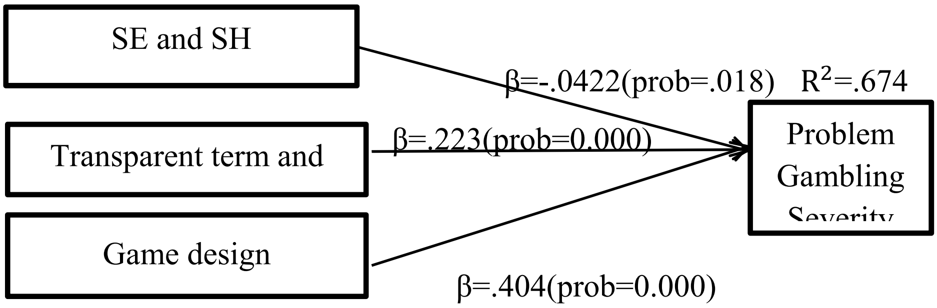
The model is reliable because Cronbach's alpha estimation is 0.915 and the AVEs and CR values are 0.605 and 0.914 respectively. In this hypothesis, three behavioral factors, transparent term and condition, SE and SH, and game design are employed. Transparent term and condition, SE and SH, and game design are positively linked with PGSI which represents the greater the scores are, the more essential transparent term and condition, SE and SH, and game design are. Moreover, transparent term and condition, SE and SH are the main behavioral elements in our study that urge a player to gamble. Our outcomes support the past reviews that game design is a significant factor which affects the player's behavior (Griffiths, 2009; Mulkeen et al., 2016).

Factors analysis results indicate that all the questions which are related to each item are acceptable because the correlation matrix in Appendix 1 for behavioral factors shows no value is more than 0.5 which indicates low level of multicolinearity and, thus explains discussing the elements independently (Alm, 1998; Gujarati, 2003).

Multinomial logistic regression results indicate that game design is considered as the most important factor that creates the difference between problem gambling and non-problem gambling. Results indicate that moderate problem gambling is more liable and gambling classification is more disposed to be inspired by game design that is the most important factor as compared to other categories. Game design is considered the core motive for Pakistan's stock exchange gamblers, and SE and SH are considered as less motivational as compared to other categories. This research recommended that moderate problem gambling is the strongest category. Transparent term and condition are insignificant in non-problem gambling and low problem gambling, and SE and SH are insignificant in moderate problem gambling.

First stage: Structural equation modeling. In our model for motivational factors and behavioral factors, we categorized SEM into two areas, the first area measures the validation and model estimation and the second area examines the causal connection among the constructs.





Note: Independent variable is PGSI individual score; VIF refers to variance inflation factor.

Figure 1. Structural equation modeling

Second stage: Multiple regression model. Multiple regression is run by using elements which are recognized by SEM and by using single scores of PGSI.

Player motivational factors**.** Table 3 shows that models are significant for player motivational factors with 99% (prob 0.000) confidence level and their R^2 value is 0.732 (adjusted R^2 =0.531).

Table 3.Regression Model$_1$ - (N=300)

Factors	β	SE	t	p	VIF	Model
Constant	0.54	0.97	5.63	b0.00	–	–
Excitement	-0.08	0.02	-3.96	b0.00	1.63	–
Escape and relaxation	0.18	0.03	5.68	b0.00	2.02	–
Financial	0.25	0.02	12.89	b0.00	1.31	–
Model parameters						
F value						113.97
Df						3
R^2						0.73
R^2 adjusted						0.53
P-value						b0.00

Player behavioral factors. Table 6 shows that models are significant with 99% (prob 0.000) confidence level and their R^2 value is 0.821 (adjusted R^2 =0.671).

Table 4. Regression Model2: Responsible Gambling Practices and Behavioral Factors and PGSI Individual Scores (N=300)

Factors	β	SE	t	P	VIF	Model
Constant	-0.53	0.11	-4.62	b0.00	–	
Transparent terms and conditions	0.22	0.04	5.061	b0.00	3.30	–
SE & SH	0.04	0.03	-1.31	0.18	2.54	–
Game design	0.40	0.39	10.50	b0.00	3.06	–
Model parameters						
F value						203.31
df						3
R^2						0.82
R^2 adjusted						0.67
P-value						b0.00

Third stage: Multinomial regression models. In stage three we regressed PGSI categories on independent variable that shows the relationship of PGSI categories with each independent variable which is impossible to calculate through SEM and multiple regressions of motivational and behavioral factors.

Player motivational factors. We apply multinomial logistic regression among PGSI categories (as a reference group) and motivational factors are shown in Table 5 and the model is significant with 99% (prob 0.000) confidence level and their R^2 value is 0.813.

Table 5. Player Motivational Factors with PGSI Categories

PGSI group	Factors	β	SE	df	p
No problem	Intercept	26.08	5.00	1	0.00
	Excitements	0.44	0.71	1	0.05
	Escape and Relaxation	-0.15	1.05	1	0.03
	Financial Motivation	-8.53	1.95	1	b0.00
Low problem	Intercept	35.21	5.45	1	0.00
	Excitement	0.72	0.69	1	0.02
	Escape and Relaxation	-1.63	1.08	1	0.013
	Financial Motivation	-10.22	2.06	1	b0.00
Moderate problem	Intercept	9.03	1.20	1	0.00
	Excitement	0.40	0.12	1	0.00
	Escape and Relaxation	-1.21	0.22	1	0.00
	Financial Motivation	-0.85	0.16	1	b0.00

PGSI group	Factors	β	SE	df	p
Model		Fitting criteria (−2 log likelihood)		Chi-square	
Intercept only		508.30			
Final		237.96	368.56	0.00	b0.00
Pseudo R^2		0.81			

Note: Independent variable is PGSI individual score; VIF refers to variance inflation factor.

Behavioral factors. We apply multinomial logistic regression among PGSI categories (as a reference group) and behavioral factors are shown in Table 6 and the model is significant with 99% (prob 0.000) confidence level and their R^2 value is 0.972.

Table 6.Responsible Gambling Practices and Behaviors with PGSI Categories

	Factors	β	SE	df	p
No problem	Intercept	175.95	39.36	1	0.00
	self-exclusion and self help	-4.026	4.62	1	0.78
	Transparent term and condition	-0.932	3.47	1	0.039
	Game design	-39.35	9.42	1	b0.00
Low problem	Intercept	180.731	33.68	1	0.00
	self-exclusion and self help	-13.044	5.05	1	0.85
	Transparent term and condition	-0.6	3.28	1	0.01
	Game design	-31.229	6.96	1	b0.00
Moderate problem	Intercept	133.309	31.28	1	0.00
	self-exclusion and self help	-5.83	2.17	1	0.05
	Transparent term and condition	0.756	3.12	1	0.00
	Game design	-22.622	6.18	1	b0.00
Model parameters		Fitting criteria (−2 log likelihood)	Chi-square		
Intercept only		608.46			
Final		50.77	557.69	9	0.00
Pseudo R^2		0.97			

The reference category is high problem at point 8 and above.

In light of our three phase investigation, motivational factors and behavioral variables, and personality traits were studied. we propose an arrangement suggestion to the internet betting area as follows: they should develop more successful frameworks for SE and SH (e.g., increase their performers' learning of how to get and use nutrition gadgets, institutionalize the route in which responsible gambling data are exhibited on betting sites, decrease players' doubts of utilizing the encouraging instruments, present necessary setting for successful time and money related cutoff points, and build up a compelling broad self-avoidance framework); and be awake, know about addictive parts of diversion outline. Extra research could be coordinated to decide if the betting business might have the capacity to add to advantages of some practices right now being created in different segments such as moral fund.

Several studies have been accomplished on PGSI, yet at the same time they have been inactive to test the comprehensive impact of motivational, behavioral factors on problem gambling severity index. Hence, in this research, we would tentatively test this question. The results of the study would help us to have more insights and observations particularly about the impact of motivational and behavioral factors on PGSI. This study emphasizes on the behavioral and motivational factors that efficiently affect the PGSI.

Conclusion

The purpose of gamblers is to earn money but this strategy suggestion relates particularly to problem gamblers who in our review will probably bet to win money and the market is socially highlighting that betting is an excitement and not an approach to gain money. Outcomes disclose that all motivational factors have significant impact on PGSI and future researches are expected to shed light on the connection among factors and to recognize PGSI categories through application of SEM, multiple regression, and multi nominal logistic regression. We conclude that financial motivation is the maximum significant element in moderate problem gambling category while escape and relaxation are in low problem category. In terms of responsible gambling practices, game design and transparent terms and conditions are the key elements of behavioral factors and SE and SH are not considered as significant factors and as well as the relationship between problem gambling severities. This research also recommends that moderate problem gambling is the strongest category.

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Appendix 1

Factor Analysis - Principle Component Analysis (PCA)

Table 7 indicates the PCA1 for motivational factors and check the level of agreement of respondents with their records of motivational factors by using Oblimin rotation; "it's exciting; to relieve boredom; to win money; to socialize, to take my mind off other things; to earn income; to compete with others; to vent aggression; it's fun; to be mentally challenged; and to do something I enjoy for a change". KMO confirmed the sampling capability for analysis (KMO = 0.86) which is worthy (Field, 2009) and the KMO values of each item is 0.613 >0.5 which is acceptable and the Bartlett's test of Chi square approximation shows the connection among items which is appropriately high for PCA (x^2=1223.311, df =21 and prob =0.000), and Table 7 shows rotate component matrix for motivational factors, the loadings show the connection among variables and tell which variables contribute more.

Table 7. Rotated Component Matrix of Motivations to Gamble (PCA1)

Variable\factor	$Factor_1$	$Factor_2$	$Factor_3$
To relieve boredom	0.813	–	–
It's exciting	0.785	–	–
To relax	–	0.82	–
To take my mind off other things	–	0.788	–
To vent aggression in a socially acceptable way	–	0.74	–
To win money	–	–	0.954
To earn income	–	–	0.778

"Note: $Factor_1$: Excitement - factors that allow the individual to be delighted and invigorated; $Factor_2$: Escape and Relaxation - factors that provide an outlet enabling the individual to forget about current problems and challenges: $Factor_3$: Financial Motivation- to earn income and win money; Each of these three extracted factors relating to 'gambling motivation' are subject to a Cronbach's Alpha test as follows: $Factor_1$ with 2 items and a Cronbach's Alpha of 0.614; $Factor_2$ with 3 items and a Cronbach's Alpha of 0.626; $Factor_3$ with 2 items and a Cronbach's Alpha of 0.929; 0.719 with a total of 12 items"

Results show that all the questions which narrate to each item are acceptable because the correlation matrix in Appendix 1 for motivational factors shows no value is more than 0.5 which indicates acceptable level of multicolinearity and, thus explains discussing the factors s independently (Alm, 1998; Gujarati, 2003).

Table 8. Rotated Component Matrix of Responsible Gambling Practices and Behaviors (PCA2)

Variable\factor	$Factor_1$	$Factor_2$	$Factor_3$
Terms and conditions for bonuses are fair.	0.949		
Terms and conditions are necessary to ensure some players do not abuse the bonus system.	0.949		
Terms and conditions for bonuses are deceptive.	0.885		
Online random number generators are used to determine the outcome of games.	0.845		
Terms and conditions for bonuses are clearly communicated.	0.833		
Internet gambling sites are open and honest regarding the terms of conditions of gambling on their site.	0.814		
Internet gambling software is fair.	0.483		
It is easy to get around the self-exclusion system for any one site (self-exclusion being where a player requests to be denied access to a site for a specified period of time).		0.868	
Self-exclusion is ineffective since players can simply choose to play at another site.		0.858	
Internet gambling websites should provide information regarding how to spot problem gambling.		0.856	
Internet gambling websites should provide information regarding where to get help.		0.845	
For self-exclusion to work all sites need to co-operate to have an industry-wide 'self-exclusion' system.		0.798	
Having detailed information on my gaming and betting choices is useful.		-	0.904
Gambling operators should not design games using characteristics they know to be addictive.			0.802
The main priority for customer service staff is to keep consumers happy so they keep spending money.			0.595
In relation to player protection and social responsibility, gambling operators should			0.513

Variable\factor	$Factor_1$	$Factor_2$	$Factor_3$
NOT be held accountable to regulators provided they are operating within the limits of the law.			
Play-for-free versions of a game should be exactly the same as the real version.			0.48

"Note: Extraction method: principal component analysis of 6 factors. Rotated method: Direct Oblimin. Converged in 23 iterationsFactor$_1$: Trans-parent terms and conditions; Factor$_2$: SE & SH; Factor$_3$: Game design. Each of these three extracted factors relating to 'responsible gambling practices are subject to a Cronbach's Alpha test as follows: Factor$_1$ with 7 items and a Cronbach's Alpha of 0.915; Factor$_2$ with 5 items and a Cronbach's Alpha of 0.955; Factor$_3$ with 5 items and a Cronbach's Alpha of 0.922;; and overall Cronbach's Alpha is 0.952 with a total of 17 items".

Table 8 specifies the PCA2 for behavioral factors and check the level of agreement of respondents with their records of behavioral factors by using Oblimin rotation. KMO confirmed the sampling capability for analysis (KMO = 0.86) which is worthy (Field, 2009), and the KMO values of each item are 0.633>0.5 which is acceptable and the Bartlett's test of Chi square approximation shows the connection among items which is appropriately high for PCA. (x^2=9327.021, df =136 and prob =0.000, and Table 8 shows rotate component matrix for behavioral factors, the loadings show the connection among variables and tell which variables contributes more.

Results show that all the questions which narrate to each item are acceptable because the correlation matrix in Appendix 1 for behavioral factors shows no value is more than 0.5 which indicates low level of multicolinearity, and thus explains discussing the factors independently (Alm, 1998; Gujarati, 2003).

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Dynamic Competitive Supply Chain Network Design with Price Dependent Demand and Huff Utility Function

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Abstract

This paper develops a two-stage model to consider a franchise/franchisee environment in which supply chains are simultaneously entering the untapped market to produce either identical or highly substitutable products and give franchise to franchisees. Customer demand is elastic, price dependent and customer utility function is based on Huff gravity rule model. The supply chains, in the first stage, shape their networks and set the market prices based on dynamic games. The franchisees, in the second stage, specify their attractiveness levels and set the locations of their retailers in simultaneous games. Possibility theory was also applied to cope with uncertainty. Finally, we applied our model to a real world problem, discussed the results, conducted some sensitivity analyses, and gained some managerial insights.

Keywords

Bi-level programming, simultaneous games, Nash equilibrium, dynamic competitive supply chain network design, Wilson algorithm.

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Introduction

Competition in business is slowly changing from “firms against firms” to “supply chains versus supply chains”; based on the literature; (Farahani et al., 2014), markets are full of different brands like Nike, Adidas, Nachi, Koyo, TTO, Nokia, SAMSUNG, Apple, Kia, Hyundai, GM, Volvo, Renault, and so on that mostly have some plants and distribution centers to produce and distribute their products to the retailers where the customers can buy the products directly. In this model, they have a semi-integral Supply Chain (SC) in which the retailers are working individually but the plants and distribution centers are working together as an integrated part of the chain. This structure can be matched with the customers’ utility function and they think where firstly to select their famous brand then will choose the suitable retailers to patronize their demand. For example, the authors ask a lot of people who want to buy a cellphone and almost all of them agreed that if they want to buy a cellphone, firstly, they select their famous brand mainly based on the brand reputation and prices, then after selecting the most preferred brand, they select a suitable franchisee to buy the cellphone. This example can be adapted to a lot of industries and shows that customers have two-stage utility functions, firstly they choose their famous brand and then their franchisees; so we consider this two-stage approach as our main assumption in the rest of the paper.

Also nowadays, most of the chains design their network structure and set the market price then use local retailers as their franchisees to serve the demands. By this way, they reduce their costs and also make some job opportunities, but also they will face the questions like: What is their equilibrium network structure? What is their equilibrium price? How many market shares can they obtain? What is the equilibrium attractiveness and locations of the franchisees? The aim of this paper is to find the solutions to these questions.

Competitive Supply Chain Network Design (CSCND) considers the impact of competitive markets in designing the network structure of a chain to improve its future competitiveness (see Farahani et al., 2014, for a review on CSCND).

CSCND problems have three main decisions: Strategic, tactical and operational decisions. Based on these decisions, the related literature of this subject can be categorized into two sub-fields such as: Competitive location problems and competitive supply chain problems in which the former usually concentrates on strategic decisions like location and the latter mostly concentrates on operational decisions like pricing. On the other hand, competition, in general, is classified into three different types as: Static competition, dynamic competition, and competition with foresight.

Moreover, in each type of competition, customer utility function and customer demand are two essential factors which shape the structure of a competition. Hotelling (1929) and Huff (1964, 1966) are the most commonly used customer utility function and price-dependent demand and inelastic demand are the most commonly used customer demand functions in the literature.

The existing literature considers different criteria for elastic demand like service levels (Boyaci & Gallego, 2004), prices (Bernstein & Federgruen, 2005; Anderson & Bao, 2010), price and service level (Tsay & Agrawal, 2000; Xiao & Yang, 2008), price and distance (Fernandez et al., 2007), distance (Plastria & Vanhaverbeke, 2008; Godinho & Dias, 2013; Godinho & Dias, 2010), distance and one or more attractiveness attributes (Aboolian et al., 2007) that are mostly modeled according to 0-1 (all or nothing) rule based on Hotelling's (1929) utility function. On the other hand, inelastic demand (Kucukaydın et al., 2011; Kucukaydın et al., 2012, Fahimi et al., 2017a) is mostly modeled according to Huff (1964, 1966). Definitely, customers have different criteria like quality, price, brand image, service level and etcetera to choose a SC and patronize their demand to the convenient retailers and do their purchasing. As our mentioned example in cellphone market customers have two-stage approach, but all the mentioned articles consider one step utility function for the customers that cannot be applied to our described environment, so we assume the customers have two-stage utility function and define our approach to model this behavior.

Three kinds of competitions can be found in the SC competition literature: Horizontal competition, a competition between firms of one tier of a SC; vertical competition, a competition between the firms of different tiers of a SC; and SC versus SC, a competition between SCs.

Most of the franchise/franchisee problems are put into competitive location problems. Kucukaydın et al. (2011) presented a franchise/franchisee problem in which a franchise entered a market with existing franchises that belonged to a competitor and wanted to shape his network by locating some new facilities and set the attractiveness of the facilities where the competitor could react to his entrance by adjusting the attractiveness of the existing facilities of his own. Kucukaydın et al. (2012) follows the introduced problem by Kucukaydın et al. (2011), they consider the same franchise/franchisee problem with this difference that the existing competitor can also open some new facilities as new franchises or close or adjust the attractiveness of the current franchises; also, they use Huff utility function with inelastic customer demand. Godinho and Dias (2010) presented a franchise/franchisee problem in which two competitors simultaneously enter the distance dependent market with elastic demand and want to shape their network and maximize profits while they also should maximize social welfare and propose an algorithm to solve the introduced problem. Following the their prior work, Godinho and Dias (2013) introduced another franchise/franchisee problem in which the franchisor defined the potential locations and rule of the game, in fact, the paper considers preferential rights and overbidding which means that one competitor has preferential right over another one in the same situation.

Watson, Dada, Grünhagen, and Wollan (2016) employed organizational identity theory to explain when the franchisor desires to select specifically franchisees that have the potential for entrepreneurial behavior. Badrinarayanan et al. (2016) offer a parsimonious framework of the antecedents of brand resonance in franchising relationships. Shaikh (2016) proposes a comprehensive conceptualization of the concept of fairness in the context of franchisor–franchisee relationship. In CSCND problem, we can mention the following works: Rezapour and Farahani (2010), Rezapour et al. (2011), Rezapour and Farahani (2014), Rezapour et al. (2014), Rezapour et al. (2015), Fallah et al. (2015), Fahimi et al. (2017a), and Fahimi et al. (2017b).

Contributions

In this paper, we turn to the essential issue of CSCND problem by assuming a two-stage customer behavior utility function. Our modeling and solution approaches are similar to Fahimi et al. (2017a) and Fahimi et al. (2017b). Our main contributions are:

- ✓ Our modeling approach that is inspired from our customer utility function driven from a real market, we assume a two-stage customer behavior utility function.
- ✓ Our parameters that are known as fuzzy numbers instead of convex functions which make them more practical.
- ✓ Our solution approach that is based on bi-level programming, differential system, enumeration method and Wilson algorithm.
- ✓ Our definition of quality that is based on discrete scale.

According to our mentioned example in the cellphone market, we model the customer behavior by two stages, firstly each customer selects a brand (SC) to patronize it based on the price and brand reputation, and next he/she chooses different franchisees to buy from them. Up to our knowledge, this point of view is novel and did not appear in the previous literature. Turning our view to the player's side, we consider n supply chains simultaneously enter the untapped market. In stage one, the SCs shape their networks and set market price in dynamic competition; in stage two, each supply chain gives franchises to m_n competing and independent franchisees. There is a high tight interaction between the SCs and their franchisees whereby the SCs specify the market price and the network to satisfy the franchisees' needs, which essentially impacts their profits.

Actually we propose a two-stage solution approach to solve the model. Stage one is related to SC's problem and constructed based on bi-level programming, differential system and Wilson algorithm. Stage two is related to franchisee's model in which by the help of enumeration method the problem is convexified and solved.

Table 1. Characteristic of the Relavant Works

Authors(s)(year)	Pre-determined component				Modeling framework				Integration degrees			Type of considered game		competitive characteristics
	SC tiers	Competition type	parameters		Bi-level	Multi-level	Customer utility function		full	semi	decentralized	dynamic	Stackelberg	
			certain	uncertain			Hoteling based	Huff based						
Rezapour and Farahani (2010)	4	Duopoly					✓					✓		Price
Godinho and Dias (2010)	2	Duopoly					✓				✓	✓		Distance
Kucukaydın et al. (2011)	2	Duopoly						✓			✓		✓	Quality, distance
Rezapour et al. (2011)	4	Duopoly					✓						✓	
Kucukaydın et al. (2012)	2	Duopoly						✓			✓		✓	Quality, distance
Godinho and Dias (2013)	2	Duopoly					✓				✓	✓		Distance
Rezapour and Farahani (2014)	4	Oligopoly					✓					✓		Price, service level
Rezapour et al. (2014)	4	Oligopoly						✓				✓		Price, distance
Rezapour et al. (2015)	4	Duopoly					✓					✓		Price
Fallah et al. (2015)	4	Duopoly					✓							Price
Fahimi et al. (2017a)	3	Duopoly					✓				✓	✓		Quality, distance
Fahimi et al. (2017b)	3	Oligopoly					✓				✓	✓		Price
This paper	4	Oligopoly					✓	✓				✓		Price, quality, distance

To clarify the primary contributions of this paper in relation to the existing literature, Table 1 summarizes the characteristics of the relevant published models, including those of the current paper. The remainder of this paper is organized as follows: Section 2 describes the problem; Section 3 presents the solution approach; Section 4 presents the numerical results and discussions; and Section 5 discusses the conclusions.

Problem Definition

In this section, we first describe the problem environment and then formulate the problem faced by the SCs, their independent and competing franchisees. n SCs are planning to enter the competitive markets in which no rival has previously existed. The SCs are centralized and have two different tiers named according to the plants and DC levels. They produce the same or highly substitutable products and sell them to customers via m_n independent and competing franchisees. They are set to shape their networks (set the plants and DC locations) and market price and award franchises to the franchisees. Figure 1 shows the problem environment. SCs shape their networks based on a dynamic game relating to specified market shares. Next, they give franchises to m_n franchisees, paying attention to the fact that customers patronize their demand to the franchisees by a probability related to the franchisees' attractiveness. In other words, customers first select the chain based on brand imaging and price and according to 0-1 rule; second, they choose to patronize their demand to the franchisees according to the franchisees' attractiveness (in this step, each franchisee has a chance to be selected according to Huff's gravity rule model).

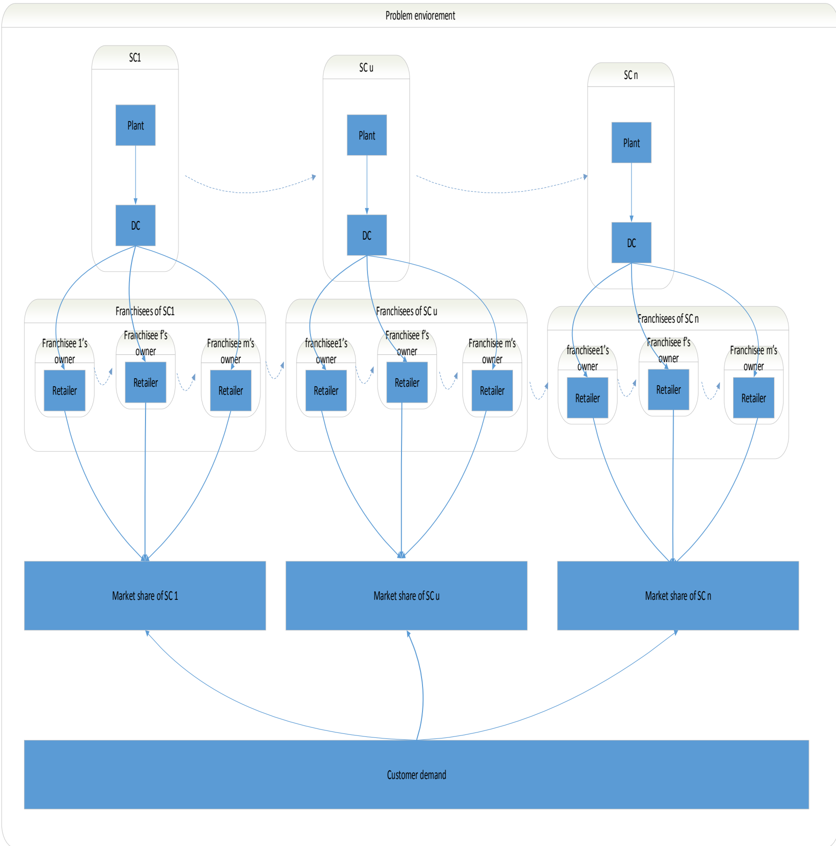

Figure 1. Problem environment

The total profit and market shares of each supply chain are dependent on their prices and the paths that they choose to satisfy the markets. The paths are based on the opened plants and the DCs of the chains. The total profits of the franchisees are also highly dependent on the prices and paths defined by the chains as well as the attractiveness of the franchisees' facilities. This definition shows that there are two stages by two different games in our proposed environment: The first one is a simultaneous game between the chains and pertains to shaping the network structures and the price specifying the equilibrium market price with respect to the fact that the prices are strictly related to the SC's opened paths (opened plants and DCs). The second game is between the franchisees, which is aimed at specifying the equilibrium qualities and distances by paying attention to the fact that m_n franchisees enter the market at the same time, thus, the second game is also a simultaneous game and will take place after the SC's game. Now, we can introduce the stages as follows:

Stage 1. SC selection

According to 0-1 rule and based on the price and reputation, customers choose one SC to patronize their demand. In this step, we use linear demand function.

Assume there are l demand points indexed by k and n incoming SCs indexed by u, then u th SC has s_u potential locations for opening plants indexed by e_u and m_u potential locations for opening DCs indexed by i_u correspondingly. So, the demand functions for u'th SC in market k can be defined as follows, similar to Tsay and Agrawal (2000):

$$d_k^{(u')}(P_k) = \tilde{\alpha}_{u'}\tilde{d}_k - \tilde{\delta}P_k^{(u')} + \tilde{\beta}\sum_{\substack{u=1 \\ u\neq u'}}^{n}\left(P_k^{(u)} - P_k^{(u')}\right) \qquad (1)$$

$\tilde{d}_k$ is the potential market size (if all prices were zero), $\tilde{\alpha}_{u'}$ is related to SC u' brand reputations, $\tilde{\alpha}_{u'}\tilde{d}_k$ is related on the basis of demand for SC u' if all prices were set to zero. Since demand cannot be negative, we assume:

$$\tilde{\alpha}_{u'}\tilde{d}_k - \tilde{\delta}P_k^{(u')} \succ \tilde{\beta}\sum_{\substack{u=1 \\ u\neq u'}}^{n}\left(P_k^{(u)} - P_k^{(u')}\right) \qquad (2)$$

Stage 2. Franchisee selection

In this step, the customers in each chain patronize their demands to the franchisees of the chain based on the Huff gravity-based rule, so each franchisee has a chance to be selected by the customers. Imagine that SC u has f_u franchisees and each franchisee has m_{f_u} potential retailers indexed by j_{f_u}, if the franchisee opens a retailer at site j_{f_u}, with $d^2_{j_{f_u}k}$ as the Euclidian distance between the retailer j_{f_u} and customer k, and with a quality level of $a_{j_{f_u}}$, so, the attractiveness of this facility for customer k is given by $\frac{a_{j_{f_u}}}{d^2_{j_{f_u}k}}$. By utilizing the gravity-based rule, the total attractiveness of franchisee f_u for customer k by the newly-opened retailers is given by $\sum_{j_{f_u}} \frac{a_{j_{f_u}}}{d^2_{j_{f_u}k}}$. Then the probability $Atr_{j_{f_u}k}$ that customer k visits facility j_{f_u} of franchisee f_u (based on all opened retailers in all franchisees of SC u) is expressed as $Atr_{j_{f_u}k} = \frac{\frac{a_{j_{f_u}}}{d^2_{j_{f_u}k}}}{\sum_{j_{f_u}}\sum_{f_u} \frac{a_{j_{f_u}}}{d^2_{j_{f_u}k}}}$ .Therefore, the revenue of franchisee f_u is as follows $\sum_{j_{f_u}}\sum_{k} m^{(u)}(P_k^{(u)} d_k^{(u)}(P_k) Atr_{j_{f_u}k})$. By a similar fashion, we can calculate the total revenue of other franchisees.

The following assumptions, parameters, and variables are used to model the introduced problems:

Assumptions

- ✓ The candidates' plant locations are known in advance.
- ✓ The candidates' DC locations are known in advance.
- ✓ There are no common potential locations between the chains.
- ✓ The demand of each customer market is concentered at discrete points.
- ✓ Demand is elastic and price dependent.
- ✓ Customer utility function is based on Huff gravity rule model.
- ✓ Products are either identical or highly substitutable.

Parameters

$\tilde{f}_{e_u}$	Fixed cost of opening a plant at location e for SC u
$\tilde{g}_{i_u}$	Fixed cost of opening a DC at location i for SC u
$\tilde{s}_{e_u}$	Unit production cost at plant e for SC u
$\tilde{c}_{e_u i_u}$	Unit transportation cost between plant e and DC i for SC u
$\tilde{h}_{i_u}$	Unit holding cost at DC i for SC u

$\tilde{f}_{j_{f_u}}$	Fixed cost of opening retail j for franchisee f at SC u
$\tilde{c}_{j_{f_u}}$	Unit attractiveness cost for retail j for franchisee f at SC u
$\tilde{h}_{j_{f_u}}$	Unit holding cost at retailer at location j for franchisee f at SC u
$\tilde{c}_{i_u j_{f_u}}$	Unit transportation cost between DC i and retailer j for franchisee f at SC u
$\tilde{c}_{j_{f_u} k}$	Unit transportation cost between retailer at location j for franchisee f at SC u and customer k
$d^2_{j_{f_u} k}$	Euclidian distance between retailer at location j for franchisee f at SC u and customer k
$P^{(1)}_{e_u}$	Number of opened plants for SC u
$P^{(2)}_{i_u}$	Number of opened DCs for SC u
$P_{j_{f_u}}$	Number of opened retailers for franchisee f at SC u
$m^{(u)}$	Percent of marginal profit for SC u

Decision variables

$y^{(1)}_{e_u}$	$\begin{cases} 1 \ if \ SC \ u \ opens \ a \ plant \ in \ location \ e \\ 0 \ otherwise \end{cases}$
$y^{(2)}_{i_u}$	$\begin{cases} 1 \ if \ SC \ u \ opens \ a \ DC \ in \ location \ i \\ 0 \ otherwise \end{cases}$
$y_{j_{f_u}}$	$\begin{cases} 1 \ if \ franchisee \ f \ in \ SC \ u \ opens \ a \ retailer \ in \ location \ j \\ 0 \ otherwise \end{cases}$
$x_{e_u i_u}$	Quantity of product shipped from plant e to DC i
$x_{i_u j_{f_u}}$	Quantity of product shipped from DC i to retailer at location j for franchisee f at SC u
$x_{j_{f_u} k}$	Quantity of product shipped from retailer at location j for franchisee f at SC u to customer k
$a_{j_{f_u}}$	Quality level of retailer at location j for franchisee f at SC u

The following model represents the problem of SC u:

$$P_{SCu} = \max Z_{SCu} = \sum_{i_u}\sum_{e_u}\sum_{k} P_k^{(u)} m^{(u)} (x_{e_u i_u}) y^{(1)}_{e_u} y^{(2)}_{i_u} - \qquad \forall u \qquad ((3)$$

$$\left(\begin{array}{l} \sum_{e_u} \tilde{f}_{e_u} y^{(1)}_{e_u} + \sum_{i_u} \tilde{g}_{i_u} y^{(2)}_{i_u} + \sum_{e_u}\sum_{i_u} \tilde{s}_{e_u} x_{e_u i_u} y^{(1)}_{e_u} y^{(2)}_{i_u} + \\ \sum_{e_u}\sum_{i_u} \tilde{c}_{e_u i_u} x_{e_u i_u} y^{(1)}_{e_u} y^{(2)}_{i_u} + \sum_{e_u}\sum_{i_u} (\frac{\tilde{h}_{i_u}}{2})(x_{e_u i_u}) y^{(2)}_{i_u} y^{(2)}_{i_u} \end{array} \right)$$

s.t

$$\sum_{i_u}\sum_{e_u} x_{e_u i_u} y_{e_u}^{(1)} y_{i_u}^{(2)} = \sum_k d_k^{(u)}(P_k) \qquad \forall u \tag{4}$$

$$\sum_{e_u} x_{e_u i_u} y_{e_u}^{(1)} = \sum_{f_u}\sum_{j_u} x_{i_u j_{f_u}} y_{i_u}^{(2)} \qquad \forall i_u \tag{5}$$

$$\sum_{e_u} y_{e_u}^{(1)} = P_{e_u}^{(1)} \tag{6}$$

$$\sum_{i_u} y_{i_u}^{(2)} = P_{i_u}^{(2)} \tag{7}$$

$$x_{e_u i_u}, x_{i_u j_{f_u}}, P_k^{(u)} \geq 0, y_{e_u}^{(1)}, y_{i_u}^{(2)} \in \{0,1\} \tag{8}$$

Term 3 represents the objective function of SC u, which includes profits captured by selling the product to the franchisees minus the fixed cost of opening plants and DCs, the production cost of plants, the transportation cost between plants and DCs, and the holding cost at DCs. Constraint 4 ensures that all the demands of the customers are satisfied by the opened plants and DCs. Constraint 5 is related to flow balance; Constraints 6 and 7 ensure that only $P_{e_u}^{(1)}, P_{i_u}^{(2)}$ plants and DCs are opened; and Constraint 8 is related to binary and non-negativity restrictions on the corresponding decision variables.

The problem of franchisee f in SC u:

$$P_{f_u}: \max Z_{f_u} = \sum_k \sum_{j_u} \left(1 - m^{(u)}\right) P_k^{(u)} x_{j_{f_u} k} y_{j_{f_u}} - \qquad \forall u, f_u \tag{9}$$

$$\begin{pmatrix} \sum_{i_u}\sum_{j_u} \left(\frac{\tilde{h}_{j_{f_u}}}{2}\right) x_{i_u j_{f_u}} + \sum_k \sum_{j_u} \tilde{c}_{j_{f_u} k} x_{j_{f_u} k} \\ + \sum_{j_u} \tilde{c}_{j_{f_u}} a_{j_{f_u}} y_{j_{f_u}} + \sum_{j_u} \tilde{f}_{j_{f_u}} \end{pmatrix} y_{j_{f_u}}$$

$s.t$

$$x_{j_{f_u} k} = d_k^{(u)}(P_k) \frac{\frac{a_{j_{f_u}}}{d_{j_{f_u} k}^2} y_{j_{f_u}}}{\sum_{j_{f_u}} \sum_{f_u} \frac{a_{j_{f_u}}}{d_{j_{f_u} k}^2} y_{j_{f_u}}} \qquad \forall u, f_u, j_{f_u} \tag{10}$$

$$\sum_{j_u} y_{j_{f_u}} = P_{j_{f_u}} \tag{11}$$

$$\sum_{i_u} x_{i_u j_{f_u}} y_{i_u}^{(2)} = \sum_{k} x_{j_{f_u} k} y_{j_{f_u}} \qquad \forall u, f_u, j_{f_u} \tag{12}$$

$$x_{j_{f_u} k}, a_{j_{f_u}} \geq 0, y_{j_{f_u}} \in \{0,1\} \tag{13}$$

Term 9 represents the objective function of franchisees in SC u, which includes the profits from selling the product to the customers minus the fixed cost of opening and setting the quality level of the facilities, the holding cost at the retailers, and the transportation cost between the retailers and customers. Constraint 10 ensures that each opened retailer satisfies the level of demand from customers; Constraint 11 specifies the number of opened retailers; Constraints 12 is related to balance flow; Constraints 13 is related to binary and non-negativity restrictions on the corresponding decision variables.

Solution Approaches

In this section, we present the solution approaches to our two-stage dynamic competitive supply chain network design. Our solution approaches are similar to Fahimi et al. (2017a) and Fahimi et al. (2017b). We also, based on the proposed modeling approach, categorize the problem into two distinct stages. In the first stage, the SCs set the market prices and shape their networks. In the second stage, the franchisees select their optimum locations and attractiveness to maximize their profits. The proposed algorithm is as follows:

Stage 1. SC selection

1- Consider the whole strategies for the SCs:

1-1 Construct an empty poly-matrix by considering all pure strategies of the SCs.

2- Calculate Nash equilibrium prices and flows for all the chains in the defined strategies.

2-1 Construct the profit function in each strategy and differentiate the terms and solve equilibrium prices for all SCs simultaneously.

3- Find the best response of all the players.

3-1 Fill the empty poly-matrix with the obtained payoffs from the previous stage and find the best network structure using Wilson algorithm.

Stage 2. Franchisee selection

4- Consider the whole strategies for the franchisees:

4-1 Construct an empty poly-matrix by considering all pure strategies of the players based on locations and quality levels.

5- Calculate Nash equilibrium locations and quality levels for all the franchisees in the defined strategies.

5-1 Use enumeration method to obtain locations and quality levels for all franchisees simultaneously

6- Find the best response of all the franchisees.

6-1 Fill the empty poly-matrix with the obtained payoffs from the previous stage and find the best network structure using Wilson algorithm.

However, in our solution approaches, we introduce a step-by-step procedure in which we can reach equilibrium networks, price, location and attractiveness. Moreover, in each step, we formulate the equivalent crisp model based on the method introduced by Inuiguchi and Ramik (2000), Liu and Iwamura (1998), Heilpern (1992), and Pishvaee et al. (2012).

Stage one: SC selection

Each SC has two intrinsically different decisions. Price and location decisions in which price is operational and location is strategic cannot be decided simultaneously as they are naturally different. Also, the model should first decide about the locations and then sets the price; in addition, the variable costs that should be considered in the price are directly related to the location of facilities and production, holding and transportation costs. Therefore, to solve this problem, we use a three-step algorithm in which step one constructs a poly matrix based on location variables of the chains; step two uses bi-level programming and sets the price and assignments; and step three selects the equilibrium networks and consequently equilibrium prices with the help of Wilson algorithm (Wilson, 1971).

Step one

This step is shaped based on the location variables of the SCs, as the number of opened plants $\begin{pmatrix} s_u \\ P_{e_u}^{(1)} \end{pmatrix}$ and DCs $\begin{pmatrix} m_u \\ P_{e_u}^{(2)} \end{pmatrix}$ in each chain is known in advance, so we can construct a poly matrix by dimension equal to $\left(\begin{pmatrix} s_1 \\ P_{e_1}^{(1)} \end{pmatrix} \cdot \begin{pmatrix} m_1 \\ P_{e_1}^{(2)} \end{pmatrix}\right) * \ldots * \left(\begin{pmatrix} s_u \\ P_{e_u}^{(1)} \end{pmatrix} \cdot \begin{pmatrix} m_u \\ P_{e_u}^{(2)} \end{pmatrix}\right) * \ldots * \left(\begin{pmatrix} s_n \\ P_{e_n}^{(1)} \end{pmatrix} \cdot \begin{pmatrix} m_n \\ P_{e_n}^{(2)} \end{pmatrix}\right)$. To clarify, consider we have two incoming SCs and each one wants to open one plant and two DCs through 5 and 3 potential locations so there exist $\begin{pmatrix} 5 \\ 1 \end{pmatrix} \cdot \begin{pmatrix} 3 \\ 2 \end{pmatrix} = 15$ pure strategy so we have a bi-matrix by dimension equal to $15 * 15$ and we encountered with 225 different problems in the next step that should be solved through differential systems and mathematical optimization. Now, we can calculate the price in each strategy in the next step.

Step two

We introduce a bi-level programming here to solve the model of the SCs in each defined strategies as follows: Inner level

This step deals with the inner part of the bi-level model, which determines the equilibrium prices for the SCs. In fact, pricing decisions are highly related to the possible paths (indexed by s) in serving the market. Each path is a combination of one plant and one DC from each chain. For example, if SC u' opens a plant and DC at location $e_{u'}, i_{u'}$ then the costs of path for the chain (including production, transportation, and holding costs) is calculated as:

$$\tilde{c}_{u'}^{s} = \tilde{s}_{e_{u'}} + \tilde{c}_{e_{u'} i_{u'}} + \left(\frac{\tilde{h}_{i_{u'}}}{2}\right) \tag{14}$$

The following models are then used to maximize the profit of the SCs:

$$\pi_{SCu'} = (P_k^{(u')} - \tilde{c}_{u'}^{s}) \left(\tilde{\alpha}\tilde{d}_k - \tilde{\delta} P_k^{(u')} + \tilde{\beta} \sum_{\substack{u=1 \\ u \neq u'}}^{n} P_k^{(u)} \right) \qquad (15)$$

$$\max\{\pi_{SCu'}\}$$

Let assume $P_k^{(u')} \geq \tilde{c}_{u'}^{s}$ then by differentiating the terms and solving equilibrium prices for all SCs simultaneously that result in equilibrium prices.

Outer level

This step deals with the outer part of the bi-level model. The mathematical model for this part is constructed as follows with respect to the fact that the opened plants and DCs are predefined in previous stage and prices here are given by the inner part.

$$P_{SCu} = \max Z_{SCu} = \sum_{i_u} \sum_{e_u} \sum_{k} P_k^{(u)*} m^{(u)} (x_{e_u i_u}) - \left(\begin{array}{l} \sum_{e_u} \tilde{f}_{e_u} + \sum_{i_u} \tilde{g}_{i_u} + \sum_{e_u} \sum_{i_u} \tilde{c}_{e_u i_u} x_{e_u i_u} + \\ \sum_{e_u} \sum_{i_u} \tilde{s}_{e_u} x_{e_u i_u} + \sum_{e_u} \sum_{i_u} (\frac{\tilde{h}_{i_u}}{2})(x_{e_u i_u}) \end{array} \right) \qquad \forall u, e_i \in \begin{pmatrix} s_1 \\ P_{e_1}^{(1)} \end{pmatrix}, i_u \in \begin{pmatrix} m_1 \\ P_{e_1}^{(2)} \end{pmatrix} \qquad (16)$$

s.t

$$\sum_{i_u} \sum_{e_u} x_{e_u i_u} = \sum_{k} d_k^{(u)} (P_k) \qquad \forall u, e_i \in \begin{pmatrix} s_1 \\ P_{e_1}^{(1)} \end{pmatrix}, i_u \in \begin{pmatrix} m_1 \\ P_{e_1}^{(2)} \end{pmatrix} \qquad (17)$$

$$\sum_{e_u} x_{e_u i_u} = \sum_{f_u} \sum_{j_u} x_{i_u j_{f_u}} \qquad \forall i_u \in \begin{pmatrix} m_1 \\ P_{e_1}^{(2)} \end{pmatrix} \qquad (18)$$

$$x_{e_u i_u}, x_{i_u j_{f_u}} \geq 0 \qquad \forall u, e_i \in \begin{pmatrix} s_1 \\ P_{e_1}^{(1)} \end{pmatrix}, i_u \in \begin{pmatrix} m_1 \\ P_{e_1}^{(2)} \end{pmatrix} \qquad (19)$$

Term 16 represents the objective function of SC u in the defined strategy and with respect to the fact that the prices here are given by the inner part. Constraint 17 is related to demand satisfactions. Constraint 18 is related to flow balance; and Constraint 19 is related to non-negativity restrictions on the corresponding decision variables.

Step three

In this step we first fill the poly matrix by the given payoffs from the previous step and then calculate equilibrium networks by the help of Wilson algorithm (see Wilson (1971) for more information).

Stage two: Franchisee selection

In the second stage, the franchisees should select the locations and set their attractiveness levels for the facilities in order to maximize their profits according to the market prices and customer demand achieved by the SCs. The franchisee's problems are formulated by a Mixed Integer Nonlinear Programming Model (MINLP) and are non-convex in terms of its attractiveness function. But with respect to the modeling structure, the only nonlinear term in the model is the attractiveness term $\frac{\frac{a_{j_{f_u}}}{d^2_{j_{f_u}k}} y_{j_{f_u}}}{\sum_{j_{f_u}} \sum_{f_u} \frac{a_{j_{f_u}}}{d^2_{j_{f_u}k}} y_{j_{f_u}}}$, which specifies the quality, distance, and location of opened retailers. If we can fix the attractiveness term, the remainder of the model's terms are linear. On the other hand, the number of opened retailers in each franchisee is known in advance $P_{j_{f_u}}$. The attractiveness level of the retailer is directly related to its quality level. For this purpose, we define some scenarios for quality levels; therefore, like the SC's problem, we construct a poly matrix based on the pure strategies of the franchisees $\binom{j_{f_u}}{P_{j_{f_u}}}$ in each chain and also define a five-scale measurement of the quality level as 1, 2, 3, 4 and 5 which are equal to very bad, bad, average, good, and very good quality levels. So this step encountered with $\left(5^{\binom{j_{1_u}}{P_{j_{1_u}}} * \binom{j_{2_u}}{P_{j_{2_u}}} * \dots * \binom{j_{f_u}}{P_{j_{f_u}}} * \dots * \binom{j_{m_u}}{P_{j_{m_u}}}}\right) * \left(\binom{j_{1_u}}{P_{j_{1_u}}} * \binom{j_{2_u}}{P_{j_{2_u}}} * \dots * \binom{j_{f_u}}{P_{j_{f_u}}} * \dots * \binom{j_{m_u}}{P_{j_{m_u}}}\right)$ different problems that should be solved to fill the poly matrix and be able to find the Nash equilibrium locations and quality levels of the franchisees by Wilson algorithm.

We therefore used Wilson algorithm and the Nash equilibrium concept and introduced a very simple and efficient procedure to obtain the Nash equilibrium point. In the proposed method, each player has several pure strategies $\begin{pmatrix} j_{f_u} \\ P_{j_{f_u}} \end{pmatrix}$ that are defined by their quality levels for the opened facilities. With this procedure, the problem is also convexified, and we can define a poly matrix based on the opened retailers and their corresponding quality levels. By this manner, there is no need for major computational calculations. Moreover, it can be easily applied to small size problems; therefore, the equivalent model of franchisee f in SC u is as follows:

$$P_{f_u}: \max Z_{f_u} = \sum_k \sum_{j_u} \left(1 - m^{(u)}\right) P_k^{(u)} x_{j_{f_u} k} - \left(\begin{array}{l} \sum_{i_u} \sum_{j_u} (\frac{\tilde{h}_{j_{f_u}}}{2}) x_{i_u j_{f_u}} + \sum_k \sum_{j_u} \tilde{c}_{j_{f_u} k} x_{j_{f_u} k} \\ + \sum_{j_u} \tilde{c}_{j_{f_u}} a_{j_{f_u}} + \sum_{j_u} \tilde{f}_{j_{f_u}} \end{array} \right) \qquad \forall u, f_u, y \in \begin{pmatrix} j_{f_u} \\ P_{j_{f_u}} \end{pmatrix} \tag{20}$$

$$s.t$$

$$x_{j_{f_u} k} = d_k^{(u)} (P_k) \frac{\dfrac{a_{j_{f_u}}}{d^2_{j_{f_u} k}}}{\sum_{j_{f_u}} \sum_{f_u} \dfrac{a_{j_{f_u}}}{d^2_{j_{f_u} k}}} \qquad \forall u, f_u, j_{f_u}, y \in \begin{pmatrix} j_{f_u} \\ P_{j_{f_u}} \end{pmatrix} \tag{21}$$

$$\sum_{i_u} x_{i_u j_{f_u}} = \sum_k x_{j_{f_u} k} \qquad \forall u, f_u, j_{f_u} \in \begin{pmatrix} j_{f_u} \\ P_{j_{f_u}} \end{pmatrix} \tag{22}$$

$$x_{j_{f_u} k} \geq 0, a_{j_{f_u}} \in \{1, 2, 3, 4, 5\} \tag{23}$$

Term 20 represents the objective function of franchisee f_u in SCu; Term 21 ensures that each opened retailer satisfies the level of patronized demands; Constraint 22 is related to balance flow and Term 23 is related to the quality, and non-negativity restrictions on the corresponding decision variables.

It is worth noting that as the proposed algorithm uses Wilson algorithm and enumeration method, it needs a lot of time, especially in its worst case, and is just suitable for small-scaled problems, so proposing a meta-heuristic solution by computing the complexity of the algorithm can be a good idea.

Numerical Study and Discussion

Our case study is related to two Iranian investors who want to produce their brands in the spare parts industry; in particular, they want to produce a kind of bearing used in washing machines. This market is untapped for the Iranian investors. Based on the quality of their product and the market price, they have no competitors. The two chains in this study are simultaneously entering the market, and each chain wants to open one plant and one DC from five potential locations. They also want to give franchises to two competing and independent franchisees named R_1^{SC1}, R_2^{SC1} in SC1 and R_1^{SC2}, R_2^{SC2} in SC2. Each franchisee has four potential locations and wants to open two retail points and set their quality based on the given prices to maximize its profit. There is one demand point. The demand functions of the chains are as follows:

$$0.55\tilde{d} - 0.03\tilde{d}P_1^{(1)} + 0.07\tilde{d}P_1^{(2)} \tag{24}$$

$$0.45\tilde{d} - 0.03\tilde{d}P_1^{(2)} + 0.07\tilde{d}P_1^{(1)} \tag{25}$$

The parameters are assumed to be trapezoidal fuzzy numbers. The following distributions are used to extract the required parameters (Table 2)

Table 2. Distribution of Parameters

$\tilde{f}_{e_u} \sim (u(1500,2000),\ u(2000,2500),\ u(2500,3000),\ u(3000,4000))$
$\tilde{g}_{i_u}, \tilde{f}^{r}_{j_u} \sim (u(900,1500),\ u(1500,2000),\ u(2000,2500),\ u(2500,3000))$
$\tilde{s}_{e_u} \sim (u \sim (2,2.5),\ u \sim (2.5,2.75),\ u \sim (2.75,3),\ u \sim (3,3.5))$
$\tilde{c}_{e_u i_u} \sim (u(0.9,1.5),\ u(1.5,2.1),\ u(2.1,2.5),\ u(2.5,3.12))$

$$\tilde{c}^{r}_{j_u k} \sim (u(1.5,2),\ u(2,2.5),\ u(2.5,3),\ u(3,3.5))$$

$$\tilde{h}_{i_u}, \tilde{h}^{r}_{j_u} \sim (u(1.25,1.5),\ u(1.5,1.75),\ u(1.75,2),\ u(2,2.25))$$

$$d \sim (u(9000,10000),\ u(10000,11000),\ u(11000,12000),\ u(12000,13000))$$

$$\tilde{c}^{r}_{j_u} \sim (u(900,1500), u(1500,2000),\ u(2000,2500), u(2500,3000))$$

The proposed algorithm was implemented in Matlab (2014a) and carried out on a Pentium dual-core 2.6 GHz with 2 GB RAM. In this study, we determine equilibrium prices and locations and specify how the chain should give franchises to franchisees, and the effect of marketing activities on their total profits. Dynamic competition occurred between them on the basis of location and price, and they used the prices obtained as the market price for their franchisees. The franchisees sold the product to the customers at the equilibrium prices specified by two SCs in the price competition. There is also a dynamic competition between the franchisees in terms of market shares. Table 3 shows the results of the study. According to this table, SC1 opens a plant at Location 5 and a DC at Location 2; SC2 opens at 3 and 5, and therefore, the opened path is (5,2,3,5). The remainder of results are presented in Table 3.

Table 3. Numerical Example

	Opened paths	Total market share	DC price	objSC		Retailer price	Equilibrium location	Equilibrium quality	objfranchisee
SC1	(5,2,3,5)	12029.6	7.95	32727	R_1^{SC1}	8.74	(1,3)	(2,3)	10905.29
					R_2^{SC1}		(2,4)	(3,3)	8407.12
SC2	(5,2,3,5)	16119.2	7.02	30729	R_1^{SC2}	7.72	(1,2)	(3,1)	13163.88
					R_2^{SC2}		(2,3)	(2,2)	5650.864

Discussion

We now discuss the sensitivity analysis of the equilibrium prices, market shares, total SC profit, total franchisee profit, opened paths, attractiveness levels, and equilibrium location of the retailers with respect to the effect of δ, β parameters, which are related to switching and marginal customers and represent different marketing decisions. Moreover, we discuss the situations in which the SCs have different levels of power, specifying by λ as the weighting factor to cooperate with each other; and simply we use weighted sum the objective function of the chains by the corresponding constraints of both and it is worth noting that $0 \le \lambda \le 1$, and we assumed that λ belongs to $\lambda \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$. In the franchisees' phase, we analyze the effect of SC decisions to give their franchise to just one franchisee instead of two. In addition, they can consider the situations in which the franchisees can sell the products of both chains, named in terms of common franchisees. In this case, we also analyze the effect of the existence of one to two independent franchisees on their attractiveness levels and profits.

Table 4 shows the behavior of the opened paths, total market share, DC price, total SC profit, equilibrium locations and qualities, and franchisees' total profit with respect to β. The amount of parameter β varies in the solved examples while δ is set to $0.03EV(d)$. According to figure 2, by increasing the competition intensity, the total market share of both chains increases, but the amount of expansion for SC2 is higher than that of SC1. In the case of low competition intensity, SC1 has gained more market share. According to figure 3, the DC price of both chains decreases by increasing β; in terms of low competition intensity, their difference is more than high competition intensity. Figure 4 shows the total profit of the chains; in the low amount of β, SC1 has gained greater profits than SC2. However, by increasing the amount of β, their total profit becomes similar because of similar DC prices, and the market share of SC2 increases. Figure 5 shows the behavior from total profit of the franchisees in SC1 with respect to β, which has the same patterns as the total profit of SC1.

Table 4 . The Change of the Opened Paths, Total Market Share, DC Price, Total SC Income, Equilibrium Locations and Qualities and Retailer's Total Income with Respect to β

$\delta = 0.03\text{EV(d)}$	Opened paths	Total market share	DC price	objSC		Retailer price	Equilibrium locations	Equilibrium qualities	objfranchisee	β
SC1	(5,2,3,5)	10073.60	10.97	57068.36377	R_1^{SC1}	12.07	(1,3)	(3,3)	25854.98	$\delta = 0.03\text{EV(d)}$
					R_2^{SC1}		(2,4)	(3,3)	18521.16	
SC2	(5,2,3,5)	9094.38	8.89	32308.68637	R_1^{SC2}	9.78	(1,2)	(3,1)	13066.9111	
					R_2^{SC2}		(2,3)	(2,2)	5649.061466	
SC1	(5,2,3,5	10238.64824	10.76	55952.82602	R_1^{SC1}	11.84	(1,3)	(3,3)	25166.05249	$\delta = 0.03d_k$
					R_2^{SC1}		(2,4)	(3,3)	18002.38625	
SC2	(5,2,3,5)	9465.504477	8.81	33021.29351	R_1^{SC2}	9.69	(1,2)	(3,1)	11704.67331	
					R_2^{SC2}		(2,3)	(3,2)	6032.590397	
SC1	(5,2,3,5)	10393.30557	10.57420813	54895.1531	R_1^{SC1}	11.63162895	(1,3)	(3,3)	24512.79151	$\delta = 0.03d_k$
					R_2^{SC1}		(2,4)	(3,3)	17510.37311	
SC2	(5,2,3,5)	9815.004571	8.722836642	33582.74695	R_1^{SC2}	9.595120306	(1,2)	(3,1)	12081.09246	
					R_2^{SC2}		(2,3)	(3,2)	6361.265591	
SC1	(5,2,3,5)	10537.80486	10.39938254	53882.85126	R_1^{SC1}	11.43932079	(1,3)	(3,3)	23887.42254	$\delta = 0.009d_k$
					R_2^{SC1}		(2,4)	(3,3)	17039.1829	
SC2	(5,2,3,5)	10145.43619	8.639002181	34019.35216	R_1^{SC2}	9.502902399	(1,2)	(3,1)	12382.03807	
					R_2^{SC2}		(2,3)	(3,2)	6623.307599	
SC1	(5,2,3,5)	10606.35822	10.31701587	53391.01336	R_1^{SC1}	11.34871746	(1,3)	(3,3)	23583.51877	$\delta = 0.01d_k$
					R_2^{SC1}		(2,4)	(3,3)	16810.11724	
SC2	(5,2,3,5)	10304.1712	8.59758153	34197.56551	R_1^{SC2}	9.457339683	(1,2)	(3,1)	12508.2258	
					R_2^{SC2}		(2,3)	(3,2)	6732.893052	
SC1	(5,2,3,5)	11552.34031	9.130492929	44874.1369	R_1^{SC1}	10.04354222	(1,3)	(3,3)	18312.03119	$\delta = 0.03d_k$
					R_2^{SC1}		(2,4)	(3,3)	12824.15562	

δ = 0.03EV(d)	Opened paths	Total market share	DC price	objSC		Retailer price	Equilibrium locations	Equilibrium qualities	objfranchisee	β
SC2	(5,2,3,5)	12843.27734	7.886032323	34631.57888	R_1^{SC2}	8.674635556	(1,2)	(3,1)	13117.57212	
					R_2^{SC2}		(2,3)	(3,2)	7236.613728	
SC1	(5,2,3,5)	11947.72798	8.424780795	38142.684	R_1^{SC1}	9.267258874	(1,3)	(3,3)	14132.53451	$\delta = 0.05d_k$
					R_2^{SC1}		(2,4)	(3,3)	9645.496299	
SC2	(5,2,3,5)	14665.67309	7.383880362	32841.03869	R_1^{SC2}	8.122268398	(1,2)	(3,1)	12329.23423	
					R_2^{SC2}		(2,3)	(3,2)	6511.584906	
SC1	(5,2,3,5)	12029.6	7.95	32727.11107	R_1^{SC1}	8.74	(1,3)	(2,3)	10905.29	$\delta = 0.07d_k$
					R_2^{SC1}		(2,4)	(3,3)	8407.12	
SC2		16119.2	7.02	30729	R_1^{SC2}	7.72	(1,2)	(3,1)	13163.88	
					R_2^{SC2}		(2,3)	(2,2)	5650.864	

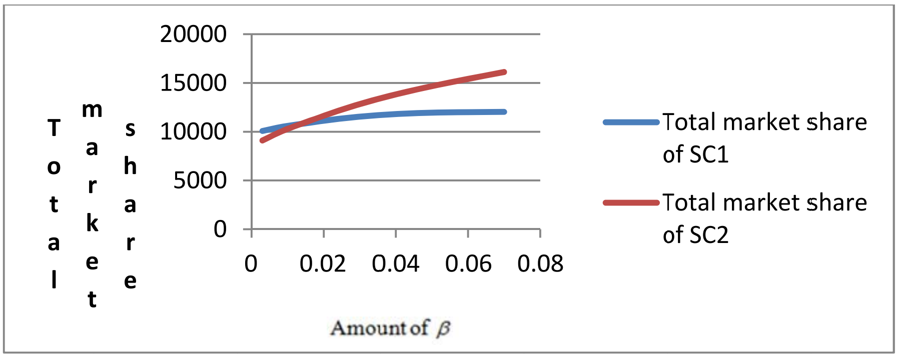

Figure 2. Behavior of total market share of SCs with respect to β

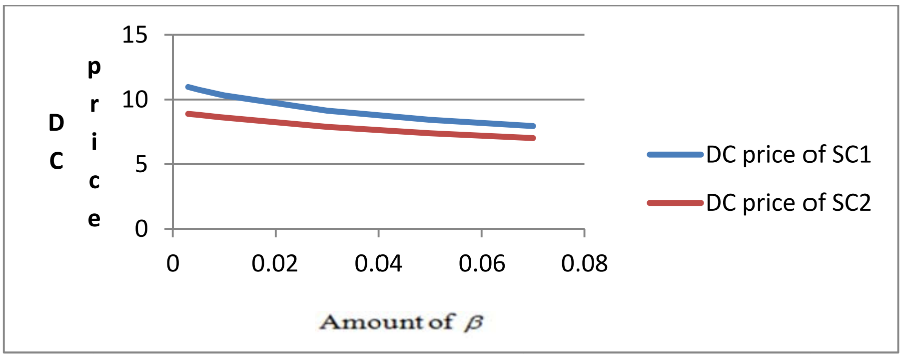

Figure 3. Behavior of DC price with respect to β

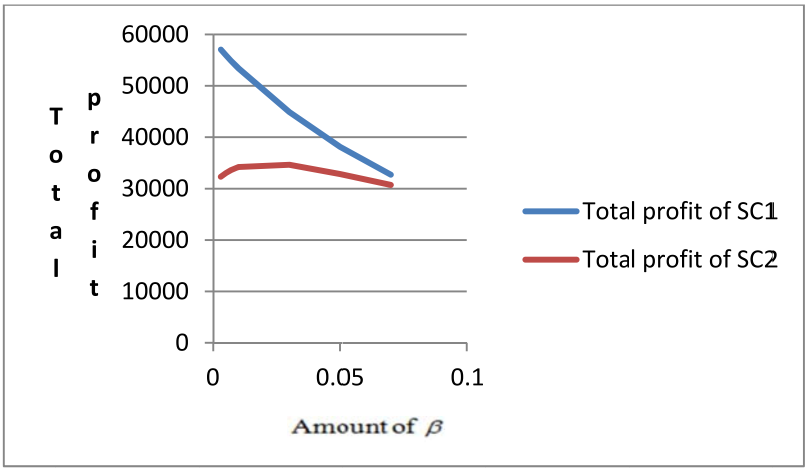

Figure 4. Behavior of total SCs profit with respect to β

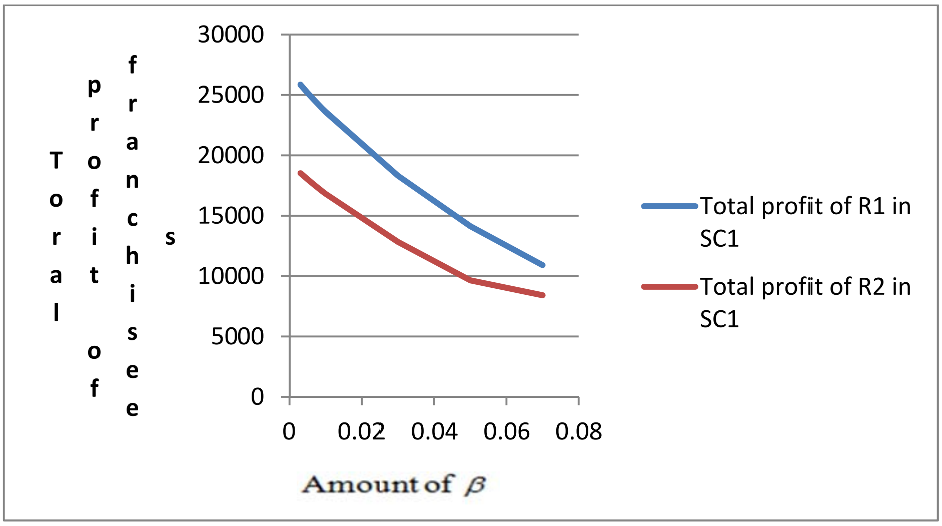

Figure 5. Behavior of total profit of franchisees in SC1 with respect to δ

Table 5 shows the behavior of the opened paths, total market share, DC price, total SC profit, equilibrium locations and qualities, and franchisees' total profit with respect to δ; the amount of parameter δ varies in the solved examples while β is set to $0.07EV(d)$. Figure 6 shows the behavior of total market share with respect to δ. According to the figure, the total market share of the chains will decrease by increasing the amount of δ; however, SC1 experiences a greater decrease in its market share than SC2. Figure 7 shows the behavior of DC prices with respect to δ, which are very similar to each other, decreasing by the increase in the amount of δ. It is observable from Figure 8 that the SCs' total profits are strictly close to each other with respect to δ, decreasing to zero by increasing δ. Figure 9 shows the behavior of the total profits of the franchisees in SC2 with respect to δ. According to this figure, at the high amount of δ, it is not profitable for the franchisees to participate in the market as their profits go below zero.

Table 5. The Change of the Opened Paths, Total Market Share, DC Price, Total SC Income, Equilibrium Locations and Qualities and Retailer's Total Income with Respect to δ

δ = 0.07EV(d)	Opened paths	Total market share	DC price	objSC		Retailer price	Equilibrium location	Equilibrium quality	objfranchisee	δ
SC1	(5,2,3,5)	25745.93956	11.90939401	177453.3519	R_1^{SC1}	13.10033341	(3,4)	(3,3)	103808.899	$\delta = 0.001d_k$
					R_2^{SC1}		(2,4)	(3,3)	72317.55712	
SC2	(5,2,3,5)	28495.21474	10.94606811	169699.9122	R_1^{SC2}	12.04067492	(1,2)	(3,3)	93452.07796	
					R_2^{SC2}		(2,3)	(3,3)	73126.97431	
SC1	(5,2,3,5)	24386.90615	11.44289412	156456.2734	R_1^{SC1}	12.58718353	(3,4)	(3,3)	90188.33852	$\delta = 0.003d_k$
					R_2^{SC1}		(2,4)	(3,3)	62724.74379	
SC2	(5,2,3,5)	27227.30455	10.48262981	149323.9415	R_1^{SC2}	11.53089279	(1,2)	(3,3)	81035.72419	
					R_2^{SC2}		(2,3)	(3,3)	62842.47724	
SC1	(5,2,3,5)	23127.35638	11.0229468	138415.2367	R_1^{SC1}	12.12524148	(3,4)	(3,3)	78483.02564	$\delta = 0.005d_k$
					R_2^{SC1}		(2,4)	(3,3)	54476.86321	
SC2	(5,2,3,5)	26059.1165	10.06563275	131851.1115	R_1^{SC2}	11.07219602	(1,2)	(3,3)	70378.91344	
					R_2^{SC2}		(2,3)	(3,3)	54014.48667	
SC1	(5,2,3,5)	21953.06767	10.64290666	122800.352	R_1^{SC1}	11.70719732	(3,4)	(3,3)	68349.73013	$\delta = 0.007d_k$
					R_2^{SC1}		(2,4)	(3,3)	47333.04659	
SC2	(5,2,3,5)	24976.41521	9.6884375	116758.7933	R_1^{SC2}	10.65728125	(1,2)	(3,3)	51227.92393	
					R_2^{SC2}		(2,3)	(3,3)	38123.93408	
SC1	(5,2,3,5)	20852.40405	10.29733622	109196.7629	R_1^{SC1}	11.32706984	(3,4)	(3,3)	59519.72117	$\delta = 0.009d_k$
					R_2^{SC1}		(2,4)	(3,3)	41104.68497	
SC2	(5,2,3,5)	23967.55285	9.345612132	103638.0913	R_1^{SC2}	10.28017335	(1,2)	(3,3)	43435.00765	
					R_2^{SC2}		(2,3)	(3,3)	31664.73598	
SC1	(5,2,3,5)	20326.61123	10.13604216	103043.72	R_1^{SC1}	11.14964638	(3,4)	(3,3)	55525.12041	δ = (

δ = 0.07EV(d)	Opened paths	Total market share	DC price	objSC		Retailer price	Equilibrium location	Equilibrium quality	objfranchisee	δ
				55	R_2^{SC1}		(2,4)	(3,3)	38285.83839	
SC2	(5,2,3,5)	23487. 73735	9.185654 809	9771 3.195 5	R_1^{SC2}	10.104 22029	(1,2)	(3,3)	39928.01551	
					R_2^{SC2}		(2,3)	(3,3)	28757.57234	
SC1	(5,2,3,5)	12029. 60419	7.950129 5	3272 7.111 07	R_1^{SC1}	8.7451 4245	(1,3)	(2,3)	10905.29151	$\delta = 0.03d_k$
					R_2^{SC1}		(2,4)	(3,3)	8407.118952	
SC2	(5,2,3,5)	16119. 18541	7.022318 052	3072 8.679 12	R_1^{SC2}	7.7245 49858	(1,2)	(3,1)	13163.88316	
					R_2^{SC2}		(2,3)	(2,2)	5650.864146	
SC1	(2,1,3,5)	5918.5 22032	6.790482 663	6949. 4260 14	R_1^{SC1}	7.4695 3093	(1,3)	(1,1)	470.9622065	$\delta = 0.05d_k$
					R_2^{SC1}		(2,4)	(1,1)	-483.002	
SC2	(2,1,3,5)	10949. 03853	5.879421 08	6867. 5244 37	R_1^{SC2}	6.4673 63188	(1,2)	(1,1)	727.3986097	
					R_2^{SC2}		(2,3)	(1,1)	-1730.79	

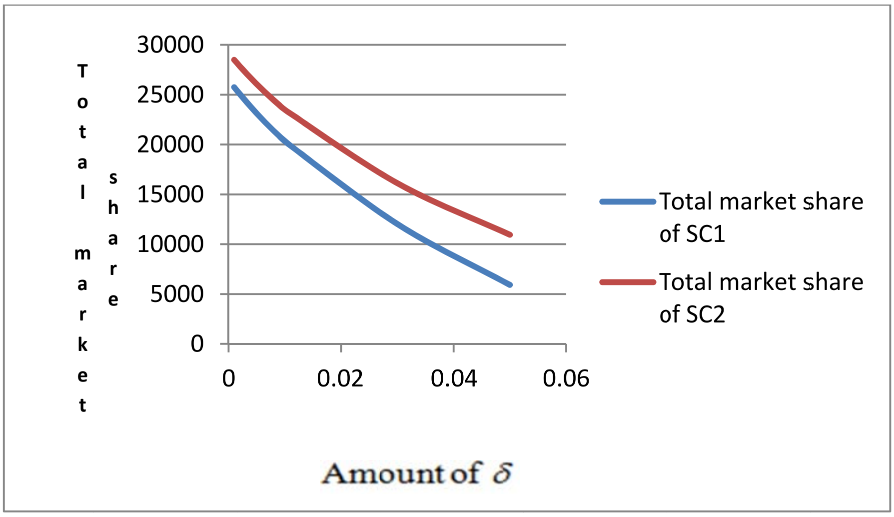

Figure 6. Behavior of total market share with respect to δ

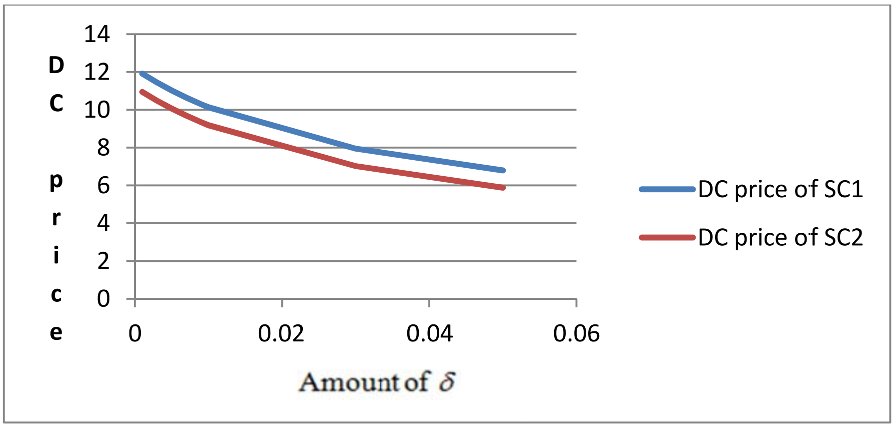

Figure 7. Behavior of DC price with respect to δ

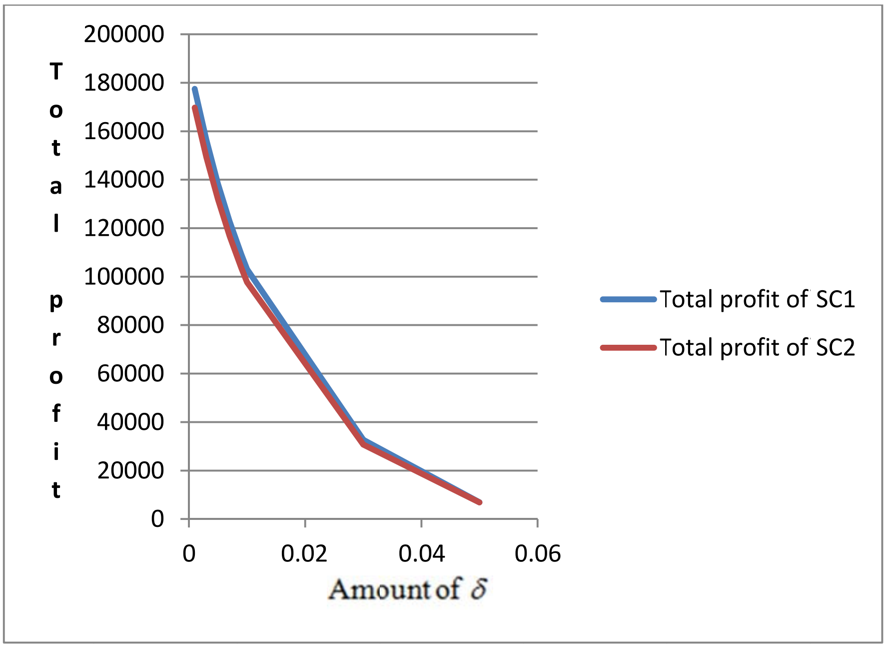

Figure 8. Behavior of total SCs profit with respect to δ

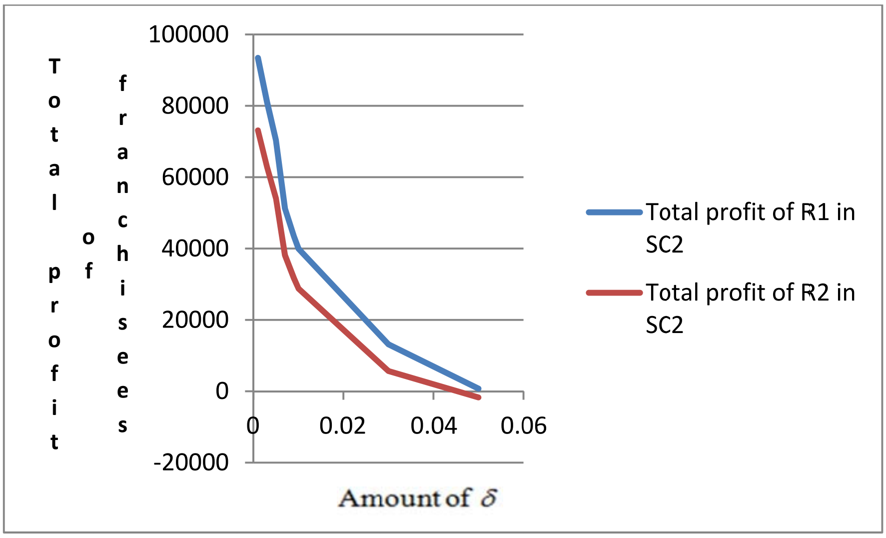

Figure 9. Behavior of total profit of franchisees in SC2 with respect to δ

As β represents competition intensity, by increasing the amount of intensity in competition, the chains were forced to decrease their price to obtain in the competition and absorb some customers, by this way, their market shares will increase, according to the demand function, but their total profits will decrease because of the lower marginal profit. On the other hand, when δ increases, the customers of the chain pay more attention on the chain price itself and in this manner, the chain is forced to decrease its price and by the same way results in decreasing the total profits (interested readers can refer Anderson and Bao (2010) for more details and mathematical proofs).

In the pricing step, the power factor has no effect on the equilibrium price because it has been omitted by the differential system. However, according to Table 6, it has this effect on the mathematical step.

In SC1, total franchisee profits in duopoly competition is 19,312; R_1^{SC1} and R_2^{SC1} total profits in monopoly competition are 35,606 and 36,925, respectively. Total franchisee profits in duopoly competition, in the case that the franchisees sell the products of both chains, if R_1^{SC1} and R_2^{SC1} served the market is 75,915; R_1^{SC1} and R_2^{SC1} total profits in monopoly competition, in the case that the franchisees sell the products of both chains, are 98,382 and 94,687, respectively. Correspondingly, for SC2, total franchisee profits in duopoly competition is 18,814; R_1^{SC2} and R_2^{SC2} total profits in monopoly competition are 36,051 and 35,482, respectively. Total franchisee profits in duopoly competition, in the case that the franchisees sell the products of both chains, if R_1^{SC2} and R_2^{SC2} served the market is 70,140; R_1^{SC2} and R_2^{SC2} total profits in monopoly competition in the case that the franchisees sell the products of both chains are 101,364 and 87,677. Obviously, the best structure for franchisees is monopoly competition, in the case that the franchisees sell the products of both chains, and the worst case is duopoly competition when the quality of the facilities is exactly vice versa. Therefore, if the SCs want to increase customer satisfaction, they should chose duopoly competition; if they want more profits, they should use some negotiating mechanism to profit from the monopoly structure (Table 7 shows these situations).

Moreover, the SCs can choose to cooperate with each other; the outcomes of this model are shown in Table 8. In this circumstance, the market share, total objective function of SCs, DC price, objective function of SC1, and objective function of Franchisee 1 and Franchisee 2 in SC1 increased by 15%, 33%, 3.7%, 55%, and 41%, respectively. Correspondingly, for SC2, they decreased by 24%, 56%, -12%, 3.7, and 4.7%, respectively.

Table 6. The Change of the Optimal Price, Market Share, SCN Structure and Total Income with Respect to Power Effect Parameter

δ = 0.07EV(d) δ = 0.03EV(d)	Opened paths	Total market share	DC price	objSC		Retailer price	Equilibrium location	Equilibrium quality	objfranchisee	λ
SC1	(5,2,3,5)	12029.60419	7.9501295	32727.11107	R_1^{SC1}	8.74514245	(1,3)	(2,3)	10905.29151	$\lambda = 0.1$; $\lambda = 0.2$; $\lambda = 0.3$; $\lambda = 0.4$; $\lambda = 0.5$;
					R_2^{SC1}		(2,4)	(3,3)	8407.118952	

δ = 0.07EV(d) δ = 0.03EV(d)	Opened paths	Total market share	DC price	objSC		Retailer price	Equilibrium location	Equilibrium quality	objfranchisee	λ
SC2	(5,2,3, 5)	16119. 18541	7.0223 18052	30728. 67912	R_1^{SC2}	7.72454 9858	(1,2)	(3,1)	13163.88316	
					R_2^{SC2}		(2,3)	(2,2)	5650.864146	
SC1	(5,2,3, 4)	14315. 99604	8.3236 98524	45208. 04785	R_1^{SC1}	9.15606 8376	(1,3)	(3,3)	18622.77321	$\lambda = 0.7$;
					R_2^{SC1}		(2,4)	(3,3)	13205.33426	$\lambda = 0.8$;
SC2	(5,2,3, 4)	11187. 11156	8.0896 5812	8960.3 83436	R_1^{SC2}	8.89862 3932	(1,2)	(3,1)	13099.65729	$\lambda = 0.9$
					R_2^{SC2}		(2,3)	(2,2)	5652.487948	

Table 7. Competition Intensity between Franchisees

	Duopoly competition			Monopoly competition			Duopoly competition, common			Monopoly competition, common		
	Equilibrium location	Equilibrium quality	Objective function	Equilibrium location	Equilibrium quality	Objective function	Equilibrium location	Equilibrium quality	Objective function	Equilibrium location	Equilibrium quality	Objective function
R_1^{SC1}	(1,3)	(2,3)	10905	(2,3)	(1,1)	35606	(1,3)	(3,3)	48837	(2,3)	(1,1)	98382
R_2^{SC1}	(2,4)	(3,3)	8407	(2,4)	(1,1)	36925	(1,2)	(3,3)	27078	(1,2)	(1,1)	94687
R_1^{SC2}	(1,2)	(3,1)	13163	(3,4)	(1,1)	36051	(1,2)	(3,3)	43765	(3,4)	(1,1)	101364
R_2^{SC2}	(2,3)	(2,2)	5651	(1,3)	(1,1)	35482	(2,3)	(3,3)	26375	(1,3)	(1,1)	87677

Table 8. Numerical Result in Cooperative Mode

Cooperation $\lambda = 0.5$	**Opened paths**	**Total market share**	**DC price**	**objSC**		**Retailer price**	**Equilibrium location**	**Equilibrium quality**	**objfranchisee**
SC1	(5,2,1,1)	13835	8.24	43516	R_1^{SC1}	9.07	(1,3)	(3,3)	16882
					R_2^{SC1}		(2,4)	(3,3)	11848
SC2	(5,2,1,1)	12224	7.86	13408	R_1^{SC2}	8.65	(1,2)	(3,1)	13663
					R_2^{SC2}		(2,3)	(2,2)	6064

The following managerial insights are derived from these sensitivity analyses:

- ✓ Increasing market competition is more profitable for the smaller SC, because its market expansion is greater than that of the larger SC.
- ✓ By increasing the number of factors δ, β, the total profit of both chains will decrease, and it would be more profitable for them to control the competition intensity at a low level.
- ✓ By decreasing the number of competing franchisees and allowing them to sell the products of both chains, their attractiveness level will decrease, but their profits will increase. This can make customers unhappy in the long run and decrease customer-based demand.
- ✓ Having more power has no effect on the pricing step, but it can help to gain more profits and change the network structure in the location phase.
- ✓ Cooperation in the location phase helps the smaller SC (the one with less market-based demand) to gain more profits, but the larger SC will gain more profits in a non-cooperative manner.

It is worth noting that according to the literature, duopoly is the most commonly used form of competition and in this way, we follow the literature trend. Moreover, Anderson and Bao (2010) gave mathematical proofs showing no difference between duopoly and oligopoly in terms of the behavior of market shares, prices, and total profits.

Conclusion

This paper has developed a dynamic competitive supply chain network design problem with price dependent demand and Huff utility function in which n supply chains tending to enter the untapped market and give franchises to competing franchisees. Customers are faced with a two-step decision model: At first, they chose a brand (SC) to buy based on the price according to 0-1 rule; then, they chose the retailers of the franchisees by a certain probability based on their attractiveness applying Huff gravity rule model. There are two games in this context. The first one is a dynamic game between the SCs, as the first stage, based on the location and price. After the franchisees, as the second stage, enter a simultaneous game to set their locations and attractiveness.

We converted the model of the SCs into a bi-level model in which the inner part sets the price and the outer part shapes the networks. We also used Nash's concept and Wilson algorithm to convexify the model of the franchisees and find equilibrium locations and qualities. Moreover, we used fuzzy set theory to cope with the uncertainty that the players encounter as they are all newcomers and have no precise knowledge and information about the parameters.

Finally, we applied our model and solution approach to a real world problem and discussed the sensitivity analysis of the total market share, DC price, total profit of both chains, equilibrium locations and qualities, and franchisees' total profit with respect to β,δ. We then considered the effect of SC power in the pricing and location phases and analyzed the effect of changing the competition intensity on the franchisees' attractiveness level and profits.

We concluded that by increasing the amount of β,δ, the profits of both chains will decrease and that power has no effect on the pricing step, although it can change the structure of the chains. Moreover, the best situation for the franchisees is one in which they can sell the products of both chains without any competitors. However, this is also the worse situation for customers, and it can decrease customer-based demand in the long run. Further, cooperation is helpful for the small SC, but it decreases the profits of the larger SC.

This model can be applied in many different industries as most industries prefer to have some independent and competing franchisees, such as the car, shoe, and retail industries. Moreover, the proposed model can be extended by different aspects. For example, the closed-loop, robust, or sustainable SC can be considered, or stochastic approaches can be used to handle uncertainty.

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Optimal Non-Parametric Prediction Intervals for Order Statistics with Random Sample Size

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Abstract

In many experiments, such as biology and quality control problems, sample size cannot always be considered as a constant value. Therefore, the problem of predicting future data when the sample size is an integer-valued random variable can be an important issue. This paper describes the prediction problem of future order statistics based on upper and lower records. Two different cases for the size of the future sample is considered as fixed and random cases. To do this, we first derive a general formula for the coverage probability of the prediction interval for each case. For the case that the sample size is a random variable, we consider two different distributions for the sample size, such as binomial and Poisson distributions and we study further details. The numerical computations are also given in this paper. Another purpose of this paper is to determine the optimal prediction interval for each case. Finally, the application of the proposed prediction interval is illustrated by analyzing the data in a real-world case study.

Keywords

Prediction interval, random sample size, complete beta function.

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Introduction

Let $X = (X_1, \cdots, X_n)$ be a sample of independent and identically distributed (iid) random variables from a distribution with cumulative distribution (CDF) F and probability density function (PDF) f. If $X_{1:n} \leq \cdots \leq X_{n:n}$ are the order statistics (OSs) from this sample, then the marginal density function of $X_{i:n}, i = 1, \cdots, n,$ is given by

$$f_{X_{i:n}}(x) = \frac{1}{\beta(i, n-i+1)} f(x)(F(x))^{i-1}\left(\bar{F}(x)\right)^{n-i}, \qquad x \in D_F, \qquad (1)$$

where $\bar{F}(x) = 1 - F(x)$ is the survival function of X-sample, $\beta(.,.)$ denotes the complete beta function.

We refer the reader to David and Nagaraja (2003) and Arnold et al. (2008) and the references therein for more details on the theory and applications of order statistics.

In a sequence of iid random variables as $\{Y_i; i \geq 1\}$ with CDF F and PDF f, an observation Y_j is called an upper (or lower) record value if $Y_j > Y_i$ (or $Y_j < Y_i$) for every $i < j$. Let the first upper and lower record be denoted by $R_1^L = R_1^U = Y_1$, and the r-th upper and lower record be taken as R_r^U and R_r^L (for $r \geq 2$), respectively. The survival function of R_r^U is (see, for example, . ,.Arnord et al, 1998):

$$\bar{F}_{R_r^U}(u) = (\bar{F}(u)) \sum_{l=0}^{r-1} \frac{\left\{-\log(\bar{F}(u))\right\}^l}{l!}, \qquad u \in D_F. \qquad (2)$$

By replacing $\bar{F}$ by F in Equation (2), the survival function of R_r^L can be derived. The theory of records can be used in various topics, including sports fields, meteorology, geophysics, seismology. Interested readers may refer to Arnord etal. (1998) for more details about records.

One of the basic concepts in statistics is the conjecture of the value of an unobserved random variable based on the information obtained from observed events, which is known as the prediction of that random variable. In many issues, such as time series, regression, quality control, random processes and survival analysis, the prediction problem is used. Also, prediction in various sciences such as meteorology, geology, biology, sociology, geography and economics can be studied. The problem of predicting future data has been studied by many researchers. See, for example, Lawless (1977), Ahsanullah (1980), Hsieh (1997), Raqab and Balakrishnan (2008), Ahmadi and MirMostafaee (2009), Ahmadi et al. (2010), Asgharzadeh and Fallah (2010), Ahmadi and Balakrishnan (2010, 2011), and also Basiri et al. (2016).

In all the articles mentioned above, the size of the sample was a fixed value. In many practical applications, the number of components which are put on the life testing itself, is frequently a random variable. One of the main reasons for this is that in many biological, agricultural and some quality control problems, it may not be possible that the sample size is fixed because some of the observations get lost during the experiment. Assuming the sample size is a random variable, predicting future ordered data has been studied by several authors. See, for example, Soliman (2000), Abd Ellah and Sultan (2005), Sultan and Abd Ellah (2006) and Al-Hussaini and Al-Awadhi (2010). Recently, Basiri and Ahmadi (2015) considered two sample prediction problems for generalized order statistics when the size is random. In this paper, we investigate nonparametric predicting future order statistics based on observed records, assuming the size of the future sample as a random variable.

The rest of this paper is set as follows: In Section 2, a general formula for the coverage probability of prediction intervals for future order statistics based on observed upper and lower records is derived. Two cases for the sample size are assumed, fixed and random. Also, two most used distributions for random sample size are considered. Section 3 is concerned with finding optimal prediction intervals for future random order statistics based on upper and lower records in the both cases of random and fixed samples. In Section 4, a real example is expressed to evaluate the methods outlined in this paper. Finally, a conclusion of the paper is presented in Section 5.

Prediction of Order Statistics

In this section, let $X_{i:N}$ be the i-th order statistic from a future X -sample. Also, let R_j^U and R_j^L , $1 \le j$, the bejupper and lower th-records, .respectivelyBy assuming $N = n_0$ as a fixed value, Ahmadi and Balakrishnan (2010) showed that $(R_r^U, R_s^U), 1 \le r < s,$ is a prediction interval for $X_{i:N}$, when N is a fixed value, with the coverage probability given by

$$\alpha(r,s;i,N) = \phi_1(s;i,N) - \phi_1(r;i,N), \tag{3}$$

Where

$$\phi_1(j;i,N) = \sum_{t=0}^{i-1} \frac{\binom{i-1}{t}(-1)^t}{\beta(i, n_0 - i + 1)(n_0 - i + t + 1)} \left\{1 - \frac{1}{(n_0 - i + t + 2)^j}\right\}. \tag{4}$$

Also, based on lower records, they provided a prediction interval as $(R_s^L, R_r^L), 1 \le r < s,$, for $X_{i:N}$ which its coverage probability is

$$\beta(r,s;i,N) = \phi_2(r;i,N) - \phi_2(s;i,N), \tag{5}$$

for

$$\phi_2(j;i,N) = \sum_{t=0}^{n_0-i} \sum_{k=j}^{\infty} \frac{\binom{n_0 - i}{t}(-1)^t}{\beta(i, n_0 - i + 1)(i + t + 1)^{k+1}}. \tag{6}$$

By considering upper and lower records jointly, Ahmadi and Balakrishnan (2010) showed that $(R_r^L, R_s^U), r, s \ge 1,$ is a prediction interval for $X_{i:N}$, with coverage probability given by

$$\gamma(r,s;i,N) = \phi_1(s;i,N) - \phi_2(r;i,N), \tag{7}$$

When $\phi_1(s;i,N)$ and $\phi_2(r;i,N)$ are defined as in Equations (4) and (6), respectively.

Now, let N be a positive integer-valued random variable. Construction of prediction intervals for future order statistics with random sample size based on upper records is stated in the following theorem.

Theorem 1: Let $X_{i:N}$ be the i-th order statistic from a future X -

sample, when N is a random variable.

Independently, let R_i^U and R_i^L be the i-th observed upper and lower records with the same parent distribution, respectively. Then, $(R_r^U, R_s^U), 1 \le r < s,$ is a prediction interval for $X_{i:N}$ with the coverage probability given by Equation (3) where

$$\phi_1(j;i,N) = \frac{1}{P(N \ge i)} \sum_{n=i}^{\infty} \sum_{t=0}^{i-1} \frac{P(N=n)\binom{i-1}{t}(-1)^t}{\beta(i,n-i+1)(n-i+t+1)} \left\{1 - \frac{1}{(n-i+t+2)^j}\right\}. \quad (8)$$

Proof. First, according to Equation (1) and the results obtained by Raghunandanan and Patil)1972(, the marginal density function of $X_{i:N}$ can be written as

$$f_{X_{i:N}}(x) = \frac{1}{P(N \ge i)} \sum_{n=i}^{\infty} f_{X_{i:n}}(x) P(N=n). \quad (9)$$

By using Equations (2) and (9), we obtain

$$P(R_s^U > X_{i:N}) = \int_{D_F} \overline{F}_{R_s^U}(x) f_{X_{i:N}}(x) dx$$

$$= \frac{1}{P(N \ge i)} \sum_{n=i}^{\infty} \sum_{l=0}^{s-1} \frac{P(N=n)}{\beta(i,n-i+1)}$$

$$\int_{D_F} \frac{(F(x))^{i-1}(\overline{F}(x))^{n-i+1}}{l!} (-\log(\overline{F}(x)))^l f(x) dx.$$

By setting $y = F(x)$, we find

$$P(R_s^U > X_{i:N}) = \frac{1}{P(N \geq i)} \sum_{n=i}^{\infty} \sum_{l=0}^{s-1} \frac{P(N=n)}{\beta(i,n-i+1)} \int_0^1 \frac{y^{i-1}(1-y)^{n-i+1}}{l!} (-\log(1-y))^l dy$$

$$= \frac{1}{P(N \geq i)} \sum_{n=i}^{\infty} \sum_{l=0}^{s-1} \sum_{t=0}^{i-1} \frac{P(N=n)\binom{i-1}{t}(-1)^t}{\beta(i,n-i+1)} \int_0^{\infty} \frac{e^{-(n-i+t+2)z}}{l!} z^l dz$$

$$= \frac{1}{P(N \geq i)} \sum_{n=i}^{\infty} \sum_{l=0}^{s-1} \sum_{t=0}^{i-1} \frac{P(N=n)\binom{i-1}{t}(-1)^t}{\beta(i,n-i+1)(n-i+t+2)^{l+1}}$$

$$= \frac{1}{P(N \geq i)} \sum_{n=i}^{\infty} \sum_{t=0}^{i-1} \frac{P(N=n)\binom{i-1}{t}(-1)^t}{\beta(i,n-i+1)(n-i+t+1)} \left\{1 - \frac{1}{(n-i+t+2)^s}\right\}$$

$$= \phi_1(s;i,N),$$

Where the second equality is obtained by taking $z = -\log(1-y)$. The required result can be obtained by using the relation $\alpha(r,s;i,N) = P(R_r^U < X_{i:N} < R_s^U) = \phi_1(s;i,N) - \phi_1(r;i,N).$

Remark2 . Let R_r^L and R_s^L, $1 \leq r < s,$ the bert- and s-thlower records, ,respectively. Then $(R_s^L, R_r^L), 1 \leq r < s,$ is a two-sided prediction interval for $X_{i:N}$, and its coverage probability is free of F and is given by Equation (5), where

$$\phi_2(j;i,N) = \frac{1}{P(N \geq i)} \sum_{n=i}^{\infty} \sum_{t=0}^{n-i} \sum_{k=j}^{\infty} \frac{P(N=n)\binom{n-i}{t}(-1)^t}{\beta(i,n-i+1)(i+t+1)^{k+1}}. \tag{10}$$

Remark3 . Let R_r^L and R_s^U, $1 \leq r,s,$ the berth- lower and s-th upperrecords , ,respectively. Then $(R_r^L, R_s^U), 1 \leq r < s,$ is a two-sided prediction interval for $X_{i:N}$, with coverage probability given in Equation (7), where $\phi_1(s;i,N)$ and $\phi_2(r;i,N)$ are defined as in Equations (8) and (10), respectively.

We now consider some of the most widely used discrete probability distributions for the sample size, N, and we study more details.

Binomial Distribution

Let N be a binomial random variable with parameters M and p, written $B(M, p)$. Then, Relation (8) can be written as:

$$\phi_1(j;i,N)=\frac{1}{\sum_{l=i}^{M}\binom{M}{l}p^l(1-p)^{M-l}}\sum_{n=i}^{M}\sum_{t=0}^{i-1}\frac{\binom{M}{n}p^n(1-p)^{M-n}\binom{i-1}{t}(-1)^t}{\beta(i,n-i+1)(n-i+t+1)}\left\{1-\frac{1}{(n-i+t+2)^j}\right\}.$$

Also, Relation (10) can be re-expressed as:

$$\phi_2(j;i,N)=\frac{1}{\sum_{l=i}^{M}\binom{M}{l}p^l(1-p)^{M-l}}\sum_{n=i}^{M}\sum_{t=0}^{n-i}\sum_{k=j}^{M}\frac{\binom{M}{n}p^n(1-p)^{M-n}\binom{n-i}{t}(-1)^t}{\beta(i,n-i+1)(i+t+1)^{k+1}}.$$

Poisson Distribution

When N has a Poisson distribution with parameter λ, written $P(\lambda)$, then Relation (8) can be changed to:

$$\phi_1(j;i,N)=\frac{1}{\sum_{l=i}^{\infty}\frac{\lambda^l}{l!}}\sum_{n=i}^{\infty}\sum_{t=0}^{i-1}\frac{\lambda^n\binom{i-1}{t}(-1)^t}{n!\,\beta(i,n-i+1)(n-i+t+1)}\left\{1-\frac{1}{(n-i+t+2)^j}\right\}.$$

Also, Relation (10) can be re-expressed as:

$$\phi_2(j;i,N)=\frac{1}{\sum_{l=i}^{\infty}\frac{\lambda^l}{l!}}\sum_{n=i}^{\infty}\sum_{t=0}^{n-i}\sum_{k=j}^{\infty}\frac{\frac{\lambda^n}{n!}\binom{n-i}{t}(-1)^t}{\beta(i,n-i+1)(i+t+1)^{k+1}}.$$

The values of $\alpha(r,s;i,N)$, $\beta(r,s;i,N)$ and $\gamma(r,s;i,N)$ for different choices of i, r, s and different cases for N, are calculated and reported in Table 1. The mathematical package Maple 18 has been used to obtain the numerical computations. From Table 1, we find that the prediction coefficients $\alpha(r,s;i,N)$ and $\beta(r,s;i,N)$ are increasing functions of s but decreasing functions of r, when all other factors are fixed, as we expected. Also, It can be observed that the prediction coefficient $\gamma(r,s;i,N)$ is an increasing function of s and r, when other values are considered fixed. For predicting lower order statistics considering lower records leads to better results while upper order statistics can be predicted better by considering upper records. Middle order statistics can be predicted better when we consider upper and lower records jointly. Moreover, $\alpha(r,s;i,N)$ is increasing in i while $\beta(r,s;i,N)$ is decreasing in i, when other parameters are fixed.

Table 1. Values of $\alpha(r,s;i,N)$, $\beta(r,s;i,N)$ and $\gamma(r,s;i,N)$ for different distributions of N and some selected values of r, s and i

Distribution of N			$\alpha(r,s;i,N)$			$\beta(r,s;i,N)$			$\gamma(r,s;i,N)$		
	i	r \ s	8	9	10	8	9	10	1	2	3
N=10	1	1	0.091	0.091	0.091	0.875	0.891	0.900	0.000	0.184	0.394
		2	0.008	0.008	0.008	0.692	0.708	0.716	0.083	0.266	0.477
		3	0.001	0.001	0.001	0.481	0.497	0.506	0.090	0.274	0.485
	5	1	0.455	0.455	0.455	0.545	0.545	0.545	0.000	0.335	0.480
		2	0.144	0.144	0.144	0.211	0.211	0.211	0.311	0.646	0.790
		3	0.037	0.037	0.037	0.066	0.066	0.066	0.418	0.752	0.897
	10	1	0.875	0.891	0.900	0.091	0.091	0.091	0.000	0.083	0.090
		2	0.692	0.708	0.716	0.008	0.008	0.008	0.184	0.266	0.274
		3	0.481	0.497	0.506	0.001	0.001	0.001	0.394	0.477	0.485
B(10, 0.2)	1	1	0.344	0.344	0.344	0.651	0.656	0.658	0.000	0.260	0.420
		2	0.130	0.130	0.130	0.381	0.386	0.388	0.210	0.480	0.640
		3	0.054	0.054	0.054	0.221	0.226	0.228	0.280	0.560	0.720
	5	1	0.790	0.797	0.801	0.193	0.193	0.193	0.000	0.160	0.190
		2	0.535	0.542	0.546	0.036	0.036	0.036	0.260	0.410	0.440
		3	0.324	0.331	0.335	0.007	0.007	0.007	0.470	0.620	0.650
	10	1	0.956	0.971	0.980	0.091	0.091	0.091	0.000	0.000	0.010
		2	0.723	0.738	0.747	0.008	0.008	0.008	0.150	0.240	0.240
		3	0.484	0.499	0.508	0.001	0.001	0.001	0.390	0.480	0.480
B(10, 0.5)	1	1	0.181	0.181	0.181	0.830	0.840	0.844	0.000	0.230	0.440
		2	0.036	0.036	0.036	0.570	0.580	0.584	0.110	0.370	0.590
		3	0.009	0.009	0.009	0.355	0.365	0.369	0.140	0.400	0.620
	5	1	0.726	0.730	0.732	0.283	0.283	0.283	0.000	0.190	0.250
		2	0.433	0.437	0.439	0.072	0.072	0.072	0.280	0.490	0.550
		3	0.234	0.238	0.240	0.012	0.012	0.012	0.480	0.690	0.750
	10	1	0.900	0.916	0.924	0.091	0.091	0.091	0.000	0.050	0.060
		2	0.685	0.701	0.709	0.008	0.008	0.008	0.180	0.270	0.280
		3	0.474	0.490	0.498	0.001	0.001	0.001	0.400	0.480	0.490
B(10, 0.8)	1	1	0.129	0.129	0.129	0.883	0.896	0.903	0.000	0.200	0.430
		2	0.017	0.017	0.017	0.643	0.656	0.663	0.070	0.310	0.540
		3	0.002	0.002	0.002	0.418	0.431	0.438	0.090	0.330	0.550
	5	1	0.637	0.638	0.638	0.220	0.220	0.220	0.000	0.260	0.330
		2	0.311	0.312	0.312	0.105	0.105	0.105	0.470	0.580	0.660
		3	0.138	0.139	0.139	0.028	0.028	0.028	0.640	0.760	0.830
	10	1	0.766	0.781	0.790	0.091	0.091	0.091	0.000	0.190	0.200
		2	0.654	0.669	0.678	0.008	0.008	0.008	0.220	0.300	0.310

Distribution of N	i	r \ s	$\alpha(r,s;i,N)$			$\beta(r,s;i,N)$			$\gamma(r,s;i,N)$		
			8	9	10	8	9	10	1	2	3
		3	0.462	0.477	0.486	0.001	0.001	0.001	0.410	0.500	0.500
P(2)	1	1	0.343	0.343	0.344	0.651	0.656	0.658	0.000	0.260	0.430
		2	0.130	0.130	0.131	0.386	0.391	0.393	0.210	0.470	0.650
		3	0.054	0.054	0.055	0.214	0.219	0.221	0.280	0.550	0.720
	5	1	0.783	0.789	0.793	0.215	0.215	0.215	0.000	0.160	0.200
		2	0.509	0.515	0.519	0.049	0.049	0.049	0.260	0.430	0.470
		3	0.298	0.304	0.308	0.009	0.009	0.009	0.470	0.640	0.680
	10	1	0.874	0.890	0.898	0.091	0.091	0.091	0.000	0.080	0.090
		2	0.692	0.708	0.716	0.008	0.008	0.008	0.180	0.260	0.270
		3	0.485	0.501	0.509	0.001	0.001	0.001	0.390	0.470	0.480
P(5)	1	1	0.195	0.195	0.195	0.772	0.781	0.785	0.000	0.240	0.450
		2	0.046	0.046	0.046	0.549	0.558	0.562	0.160	0.390	0.600
		3	0.011	0.011	0.011	0.339	0.348	0.352	0.200	0.420	0.630
	5	1	0.681	0.684	0.685	0.197	0.197	0.197	0.000	0.220	0.290
		2	0.390	0.393	0.394	0.080	0.080	0.080	0.400	0.520	0.580
		3	0.202	0.205	0.206	0.011	0.011	0.011	0.590	0.700	0.770
	10	1	0.876	0.891	0.900	0.091	0.091	0.091	0.000	0.080	0.090
		2	0.693	0.708	0.717	0.008	0.008	0.008	0.180	0.270	0.270
		3	0.486	0.501	0.510	0.001	0.001	0.001	0.390	0.470	0.480
P(8)	1	1	0.135	0.135	0.135	0.866	0.877	0.883	0.000	0.200	0.430
		2	0.021	0.021	0.021	0.636	0.647	0.653	0.090	0.320	0.540
		3	0.003	0.003	0.003	0.411	0.422	0.428	0.100	0.340	0.560
	5	1	0.594	0.596	0.596	0.519	0.519	0.519	0.000	0.270	0.370
		2	0.299	0.301	0.301	0.135	0.135	0.135	0.180	0.560	0.660
		3	0.129	0.131	0.131	0.035	0.035	0.035	0.350	0.730	0.830
	10	1	0.876	0.891	0.900	0.091	0.091	0.091	0.000	0.080	0.090
		2	0.693	0.708	0.717	0.008	0.008	0.008	0.180	0.270	0.270
		3	0.486	0.501	0.510	0.001	0.001	0.001	0.390	0.470	0.480

Optimal Prediction Intervals for Random Order Statistics

Obviously, for given α_0, a prediction interval, as $(R_r^U, R_s^U), 1 \le r < s$, exists if and only if $\alpha(1, M_0; i, N) \ge \alpha_0$, where M_0 is the number of observed upper records. From Equations (3) and (8), this condition is equivalent to:

$$\frac{1}{P(N \ge i)} \sum_{n=i}^{\infty} \sum_{t=0}^{i-1} \frac{P(N=n)\binom{i-1}{t}(-1)^t}{\beta(i, n-i+1)(n-i+t+1)} \left\{ \frac{1}{(n-i+t+2)^1} - \frac{1}{(n-i+t+2)^{M_0}} \right\} \ge \alpha_0. \tag{11}$$

Under Condition (11), if the values i and the coverage level α_0 as well as the distribution of N are all given. Since various indices can be used for constructing the prediction intervals for a pre-fixed level, choosing the best values for these indices is an important issue. It seems reasonable to choose these indices so that the prediction interval has the shortest length among all the prediction intervals in the same coverage level, which is called the optimal prediction interval. Therefore, in order to determine the optimal prediction interval, we must minimize the mean length of the prediction interval, $E\left(R_s^U - R_r^U\right)$ as an optimization criterion. Since the average length of the interval depends on the parent distribution, we minimize the difference between the predicted distance indices $s-r$ (see, for example, Balakrishnan et al., 2013) as an equivalent approach. Towards this end, first, we take:

$$A(l;i,N)=\frac{1}{P(N\geq i)}\sum_{n=i}^{\infty}\sum_{t=0}^{i-1}\frac{P(N=n)\binom{i-1}{t}(-1)^t}{\beta(i,n-i+1)(n-i+t+2)^{l+1}}.$$

Then, from Equations (3) and (8), we get $\alpha(r,s;i,N)=\sum_{l=r}^{s-1}A(l;i,N).$

The algorithm below describes the determination of the optimal indices for constructing prediction intervals, which are represented by the symbol (r_{opt}, s_{opt}).

Algorithm 1: Suppose the distribution of N is known and the values i and α_0 are all given. Moreover, let Condition (11) hold. In addition, let M_0 be the number of observed upper records, then, the procedure depicted in Figure 1 gives an optimal prediction interval for $X_{i:N}$.

Similar procedures can be considered for finding optimal indices of lower records.

By using Algorithm 1, the optimal indices (r_{opt}, s_{opt}) are specified and are presented in Table 2 for $\alpha_0 = 0.80$ and some selected choices of i when N has one of the three mentioned discrete probability distributions as in Section 2. The results have been obtained by using Maple 18. The optimization command has been utilized for doing Algorithm 1. In Table 2, dash (-) shows that there is no prediction interval at that level.

From Table 2 it can be observed that optimal prediction intervals obtained for different distributions are quite similar for most cases. So, the optimal prediction intervals are relatively stable. Optimal prediction intervals for upper order statistics can be derived by using upper records while for lower order statistics based on lower records. Using upper and lower records jointly can be appropriate for constructing optimal prediction intervals for both upper and lower order statistics.

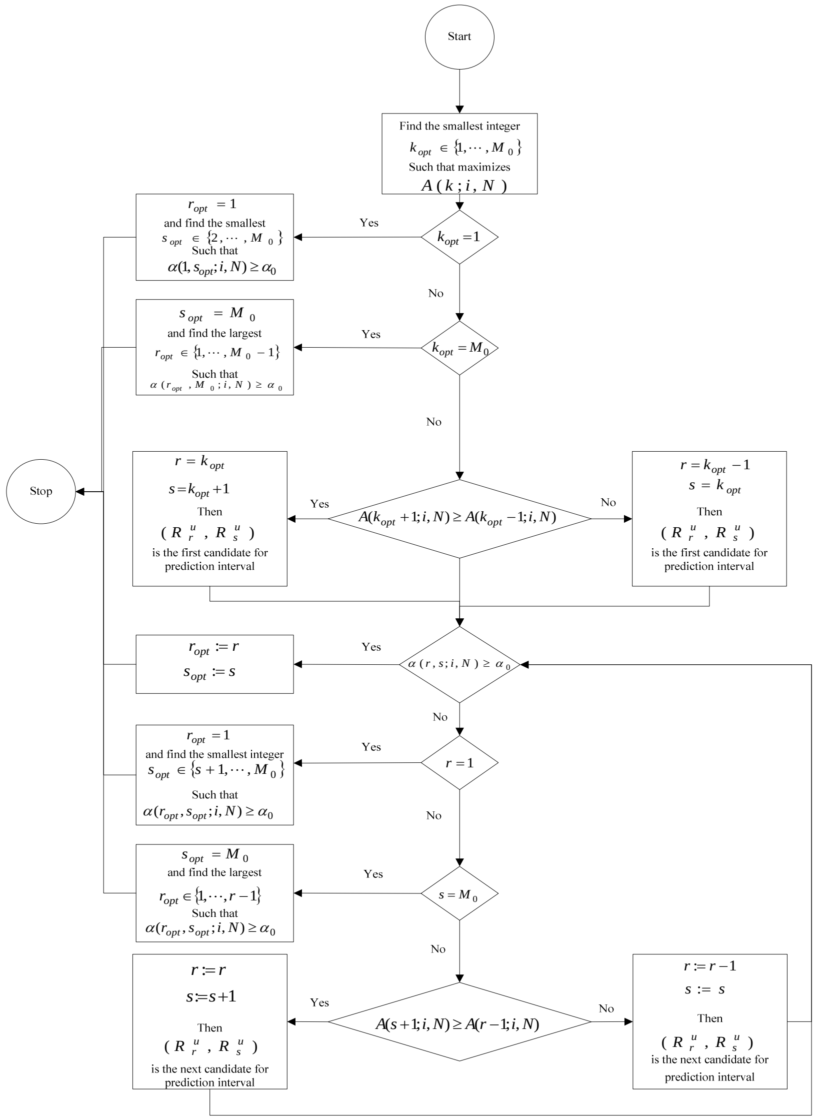

Figure 1. The procedure for finding optimal indices for prediction intervals

Table 2. Values of (r_{opt}, s_{opt}) for $\alpha_0 = 0.80$ and some selected values of i and different distributions for N

Distribution of N	$(R^U_{r_{opt}}, R^U_{s_{opt}})$			$(R^L_{s_{opt}}, R^L_{r_{opt}})$			$(R^L_{r_{opt}}, R^U_{s_{opt}})$		
	i=1	i=5	i=10	i=1	i=5	i=10	i=1	i=5	i=10
N=10	-	-	(1, 7)	(1,7)	-	-	(6,2),(7,1)	(4,2),(3,3)	(1,7),(2,6)
B(10, 0.2)	-	-	(1, 7)	(1,9)	-	-	(5,2),(4,3)	(3,4),(2,5)	(1,6)
B(10, 0.5)	-	-	(1, 7)	(1,6)	-	-	(5,2)	(2,4)	(1,7),(2,6)
B(10, 0.8)	-	-	(1, 7)	(1,7)	-	-	(5,2)	(3,3),(2,4)	(1,6)
P(2)	-	-	(1, 6)	(1,8)	-	-	(5,2),(4,3)	(3,4),(2,5)	(1,6)
P(5)	-	-	(1, 8)	(1,7)	-	-	(5,2)	(2,4)	(1,6)
P(8)	-	-	(1, 7)	(1,6)	-	-	(5,2)	(3,3),(2,4)	(1,6)

Real Data Example

In order to examine the methods outlined in this paper, we consider Sajedi Refining and Packing Raisins Factory as a real case study. The factory was established in 1992, in Quchan, Razavi Khorasan Province. Along with the advancement of technology in this industry, the company tries to improve the quality of products as much as possible. Estimating the number of defective items produced by a machine is an important problem in statistical process control. In a lot of economic sampling plans, the solution of the optimization problem is strongly dependent on the estimation of the fraction of defective items. The biased estimation may lead to improper choice in optimization and, consequently, huge economic penalties (Dasgupta & Mandal, 2008). Estimating the number of defective items has been studied by a few researchers. In this paper, we consider the real data set representing the number of damaged raisins in every 100gr samples of raisins recorded in 2015. By counting the number of inspected raisins in every 100gr samples, we could acquire the fraction of defective raisins is a continuous random variable and takes a value between zero and one. Upper and lower records extracted from these data are reported in Table 3. Here, using the results obtained in Section 3 and Table 2, the optimal prediction intervals are determined and are presented in Table 4. The three mentioned distributions mentioned in Section 2 are considered for the size of the future sample, when $\alpha_0 = 0.80$.

Table 3. The upper and lower records extracted from the fraction of defective raisins

j	1	2	3	4	5	6	7	8	9
R_j^U	0.028	0.031	0.035	0.039	0.041	0.042	0.048	0.056	
R_j^L	0.028	0.026	0.017	0.013	0.010	0.008	0.006	0.003	0.000

Table 4. 80% optimal prediction intervals for some selected values of i and different distributions for N

	$(R_{r_{opt}}^U, R_{s_{opt}}^U)$			$(R_{s_{opt}}^L, R_{r_{opt}}^L)$			$(R_{r_{opt}}^L, R_{s_{opt}}^U)$		
Distribution of N	i=1	i=5	i=10	i=1	i=5	i=10	i=1	i=5	i=10
N=10	-	-	(0.028,0.048)	(0.006,0.028)	-	-	(0.008,0.031), (0.006,0.028)	(0.013,0.031), (0.017,0.035)	(0.028,0.048), (0.026,0.042)
B(10, 0.2)	-	-	(0.028,0.048)	(0.000,0.028)	-	-	(0.010,0.031), (0.013,0.035)	(0.017,0.039), (0.026,0.041)	(0.028,0.042)
B(10, 0.5)	-	-	(0.028,0.048)	(0.008,0.028)	-	-	(0.010,0.031)	(0.026,0.039)	(0.028,0.048), (0.026,0.042)
B(10, 0.8)	-	-	(0.028,0.048)	(0.006,0.028)	-	-	(0.010,0.031)	(0.017,0.035), (0.026,0.039)	(0.028,0.042)
P(2)	-	-	(0.028,0.042)	(0.003,0.028)	-	-	(0.010,0.031), (0.013,0.035)	(0.017,0.039), (0.026,0.041)	(0.028,0.042)
P(5)	-	-	(0.028,0.056)	(0.006,0.028)	-	-	(0.010,0.031)	(0.026,0.039)	(0.028,0.042)
P(8)	-	-	(0.028,0.048)	(0.008,0.028)	-	-	(0.010,0.031)	(0.017,0.035), (0.026,0.039)	(0.028,0.042)

Concluding Remarks

In many experiments, such as biology and quality control, sample size cannot always be considered constant. Therefore, the problem of predicting future data when the sample size is a random variable can be an important issue. In this paper, we first consider the prediction of future order statistics while the sample size is a random variable. Three different distributions, such as degenerate, binomial and Poisson distributions were considered for the size of the future sample. Then, taking into account the optimization criterion for the shortest interval length, which can be obtained by minimizing the mean length of the prediction interval, we determined the optimal prediction intervals in each case, and then compared the results. Finally, it can be concluded that the results are similar for different distributions of future sample size. In other words, the prediction intervals are not very affected by the distribution of the sample size and are almost stable.

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Attraction–Selection–Attrition Theory in the Public Organization: The Effects of Personality Traits on Psychological Ownership with Regard to the Mediating Role of Emotional Intelligence

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Abstract

Personality traits and their relation with emotional intelligence and psychological ownership (PO) have to be considered in public-sector organizations, because employees who work in the public sector may have fewer mechanisms to increase their feelings of PO toward their organization. Thus, with regard to conditions of public organizations, more attention should be paid to structural and organizational contexts while investigating the relations between personality traits, emotional intelligence and PO. The aim of the research is to probe the effect of personality traits on PO in a public organization with regard to the mediating role of emotional intelligence. SPSS and Smart PLS software applications were used to test the research hypotheses. Data were collected from 384 participants, engaged in a public organization administrative department. The results revealed that traits, including extroversion, agreeableness, conscientiousness, openness and neuroticism influence emotional intelligence; emotional intelligence, in turn, is positively associated with PO; these personality traits are directly associated with PO and influence PO indirectly through emotional intelligence.

Keywords

Personality traits, emotional intelligence, psychological ownership, public Administration.

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Introduction

As one of the positive organizational behaviors, Psychological Ownership (PO) will be the main factor which contributes to competitiveness of organizations during the twenty first century (Brown, 1989). Employees' PO to the organization is receiving an increasing attention of managers and researchers, because this concept is the main antecedent of positive attitudes, behaviors and performance of employees thorough commitment, satisfaction, accountability, extra-role behaviors, citizenship behavior, self-esteem, performance, and intent to stay (Avey et al., 2009; Brown, 1989; Pierce et al., 2001; Pierce et al., 2009). Although PO has been the focus of many researches (for example, Pierce et al., 2001, 2003; Pierce et al., 2004; Van Dyne & Pierce, 2004), only a few researches have concentrated on the relationships between the PO experience of employees and other related organizational behaviors and attitudes in public organizations.

Previous researches examining the factors influencing PO have focused typically on group and organizational-level antecedents, with little attention being paid to the effect of personality characteristics and other important individual and personal difference factors (Dawkins et al., 2015). Pierce et al. (2003) asserted that personal difference factors such as personality characteristics may influence how a person goes about pursuing relationships with possession objects and the kinds of objects deemed appropriate, building on primary empirical evidence (McIntyre et al., 2009; Kaur et al., 2013). Further, characteristics affect behavior only in some situations (Kenrick & Funder, 1988), and types of organizations such as public and private can be the most important factor in this regard. Also, differences between the context and structural properties of organizations, such as public and private, tend to attract people with differences in personality and individual characteristics (Perry & Wise, 1990).

Researchers have indicated that behaviors of employees in public-sector and for-profit organizations can differ substantially because behaviors of employees are derived by initiatives of organizations, and these two various organizational environments often have different work and vision climates and conditions (Goulet & Frank 2002). On the other hand, the modern public bureaucratic system requires employees to use their emotional intelligence to communicate with people and citizens effectively (Lee, 2013). Employees of public service who are able to manage their feelings and emotions and perceive other people's emotions may enhance the performance of organizations and promote people's and citizens' satisfaction (Lee, 2013). At the organizational level of analysis, the Attraction–Selection–Attrition (ASA) theory explains that similar people are selected and attracted by organizations, while dissimilar people are likely to leave these organizations due to attrition. In consequence, the ASA model leads to an increase in homogeneity in emotional intelligence and personality traits of people within one organization. Also, one of the main identified predictors of PO is emotional intelligence (Dawkins et al., 2015). Kaur et al. (2013) concluded that emotional intelligence of employees positively predicted individuals' PO, and finally their caring behavior. As a result, congruence between the person and organization with regard to the ASA theory can lead to an increase in the emotional intelligence and PO.

Furthermore, most researches on PO variables have been done in for-profit organizations (Van Dyne & Pierce 2004; Avey et al., 2009) and information about employees of public-sector is inconsistent and scarce. Personality traits and their relations with emotional intelligence and PO should be considered in public-sector organizations because in comparison with people who are active in the for-profit sector, those in the public sector organizations may have fewer methods and mechanisms to increase their emotions and feelings of PO toward their work and organization (Park et al., 2013). However, most researches that have investigated these concepts are limited to the organizations of private sector, and fewer studies have been done on the public sector jobs and organizations. Thus, with regard to the special cultural characteristics of the Iranian people such as collectivism and high levels of power distance and special conditions of public organizations such as formality, hierarchy and bureaucracy, greater attention is needed in considering cultural, structural and organizational context for investigating relations between personality traits, emotional intelligence and PO.

Personality Traits and Emotional Intelligence

Based on the ASA model, organizations emphasizing a certain type of values select and attract people who agree with the norms and values or people whose traits are congruent with the organization values (Li et al., 2008). Also, people with high emotional intelligence are likely to be selected by and attracted to organizations whose individuals have high emotional intelligence and very strong power of emotion management (Menges & Bruch, 2009). In consequence, the ASA model leads to an increase in homogeneity in personality traits and emotional intelligence of employees within one job and organization (Menges & Bruch, 2009). Theory suggests that where people do not fit the core goals and values of the organization, they will tend to leave their organization (Aishah Hassan & Shabani, 2013). Thus, it can be concluded that the congruence between traits and organizational values and conditions with regard to ASA model can lead to positive and significant effects on emotional intelligence.

Agreeableness is related to behaviors favoring collaboration and investing on a common good, which is closely associated with the desire to serve both the public and citizens' interests (Witteloostuijn et al., 2016). Among dimensions of the Big Five model of personality (McCrae & Costa, 1997), Agreeableness trait was most likely to be highly associated with an employee's propensity toward work in the public service. In addition, conscientious employees are more likely to appreciate bureaucratic rules and structures, therefore, they are also expected to be predisposed to higher levels of satisfaction in the job (Judge et al., 2002), particularly in the public sector organizations (Cooper et al., 2014). It was showed that the extroversion trait was indirectly associated with the attraction to policy making in public sector organizations (Ain et al., 2015). Briefly, personality traits of the Big Five have a positive and significant relationship with public service motivation (Ain et al., 2015). Consequently and with regard to the ASA framework, it can be concluded that there is a compatibility between values of public organizations and personality traits such as conscientiousness, extroversion and agreeableness.

The evidence for a correlation between emotional intelligence and personality variables is very significant and strong (Van der Zee et al., 2002; Saklofske & Zeidner, 1995). Emotional intelligence can have an indirect, positive and significant relationship with the contentiousness, openness, extroversion, agreeableness traits and a negative relationship with the neuroticism trait (Perez-Gonzalez & Sanchez-Ruiz, 2014; Petrides et al., 2010).

There is a negative and significant correlation between impulsivity as the negative axis of conscientiousness trait and intelligence of employees (Vigil-Colet & Morales-Vives, 2005; Lozano et al., 2014). Conscientiousness trait has been related to a focus on complying with rules, principles and, moral and spiritual standards (Costa & McCrae, 1992). With regard to the particular philosophy of public organizations such as attention to citizen's interests and social responsibility, conscientiousness can be related to employees' emotional intelligence in public organizations. Also, agreeable individuals are likely to help, and are motivated to maintain positive relationships with other people. Bracket and Mayer (2003) showed a significant and positive relationship between employees' emotional intelligence and agreeableness trait. Specificity of the organizations of public sector stems from their preparation for meeting public order and public needs (Aykac & Metin, 2012). With regard to the particular philosophy of public organizations such as attention to citizens' interests, it can be argued that agreeableness in public organizations can be related to the employees' emotional intelligence. In addition, extroverted people are open to other people and tend to be informal and unreserved in their communications with others. Various researches have detected a relationship between employees' emotional intelligence and their extroversion (Van der Zee et al., 2002; Roger & Najarian, 1989). In consequence, the extroversion trait can be linked to employees' emotional intelligence. Also, negative feelings and emotions will be most strongly linked to the neuroticism trait (Costa & McCrae, 1992). By contrast, people with high neuroticism, seem to have unhappy memories and report less happiness (Ruiz-Caballero & Bermudez, 1995) that can illustrate much lower emotional intelligence. This trait is sometimes referred to as negative feelings and emotions (Watson & Clark, 1984) and finally neuroticism has been related negatively to employees’ emotional intelligence. Finally, researches indicated that the strongest relationship observed between personality trait and cognitive ability is reported for the openness to experience trait (Blanco et al., 2016). According to openness to experience, it has been suggested that people who are high in openness to experience have an excellent motivation to commit intellectual activities, which makes them develop their intelligence (Brand, 1994). Thus, openness to experience has been related to employees’ emotional intelligence.

Hypothesis 1. In public organizations, extroversion (H1a), agreeableness (H1b), conscientiousness (H1c) and openness (H1d) positively and neuroticism (H1e) negatively influence emotional intelligence.

Emotional Intelligence and Psychological Ownership

Kaur et al. (2013) concluded that an individual's emotional intelligence positively predicted employees’ PO. There is a negative relationship between structural features of work environment such as participative decision making, autonomy, technology reutilization and PO for the organization and job (O’Driscoll et al., 2006; Pierce et al., 2004). Organizations with less structured conditions and environments are more likely to induce ownership feelings for the job and organization. On the other hand, flexible and organic organizational structures will increase in the organizations of the public sector (Ozer, 2005) and the formal structure of the public sector organizations which have adhocratic, centralized and resistant organizational structures will become more flexible (Eryilmaz, 2010). Furthermore, organizations with more flexible and less bureaucratic structures may create rules and norms for alternative models of emotion and feeling management

(Martin et al., 1998). Thus, organizational structure in public sector organizations can be effective on emotional intelligence and PO.

There are different relationships between emotional intelligence and decisional styles (Kenny et al., 2012). Also, empirical studies has confirmed a strong and significant relationship between participation of employees in decision-making and PO based on the organization (Han et al., 2010; Liu et al., 2012). On the other hand and from a cultural perspective, Iranian people illustrate high levels of collectivism (Canestrino et al., 2015) and collectivist traits can increase employees' participation in Iranian organizations. Thus, based on the special culture of Iran, emotional intelligence is related to PO with regard to variables such as participation.

Empirical studies and theoretical research have positively linked emotional intelligence to the internal locus of control (Singh, 2006). Additionally, control has been indicated to be an important antecedent of ownership feelings (Furby, 1978). PO of employees is like having an internal control locus because it provides an internally based drive to influence circumstances (Kaur et al., 2013). Also, jobs and duties with high autonomy imply a greater degree of control, and finally, they would be expected to increase the PO experience of employees (Pierce et al., 2001). Thus, control is an effective tie with regard to the relationship between emotional intelligence and PO.

Two key national culture dimensions include individualism and power distance (Hofstede, 1980). From a cultural perspective, Iran shows high levels of collectivism (Canestrino et al., 2015). Also, because of the administrative hierarchy and bureaucracy in public organizations, it can be argued that power distance in these organizations is high. Also, with regard to changes in the future of public organizations and despite the increase in flexibility, bureaucracy and bureaucratic structures will not diminish (Aykac & Metin, 2012). Thus, it can be concluded that power distance in public organizations is very high. Also, power distance can be associated with a better control of feelings and emotions and thereby emotion suppression (Matsumoto et al., 2008). Thus, power distance is associated with positive regulation of emotions regarding the relationship between collectivism and high distance of power (Hofstede, 1991), it can be argued that high power distance can lead to higher PO due to the collectivist culture and changes in future.

Finally, there is a significant relationship between emotional intelligence and job insecurity (Kappagoda, 2013). Also, feeling of ownership or possession provides an individual with a sense of belongingness or place, which is necessary for presenting feelings of pleasure, comfort and security (Heidegger, 1967). Thus, emotional response and PO can be related to each other due to job security.

Hypothesis 2. Emotional intelligence of employees positively influences PO in public organizations.

Personality Traits and Psychological Ownership

Key personality traits have been extensively used to investigate differences in person and team behavior (Witteloostuijn et al., 2016). Research by Pierce, Kostova and Dirks (2003) showed that personal factors such as period of service, roles and statutes, age, gender and personality might affect the ownership feeling psychologically.

More research is needed to examine how and to what extent the main personal difference factors may influence PO. One of these key differences are personality characteristics (Dawkins et al., 2015). Previous researches have investigated the predictors of psychological ownership with little attention being paid to the effect of personality characteristics and other important personal difference factors (Dawkins et al., 2015). Mcintyre et al. (2009) suggest that feelings of ownership can increase by having an appropriate type of personality characteristic that is compliant with different motivations.

Personality traits of the Big Five, such as extroversion trait (Watson & Clark, 1992), can be positively or negatively related to positive emotions and also positive emotions can be consistent with the routes of the PO (Haase et al., 2012; Krupic & Corr, 2014; Novovic et al., 2012). Also, characteristics influence behavior only in related situations (Kenrick & Funder, 1988). With regard to the protection of long-term legal commitment to and powerful psychological contacts with organizations, people in public organizations may view ownership differently from people in private organizations, with limited employee stock ownership plan. Furthermore, because people's ownership in public sector organizations differs from employees' ownership in private sector organizations due to the comparative defect of formal ownership, the effect of PO on attitudes and behaviors of employees may be relatively important in public sector organizations as a result (Park, 2013).

Hypothesis 3. Personality traits of employees including extroversion (H3a), agreeableness (H3b), conscientiousness (H3c) and openness (H3d) positively and neuroticism (H3e) negatively influence PO in public organizations.

Emotional intelligence can also be investigated as a mediating variable as it has already been done in many studies (for example, Marks et al., 2016; Wischerth et al., 2016; Zhang et al., 2016). The ASA model indicates that employees choose job roles and stay with their organizations based upon highly relevant levels of congruence between values of individuals and those of the organization (Cable & Judge, 1997). On the one hand, empirical evidences suggest that organizations emphasizing a certain type of values select and attract individuals who agree with the values or individuals whose traits are congruent with the values of the organization (Li et al, 2008) and organizational emotional intelligence of employees is likely to be comparatively homogeneous within organizations with regard to ASA model and socialization processes. On the other hand, emotional intelligence can lead to positive emotions and these positive emotions increase positive psychological states such as PO.

Hypothesis 4. Personality traits including extroversion (H4a), agreeableness (H4b), conscientiousness (H4c), openness (H4d) and neuroticism (H4e) influence PO indirectly and through emotional intelligence.

Method

Sample

The used instrument in this research is standardized questionnaire.

Also, selecting people has been done through random sampling. To test research hypotheses, 384 full-time employees were recruited from a large public organization in the city of Tehran, Iran. Employees of public sector organizations are suitable participants for this research for several reasons. Their average age was 33.35 years, the average of organizational tenure was 4.17 years, and 54.9% of the participants were male. The population under analysis includes employees of the Taxation Affairs Organization in the city of Tehran which consisted of 211 men and 173 women, all of whom were administrative employees. All employees provided their informed consent before completing the research questionnaire. All scales were subjected to reliability and validity analyses.

Procedure

A quantitative analysis was conducted in order to investigate the relationship between personality traits, emotional intelligence and PO in a public organization. All questions were completed on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). With regard to the aim of the study, the present research is descriptive and developmental based on the data collection method. Also, according to the classification, the present research is correlational.

The Scale of Variables

The independent variable is personality traits. The questionnaire of Big Five personality traits (John & Srivastava, 1999) was used to evaluate personality of the sample. This model has been selected because these traits (agreeableness, extroversion, openness, conscientiousness, and neuroticism) have been empirically shown to be capable of describing the personality dimensions. A 44-item scale was designed to assess the five domains of personality: Agreeableness (1-9 items), extroversion (10-17 items), conscientiousness (18-26 items), neuroticism (27-34 items) and openness (35-44 items). Also, the 16-item questionnaire developed by Wong and Law (2002) was used to evaluate the employees' emotional intelligence. Four dimensions of emotional intelligence have been measured in this study. The dimensions are self-emotion appraisal, others' emotion appraisal, use of emotion, and regulation of emotion. The scale includes 16 items (4 items for each dimension). Finally, the scale of PO was measured with a 12-item questionnaire (Avey et al., 2009), which covered four dimensions of belongingness, self-efficacy, self-identity, and accountability, each with three items.

Statistical Analyses

SPSS and SmartPLS software programs were used to test the hypotheses of the present study and to evaluate the appropriateness of the proposed theoretical framework. In relation to SEM analysis of full latent variable models, it was necessary to verify the validity of the measurement portion of research model (Byrne, 2006).

Reliability and Validity

Reliability

Cronbach's alpha: Alpha values greater than 0.7 indicate high internal consistency whereas 0.5–0.6 alpha values indicate adequate and lower limit of acceptability.

Composite reliability (CR): Additionally, Bagozzi and Yi (1988) confirmed that an instrument is reliable if composite reliability is 0.7 or over. Hence, our instrument meets the criterion for reliability.

Construct reliability: factor loadings have been used in order to confirm the reliability. Factor loadings values greater than 0.4 indicate high construct reliability whereas 0.2 or 0.3 factor loadings indicate inadequate and lower limit of acceptability.

Validity

Content validity: Content validity is established through an iterative process of reviewing and revising the indicator items by a group of potential respondents and experts. In order to evaluate the validity of the achieved data through the instrument, it has been used opinions of the readers, advisors, and experts.

Convergent validity: To assess the convergent validity, we computed the Average Variance Extracted (AVE) for each construct. An instrument has convergent validity if AVE is 0.5 or higher (Bagozzi & Yi, 1988).

Results

Assessment of the Outer Model

Composite reliability and the Cronbach's alpha of all the constructs were higher than 0.70, indicating reliable measurements. Also, convergent validity was measured by investigating the average variance extracted (AVE) from the constructs. The recommended value has been more than 0.50 percent, indicating high convergent validity. Table 1 describes the results of the outer model.

Table 1. Inter-Construct Correlations and the Square-Root of the AVE

Construct	AVE	CR	Cronbach's α	R^2
extroversion	0.687	0.945983	0.934079	0.000
agreeableness	0.727	0.959769	0.952049	0.000
conscientiousness	0.682	0.950873	0.941805	0.000
openness	0.601	0.936879	0.924270	0.000
Neuroticism	0.532	0.900428	0.873524	0.000
Emotional Intelligence	0.531	0.946659	0.939413	0.786
PO	0.647	0.956326	0.949879	0.897

Factor loadings values greater than 0.4 indicate high construct reliability. All related factor loadings were equal to or higher than 0.5. This is a conservative cut-off level indicating reliability of the questions. Thus, construct reliability is acceptable.

Table 2. Factor Loadings Values

Q	FL	Q	FL	Q	FL	Q	FL	Q	FL	Q	FL
1	0.66	13	0.77	25	0.69	37	0.63	49	0.74	61	0.66
2	0.58	14	0.71	26	0.54	38	0.80	50	0.74	62	0.83
3	0.45	15	0.83	27	0.58	39	0.70	51	0.67	63	0.85
4	0.74	16	0.88	28	0.70	40	0.75	52	0.84	64	0.87
5	0.47	17	0.93	29	0.65	41	0.63	53	0.69	65	0.83
6	0.66	18	0.91	30	0.45	42	0.80	54	0.45	66	0.80
7	0.55	19	0.91	31	0.49	43	0.70	55	0.74	67	0.76
8	0.70	20	0.67	32	0.51	44	0.75	56	0.67	68	0.80
9	0.75	21	0.53	33	0.69	45	0.78	57	0.84	69	0.80
10	0.68	22	0.58	34	0.65	46	0.81	58	0.69	70	0.81
11	0.78	23	0.64	35	0.73	47	0.79	59	0.45	71	0.74
12	0.88	24	0.71	36	0.53	48	0.78	60	0.74	72	0.81

Inner Model Assessment

The path relationships were measured by the endogenous constructs variance and on the basis of the path coefficients sign, significance and magnitude. The predictive power of the research structural model is measured by the R2 amounts. Explained variance for the inner constructs, both first and second order, is more than 0.1. In this research, the PO (final dependent construct) has an R2 value of 0.897, which can be investigated taking into account the model complexity. Emotional Intelligence variable has an R2 value of 0.786, which indicates the strong and significant predictive power of extroversion, agreeableness, conscientiousness and openness on PO.

After calculating the path estimates in the structural model of research, to investigate the statistical significance of the path coefficients, bootstrapping has been conducted in Smart PLS. The path coefficients have been measured by using the one-tailed t-test. The values are significant at the 5% level if the investigating values are higher than 1.648 and they are significant at the 1% level if the t-values are higher than 1.96.

Table 3. Relations between Variables

Relationship	t-statistic	Path coefficient	Statistical significance	Result
Extroversion and EI	6.605	0.330879	Sig.	confirmed
agreeableness and EI	5.614	0.330995	Sig.	confirmed
conscientiousness and EI	3.234	0.165666	Sig.	confirmed
openness and EI	2.502	0.130049	Sig.	confirmed
Neuroticism and EI	1.037	-0.031	Not sig.	Rejected
EI and PO	7.728	0.293802	Sig.	confirmed

The t-statistics and path coefficient of the structural relationships of research model are shown in Table 3. The results show that extroversion has a significant and positive impact on emotional intelligence (β=.033, t=6.6) and, therefore, H1a is supported. Agreeableness has a positive and significant impact on emotional intelligence (β=.33, t= 5.61). Thus, H1b is supported, too. Additionally, conscientiousness has a positive and significant impact on emotional intelligence (β=0.16, t=3.23) supporting H1c. Furthermore, openness has a positive and significant impact on emotional intelligence (β=0.13, t=2.502). Thus, H1d is supported. Finally, Neuroticism does not have a significant and positive effect on emotional intelligence (β=-0.03, t=1.03). Thus, H1e is not supported. In addition, PO is influenced significantly by emotional intelligence (β=0.29, t=7.72). Thus, H2 is supported.

Test of the Mediating Effect

Hypotheses 4a, 4b, 4c, 4d and 4e were mediating hypotheses and required necessarily varied conditions to test. In order for the mediating effect to occur, Baron and Kenny (1986) propose that several conditions need to be met. First, the predictor variables (e.g., extroversion, agreeableness, conscientiousness, and openness) must be significantly related to the mediator variable, that is emotional intelligence, and the criterion variable, that is PO, and next the mediator variable, that is emotional intelligence, should be significantly related to the criterion variable. Finally, when the mediator variable is entered into the structural relationship, the relationship between predictor variable and criterion variable must be insignificant for full mediation or weak for partial mediation.

Hypothesis 4a indicates that the variable of emotional intelligence mediates the relationship between extroversion and PO. As seen in Figure 1, extroversion has a sig significant and positive effect on PO (β=0.805, t=24.05) in the absence of the mediator influence of emotional intelligence. Thus, H3a is supported. Then, extroversion has a significant and positive effect on the mediator variable of emotional intelligence (β=0.81, t=23.37). Next, emotional intelligence is significantly associated with PO (β=0.69, t=8.49). Baron and Kenny (1986) have used the Sobel test to test the influence of the mediating variable. When the variable of emotional intelligence was included in the present model, the predictive power of extroversion on PO significantly reduced from β=0.805 to β=0.24 and based on the Sobel test calculation (z=7.84), which implies a significant and strong mediating influence. In total, these findings present support for Hypothesis H4a.

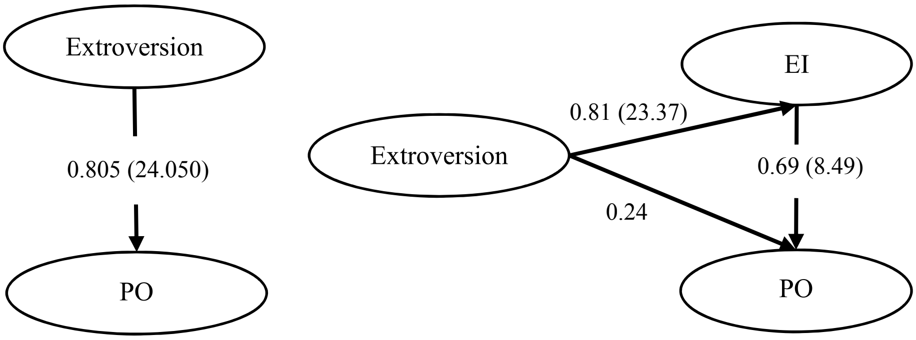

Figure 1. Role of emotional intelligence on relationship between extroversion and PO

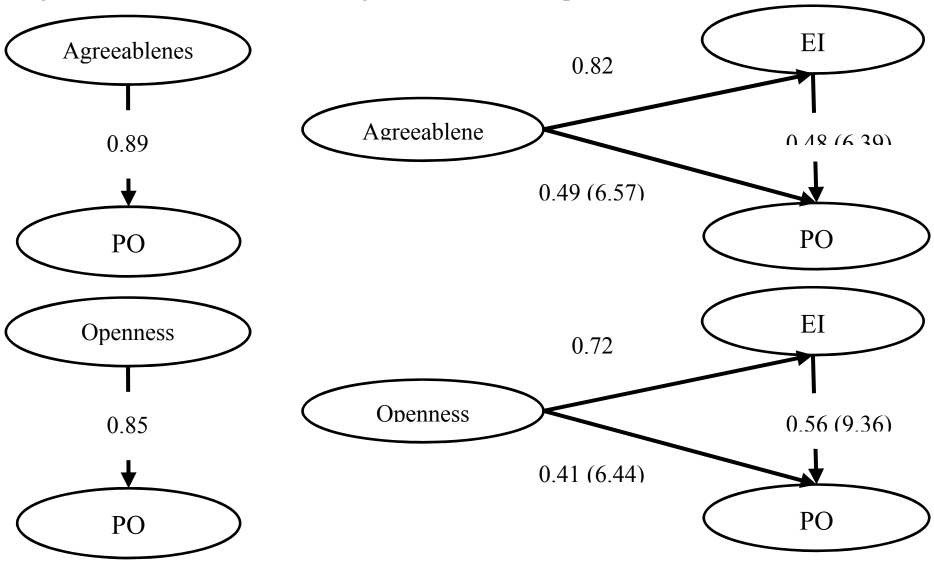

Figure 2. Results of Hypotheses 4b, 4c

Accordingly and based on Figures 2 and 3, Hypotheses 4b, 4c, 4d have been confirmed and Hypotheses 4e has been rejected.

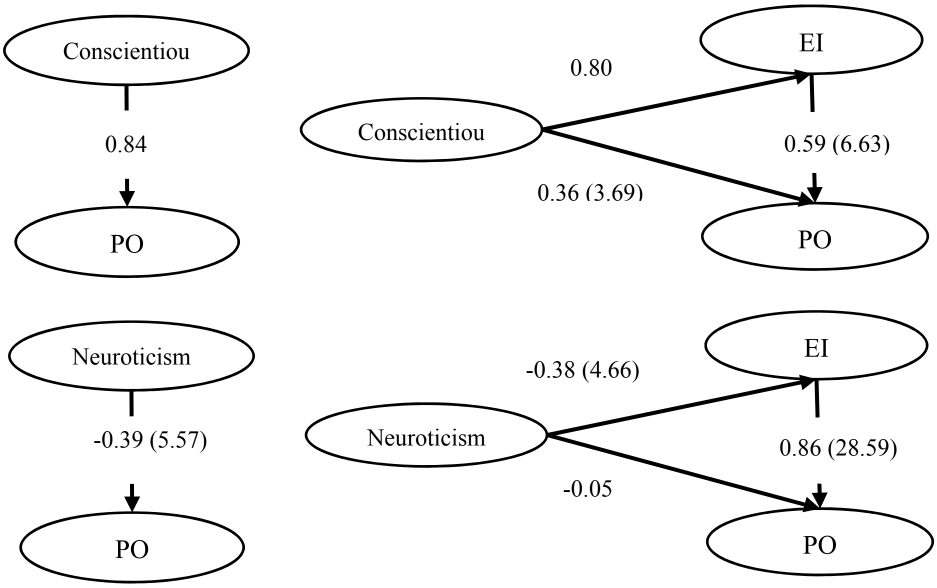

Figure 3. Results of Hypotheses 4d and 4e

Overall Conclusion and Discussion

Personality traits, including extroversion, agreeableness, conscientiousness and openness, influence emotional intelligence and that relationship is stronger when compatibility between organization values and personality characteristics is higher. Also, emotional intelligence of employees will be positively associated with their PO in a public organization and that relationship is stronger when work environment has less structure, less job insecurity, collaborative decision-making styles and higher internal locus of control. In addition, personality traits of employees including extroversion, agreeableness, conscientiousness, and openness will be positively and directly associated with PO in a public organization. Additionally, personality traits including extroversion, agreeableness, conscientiousness and openness influence PO indirectly and through emotional intelligence. In other words, emotional intelligence has a mediating role in the relationship with personality traits and PO in a public organization. Finally, emotional intelligence positively mediated the relationship between extroversion, agreeableness, conscientiousness, and openness, and neuroticism negatively mediated the relationship between PO and emotional intelligence

In the first hypothesis, the results from the present research revealed that personality traits influence emotional intelligence. These results are consistent with the research literature (Pierce et al, 2003; Mcintyre et al., 2009). Research on ASA framework presents further support for the expected effect of organizational culture on the requirement of work-related personality and demonstrates that the congruence between specific organizational culture of public organizations and individual's personality traits is very important in this respect. On the other hand, organizational culture plays a key role in the ASA framework because empirical evidence indicates that organizations emphasizing a certain type of values select and attract people who agree with the organization values or people whose traits are congruent with the organization values (Li et al., 2008). ASA model explains why similar people are selected by organizations, while inconsistent people are likely to leave these organizations due to attrition. As a result, the ASA process leads to an increase in homogeneity in emotional intelligence within one organization (Menges & Bruch, 2009).

Regarding the second hypothesis, the findings of the present research showed that emotional intelligence of employees will be positively associated with their PO. Research concluded that an individual's emotional intelligence positively predicted employees' PO (Kaur et al, 2013). For example, empirical studies and theoretical research have positively linked emotional intelligence to the internal locus of control (Singh, 2006). Additionally, control has been indicated to be an important antecedent of ownership feelings (Furby, 1978). Thus, control is an effective tie with regard to the relationship between emotional intelligence and PO.

With respect to the third hypothesis, personality traits of employees including extroversion, agreeableness, conscientiousness, and openness will be positively and directly associated with PO. In this regard, social exchange theory suggests one possible explanation. Blau (1964) believes that social exchanges are practices that are conditional on rewarding responses from other people. When the process of social exchange is built based on beneficial and reciprocal transactions between the employees and employer, the outcome will be beneficial and positive attitudes or behaviors (Cropanzano & Mitchell, 2005) such as PO (Park et al., 2013). Thus, with regard to social exchange theory, it can be argued that congruence between specific organizational culture of public organizations and people's personality traits can lead to positive behaviors or attitudes such as PO. In addition, the relationship between personality traits can be considered with regard to trait-activation theory (Dawkins et al., 2015). The key assumption of trait-activation theory is that conditions and personality characteristics are reasons of behavioral conflict and variance, and personality traits are expressed as answers to trait-relevant cues (Tett & Guterman, 2000). Therefore, rather than supposing that personality traits influence the reinforcement of PO in some recognizable manner, trait activation theory proposes that traits influence behavior of people just in relevant situations (Kenrick & Funder, 1988), and type of organization such as public and private can be the most important influential factor in this regard.

With reference to the fourth hypothesis, personality traits including extroversion, agreeableness, conscientiousness, and openness influence PO indirectly and through emotional intelligence. The relationship between employees' personality types and their perception of organizational culture and their impact on PO were examined. The results of the study presented a better perception of individuals' turnover intention in an organization due to explanations of PO (Giffen, 2015).

Results indicated that emotional intelligence positively mediated the relationship between extroversion, agreeableness, conscientiousness, and openness and negatively mediated the relationship between neuroticism and PO. The mediating role of emotional intelligence in the relationship between dimensions of personality traits and PO is explainable with regard to two theories. First, ASA theory in public administration confirms that dimensions of personality traits such as extroversion, agreeableness and conscientiousness are consistent with goals, mission, values and structure of public organizations and employees are congruent in their personality dimensions with the characteristics of the public agencies. Also, the results indicated that ASA can lead to an increase in the emotional intelligence. Second, with regard to the social cognitive theory, control of emotions is critical in development of self-efficacy (Gundlach et al., 2003), and perceptions of self-efficacy is one of the important dimensions of PO.

Managerial Implications

Authors believe that the study presented here have very important implications for public administration managers. Organizations' managers have to pay special consideration and attention toward the perception of psychological ownership of employees due to its effects on many organizational outcomes including employee's performance and their organizational citizenship behavior. Organizations' managers have to develop the attributes of the potential ownership targets by making them attractive, obvious, accessible, and malleable which can increase the potential in order to have psychological ownership. Also, managers can work on the psychological ownership routes. For example, they could organize the work in such a way that there would be increased opportunities for employees to exercise participation over different targets, to create control of the targets and collaborative decision-making to be in frequent and close association with the targets, and to be able to make significant investments of themselves into the targets because people who have a say in their decision making may develop a feeling of PO that makes them feel that the job and organization is theirs. Managers have to know that individuals who were not a good fit with an organization due to organizational culture or job tasks were likely to quit the organization and organizations choose individuals who fit their values and goals due to selection strategies because congruence between organization and person's characteristics in the public organization is very important in order to have effectiveness in these organizations. Also, managers of public organizations have to increases job security, collaborative decision-making styles, and higher internal locus of control in their organizations. Finally, managers of public organizations have to consider employees participation, lower role ambiguity and self-efficiency because based on the special culture of Iran, emotional intelligence is related to PO with regard to variables such as participation, lower role ambiguity and self-efficiency.

Limitations and Future Directions

This research has some limitations. One of the limitations is the small size of sample that limiting the generalizability. Also, the research suffers from some limitations of survey method that uses self-reported measures that are exposed to bias of social desirability. The present research also has been conducted on a public organization, which consequently decreases generalizability of the research findings to other sector employees because every organization is incomparable and unique from organizations others based on the practices, policies, challenges etcetera. Thus, future studies have to investigate psychological ownership in various settings such as in private and non-public organizations. Furthermore, information collection on the research at one point of time may not give a detailed and accurate picture. Future studies have to investigate contract violation on longitudinal or experimental designs and present more convincing evidence on the investigated variable. This research has been conducted on the respective boundaries of professional and cultural factors. Researchers propose that future studies investigates psychological ownership in various settings, such as other public sectors, private sector organizations in different industries where dynamic contexts and different legal arrangements may influence ownership conceptualizations. Also, the construct reliability and validity in this research is another limitation. Future research may be essential to validate the findings and increase the accuracy of research results by obtaining data from employees of different organizations and sectors. Finally, based on the future theory research and construction, authors suggest consideration of whether or not there are some collective motives related to the emergence of psychological ownership collectively.

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Attraction–Selection–Attrition Theory in the Public Organization: The Effects of Personality Traits on Psychological Ownership with Regard to the Mediating Role of Emotional Intelligence

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Abstract

Personality traits and their relation with emotional intelligence and psychological ownership (PO) have to be considered in public-sector organizations, because employees who work in the public sector may have fewer mechanisms to increase their feelings of PO toward their organization. Thus, with regard to conditions of public organizations, more attention should be paid to structural and organizational contexts while investigating the relations between personality traits, emotional intelligence and PO. The aim of the research is to probe the effect of personality traits on PO in a public organization with regard to the mediating role of emotional intelligence. SPSS and Smart PLS software applications were used to test the research hypotheses. Data were collected from 384 participants, engaged in a public organization administrative department. The results revealed that traits, including extroversion, agreeableness, conscientiousness, openness and neuroticism influence emotional intelligence; emotional intelligence, in turn, is positively associated with PO; these personality traits are directly associated with PO and influence PO indirectly through emotional intelligence.

Keywords

Personality traits, emotional intelligence, psychological ownership, public Administration.

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Introduction

As one of the positive organizational behaviors, Psychological Ownership (PO) will be the main factor which contributes to competitiveness of organizations during the twenty first century (Brown, 1989). Employees' PO to the organization is receiving an increasing attention of managers and researchers, because this concept is the main antecedent of positive attitudes, behaviors and performance of employees thorough commitment, satisfaction, accountability, extra-role behaviors, citizenship behavior, self-esteem, performance, and intent to stay (Avey et al., 2009; Brown, 1989; Pierce et al., 2001; Pierce et al., 2009). Although PO has been the focus of many researches (for example, Pierce et al., 2001, 2003; Pierce et al., 2004; Van Dyne & Pierce, 2004), only a few researches have concentrated on the relationships between the PO experience of employees and other related organizational behaviors and attitudes in public organizations.

Previous researches examining the factors influencing PO have focused typically on group and organizational-level antecedents, with little attention being paid to the effect of personality characteristics and other important individual and personal difference factors (Dawkins et al., 2015). Pierce et al. (2003) asserted that personal difference factors such as personality characteristics may influence how a person goes about pursuing relationships with possession objects and the kinds of objects deemed appropriate, building on primary empirical evidence (McIntyre et al., 2009; Kaur et al., 2013). Further, characteristics affect behavior only in some situations (Kenrick & Funder, 1988), and types of organizations such as public and private can be the most important factor in this regard. Also, differences between the context and structural properties of organizations, such as public and private, tend to attract people with differences in personality and individual characteristics (Perry & Wise, 1990).

Researchers have indicated that behaviors of employees in public-sector and for-profit organizations can differ substantially because behaviors of employees are derived by initiatives of organizations, and these two various organizational environments often have different work and vision climates and conditions (Goulet & Frank 2002). On the other hand, the modern public bureaucratic system requires employees to use their emotional intelligence to communicate with people and citizens effectively (Lee, 2013). Employees of public service who are able to manage their feelings and emotions and perceive other people's emotions may enhance the performance of organizations and promote people's and citizens' satisfaction (Lee, 2013). At the organizational level of analysis, the Attraction–Selection–Attrition (ASA) theory explains that similar people are selected and attracted by organizations, while dissimilar people are likely to leave these organizations due to attrition. In consequence, the ASA model leads to an increase in homogeneity in emotional intelligence and personality traits of people within one organization. Also, one of the main identified predictors of PO is emotional intelligence (Dawkins et al., 2015). Kaur et al. (2013) concluded that emotional intelligence of employees positively predicted individuals' PO, and finally their caring behavior. As a result, congruence between the person and organization with regard to the ASA theory can lead to an increase in the emotional intelligence and PO.

Furthermore, most researches on PO variables have been done in for-profit organizations (Van Dyne & Pierce 2004; Avey et al., 2009) and information about employees of public-sector is inconsistent and scarce. Personality traits and their relations with emotional intelligence and PO should be considered in public-sector organizations because in comparison with people who are active in the for-profit sector, those in the public sector organizations may have fewer methods and mechanisms to increase their emotions and feelings of PO toward their work and organization (Park et al., 2013). However, most researches that have investigated these concepts are limited to the organizations of private sector, and fewer studies have been done on the public sector jobs and organizations. Thus, with regard to the special cultural characteristics of the Iranian people such as collectivism and high levels of power distance and special conditions of public organizations such as formality, hierarchy and bureaucracy, greater attention is needed in considering cultural, structural and organizational context for investigating relations between personality traits, emotional intelligence and PO.

Personality Traits and Emotional Intelligence

Based on the ASA model, organizations emphasizing a certain type of values select and attract people who agree with the norms and values or people whose traits are congruent with the organization values (Li et al., 2008). Also, people with high emotional intelligence are likely to be selected by and attracted to organizations whose individuals have high emotional intelligence and very strong power of emotion management (Menges & Bruch, 2009). In consequence, the ASA model leads to an increase in homogeneity in personality traits and emotional intelligence of employees within one job and organization (Menges & Bruch, 2009). Theory suggests that where people do not fit the core goals and values of the organization, they will tend to leave their organization (Aishah Hassan & Shabani, 2013). Thus, it can be concluded that the congruence between traits and organizational values and conditions with regard to ASA model can lead to positive and significant effects on emotional intelligence.

Agreeableness is related to behaviors favoring collaboration and investing on a common good, which is closely associated with the desire to serve both the public and citizens' interests (Witteloostuijn et al., 2016). Among dimensions of the Big Five model of personality (McCrae & Costa, 1997), Agreeableness trait was most likely to be highly associated with an employee's propensity toward work in the public service. In addition, conscientious employees are more likely to appreciate bureaucratic rules and structures, therefore, they are also expected to be predisposed to higher levels of satisfaction in the job (Judge et al., 2002), particularly in the public sector organizations (Cooper et al., 2014). It was showed that the extroversion trait was indirectly associated with the attraction to policy making in public sector organizations (Ain et al., 2015). Briefly, personality traits of the Big Five have a positive and significant relationship with public service motivation (Ain et al., 2015). Consequently and with regard to the ASA framework, it can be concluded that there is a compatibility between values of public organizations and personality traits such as conscientiousness, extroversion and agreeableness.

The evidence for a correlation between emotional intelligence and personality variables is very significant and strong (Van der Zee et al., 2002; Saklofske & Zeidner, 1995). Emotional intelligence can have an indirect, positive and significant relationship with the contentiousness, openness, extroversion, agreeableness traits and a negative relationship with the neuroticism trait (Perez-Gonzalez & Sanchez-Ruiz, 2014; Petrides et al., 2010).

There is a negative and significant correlation between impulsivity as the negative axis of conscientiousness trait and intelligence of employees (Vigil-Colet & Morales-Vives, 2005; Lozano et al., 2014). Conscientiousness trait has been related to a focus on complying with rules, principles and, moral and spiritual standards (Costa & McCrae, 1992). With regard to the particular philosophy of public organizations such as attention to citizen's interests and social responsibility, conscientiousness can be related to employees' emotional intelligence in public organizations. Also, agreeable individuals are likely to help, and are motivated to maintain positive relationships with other people. Bracket and Mayer (2003) showed a significant and positive relationship between employees' emotional intelligence and agreeableness trait. Specificity of the organizations of public sector stems from their preparation for meeting public order and public needs (Aykac & Metin, 2012). With regard to the particular philosophy of public organizations such as attention to citizens' interests, it can be argued that agreeableness in public organizations can be related to the employees' emotional intelligence. In addition, extroverted people are open to other people and tend to be informal and unreserved in their communications with others. Various researches have detected a relationship between employees' emotional intelligence and their extroversion (Van der Zee et al., 2002; Roger & Najarian, 1989). In consequence, the extroversion trait can be linked to employees' emotional intelligence. Also, negative feelings and emotions will be most strongly linked to the neuroticism trait (Costa & McCrae, 1992). By contrast, people with high neuroticism, seem to have unhappy memories and report less happiness (Ruiz-Caballero & Bermudez, 1995) that can illustrate much lower emotional intelligence. This trait is sometimes referred to as negative feelings and emotions (Watson & Clark, 1984) and finally neuroticism has been related negatively to employees’ emotional intelligence. Finally, researches indicated that the strongest relationship observed between personality trait and cognitive ability is reported for the openness to experience trait (Blanco et al., 2016). According to openness to experience, it has been suggested that people who are high in openness to experience have an excellent motivation to commit intellectual activities, which makes them develop their intelligence (Brand, 1994). Thus, openness to experience has been related to employees’ emotional intelligence.

Hypothesis 1. In public organizations, extroversion (H1a), agreeableness (H1b), conscientiousness (H1c) and openness (H1d) positively and neuroticism (H1e) negatively influence emotional intelligence.

Emotional Intelligence and Psychological Ownership

Kaur et al. (2013) concluded that an individual's emotional intelligence positively predicted employees’ PO. There is a negative relationship between structural features of work environment such as participative decision making, autonomy, technology reutilization and PO for the organization and job (O’Driscoll et al., 2006; Pierce et al., 2004). Organizations with less structured conditions and environments are more likely to induce ownership feelings for the job and organization. On the other hand, flexible and organic organizational structures will increase in the organizations of the public sector (Ozer, 2005) and the formal structure of the public sector organizations which have adhocratic, centralized and resistant organizational structures will become more flexible (Eryilmaz, 2010). Furthermore, organizations with more flexible and less bureaucratic structures may create rules and norms for alternative models of emotion and feeling management

(Martin et al., 1998). Thus, organizational structure in public sector organizations can be effective on emotional intelligence and PO.

There are different relationships between emotional intelligence and decisional styles (Kenny et al., 2012). Also, empirical studies has confirmed a strong and significant relationship between participation of employees in decision-making and PO based on the organization (Han et al., 2010; Liu et al., 2012). On the other hand and from a cultural perspective, Iranian people illustrate high levels of collectivism (Canestrino et al., 2015) and collectivist traits can increase employees' participation in Iranian organizations. Thus, based on the special culture of Iran, emotional intelligence is related to PO with regard to variables such as participation.

Empirical studies and theoretical research have positively linked emotional intelligence to the internal locus of control (Singh, 2006). Additionally, control has been indicated to be an important antecedent of ownership feelings (Furby, 1978). PO of employees is like having an internal control locus because it provides an internally based drive to influence circumstances (Kaur et al., 2013). Also, jobs and duties with high autonomy imply a greater degree of control, and finally, they would be expected to increase the PO experience of employees (Pierce et al., 2001). Thus, control is an effective tie with regard to the relationship between emotional intelligence and PO.

Two key national culture dimensions include individualism and power distance (Hofstede, 1980). From a cultural perspective, Iran shows high levels of collectivism (Canestrino et al., 2015). Also, because of the administrative hierarchy and bureaucracy in public organizations, it can be argued that power distance in these organizations is high. Also, with regard to changes in the future of public organizations and despite the increase in flexibility, bureaucracy and bureaucratic structures will not diminish (Aykac & Metin, 2012). Thus, it can be concluded that power distance in public organizations is very high. Also, power distance can be associated with a better control of feelings and emotions and thereby emotion suppression (Matsumoto et al., 2008). Thus, power distance is associated with positive regulation of emotions regarding the relationship between collectivism and high distance of power (Hofstede, 1991), it can be argued that high power distance can lead to higher PO due to the collectivist culture and changes in future.

Finally, there is a significant relationship between emotional intelligence and job insecurity (Kappagoda, 2013). Also, feeling of ownership or possession provides an individual with a sense of belongingness or place, which is necessary for presenting feelings of pleasure, comfort and security (Heidegger, 1967). Thus, emotional response and PO can be related to each other due to job security.

Hypothesis 2. Emotional intelligence of employees positively influences PO in public organizations.

Personality Traits and Psychological Ownership

Key personality traits have been extensively used to investigate differences in person and team behavior (Witteloostuijn et al., 2016). Research by Pierce, Kostova and Dirks (2003) showed that personal factors such as period of service, roles and statutes, age, gender and personality might affect the ownership feeling psychologically.

More research is needed to examine how and to what extent the main personal difference factors may influence PO. One of these key differences are personality characteristics (Dawkins et al., 2015). Previous researches have investigated the predictors of psychological ownership with little attention being paid to the effect of personality characteristics and other important personal difference factors (Dawkins et al., 2015). Mcintyre et al. (2009) suggest that feelings of ownership can increase by having an appropriate type of personality characteristic that is compliant with different motivations.

Personality traits of the Big Five, such as extroversion trait (Watson & Clark, 1992), can be positively or negatively related to positive emotions and also positive emotions can be consistent with the routes of the PO (Haase et al., 2012; Krupic & Corr, 2014; Novovic et al., 2012). Also, characteristics influence behavior only in related situations (Kenrick & Funder, 1988). With regard to the protection of long-term legal commitment to and powerful psychological contacts with organizations, people in public organizations may view ownership differently from people in private organizations, with limited employee stock ownership plan. Furthermore, because people's ownership in public sector organizations differs from employees' ownership in private sector organizations due to the comparative defect of formal ownership, the effect of PO on attitudes and behaviors of employees may be relatively important in public sector organizations as a result (Park, 2013).

Hypothesis 3. Personality traits of employees including extroversion (H3a), agreeableness (H3b), conscientiousness (H3c) and openness (H3d) positively and neuroticism (H3e) negatively influence PO in public organizations.

Emotional intelligence can also be investigated as a mediating variable as it has already been done in many studies (for example, Marks et al., 2016; Wischerth et al., 2016; Zhang et al., 2016). The ASA model indicates that employees choose job roles and stay with their organizations based upon highly relevant levels of congruence between values of individuals and those of the organization (Cable & Judge, 1997). On the one hand, empirical evidences suggest that organizations emphasizing a certain type of values select and attract individuals who agree with the values or individuals whose traits are congruent with the values of the organization (Li et al, 2008) and organizational emotional intelligence of employees is likely to be comparatively homogeneous within organizations with regard to ASA model and socialization processes. On the other hand, emotional intelligence can lead to positive emotions and these positive emotions increase positive psychological states such as PO.

Hypothesis 4. Personality traits including extroversion (H4a), agreeableness (H4b), conscientiousness (H4c), openness (H4d) and neuroticism (H4e) influence PO indirectly and through emotional intelligence.

Method

Sample

The used instrument in this research is standardized questionnaire.

Also, selecting people has been done through random sampling. To test research hypotheses, 384 full-time employees were recruited from a large public organization in the city of Tehran, Iran. Employees of public sector organizations are suitable participants for this research for several reasons. Their average age was 33.35 years, the average of organizational tenure was 4.17 years, and 54.9% of the participants were male. The population under analysis includes employees of the Taxation Affairs Organization in the city of Tehran which consisted of 211 men and 173 women, all of whom were administrative employees. All employees provided their informed consent before completing the research questionnaire. All scales were subjected to reliability and validity analyses.

Procedure

A quantitative analysis was conducted in order to investigate the relationship between personality traits, emotional intelligence and PO in a public organization. All questions were completed on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). With regard to the aim of the study, the present research is descriptive and developmental based on the data collection method. Also, according to the classification, the present research is correlational.

The Scale of Variables

The independent variable is personality traits. The questionnaire of Big Five personality traits (John & Srivastava, 1999) was used to evaluate personality of the sample. This model has been selected because these traits (agreeableness, extroversion, openness, conscientiousness, and neuroticism) have been empirically shown to be capable of describing the personality dimensions. A 44-item scale was designed to assess the five domains of personality: Agreeableness (1-9 items), extroversion (10-17 items), conscientiousness (18-26 items), neuroticism (27-34 items) and openness (35-44 items). Also, the 16-item questionnaire developed by Wong and Law (2002) was used to evaluate the employees' emotional intelligence. Four dimensions of emotional intelligence have been measured in this study. The dimensions are self-emotion appraisal, others' emotion appraisal, use of emotion, and regulation of emotion. The scale includes 16 items (4 items for each dimension). Finally, the scale of PO was measured with a 12-item questionnaire (Avey et al., 2009), which covered four dimensions of belongingness, self-efficacy, self-identity, and accountability, each with three items.

Statistical Analyses

SPSS and SmartPLS software programs were used to test the hypotheses of the present study and to evaluate the appropriateness of the proposed theoretical framework. In relation to SEM analysis of full latent variable models, it was necessary to verify the validity of the measurement portion of research model (Byrne, 2006).

Reliability and Validity

Reliability

Cronbach's alpha: Alpha values greater than 0.7 indicate high internal consistency whereas 0.5–0.6 alpha values indicate adequate and lower limit of acceptability.

Composite reliability (CR): Additionally, Bagozzi and Yi (1988) confirmed that an instrument is reliable if composite reliability is 0.7 or over. Hence, our instrument meets the criterion for reliability.

Construct reliability: factor loadings have been used in order to confirm the reliability. Factor loadings values greater than 0.4 indicate high construct reliability whereas 0.2 or 0.3 factor loadings indicate inadequate and lower limit of acceptability.

Validity

Content validity: Content validity is established through an iterative process of reviewing and revising the indicator items by a group of potential respondents and experts. In order to evaluate the validity of the achieved data through the instrument, it has been used opinions of the readers, advisors, and experts.

Convergent validity: To assess the convergent validity, we computed the Average Variance Extracted (AVE) for each construct. An instrument has convergent validity if AVE is 0.5 or higher (Bagozzi & Yi, 1988).

Results

Assessment of the Outer Model

Composite reliability and the Cronbach's alpha of all the constructs were higher than 0.70, indicating reliable measurements. Also, convergent validity was measured by investigating the average variance extracted (AVE) from the constructs. The recommended value has been more than 0.50 percent, indicating high convergent validity. Table 1 describes the results of the outer model.

Table 1. Inter-Construct Correlations and the Square-Root of the AVE

Construct	AVE	CR	Cronbach's α	R^2
extroversion	0.687	0.945983	0.934079	0.000
agreeableness	0.727	0.959769	0.952049	0.000
conscientiousness	0.682	0.950873	0.941805	0.000
openness	0.601	0.936879	0.924270	0.000
Neuroticism	0.532	0.900428	0.873524	0.000
Emotional Intelligence	0.531	0.946659	0.939413	0.786
PO	0.647	0.956326	0.949879	0.897

Factor loadings values greater than 0.4 indicate high construct reliability. All related factor loadings were equal to or higher than 0.5. This is a conservative cut-off level indicating reliability of the questions. Thus, construct reliability is acceptable.

Table 2. Factor Loadings Values

Q	FL	Q	FL	Q	FL	Q	FL	Q	FL	Q	FL
1	0.66	13	0.77	25	0.69	37	0.63	49	0.74	61	0.66
2	0.58	14	0.71	26	0.54	38	0.80	50	0.74	62	0.83
3	0.45	15	0.83	27	0.58	39	0.70	51	0.67	63	0.85
4	0.74	16	0.88	28	0.70	40	0.75	52	0.84	64	0.87
5	0.47	17	0.93	29	0.65	41	0.63	53	0.69	65	0.83
6	0.66	18	0.91	30	0.45	42	0.80	54	0.45	66	0.80
7	0.55	19	0.91	31	0.49	43	0.70	55	0.74	67	0.76
8	0.70	20	0.67	32	0.51	44	0.75	56	0.67	68	0.80
9	0.75	21	0.53	33	0.69	45	0.78	57	0.84	69	0.80
10	0.68	22	0.58	34	0.65	46	0.81	58	0.69	70	0.81
11	0.78	23	0.64	35	0.73	47	0.79	59	0.45	71	0.74
12	0.88	24	0.71	36	0.53	48	0.78	60	0.74	72	0.81

Inner Model Assessment

The path relationships were measured by the endogenous constructs variance and on the basis of the path coefficients sign, significance and magnitude. The predictive power of the research structural model is measured by the R2 amounts. Explained variance for the inner constructs, both first and second order, is more than 0.1. In this research, the PO (final dependent construct) has an R2 value of 0.897, which can be investigated taking into account the model complexity. Emotional Intelligence variable has an R2 value of 0.786, which indicates the strong and significant predictive power of extroversion, agreeableness, conscientiousness and openness on PO.

After calculating the path estimates in the structural model of research, to investigate the statistical significance of the path coefficients, bootstrapping has been conducted in Smart PLS. The path coefficients have been measured by using the one-tailed t-test. The values are significant at the 5% level if the investigating values are higher than 1.648 and they are significant at the 1% level if the t-values are higher than 1.96.

Table 3. Relations between Variables

Relationship	t-statistic	Path coefficient	Statistical significance	Result
Extroversion and EI	6.605	0.330879	Sig.	confirmed
agreeableness and EI	5.614	0.330995	Sig.	confirmed
conscientiousness and EI	3.234	0.165666	Sig.	confirmed
openness and EI	2.502	0.130049	Sig.	confirmed
Neuroticism and EI	1.037	-0.031	Not sig.	Rejected
EI and PO	7.728	0.293802	Sig.	confirmed

The t-statistics and path coefficient of the structural relationships of research model are shown in Table 3. The results show that extroversion has a significant and positive impact on emotional intelligence (β=.033, t=6.6) and, therefore, H1a is supported. Agreeableness has a positive and significant impact on emotional intelligence (β=.33, t= 5.61). Thus, H1b is supported, too. Additionally, conscientiousness has a positive and significant impact on emotional intelligence (β=0.16, t=3.23) supporting H1c. Furthermore, openness has a positive and significant impact on emotional intelligence (β=0.13, t=2.502). Thus, H1d is supported. Finally, Neuroticism does not have a significant and positive effect on emotional intelligence (β=-0.03, t=1.03). Thus, H1e is not supported. In addition, PO is influenced significantly by emotional intelligence (β=0.29, t=7.72). Thus, H2 is supported.

Test of the Mediating Effect

Hypotheses 4a, 4b, 4c, 4d and 4e were mediating hypotheses and required necessarily varied conditions to test. In order for the mediating effect to occur, Baron and Kenny (1986) propose that several conditions need to be met. First, the predictor variables (e.g., extroversion, agreeableness, conscientiousness, and openness) must be significantly related to the mediator variable, that is emotional intelligence, and the criterion variable, that is PO, and next the mediator variable, that is emotional intelligence, should be significantly related to the criterion variable. Finally, when the mediator variable is entered into the structural relationship, the relationship between predictor variable and criterion variable must be insignificant for full mediation or weak for partial mediation.

Hypothesis 4a indicates that the variable of emotional intelligence mediates the relationship between extroversion and PO. As seen in Figure 1, extroversion has a sig significant and positive effect on PO (β=0.805, t=24.05) in the absence of the mediator influence of emotional intelligence. Thus, H3a is supported. Then, extroversion has a significant and positive effect on the mediator variable of emotional intelligence (β=0.81, t=23.37). Next, emotional intelligence is significantly associated with PO (β=0.69, t=8.49). Baron and Kenny (1986) have used the Sobel test to test the influence of the mediating variable. When the variable of emotional intelligence was included in the present model, the predictive power of extroversion on PO significantly reduced from β=0.805 to β=0.24 and based on the Sobel test calculation (z=7.84), which implies a significant and strong mediating influence. In total, these findings present support for Hypothesis H4a.

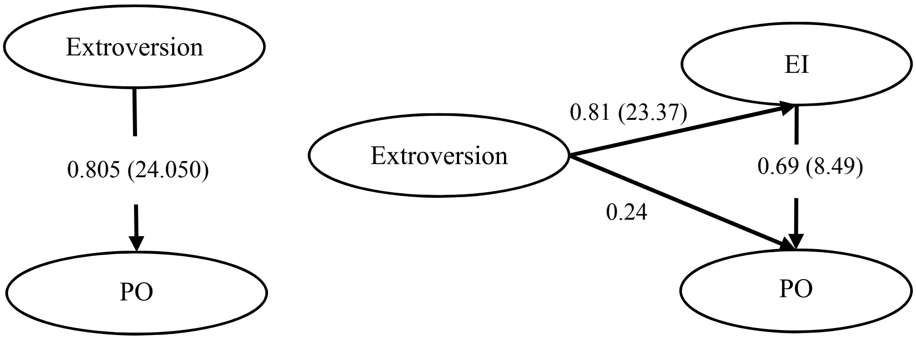

Figure 1. Role of emotional intelligence on relationship between extroversion and PO

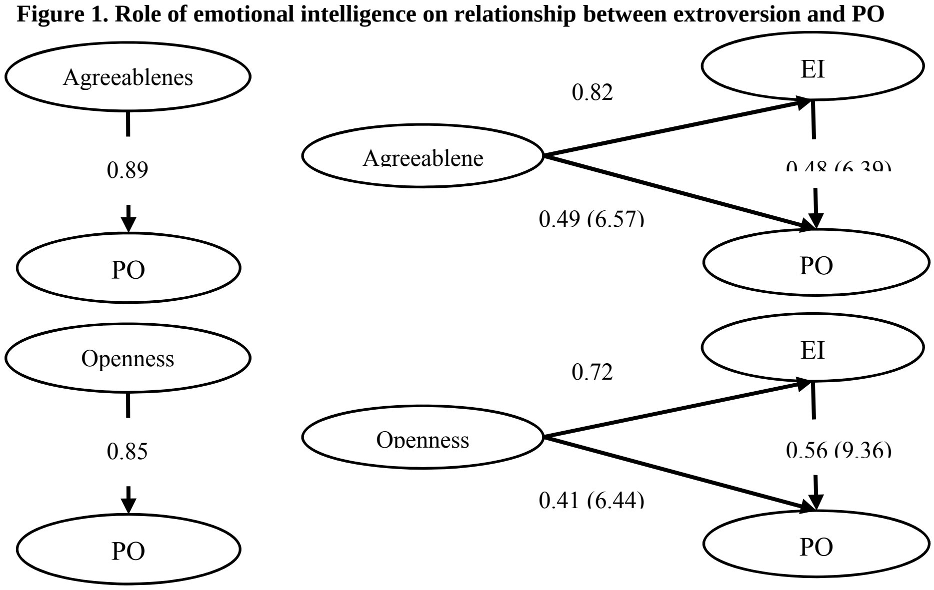

Figure 2. Results of Hypotheses 4b, 4c

Accordingly and based on Figures 2 and 3, Hypotheses 4b, 4c, 4d have been confirmed and Hypotheses 4e has been rejected.

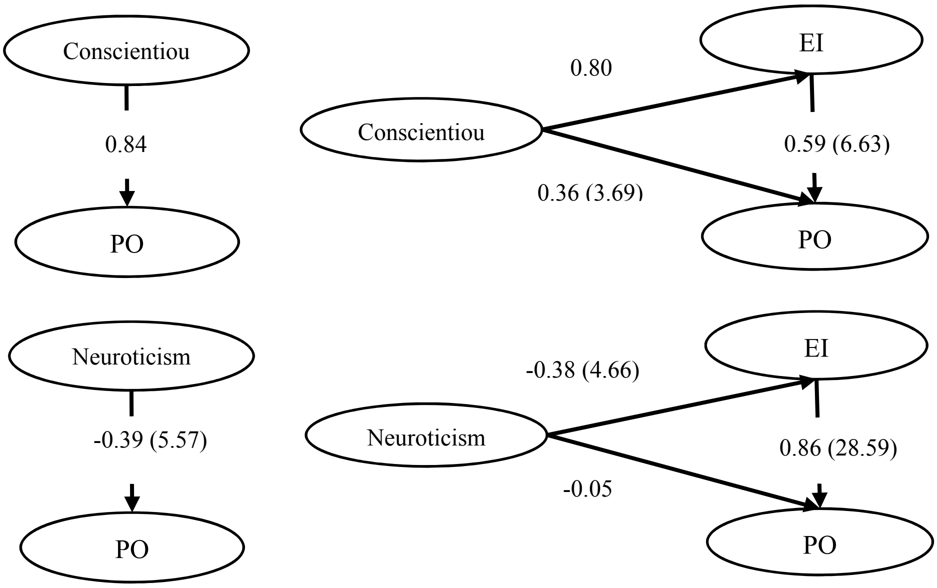

Figure 3. Results of Hypotheses 4d and 4e

Overall Conclusion and Discussion

Personality traits, including extroversion, agreeableness, conscientiousness and openness, influence emotional intelligence and that relationship is stronger when compatibility between organization values and personality characteristics is higher. Also, emotional intelligence of employees will be positively associated with their PO in a public organization and that relationship is stronger when work environment has less structure, less job insecurity, collaborative decision-making styles and higher internal locus of control. In addition, personality traits of employees including extroversion, agreeableness, conscientiousness, and openness will be positively and directly associated with PO in a public organization. Additionally, personality traits including extroversion, agreeableness, conscientiousness and openness influence PO indirectly and through emotional intelligence. In other words, emotional intelligence has a mediating role in the relationship with personality traits and PO in a public organization. Finally, emotional intelligence positively mediated the relationship between extroversion, agreeableness, conscientiousness, and openness, and neuroticism negatively mediated the relationship between PO and emotional intelligence

In the first hypothesis, the results from the present research revealed that personality traits influence emotional intelligence. These results are consistent with the research literature (Pierce et al, 2003; Mcintyre et al., 2009). Research on ASA framework presents further support for the expected effect of organizational culture on the requirement of work-related personality and demonstrates that the congruence between specific organizational culture of public organizations and individual's personality traits is very important in this respect. On the other hand, organizational culture plays a key role in the ASA framework because empirical evidence indicates that organizations emphasizing a certain type of values select and attract people who agree with the organization values or people whose traits are congruent with the organization values (Li et al., 2008). ASA model explains why similar people are selected by organizations, while inconsistent people are likely to leave these organizations due to attrition. As a result, the ASA process leads to an increase in homogeneity in emotional intelligence within one organization (Menges & Bruch, 2009).

Regarding the second hypothesis, the findings of the present research showed that emotional intelligence of employees will be positively associated with their PO. Research concluded that an individual's emotional intelligence positively predicted employees' PO (Kaur et al, 2013). For example, empirical studies and theoretical research have positively linked emotional intelligence to the internal locus of control (Singh, 2006). Additionally, control has been indicated to be an important antecedent of ownership feelings (Furby, 1978). Thus, control is an effective tie with regard to the relationship between emotional intelligence and PO.

With respect to the third hypothesis, personality traits of employees including extroversion, agreeableness, conscientiousness, and openness will be positively and directly associated with PO. In this regard, social exchange theory suggests one possible explanation. Blau (1964) believes that social exchanges are practices that are conditional on rewarding responses from other people. When the process of social exchange is built based on beneficial and reciprocal transactions between the employees and employer, the outcome will be beneficial and positive attitudes or behaviors (Cropanzano & Mitchell, 2005) such as PO (Park et al., 2013). Thus, with regard to social exchange theory, it can be argued that congruence between specific organizational culture of public organizations and people's personality traits can lead to positive behaviors or attitudes such as PO. In addition, the relationship between personality traits can be considered with regard to trait-activation theory (Dawkins et al., 2015). The key assumption of trait-activation theory is that conditions and personality characteristics are reasons of behavioral conflict and variance, and personality traits are expressed as answers to trait-relevant cues (Tett & Guterman, 2000). Therefore, rather than supposing that personality traits influence the reinforcement of PO in some recognizable manner, trait activation theory proposes that traits influence behavior of people just in relevant situations (Kenrick & Funder, 1988), and type of organization such as public and private can be the most important influential factor in this regard.

With reference to the fourth hypothesis, personality traits including extroversion, agreeableness, conscientiousness, and openness influence PO indirectly and through emotional intelligence. The relationship between employees' personality types and their perception of organizational culture and their impact on PO were examined. The results of the study presented a better perception of individuals' turnover intention in an organization due to explanations of PO (Giffen, 2015).

Results indicated that emotional intelligence positively mediated the relationship between extroversion, agreeableness, conscientiousness, and openness and negatively mediated the relationship between neuroticism and PO. The mediating role of emotional intelligence in the relationship between dimensions of personality traits and PO is explainable with regard to two theories. First, ASA theory in public administration confirms that dimensions of personality traits such as extroversion, agreeableness and conscientiousness are consistent with goals, mission, values and structure of public organizations and employees are congruent in their personality dimensions with the characteristics of the public agencies. Also, the results indicated that ASA can lead to an increase in the emotional intelligence. Second, with regard to the social cognitive theory, control of emotions is critical in development of self-efficacy (Gundlach et al., 2003), and perceptions of self-efficacy is one of the important dimensions of PO.

Managerial Implications

Authors believe that the study presented here have very important implications for public administration managers. Organizations' managers have to pay special consideration and attention toward the perception of psychological ownership of employees due to its effects on many organizational outcomes including employee's performance and their organizational citizenship behavior. Organizations' managers have to develop the attributes of the potential ownership targets by making them attractive, obvious, accessible, and malleable which can increase the potential in order to have psychological ownership. Also, managers can work on the psychological ownership routes. For example, they could organize the work in such a way that there would be increased opportunities for employees to exercise participation over different targets, to create control of the targets and collaborative decision-making to be in frequent and close association with the targets, and to be able to make significant investments of themselves into the targets because people who have a say in their decision making may develop a feeling of PO that makes them feel that the job and organization is theirs. Managers have to know that individuals who were not a good fit with an organization due to organizational culture or job tasks were likely to quit the organization and organizations choose individuals who fit their values and goals due to selection strategies because congruence between organization and person's characteristics in the public organization is very important in order to have effectiveness in these organizations. Also, managers of public organizations have to increases job security, collaborative decision-making styles, and higher internal locus of control in their organizations. Finally, managers of public organizations have to consider employees participation, lower role ambiguity and self-efficiency because based on the special culture of Iran, emotional intelligence is related to PO with regard to variables such as participation, lower role ambiguity and self-efficiency.

Limitations and Future Directions

This research has some limitations. One of the limitations is the small size of sample that limiting the generalizability. Also, the research suffers from some limitations of survey method that uses self-reported measures that are exposed to bias of social desirability. The present research also has been conducted on a public organization, which consequently decreases generalizability of the research findings to other sector employees because every organization is incomparable and unique from organizations others based on the practices, policies, challenges etcetera. Thus, future studies have to investigate psychological ownership in various settings such as in private and non-public organizations. Furthermore, information collection on the research at one point of time may not give a detailed and accurate picture. Future studies have to investigate contract violation on longitudinal or experimental designs and present more convincing evidence on the investigated variable. This research has been conducted on the respective boundaries of professional and cultural factors. Researchers propose that future studies investigates psychological ownership in various settings, such as other public sectors, private sector organizations in different industries where dynamic contexts and different legal arrangements may influence ownership conceptualizations. Also, the construct reliability and validity in this research is another limitation. Future research may be essential to validate the findings and increase the accuracy of research results by obtaining data from employees of different organizations and sectors. Finally, based on the future theory research and construction, authors suggest consideration of whether or not there are some collective motives related to the emergence of psychological ownership collectively.

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A New Approach for Customer Clustering by Integrating the LRFM Model and Fuzzy Inference System

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Abstract

This study aimed at providing a systematic method to analyze the characteristics of customers' purchasing behavior in order to improve the performance of customer relationship management system. For this purpose, the improved model of LRFM (including Length, Recency, Frequency, and Monetary indices) was utilized which is now a more common model than the basic RFM model apt for analyzing the customer lifetime value. Since the RFM model does not take the customers' loyalty into consideration, the LRFM model has instead been applied for making amendments. Contrary to most of the past studies in which the statistical clustering techniques were used besides the RFM or LRFM model, the current study has provided the possibility of clustering analysis by importing the LRFM indices into the framework of a fuzzy inference system. The results obtained for a wholesale firm based on the proposed approach indicated that there was a significant difference between clusters in terms of the four indices of LRFM. Therefore, this approach can be well utilized for clustering the customers and for studying their characteristics. The strong point of this approach compared to the older ones is its high flexibility, because in which it is not needed to re-cluster the customers and to reformulate the strategies when the number of customers is increased or decreased. Finally, after analyzing the attributes of each cluster, some suggestions on marketing strategies were made to be compatible with clusters, and totally, to improve the performance of customer relationship management system.

Keywords

Customer Relationship management, Customer Lifetime Value, LRFM Model, Customer Clustering Analysis, Fuzzy Inference System.

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Introduction

Today's new economy is widely focused on better service providing, and the present age is called as the customer oriented economy by most of the analysts; an approach by adopting which the organizations are forced to establish long-term relationships with their customers rather than interacting temporarily (Gupta et al., 2006; Chen, 2006). Accordingly, in the highly competitive markets in which most firms are customer oriented, the CRM system is subsequently complicated. The Pareto Principle, also known as the 80:20 rule, suggests that 20% of each company's customers are corresponded for 80% of its transactions, profit, and even its problems (Kumar, 2010). Considering this issue, many experts believe that companies should not incur extra costs to acquire any customer at any profitability level; instead, they should make an optimal use of their restricted resources in order to acquire and retain the key customers (Blattberg, Gary, & Jacquelyn, 2001). Therefore, a large number of previous studies have focused more on allocation of marketing resources (Blattberg & Deighton, 1996) and on impact of marketing strategies on future value of the attracted customers (Gupta et al., 2006; Gupta & Zeithaml, 2006).

Most of the companies have understood that customer databases are very important assets (Jones, Mothersbaugh, & Beatty, 2000) that could be used to analyze the customer characteristics in order to formulate the appropriate marketing strategies and to customize them (Kim, Suh, & Hwang, 2003). The RFM (Recency, Frequency, Monetary indices) is one of the models for analyzing the customer characteristics based upon customer data mining, which has a long history of being applied in the direct marketing (Wei, Lin, Weng, & Wu, 2012; Kafashpoor & Alizadeh, 2012).

Despite being used in so many studies, according to some researchers, the basic RFM model cannot effectively distinguish between the different customers based on the length of their relationship (Reinartz & Kumar, 2000). The length of the relationship means the interval between the first and the last purchases of a certain customer. Given this issue, the current study attempts to analyze the customer characteristics using the four-dimensional LRFM model (Chang & Tsay, 2004) derived from the basic RFM model and customer clustering analysis. This model is considered as a data mining tool in the CRM system (Ngai, Xiu, & Chau, 2009) in which L represents for the length of the relationship.

Even though most LRFM-based researches have drawn on statistical clustering techniques, the current research opens a new way for customer clustering analysis by drawing on Fuzzy Inference System (FIS). In other words, previous studies have clustered the customers by means of statistical techniques; while in the current paper, the customer clustering is performed based on LRFM indices within the framework of an FIS. This highly flexible system provides a definition of clusters based on all the possible combinations of the four LRFM dimensions and determines the status of each of the given customers within the different clusters.

The proposed approach provides a basis for identifying the customer characteristics, selecting the appropriate marketing strategies, and optimally allocating the resources to improve the performance of CRM system.

Literature Review

Customer Relationship Management

Though the emergence of CRM, commonly known as a significant approach in business, dates back to the 1990s, it still does not have a unique accepted definition (Ngai, 2005; Ling & Yen, 2001). New definitions of CRM have much considered it as a comprehensive and strategic process used for maximizing the customer value (Ngai, Xiu, & Chau, 2009). Accordingly, Parvatiyar and Sheth (2001) defined the CRM as an all-inclusive strategic process of attraction, retention and partnership of the selected customers with regard to the generated value for both the company and the customer. Similarly, Kumar and Reinartz (2006) defined the CRM as a strategic process of selecting the customers of high profitability and interacting with them to optimize their current and future value for the organization.

A CRM system is divided into three general dimensions by Mishra and Mishra (2009): Operational, analytical, and collaborative CRM. The first part is focused on automation of business processes (He, Xu, Huang, & Deng, 2004), or in another sense of the word, supports the administrative processes. The second one analyzes the customers' behavioral characteristics in line with the CRM strategies by utilizing data mining tools (Mishra & Mishra, 2009) for effectively allocating the resources to the profitable customers cluster. The last one comes to build relationships as well as to coordinate and collaborate with customers ensuring their future contact with the company through telephone, electronic post, website, etcetera (Teo, Devadoss, & Pan, 2006).

We are of the opinion that, amongst the above mentioned dimensions, the analytical CRM plays a pivotal role; particularly, for analyzing the Customer Lifetime Value (CLV). The customer lifetime is comprised of three distinct phases: 1) attracting the customers by identifying the status of potential and actual customers; 2) increasing the customers' value by recognizing the CLV and customizing the products and services to comply with the customers' needs; and 3) retaining the good customers by identifying the loyal customers and formulating the appropriate marketing strategies and programs for them as well as for those who are more likely to leave the company (Snoeck, 2012). The strategy of customer relationship management has been of great research interests of academicians, to such an extent that more than 600 studies have been conducted only during the years 1997 to 2001 (Romano, 2001).

Customer Lifetime Value Analysis

CLV is one of the most widely used approaches in analytical CRM which can be utilized as a CRM tool for analyzing the customers' characteristics and behaviors (Krstevski & Mancheski, 2016). There is a variety of definitions for CLV. Kotler (2003) has defined CLV as the Net Present Value (NPV) that can be acquired during a customer's lifetime. Accordingly, a profitable customer is a person or a company whose earning flow is greater than the costs spent on attracting, selling to, and servicing. Kumar and Shah (2004) have also defined CLV as the expected value of a company from interacting with a customer from now until a certain point in the future. Generally, in the last two decades, a surge of studies on CLV have been conducted (e.g., Gupta et al., 2006; Kahreh, Tive, Babania, & Hesan, 2014; Rust, Lemon, & Zeithaml, 2004; Verhoef, Franses, & Hoekstra, 2001, Vigneau, Endrizzi, & Qannari, 2011; Xu, Tang, & Yao, 2008), citing this notion along with similar terms such as customer value, lifetime value, customer equity, and customer profitability (Hwang, Jung, & Suh, 2004).

As most experts believe (e.g., Blattberg, Gary, & Jacquelyn, 2001; Gupta et al., 2006; Castéran, Meyer-Waarden, & Reinartz, 2017), rather than paying costs for obtaining any customer with any level of profitability, companies should allocate their limited resources to worthier customers. In doing so, CLV has increasingly been valued as an important aspect of marketing (Donkers, Verhoef, & Jong, 2007; Venkatesan & Kumar, 2004; Verhoef et al., 2001; Kumar & Pansari, 2016). Creating customer value in alignment with decision making can promote the worth of a company. As yet researchers have introduced and applied a variety of methods for the analysis of CLV, namely, the RFM and LRFM models which are depicted below.

RFM and LRFM Models

The RFM is one of the most well-known methods used for customer value analysis and customer clustering (Chang, Huang, & Wu, 2010; Chen, 2012; Zalaghi & Varzi, 2014), and essentially provides desirable statistical data for such purposes. It was originally introduced by Hughes (1994) with a three-dimensional framework comprised of recency (i.e., recent transaction time), frequency (i.e., buying frequency) and monetary (i.e., monetary value) indices. Recency refers to the number of days or months since the last purchase was made in a given time period. Frequency is defined as the number of purchases in a certain time period. Monetary refers to the total amount of money spent during a specific period of time (Kafashpoor & Alizadeh, 2012).

The RFM model has been applied in industry and direct marketing for more than 30 years, mostly due to its simplicity (Gupta et al., 2006). This model is grounded on the analysis of customer's past behavior and assumes that those with a desirable value for each of the model's indices are the best customers as long as their future behavior is the same as the past (Keiningham, Aksoy, & Bejou, 2006). Miglautsch (2000) drew on this model to open a way for figuring out the CLV. In addition, Hu and Jing (2008) performed customer segmentation in aftersales firms via the RFM model. They classified relevant customers into 8 clusters using K-means clustering method, and ultimately, after analyzing customer characteristics, determined their lifetime value in each cluster. Moreover, this model was utilized for analyzing the customer value in an outfitter (Wu, Chang, & Lo, 2009). After collecting data, the customers were clustered into 6 groups via K-Means method using RFM indices, and customers' characteristics within the clusters were analyzed using CLV analysis; suggestions were made on the implementation of promotion programs which were proportional to different customer clusters.

As many researchers postulate (e.g., Daoud, Amine, Bouikhalene, & Lbibb, 2015; Chow & Holden, 1997; Kao, Wu, Chen, & Chang, 2011), the basic RFM model never copes with customer loyalty, which principally refers to the relationship between customer and company. This model, as Reinartz and Kumar (2000) posit, is unable to make distinctions between the customers of long-term relationship and those of short-term whilst rise in the length of the relationship will improve customer loyalty. Considering this fact, Chang and Tsay (2004) added another dimension (i.e., customer relationship length) to the initial RFM model and developed a new one in which the customers are classified into 5 groups and 16 clusters based on different combinations of LRFM indices (see Figure 1). In this model, the symbol (↑) stands for a temporal index whose medium value in the cluster is higher than its medium value in all data, and the symbol (↓) refers to an index which its medium value in the cluster is lower than that in all data. For instance, in the cluster of high value loyal customers (LRFM ↑↓↑↑), the medium values of length, frequency, and monetary indices are higher than their medium value in all data; and the medium value of recency index is lower than its medium value in all data. As such, clustering analysis of all the customers can be implemented. Table 1 illustrates the definition of LRFM indices as they were used in Chang and Tsay's study (2004) and in the current study.

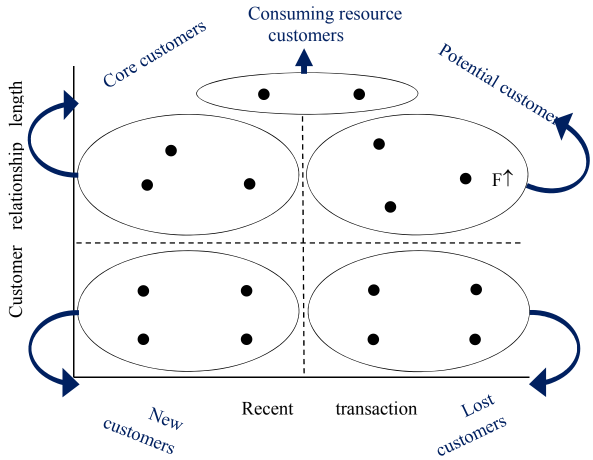


Figure 1. Customer clustering on a customer loyalty matrix basis (Chang & Tsay, 2004)

Table 1 . Definition for Dimensions of LRFM Model

Dimensions	Definitions
Length (L)	The number of days from the first to the last visit date in a given time period
Recency (R)	The number of days since the last purchase in a given time period
Frequency (F)	The number of purchase made in a given time period
Monetary (M)	The total amount of money spent during a given period of time

Li, Dai, and Tseng (2011) analyzed customer characteristics of a textiles factory through a two-stage clustering method which its basis was the LRFM model. After data were processed, the optimum number of clusters was determined via the Ward index and customers were segmented into five clusters using K-means, and analysis of the attributes of each cluster was carried out by LRFM scoring method. This model was also employed for market segmentation of a children's dental clinic in Taiwan by Wei et al. (2012) who made use of the adopting Self-Organizing Maps (SOM) technique to perform customer clustering and to analyze the attributes of each identified clusters. Table 2 provides a summary of the most relevant researches on customers' purchasing behavior based on indices of RFM and LRFM models.

Table 2. A Review on Previous Researches

Research	Indices	Clustering method
Hughes (1994)	RFM	-
Miglautsch (2000)	RFM	-
Shih and Liu (2003)	RFM	K-means clustering
Chang and Tsay (2004)	LRFM	Self-organizing maps (SOM)
Hu and Jing (2008)	RFM	K-means clustering
Bin, Peiji, and Dan (2008)	RFM	K-means clustering
Wu et al. (2009)	RFM	K-means clustering
Chang et al. (2010)	RFM	K-means clustering
Li et al. (2011)	LRFM	Two-Step clustering
Wei et al. (2012)	LRFM	SOM
Chen (2012)	RFM	C-means clustering
Kafashpoor and Alizadeh (2012)	RFM	Hierarchical Clustering
Alvandi, Fazli, and Abdoli (2012)	LRFM	K-means clustering
Zalaghi and Varzi (2014)	RFM	K-means clustering
Daoud et al. (2015)	LRFM	K-means clustering and SOM

As seen, the statistical techniques such as K-means clustering, C-means clustering, hierarchical clustering, and etcetera are usually utilized for clustering analysis of customers' purchasing behavior. In such techniques, every time the number of customers changes, the clustering analysis and formulating the appropriate marketing strategies must be reaccomplished. To cope with such a limitation, the current study has exploited the FIS for clustering analysis. In this system, in order to analyze the customers' behaviors, Fuzzy general rules as well as the appropriate strategies are already defined. And so, by entering each customer data into the system, the position of the customer amongst the defined clusters, and subsequently, the appropriate strategy are determined. Therefore, compared to other clustering statistical techniques, FIS is having more flexibility and functionality.

Fuzzy Inference System

The term "fuzzy sets" was initially coined in an article published by Zadeh (1965) exactly with the same title. Contrary to the classical sets, a fuzzy set has no certain boundaries, and accordingly, fuzzy logic or reasoning of fuzzy sets, contradicts the logic of crisp numbers (Klir & Yuan, 1995). FIS is a computational framework based upon fuzzy sets, if-then rules, and fuzzy reasoning through which the mapping from given inputs to outputs is formulated by fuzzy logic (Opresnik, Fiasché, Taisch, & Hirsch, 2017). FIS was first employed by Mamdani and Assilian (1975) to synthesize linguistic control rules for human operators' experiences. Since then, the system has been applied to a wide range of fields.

As demonstrated by Figure 2, an FIS has 5 major components (Foong, Chee, & Wei, 2009): 1) input variables fuzzification process, where the degrees of membership in each of the fuzzy sets are assigned to inputs using membership functions, 2) application of fuzzy operators: fuzzy operators (i.e., OR & AND) are used for combining the truth degrees of the components and producing a value as the truth degree of the given proposition, the resultant (crisp) value obtained from this process is applied to the output function, 3) application of the implication method, where the value obtained from the previous stage is transformed and converted into a fuzzy set using a function based on the defined rules, 4) aggregation of the outputs, a process in which the fuzzy sets representing the outputs from each of the rules are combined and put into a fuzzy set framework; in other words, the output of this process is fuzzy sets per output variable, and 5) defuzzification: since the resultant product of the prior stage is a limited range of output values, it is necessary to obtain a crisp value for output in order to make the final decision; this is what the defuzzification process does.

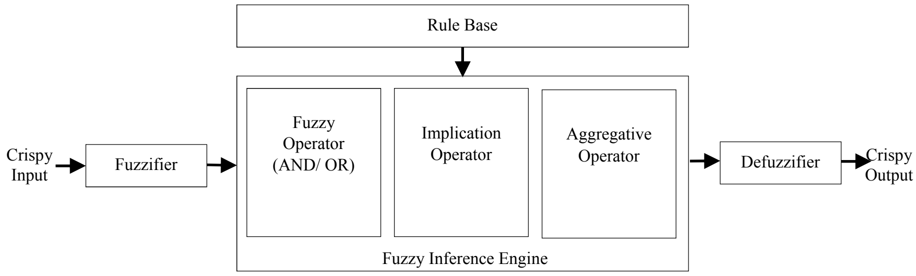


Figure 2. Components of the FIS (Foong et al., 2009)

Research method

Research Framework

The current study has integrated the LRFM model into an FIS framework in order to render customer clustering analysis for market segmentation. Our proposed approach was applied to 210 customers of a glass and crystal dishes wholesale company, titled as Quds Crystal & Glass Commercial Company located in Razavi Khorasan Province, northeast of Iran. Figure 3 shows the executive framework of this research. As evident from this process, first of all, the indices of the LRFM model (Length, Recency, Frequency, and Monetary) for each customer are extracted from customer database. Afterwards, these data are entered into the designed FIS, and customers are classified into different clusters within a framework based upon the system output. After validating the clustering, the characteristics of the customers of each cluster are analyzed. Ultimately, marketing strategies suited to customers in each cluster are suggested on the basis of market segmentation. The following gives a more detailed account of this process.

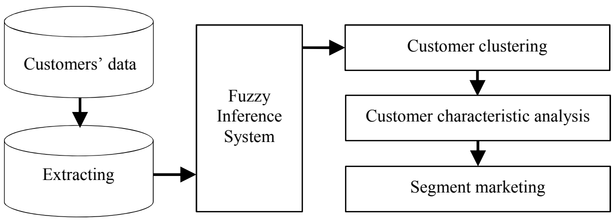


Figure 3. Framework of the study

Defining and Extracting the LRFM Indices

The timescale considered for the extraction of LRFM indices from the company's customer database was from March 23 in 2012 to March 20 in 2015. This study took into account the following definitions for these indices: The length index referred to as the time interval (number of days) between the first and the last purchases by the customer within the given timescale; the recency index as the time interval (day) between the last purchase and by the end of the mentioned timescale; the frequency index defined as the number of times purchase was made by the customer within the above timescale; and monetary index as the sum of the amount of money spent by the customer (on the basis of Iran's monetary unit, in million Rial) for purchasing within the given timescale. Table 3 illustrates the descriptive statistics of collected data.

Table 3. Descriptive Statistics of LRFM

	Length (L)	Recency (R)	Frequency (F)	Monetary (M)
Min	355	344	224	6507
Max	15	1	1	3
Average	150.9	73.84	18.11	220.76
Standard deviation	103.77	85.81	33.8	688.65

Designing the Fuzzy Inference System

This paper made use of the software program MATLAB R2014a to design the adopted Mamdani-type FIS. To set the initial parameters for designing the system, the following methods were used: The Min inference method for AND operator, Min method for implication, Max method for aggregation, and Mean of Maximum (MoM) method for defuzzification. The fuzzy logic controller of MoM defuzzification method, at first, reveals the scaled function of having the greatest membership degree, and then, it specifies a typical numerical value for that membership function. This value is the average of values corresponding to the membership degree at which the function was scaled. The inputs for the designed inference system included length, recency, frequency, and monetary indices and the output of this system was a score. Figure 4 displays an overall scheme of the system. The ways through which system inputs, rules, and outputs were defined are as follows.

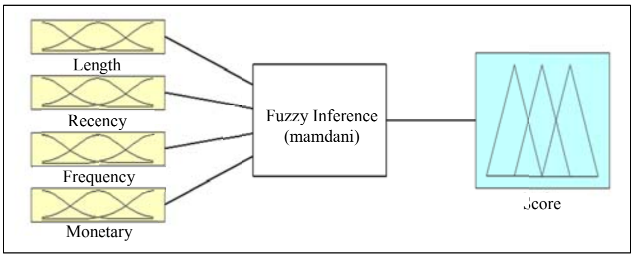
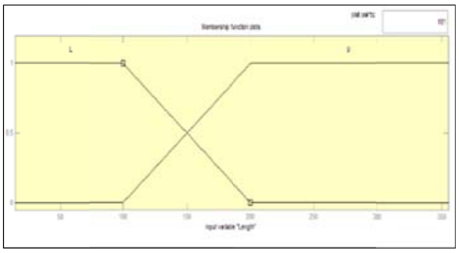


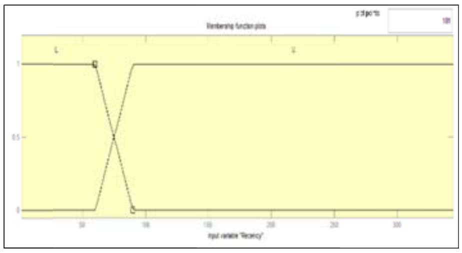
Figure 4. The fuzzy inference system

Defining the membership functions of the system inputs

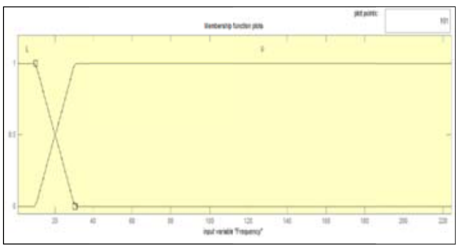
For defining the membership functions of the system inputs (LRFM dimensions), a low limit (Low) and a high limit (Up) were defined for each dimension via a one-sided trapezoidal membership function and according to viewpoints of the company's main decision makers. The following table and figure represent the definitions of these membership functions.



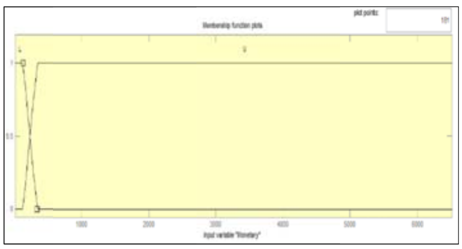
Length



Recency



Frequency



Monetary

Figure 5. Membership functions for LRFM indices

Table 4. Describing the Membership Functions for Inputs

Inputs	Numerical parameters	
	Low (L)	Up (U)
Length (L)	(-,15,100,200)	(100,200,355,-)
Recency (R)	(-,1,60,90)	(60,90,344,-)
Frequency (F)	(-,1,10,30,30)	(10,30,244,-)
Monetary (M)	(-,3,120,320)	(120,320,6507,-)

Defining the fuzzy rules of the system

In order to define the attributes of clusters, Chang and Tsay's (2004) classification was utilized. They identified 16 clusters within a 5-group framework based upon different combinations of LRFM dimensions. Table 5 shows the details based on which the clusters are defined as well as the attributes of each cluster. The fifth column of the table demonstrates the status of each of the LRFM indices.

Table 5. Describing the Groups and Clusters

Group	Group name	Cluster	Cluster name	LRFM	Cluster Type
1	Core customers	C1	High value loyal customers	↑↓↑↑	LFM
		C2	Platinum customers	↑↓↓↑	LM
		C3	High frequency buying customers	↑↓↑↓	LF
2	Potential customers	C4	Potential loyal customers	↑↑↑↑	LRFM
		C5	Potential consumption customers	↑↑↓↑	LRM
		C6	Potential high frequency customers	↑↑↑↓	LRF
3	New customers	C7	High value new customers	↓↓↑↑	FM
		C8	Spender promotion customers	↓↓↓↑	M
		C9	Frequency promotion customers	↓↓↑↓	F
		C10	Uncertain new customers	↓↓↓↓	Uncertain
4	Lost customers	C11	High value lost customers	↓↑↑↑	RFM
		C12	Consumption lost customers	↓↑↓↑	RM
		C13	Frequency lost customers	↓↑↑↓	RF
		C14	Uncertain lost customers	↓↑↓↓	R
5	Consuming resource customers	C15	Low consumption cost customers	↑↓↓↓	L
		C16	High consumption cost customers	↑↑↓↓	LR

In the basic RFM model, the symbols of (↑) and (↓) has been respectively used for the values higher and lower than the average; however, in this study, the symbol (↑) stands for the status of a given index as being placed in the high class (Up) and the symbol (↓) as being placed in the low class (Low). The type of the clusters is also determined with respect to the status of the items. For instance, the items of L, F, and M took the status of (↑) in Cluster 1; thereby, this cluster being designated as LFM.

In order to define the fuzzy rules based on definitions of customer clusters and groups, the if-then logic was applied. Since the approach of the current study for clustering is the same as Chang and Tsay's (2004), 16 rules were ultimately defined with regard to the features attributed to each of the 16 clusters of the above-mentioned classification, which its more details can be seen in Table 6.

Table 6. The Rules of the FIS

1. If (Length is U) and (Recency is L) and (Frequency is U) and (Monetary is U) then (Type is LFM)
2. If (Length is U) and (Recency is L) and (Frequency is L) and (Monetary is U) then (Type is LM)
3. If (Length is U) and (Recency is L) and (Frequency is U) and (Monetary is L) then (Type is LF)
4. If (Length is U) and (Recency is U) and (Frequency is U) and (Monetary is U) then (Type is LRFM)
5. If (Length is U) and (Recency is U) and (Frequency is L) and (Monetary is U) then (Type is LRM)
6. If (Length is U) and (Recency is U) and (Frequency is U) and (Monetary is L) then (Type is LRF)
7. If (Length is L) and (Recency is L) and (Frequency is U) and (Monetary is U) then (Type is FM)
8. If (Length is L) and (Recency is L) and (Frequency is L) and (Monetary is U) then (Type is M)
9. If (Length is L) and (Recency is L) and (Frequency is U) and (Monetary is L) then (Type is F)
10. If (Length is L) and (Recency is L) and (Frequency is L) and (Monetary is L) then (Type is uncertain)
11. If (Length is L) and (Recency is U) and (Frequency is U) and (Monetary is U) then (Type is RFM)
12. If (Length is L) and (Recency is U) and (Frequency is L) and (Monetary is U) then (Type is RM)
13. If (Length is L) and (Recency is U) and (Frequency is U) and (Monetary is L) then (Type is RF)
14. If (Length is L) and (Recency is U) and (Frequency is L) and (Monetary is L) then (Type is R)
15. If (Length is U) and (Recency is L) and (Frequency is L) and (Monetary is L) then (Type is L)
16. If (Length is U) and (Recency is U) and (Frequency is L) and (Monetary is L) then (Type is LR)

Defining the membership functions of the system outputs

As it can be observed in Table 7, for defining the membership functions of the system's outputs, triangular membership functions were used. This table shows a scoring range for each of the clusters. Indeed, the output of designed FIS is a value between 0 and 16 for each of the customers based on which specific cluster is assigned to them. The scoring range allocated to each of the clusters is determined arbitrarily (for more details, see Figure 6).

In the designed system, a customer may be placed in and belong to more than one cluster due to the fuzzy definition of inputs; this conveys the concept of fuzzy clustering. Putting it differently, the designed system is capable of displaying the status of each customer amongst the different clusters in the fuzzy form through the system output. Besides, as the system employed the MoM method for defuzzification process, a customer's final score was determined based on the highest score amongst the relevant clusters. In other words, in this case, the system identifies the status of a customer based upon the highest degree of membership in clusters. Therefore, this further capability has been added to the system so as to finally specify the cluster in which a customer has the highest membership; this can be accomplished by the allocated score.

Table 7. Describing the Membership Functions for Outputs

Cluster	Type	Numerical parameters	Score
1	LFM	(15,16,16)	(15,16]
2	LM	(14,15,15)	(14,15]
3	LF	(13,14,14)	(13,14]
4	LRFM	(12,13,13)	(12,13]
5	LRM	(11,12,12)	(11,12]
6	LRF	(10,11,11)	(10,11]
7	FM	(9,10,10)	(9,10]
8	M	(8,9,9)	(8,9]
9	F	(7,8,8)	(7,8]
10	uncertain	(6,7,7)	(6,7]
11	RFM	(5,6,6)	(5,6]
12	RM	(4,5,5)	(4,5]
13	RF	(3,4,4)	(3,4]
14	R	(2,3,3)	(2,3]
15	L	(1,2,2)	(1,2]
16	LR	(0,1,1)	(0,1]

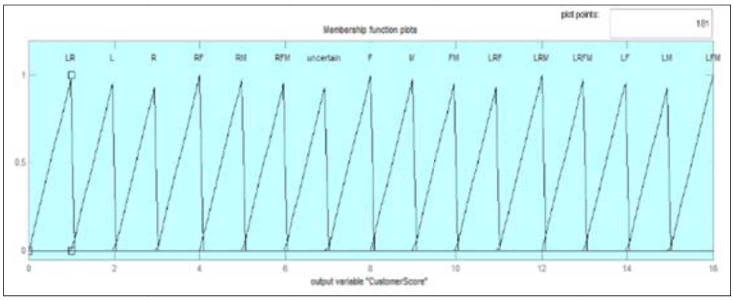


Figure 6. Membership functions for outputs (customer score)

Experimental Results

According to the above explanations, an FIS was designed based on LRFM model in order to analyze the customers' characteristics of the company under study. The status of LRFM indices in the designed FIS is illustrated via three-dimensional diagrams in Figure 7.

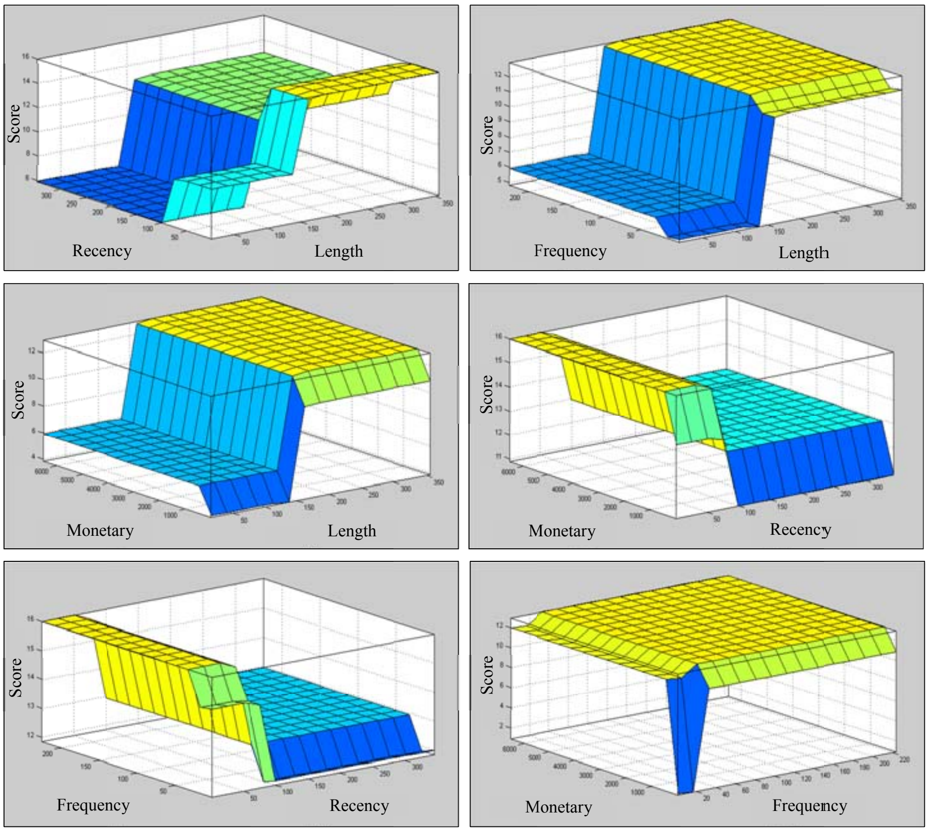


Figure 7. The status of LFRM dimensions for designed FIS

In each of the different states, two axes are associated with the defined values for the indices and one axis shows the output score of the designed system. In other words, the relationship between the values of the two given indices is determined by the system's final score. Created based on different possible combinations, these states are displayed in a 6-frame diagram. As observed, the diagram shows that in the LRFM-based designed FIS, the following combinations caused an elevation of the score: length ↑ (up) and recency ↓ (low); length ↑ and frequency ↑; length ↑ and monetary ↑; recency ↓ and frequency ↑; recency ↓ and monetary ↑; frequency ↑ and monetary ↑.

Data on 210 customers were extracted from the company's customer database, and then, entered into the designed FIS and the system output was extracted in the form of a score for each of the customers. As an example, Figure 8 demonstrates the profile and status of a customer for whom the length, recency, frequency, and monetary index values were respectively obtained as 296, 103, 176, and 3 (Example 1). As observed, the system output shows the score 10.9 for this customer which is associated with Cluster 6 (LRF type). Thus, this customer is of the potential high frequency customers type and belongs to the potential customers group.

Figure 8. Example 1 for the output of FIS

In the second example shown in Figure 9, the customer with the values 80, 43, 25, and 675 for the length, recency, frequency, and monetary indices, belongs to both the clusters of number 7 and 8 with different membership degrees indicating the fuzzy clustering concept. Having a higher membership degree in Cluster 7, the customer is placed in this cluster. This is affirmed by the score 9.84 allocated to this customer, thereby belonging to the high value new customers type and to the new customers group.

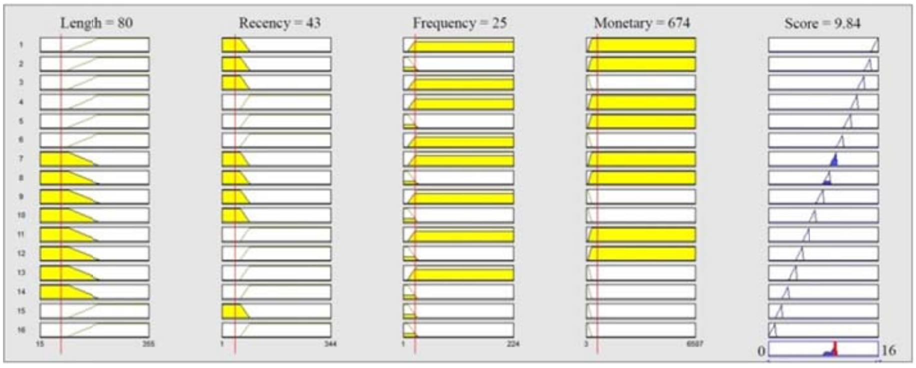


Figure 9. Example 2 for the output of FIS

After entering customers' information, the scores obtained by FIS output were analyzed. Table 8 gives a report on analysis of these results. As evident, amongst the studied customers, none of them was placed in Clusters 4, 11 and 13. In other words, for the company mentioned earlier, no customer belonged to the following types: Potential loyal customers, high value lost customers, and frequency lost customers. Considering these explanations, the customers in the current research were ultimately segmented into 13 clusters. Mean values pertaining to LRFM dimensions were determined for each of the clusters based on the highest value for the length index, the lowest value for the recency index, and maximum values for the frequency and monetary indices were respectively associated with clusters 1,14,16, and 1.

According to results, Cluster 10 accommodates the highest number of customers (42 people; 20%) and Cluster 8 accommodates the lowest (2 people; 0.95%). In other words, most of the customers are identified as to be the type of uncertain new customers and the least as to be the type of spender promotion customers. In terms of having the greatest number of customers, the order of clusters was as follows: 10, 14, 15, 16, 1, 9, 12, 3, 7, 5, 2, 6, and 8. As for analysis of the customer groups, 11.91% of customers were placed in Group 1 (core customers), 4.29% in Group 2 (potential customers), 29.52% in Group 3 (new customers), 24.76% in Group 4 (lost customers) and 29.52% in Group 5 (consuming resource customers). Therefore, the highest number of customers belonged to the groups of new customers and consuming resource customers, and the lowest number to the potential customers group.

Table 8. Results of Customer Clustering in the FIS

Group	Cluster	Average				Value in cluster (%)	Value in group (%)
		Length (L)	Recency (R)	Frequency (F)	Monetary (M)		
1	C1	1227.48	63.26	25.16	213.55	14 (6.66)	25 (11.91)
	C2	406.86	27.87	40.87	170.04	4 (1.9)	
	C3	207.70	22.95	49.47	149.95	7 (3.33)	
2	C4	-	-	-	-	0	9 (4.29)
	C5	399.46	29.33	41.33	160.05	5 (2.38)	
	C6	98.35	20.75	48.41	149.20	4 (1.9)	
3	C7	519.34	38.54	32.46	172.00	6 (2.86)	62 (29.52)
	C8	144.01	21.18	45.28	150.71	2 (0.95)	
	C9	70.40	15.65	56.52	149.02	12 (5.71)	
	C10	44.26	10.56	73.69	136.41	42 (20)	
4	C11	-	-	-	-	0	52 (24.76)
	C12	85.89	13.48	63.87	141.07	11 (5.24)	
	C13	-	-	-	-	0	
	C14	31.09	8.81	88.16	138.42	41 (19.52)	
5	C15	36.78	9.53	81.08	138.85	39 (18.57)	62 (29.52)
	C16	30.05	8.74	88.06	138.79	23 (10.95)	
Sum						210 (100%)	210 (100%)

In order to validate the performed clustering, the ANOVA technique was conducted to evaluate the significance of difference in the mean value of length, recency, frequency, and monetary indices between the different clusters. Previously, we checked normality of clusters and made sure that we face with clusters of having normal distribution, because all the kurtosis and skewness coefficients were placed in allowed range of ±2. Referring to this, we were authorized to use this technique results which are shown in Table 9. As it can be seen and given this fact that the p-value for all the LRFM indices is less than .01, this hypothesis that the mean value of LRFM indices significantly differ between clusters was confirmed (at confidence level of .99). With regard to F-statistics for each of the LRFM indices, the length index with the highest value (91.272) has made the greatest contribution to create the clusters or to differentiate them from each other. In this respect, the recency, frequency, and monetary indices are given the next ranks.

Table 9. Results of ANOVA for LRFM Indices

		Sum of Squares	Degree of freedom	Mean Square	F-test	p-value
Length	Between Groups	1916699.048	12	159724.921	91.272	0.000
	Within Groups	344745.852	197	1749.979		
	Total	2261444.900	209			
Recency	Between Groups	993593.581	12	82799.465	29.508	0.000
	Within Groups	552777.543	197	2805.977		
	Total	1546371.124	209			
Frequency	Between Groups	150507.925	12	12542.327	27.620	0.000
	Within Groups	89457.332	197	454.098		
	Total	239965.257	209			
Monetary	Between Groups	56384652.995	12	4698721.083	21.424	0.000
	Within Groups	43205765.494	197	219318.607		
	Total	99590418.489	209			

Discussion and Implications

In this study, an FIS was designed based on LRFM indices in order to label customer clusters and to improve the performance of CRM system. In previous studies focusing on RFM model (e.g., Hu & Jing, 2008; Wu et al., 2009) and those focusing on LRFM model (e.g., Li et al., 2011; Wei et al., 2012), the customers are clustered by using the statistical techniques. Unlikely, the current study has performed the customer clustering based on LRFM indices but in the framework of an FIS. The strong point of FIS compared to statistical techniques is its high flexibility. As the number of customers is increased or decreased, when using the statistical techniques, each time it is needed to re-cluster the customers and based on which reformulate the appropriate marketing and CRM strategies. That is while in FIS-based clustering, the clusters of having predefined rules, and subsequently, their relating strategies do not change, but the position of each new customer within the clusters would be determined according to the system output.

This system is capable of identifying customers' profile based on the status of LRFM indices so as to pinpoint their place within one of the 16 clusters created from different combinations of these indices, and within the five customer groups including the core customers, potential customers, new customers, lost customers, and consuming resource customers. By entering the index values for each customer, the designed system has the ability to both exhibit a customer's status between different clusters in fuzzy form and determine the cluster in which the customer has the highest membership degree using the allocated score.

By implementing this system for clustering the customers of Quds Crystal and Glass Company, they were ultimately put into 13 clusters and it was recognized that the following three customer types did not exist for the company: Potential loyal customers, high value lost customers, and frequency lost customers. Out of the studied customers, 11.9% were placed in core customers group, 4.29% in potential customer, 29.52% in new customers, 24.76% in lost customers, and 29.52% in consuming resource customers. As evident, most of the company's customers belong to the types of new customers and consuming resource customers. With a closer look, they were put in the following clusters based on the population density respectively: 20% in the uncertain new customers cluster, 19.52% in the uncertain lost customers, 18.57% in low consumption cost customers, 6.66% in high value loyal customers, 5.71% in frequency promotion customers, 5.24% in consuming lost customers, 3.33% in high frequency buying customers, 2.86% in high value new customers, 2.38% in the potential consumption customers, 1.9% in each of the clusters of platinum customers, and .95% in the potential high frequency customers cluster.

The analysis of customers' characteristics for each cluster will contribute to adopt the appropriate marketing strategies in line with the company's CRM system. On the other hand, implementing the marketing strategies compatible with each cluster will result in optimal allocation of resources. In other words, by putting away the policy of applying the same marketing strategies, and instead, by implementing the effective strategies compatible with each cluster considering the customers' characteristics we can save the company's financial resources and improve the effectiveness of allocating the other resources as well.

Grounded on this, we recommend the company to further focus on those belonging to the core customers group and attempt to retain such customers via developing suitable interaction facilities and promotional tools, because they are the worthiest or gold customers. Furthermore, since the recency index has been low in the potential customers group, the company should discover the reason for such a distance by contacting through telephone, email, fax, and etcetera, and come to solve the problem using the leverages like informative advertisements. In terms of new customers group, we suggest that more attention should be paid to high value new customers and loyalty would be inspired by providing them with transactional satisfaction. In addition, by considering special volume discounts consistent with the status of customers in Cluster 3 (high frequency buying customers), Cluster 6 (potential high frequency customers), and Cluster 9 (frequency promotion customers), the value of monetary index for these customer types can be increased. Even though the customers in other groups are less worthy, they should not be treated with incuriosity; rather, various studies and analyses are required for understanding their behavioral attributes given their identified clusters. Overall, the proposed approach of this study can provide an outline for understanding and analyzing the characteristics of different customers and for selecting the appropriate marketing strategies in order to improve the performance of CRM system.

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Integration of the Decisions Associated with Maintenance Management and Process Control for a Series Production System

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Abstract

This paper studies a series production system through the integration of the decisions associated with Maintenance Management (MM) and Statistical Process Control (SPC). Hence, the primary question of the paper can be stated as follows: In a series production system, how can the decisions of MM and SPC be coordinated? To this end, an integrated mathematical model of MM and SPC is developed. Using a method of factorial design, sensitivity analyses are performed. According to a stand-alone maintenance model, the effectiveness of the integrated model is assessed. The series production system investigated consists of identical units. Each unit has two operational states including an in-control state and an out-of-control state. The system is in-control if both units of the system operate in the in-control state. On the other hand, the system is out-of-control, if at least one of the units operates in the out-of-control state. The failure mechanism of each unit is based on a random variable with a continuous distribution. The results of analyses clarify that the integrated model improves the profit of the system.

Keywords

Control chart, statistical process control, maintenance management, series system.

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Introduction

Maintenance Management (MM) and Statistical Process Control (SPC) play a key role in managing production systems. As discussed by many practitioners and researchers, there are many interdependencies between MM and SPC verifying the study of the integrated models (Liu, Jiang, & Zhang, 2017). This section is organized into three subsections. In the first, second and third subsections, the basic concepts of maintenance management, statistical process control, and series system are introduced, respectively.

Maintenance Management (MM)

MM includes activities that are implemented with the aim of restoring or maintaining a production system in a state that the required functions of the system can be economically performed (Ahmad & Kamaruddin, 2012). Four main objectives are mentioned for MM including 1- ensuring system function (availability, efficiency and product quality), 2- ensuring system life (asset management), 3- ensuring safety, 4- ensuring human well-being (Dekker, 1996). Ding and Kamaruddin (Ding & Kamaruddin, 2015) classified the MM policies into five groups including corrective maintenance, preventive maintenance, CBM or predictive maintenance, autonomous maintenance, and design-out maintenance.

Corrective maintenance is the oldest type of maintenance policy and its actions taken to restore a failure system into operational states (Ahmad & Kamaruddin, 2012). Thus, this policy includes the simple actions that are usually performed after the system completely fails or its function reduces to an unacceptable level. Preventive maintenance policy is a more advanced policy for maintenance planning. In the simplest state, this policy prescribes the maintenance actions at the equal distant intervals irrespective of the system operational state. The aim of a preventive maintenance is to retain a system in the operational state and avoid its complete failure (Ahuja & Khamba, 2008). CBM or predictive maintenance is a modern maintenance policy that its aim is to optimize the performance of preventive maintenance (Alaswad & Xiang, 2017). This policy was introduced in 1975 with the aim of optimizing the performance of preventive maintenance. The basic of the CBM policy is condition monitoring. In condition monitoring, the information about the system operational state is collected, then this information is analyzed and based on these analyses, an appropriate decision about the maintenance actions are taken. In autonomous maintenance, the maintenance and production department cooperate to perform maintenance jobs. Design-out maintenance is a policy that its aim is to improve rather than just conducting maintenance actions (Ding & Kamaruddin, 2015).

Statistical Process Control (SPC)

SPC consists of some problem-solving tools that are effective in reducing process variation and improving process capability and stability. Thus, reducing process variation can be stated as the primary goal of SPC (Montgomery, 2009). SPC includes seven major tools: 1- Histogram or steam-and-leaf plot, 2- check sheet, 3- Pareto chart, 4- cause-and-effect diagram, 5- defect concentration diagram, 6- scatter diagram, and 7- control chart. Elimination of the process variation is the eventual goal of SPC (Montgomery, 2009).

In each production process, two types of variation exist including chance cause of variation and assignable cause of variation. Chance cause of variation is a natural or inherent part of a production process. It is usually cumulative of many small effects, essentially unavoidable. On the other hand, assignable causes of variation are generally larger than chance causes of variation. Three main sources exist for the assignable causes which include operator errors, defective raw material and improperly adjusted machine. A process is in-control if only chance causes affect it. On the other hand, a process is out-of-control if an assignable cause affects the process. Using control charts leads to early detection of the occurrence of the assignable cause, and hence improve the process stability and reduce the process variation.

Series System

Series and parallel systems consisting of several components or units are the classical reparable systems. These systems have received considerable attention in the literature about the reliability and quality engineering (Liu, Yu, Ma, & Tu, 2013). In a series system, failure of each unit leads to the fault of the whole system. In contrast, a parallel system fails while all of its components fail. Reliability of a series system is obtained from the product of the reliability of its component. Thus, the reliability of a series system is less than the reliability of each its units. Figure 1 shows a series and a parallel system.

The rest of the paper is presented as follows: Section 2 is about the problem statement. In Section 3, the importance, aim and the main questions of the research are elaborated. In Section 4, a literature review about the integrated model of SPC and MM is performed. Section 5 develops the integrated model of SPC and MM. In Section 6, the maintenance stand-alone model is derived. Section 7 presents a numerical example and a comparative study of the models. Also, in Section 7, using a design of experiment, the performance of the integrated model is elaborated. Finally, Sections 8 and 9 are dedicated to discussion and conclusion of the paper, respectively.

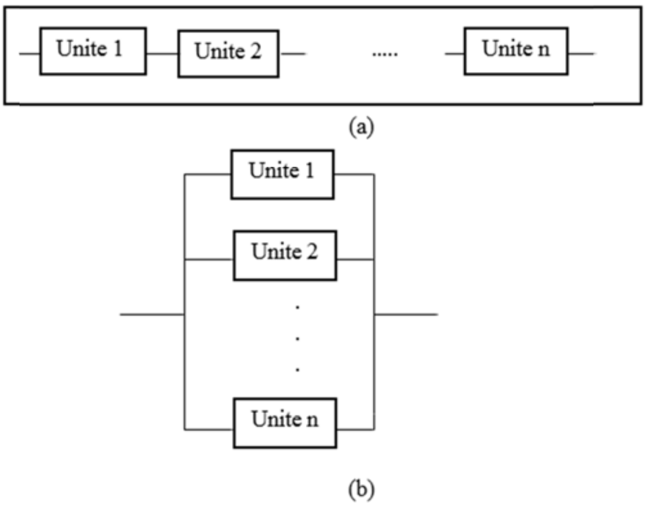


Figure 1. (a) A series production system; (b) a parallel production system

Problem Statement

A series system that has two similar units is studied. Each unit has two operational states: An in-control state that is denoted by State 0, and an out-of-control state that is denoted by State 1. The system is in-control if both units of the system operate in State 0. On the other hand, the system is out-of-control, if at least one unit of the system operates in State 1. The operation of the system in the out-of-control state is undesirable because compared to the in-control state, it leads to much more operational cost and also yields the higher quality costs. For each unit, the time spending in State 0 before a transition to State 1, is considered as a random variable with a continuous distribution that has a general form.

Monitoring the system is conducted as follows: At specific time points such as $(t_1,t_2,\ldots,t_{m-1})$, n units of the items produced by the system are randomly selected and suitable quality characteristic (characteristics) is (are) measured, and a suitable statistic is calculated. This statistic is plotted on the desired control chart. If this statistic falls within the control limits of the control chart, the process will continue its operation without any interruption. If the statistic falls outside the control limits, an alarm is released by the control chart. After that, an investigation is performed on the system to verify this alarm. If this investigation concludes that the chart signal is incorrect, Compensatory Maintenance (CM) is conducted on the system. But if this investigation concludes that the chart signal is correct, Reactive Maintenance (RM) is conducted. In this situation, if both units of the system are in state 1, reactive maintenance of Type 2 (RM (2)) is applied while if only one unit is in State 1, reactive maintenance of Type 1 (RM (1)) is conducted.

Thus, the system is under two types of inspections: The inspections performed based on the sampling from the product at the specific time points such as $(t_1,t_2,\ldots,t_{m-1})$. Henceforth, this inspection is called the sampling inspection. The second type of inspection is conducted at the time that the control chart announces an out-of-control alarm. We call the investigation performed after releasing a signal from the control chart as the maintenance inspection. The sampling inspection is susceptible to a Type I error and Type II error that occur in any control chart in the SPC theory. In a Type I error, it is inferred that the process is out-of-control while it is actually in-control. The probability of this error is usually stated as α. Type II error occurs when the system is out-of-control but the control chart cannot detect this state. The probability of this error is usually denoted as β. In contrast to the sampling inspection, the maintenance inspection can exactly determine the true state of the process. So the maintenance inspection is performed at each of the time points ($t_1,\ldots,t_{m-1}$) if and only if the control chart releases an out-of-control signal.

Different scenarios that may occur during a production cycle are shown in Figure 2. Also, the figure illustrates the structure of the integrated model. This structure is as follows: At each time points of ($t_1,\ldots,t_{m-1}$) that sampling inspection is conducted, if the chart releases an alarm, the maintenance inspection is applied to verify this alarm. If the maintenance inspection specifies the correctness of the alarm, that is, the system is truly announced out-of-control, then Reactive Maintenance (RM) is conducted (Scenarios 5 and 6). In this situation, if both units of the system are in State 1, then reactive maintenance of Type 2 (RM (2)) is implemented, but if only one unit of the system is in State 1, then reactive maintenance of Type 1 (RM (1)) is implemented. The cost and time of RM (2) is more than the cost and time of RM (1). On the other hand, if the maintenance inspection specifies that the alarm released by the control chart is not true, that is, the process is announced out-of-control by mistake, then Compensatory Maintenance (CM) is conducted (Scenario 2).

In addition to the situations explained above, it is also possible the situations in which no alarm is released from the control chart in any of the m-1 inspection time points (scenarios 1, 3, 4). If these scenarios occur, to determine the state of the system at the end of the production cycle, the maintenance inspection is performed on the system in the last period (at time t_m). If this inspection determines that two units are in State 0, Preventive Maintenance (PM) is conducted (Scenario 1). If the maintenance inspection at t_m concludes that each unit of the system is out-of-control, RM is performed on the system (Scenarios 3, 4). RM (1) is applied if only one unit is out-of-control, and RM (2) is applied when both units are out-of-control. Thus, at t_m (at the end of the production cycles) sampling is not conducted, and maintenance inspection is definitely applied. Based on the policy employed, it is clear that maintenance inspection in each production cycle is performed only one time and after that RM, CM or PM is implemented and the process is renewed.

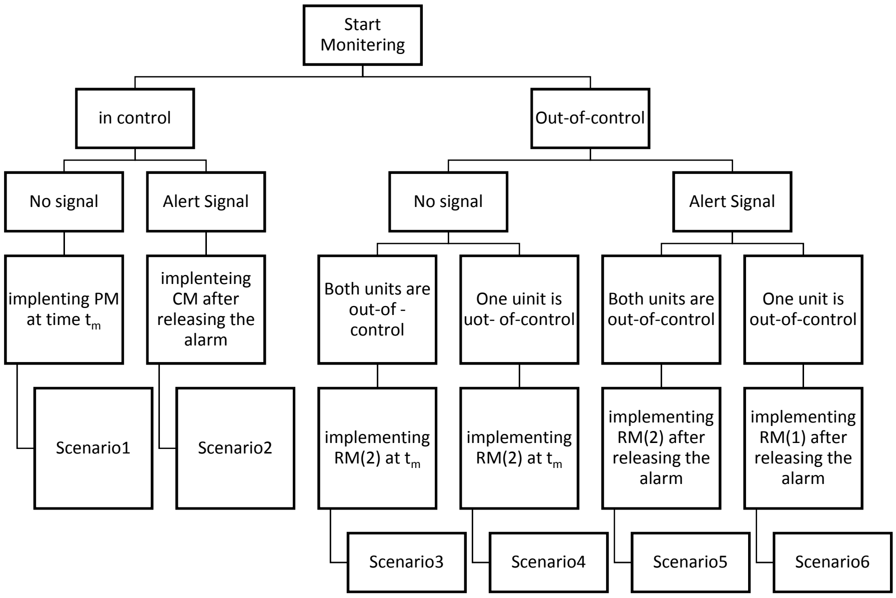


Figure 2. Different scenarios that may occur within a production cycle

Importance, Aim and the Main Questions of the Research

Over the years, as the production systems have shifted from workers to machines, managers have paid increasing attention to the affairs related to maintenance. Automation and mechanization have increased the importance of maintenance management. As a result, the fraction of operational costs associated with maintenance has grown, and the production personnel has reduced (Garg & Deshmukh, 2006). Also, as stated by Wang (2012), next to energy costs, the costs of maintenance can be the largest part of operational costs. This trend leads to increase the role of equipment conditions in controlling the production process and enhancing the product quality. Thus, with the aim of optimizing the profitability of production systems, development of integrated models of MM and SPC has become more and more important.

The aim of this paper is to optimize the profit of the series production system through the integration of the decisions associated with MM and SPC. Hence, the primary question of the paper can be stated as follows: In a series production system, how can the decisions of MM and SPC be coordinated? The second question of the paper is as follows: What is the impact of the system parameters on the decision variables and the objective function of the integrated model? And the last question of the paper is as follows: Compared with the stand-alone model, does the integrated model have a better performance?

To respond to the first question, an integrated model is developed for the system. This model coordinates the decisions of SPC and MM so that the expected profit of the system per time unit (EPT) is maximized. Using a method of experimental design, sensitivity analyses are conducted and the second question of the research is responded. Finally, the last question is responded by developing a stand-alone model and comparing the performance of the integrated model with it.

Experimental design is a statistical method to study systems. In a designed experiment, the input parameters of a system, according to some rules, are systematically changed so that the effect of the changes on the outputs of the system can be observed and analyzed. The input parameters are usually called the factors, and the outputs are called response variables. According to the results of a designed experiment, the effect of the factors on the response variables can be studied. A design includes multiple runs. In each run, the factors are changed and adjusted according to the rules of the design, and then the experiment is conducted and the results are recorded. There are different types of experimental designs such as experiment with a single factor, factorial design, fractional factorial design, and tow-level factorial design (Montgomery, 2013).

Literature Review

In this section, some studies that are closer to the approach of the paper are reviewed. Wan et al. (2018) derived an integrated model of MM and SPC. They applied a synthetic $\overline{X}$ control chart to process monitoring. The effectiveness of the integrated model is demonstrated through comparing it with two stand-alone models. Yang et al. (2009) derived a multi-level maintenance strategy for a production system. The model minimizes the expected cost per time unit through the optimization of replacement age, control limits and two inspection intervals. Liu et al. (2017) according to the geometric process, proposed an integrated model for condition based maintenance and SPC. Zhong and Ma (2017) proposed an integrated SPC and MM model for a two-stage process. They applied a Shewhart control chart and a cause-selecting control chart for monitoring the process. Rasay et al. (2018) developed a mathematical model for integrating maintenance and process control in a multi-stage dependent process. Chi-square control chart is applied in their model. Yin et al. (2015) proposed an integrated model of MM and SPC based on a delayed monitoring. Deterioration of the process is based on a Weibull distribution, and two operational states and a complete failure state are considered for the system. Zhang et al. (2015) employed $\overline{x}$ control chart in the proposed integrated model for SPC and MM. They applied delayed maintenance policy and used Markov chain for modeling of the system.

Naderkhani and Makis (2015) proposed an optimal Bysian control policy to minimize the maintenance costs. The model is characterized by two sampling intervals and two control thresholds. Xiang (2013) proposed an integrated model for a system deterioration while the system has multiple operational states. He employed $\overline{x}$ control chart to monitor the system, and Markov process is applied for modeling of the system. In this model, the impact of preventive maintenance on the system is imperfect so that maintained system restores to a state between the current state and “as-good-as-new state”. Liu et al. (2013) studied an integrated model for a series system that has two similar units. They applied $\bar{x}$ chart for monitoring of the process, and deterioration mechanism of each unit of system is described based on an exponential distribution. Due to the exponential assumption about the deterioration mechanism, they apply Markov chain for modeling and analyzing of the system. Also, the system monitoring is conducted at the fixed sampling periods. Panagiotidou and Tagaras (2012) considered a process with two operational states and a failure state. The system has one unit and deterioration mechanism follows a general continuous distribution. Three types of maintenances are applied in the system: Preventive, corrective and minimal maintenance. Preventive and corrective maintenances are considered perfect while minimal maintenance is imperfect.

The novelty of the paper can be stated as development of the model of Liu et al. (2013) in three main directions: (1) Releasing the assumption about the process failure mechanism, hence, no restrictive assumption is applied about the process failure mechanism except that it is continuous with non-decreasing failure rate; (2) this model can be applied for different types of inspection policies such as constant hazard policy or fixed sampling period policy; and (3) the integrated model can be applied for different types of control charts.

Notations and Development of the Integrated Model

First, the notations used in the models of the paper are presented.

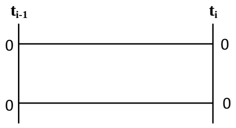
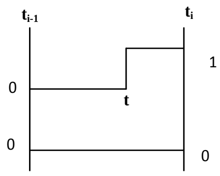
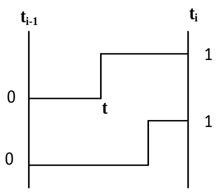
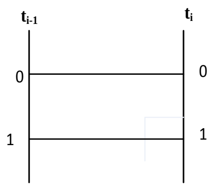
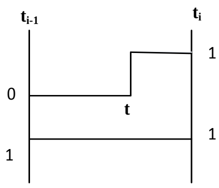
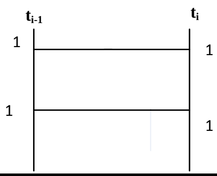
Notation	Description
R_i	Expected net revenue for the operation of the system per time unit when the system is in State i (i=0 system is in-control ,i=1 system is out-of- control; $R_0>R_1$)
W_{QC}	Sampling cost
W_{PM}	The cost of preventive maintenance
$W_{RM(j)}$	The cost of the reactive maintenance of type j (j=1,2)
W_{CM}	Compensatory maintenance cost
W_I	The cost of the maintenance inspection
Z_{PM}	Expected time required for the preventive maintenance
$Z_{RM(j)}$	Expected time required for the reactive maintenance of type j (j=1,2)

Z_{CM}	Expected time required for the compensatory maintenance
Z_I	Expected time required for the maintenance inspection
t	A random variable denoting the time at which the system or one unit of system transits to the out-of-control state
f(t)	Distribution of a random variable representing the time of the quality shift from State 0 to State 1 for each unit of the system
F(t)	Cumulative distribution function (c.d.f) of the time of the quality shift for each unit of the system
g(t)	Distribution of a random variable representing the time of the quality shift from in-control state to out-of - control state for the system
G(t)	Cumulative distribution function (c.d.f) of the time of the quality shift for the system
t_i (i=1,..,m-1)	Time points of sampling inspection (they are the decision variables of the integrated model)
t_m	Time of performing the preventive maintenance (it is the decision variable of the model)
m	Maximum number of inspection periods in each production cycle
n	The size of the samples in each sampling inspection (it is a decision variable of the model)

System Evolution in an Inspection Period

Consider a single arbitrary inspection period such as (t_{i-1},t_i), given the state of each unit of the system, just after the inspection at t_{i-1}, six different scenarios can be considered for the evolution of the system in this period. Table 1 depicts these scenarios, their corresponding probabilities and in-control and out-of-control durations for the system operation in this i period. The scenarios are elaborated in Table 1.

Table 1 .Different Scenarios for the System Evolution During Period (t_{i-1},t_i)

Case	Evolution	Probability of occurrence	Duration of time that the system is out-of-control	Duration of time that the system is in-control
a		$P(a_{t_{i-1}})=\left[\frac{\overline{F}(t_i)}{\overline{F}(t_{i-1})}\right]^2$	0	t_i-t_{i-1}
b		$P(b_{t_{i-1}}) = 2\frac{\overline{F}(t_i)}{\overline{F}(t_{i-1})}\int_{t_{i-1}}^{t_i}\frac{f(t)dt}{\overline{F}(t_{i-1})}$	t_i-t	t-t_{i-1}
c		$P(c_{t_{i-1}}) = 1-p(a_{t_{i-1}})-p(b_{t_{i-1}}$	t_i-t	t-t_{i-1}
d		$P(d_{t_{i-1}})=\frac{\overline{F}(t_i)}{\overline{F}(t_{i-1})}$	t_i-t_{i-1}	0
e		$P(e_{t_{i-1}})=1-p(d_{t_{i-1}})$	t_i-t_{i-1}	0
f		$P(f_{t_{i-1}})=1$	t_i-t_{i-1}	0

Case a. In this case, immediately after the inspection at t_{i-1}, both units of the system were operating in-control (State 0), and in the inspection period (t_{i-1},t_i), none of the unit shift were State 1. Hence, both units of the system are also in control at t_i. Thus, provided that the system is in control at t_{i-1} , the system is in-control at t_i, , if and only if, non-units shifts are in State 1 during this interval. Consequently, the probability of evolution of the system based on the case a in the period (t_{i-1},t_i) is computed based on the following conditional probability:

$$P(a_{t_{i-1}}) = P^2\left(t > t_i \mid t > t_{i-1}\right) = \left[\frac{P(t > t_i)}{P(t > t_{i-1})}\right]^2 = \left[\frac{\overline{F}(t_i)}{\overline{F}(t_{i-1})}\right]^2 \tag{1}$$

In Equation 1, $\overline{F}(t)$ is a complement of F(t). In other words, $\overline{F}(t) = 1 - F(t)$.

Case b. The system is in-control at t_{i-1}, because both units are in State 0. In the period (t_{i-1},t_i),nand at time t $(t_{i-1}<t<t_i)$, one of the units transits to State 1 while the other unit continues to operate in State 0, till the end of this period. Hence, at t_i the system is out-of-control. Thus, the evolution probability of the system, based on Scenario b in period (t_{i-1},t_i), is given by:

$$P(b_{t_{i-1}}) = 2P(t > t_i \mid t > t_{i-1}) \times P(t_{i-1} < t < t_i \mid t > t_{i-1}) = 2\frac{\overline{F}(t_i)}{\overline{F}(t_{i-1})}\int_{t_{i-1}}^{t_i}\frac{f(t)dt}{\overline{F}(t_{i-1})} \tag{2}$$

Case c. In this case the system is in-control at t_{i-1}, while it is out-of-control at t_i , because both units are in State 1 at t_i. Given that system was operating in control at t_{i-1}, only three scenarios (case a, b, c) are possible in the period (t_{i-1},t_i). Thus, the probability of the system evolution based on Scenario c during period (t_{i-1},t_i) is as follows:

$$P(c_{t_{i-1}}) = 1 - p(a_{t_{i-1}}) - p(b_{t_{i-1}}) \tag{3}$$

Case d. In this case, the system is out-of-control at t_{i-1} and t_i. Given that at t_{i-1} one unit is in State 0 and the other unit is in State 1, this scenario will occur if and only if the unit that is in-control at t_{i-1}, does not shift to State 1 in period (t_{i-1},t_i). Thus, the probability of system evolution based on Case d in interval (t_{i-1},t_i) is:

$$P(d_{t_{i-1}}) = \frac{\overline{F}(t_i)}{\overline{F}(t_{i-1})} \tag{4}$$

Case e. If one unit of the system was operating in State 1 and the other unit was operating in State 0 at t_{i-1}, only two scenarios are possible in period (t_{i-1},t_i), namely Scenarios d and e. The probability of Case d is derived, consequently, the probability for the evolution of the system operation based on Case e can be computed as:

$$P(\mathrm{e}_{t_{i-1}}) = 1 - p(d_{t_{i-1}}) \tag{5}$$

Case f. If both units were operating in State 1, immediately after inspection at t_{i-1}, they certainly remain in this state till the next inspection time, t_i. Thus, the probability for evolution of system operation based on Case f in period (t_{i-1},t_i) is 1.

It is worth mentioning the following remarks about the system evolution in the period (t_{i-1},t_i) and sampling inspection at t_i. If the system, before inspection at t_i, operates in State 0, after inspection at t_i, system will continue to its in-control operation with the probability of $1-\alpha$, because it is possible that at the inspection of t_i, control chart releases a false alarm with the probability α. After releasing a false alarm, CM is implemented and the system is renewed at t_i.

On the other hand, if the system is out-of-control, just before inspection at t_i, with the probability β, the sampling inspection and control chart cannot release the out-of-control state and therefore the system will continue its operation in the out-of-control state after inspection t_i. Hence, the state of the system after t_i remains out-of-control. Also, when the system is out-of-control, immediately before t_i, the control chart detects this state with the probability $1-\beta$. Consequently, RM is conducted and the system is renewed.

System State at the Start of Each Inspection Period

Suppose that $P_{t_i}^{00}, P_{t_i}^{01}, P_{t_i}^{11}$ be the probabilities that immediately after inspection at t_i, both units operate in State 0, one unit operates in State 0 and the other unit operates in State 1, and both units operate in State 1, respectively. Now, we proceed to the calculation of these probabilities.

$P_{t_i}^{00}$ is given by:

$$p_{t_i}^{00} = \left[\overline{F}(t_i)\right]^2 (1-\alpha)^i \tag{6}$$

Derivation of Equation 6 is as follows: Both units operate in State 0 at t_i, if the time of the shift to State 1 for both units becomes more than t_i , and in the all previous inspection time points, the control chart correctly indicates that the system is in-control. Note that if the system operates in in-control state, the probability that the control chart identifies this state correctly is $1-\alpha$, but if the control chart releases a false alarm, the CM is implemented and system is renewed

$P_{t_i}^{01}$ is calculated based on this recursive formula:

$$p_{t_i}^{01} = \beta\left[p_{t_{i-1}}^{00} \times p(b_{t_{i-1}}) + p_{t_{i-1}}^{01} \times p(\mathrm{d}_{t_{i-1}})\right] \tag{7}$$

This equation is obtained as follows: With respect to Table 1, it is clear that the cases in which, at the end of the period (t_{i-1},t_i), one unit is in-control and the other unit is out-of-control, correspond to Cases b and d. Hence, the sum of terms inside the brackets is the probability of operation of the system in the situation that one unit is in State 0 and the other unit is in State 1, just before the inspection at t_i. Also, if during an interval the system transits to out-of-control state, with the probability of β , the control chart cannot detect this state at t_i, and the system will continue its operation in the out-of-control state. Thus, the two terms inside the square brackets are multiplied by β .

In the similar way that Equation 7 is derived, the following equation is obtained for $P_{t_i}^{11}$:

$$p_{t_i}^{11} = \beta\left[p_{t_{i-1}}^{00} \times p(\mathrm{c}_{t_{i-1}}) + p_{t_{i-1}}^{01} \times p(\mathrm{e}_{t_{i-1}}) + p_{t_{i-1}}^{11} \times 1\right] \tag{8}$$

Because all the maintenance types are assumed perfect, at the start of each production cycle the following equation is held:

$$P_0^{00} = 1, P_0^{01} = 0, P_0^{11} = 0 \tag{9}$$

Expected in-Control and Out-of-Control Time during Each Interval

Let define T_0^i as the expected time that the system operates in State 0 during the period (t_{i-1},t_i), then T_0^i is obtained based on the following equation:

$$T_0^{\,i} = \mathrm{p}_{t_{i-1}}^{00} \times p(a_{t_{i-1}}) \times (t_i - t_{i-1}) + \mathrm{p}_{t_{i-1}}^{00} \times \int_{t_{i-1}}^{t_i} \frac{2f(t)\overline{F}(t)}{\left[\overline{F}(t_{i-1})\right]^2}(t - t_{i-1})dt \quad ,1 \le i \le m \tag{10}$$

With regard to Table 1, derivation of the first term of Equation 10 is simple. Details for deriving the second term are presented in Appendix 1.

Based on the probability of Case a in Table 1, Equation (10) can be rewritten as:

$$T_0^{\,i} = \mathrm{p}_{t_{i-1}}^{00} \times \left[[\frac{\overline{F}(t_i)}{\overline{F}(t_{i-1})}]^2 (t_i - t_{i-1}) + \int_{t_{i-1}}^{t_i} \frac{2f(t)\overline{F}(t)}{\left[\overline{F}(t_{i-1})\right]^2}(t - t_{i-1})dt \right], \qquad 1 \le i \le m \tag{11}$$

If T_1^i is defined as the expected time that the system operates State 1 during the period (t_{i-1},t_i), the following equation is computed:

$$T_1^{\,i} = (\mathrm{p}_{t_{i-1}}^{01} + \mathrm{p}_{t_{i-1}}^{11}) \times (t_i - t_{i-1}) + \mathrm{p}_{t_{i-1}}^{00} \times \int_{t_{i-1}}^{t_i} \frac{2f(t)\overline{F}(t)}{\left[\overline{F}(t_{i-1})\right]^2}(t_i - t)dt, \qquad 1 \le i \le m \tag{12}$$

The first term in Equation 12is easily obtained using Table 1, and derivation of the second term is similar to the derivation of the second term of Equation 10.

Probability of Performing Each Type of Maintenance

Let P_{CM}^i be defined as the probability of performing CM just after the inspection at t_i. The following equation is derived:

$$P_{CM}^i = \left[\overline{F}(t_i)\right]^2 \times (1-\alpha)^{i-1}\alpha, \quad 1 \le i \le m-1 \tag{13}$$

To obtain this equation, note that CM is implemented on the system at t_i if, first, the time of the shift for both units becomes more than t_i, and second, the control chart truly indicates that the system is in-control in the i-1 previous inspections, and finally control chart release a false alarm at the i_{th} inspection. Note that in the last inspection period there is no CM. Also, in the special case that m=1 the $P_{CM} = 0$

If $P_{RM(j)}^i$ is defined as the probability of conducting reactive maintenance of type j (j=1,2) then it can be computed using the following equation:

$$P^{i}_{RM\,(1)} = (1-\beta)\times\left[P^{00}_{t_{i-1}}\times P(b_{t_{i-1}}) + P^{01}_{t_{i-1}}\times P(d_{t_{i-1}})\right] \qquad 1\le i \le m-1 \tag{14}$$

Equation 14 can be elaborated as follows. At the end of an inspection period (t_{i-1},t_i), RM (1) is conducted on the system, if one unit operates in State 0, and the other unit operates in State 1. Also, referring to Table 1, the cases in which one unit is in State 0 and the other unit is in State 1, correspond to Cases b and d. Also, RM (1) would be implemented at t_i, if the control chart can detect the out-of-control state. Thus, the two terms inside the square brackets are multiplied by $1-\beta$. Sampling inspection is not conducted in the last inspection period, that is at time t_m, thus, $P^{m}_{RM(1)}$ can be computed based on this formula:

$$P^{\mathrm{m}}_{RM\,(1)} = P^{00}_{t_{m-1}}\times P(\mathrm{b}_{\mathrm{t}_{m-1}}) + P^{01}_{t_{m-1}}\times P(\mathrm{d}_{\mathrm{t}_{m-1}}) \tag{15}$$

Also, the following formulas can be obtained for computing $P^{i}_{RM\,(2)}$:

$$P^{i}_{RM\,(2)} = (1-\beta)\times\left[P^{00}_{t_{i-1}}\times P(\mathrm{c}_{t_{i-1}}) + P^{01}_{t_{i-1}}\times P(\mathrm{e}_{t_{i-1}}) + P^{11}_{t_{i-1}}\right],\ 1\le i \le m-1 \tag{16}$$

And in the last inspection period we have:

$$P^{\mathrm{m}}_{RM\,(2)} = P^{00}_{t_{m-1}}\times P(\mathrm{c}_{\mathrm{t}_{m-1}}) + P^{01}_{t_{m-1}}\times P(\mathrm{e}_{\mathrm{t}_{m-1}}) + P^{11}_{t_{m-1}} \tag{17}$$

Since, the states of the system follow Equation 9at the start of each production cycle, for the special case that m=1, the probabilities $P_{RM(1)}, P_{RM(2)}$ are obtained as following:

$$P^{1}_{RM\,(1)} = P(\mathrm{b}_{t_0});\quad P^{1}_{RM\,(2)} = P(c_{t_0}) \tag{18}$$

According to the assumptions explained about the system, a production cycle is terminated by conducting one of the RMs (RM (1) or RM (2)), CM or PM. Hence, the probability of terminating a production cycle due to performance of PM is:

$$P_{PM} = 1-\sum_{i=1}^{m-1}P^{i}_{CM} - \sum_{i=1}^{m}P^{i}_{RM\,(1)} - \sum_{i=1}^{m}P^{i}_{RM\,(2)} \tag{19}$$

Let define P^{i}_{QC} as the probability of conducting sampling at the end of the period (t_{i-1},t_i), then it can be computed based on the following equation:

$$P_{QC}^{i} = P_{t_{i-1}}^{00} + P_{t_{i-1}}^{01} + P_{t_{i-1}}^{11}; \quad 1 \le i \le m-1 \tag{20}$$

Not that, for the last inspection period (at t_m), sampling is not conducted and only maintenance inspection is implemented. Also, in the special case that m=1, $P_{QC}^{1} = 0$.

Expected Profit per Time Unit

The integrated model can be explained according to a renewal reward process. Thus, the expected profit of the system per time unit, EPT, can be described as the ratio of the expected profit of a production cycle, E(P), over the expected duration of a production cycle E(T):

$$EPT = \frac{E[P]}{E[T]} \tag{21}$$

Based on the notations and assumptions introduced so far, E[P] and E[T] in Equation 21 are given by these equations:

$$\begin{aligned} E[P] = {} & \mathrm{R}_0 \sum_{i=1}^{m} T_0^{\,i} + \mathrm{R}_1 \sum_{i=1}^{m} T_1^{\,i} - \mathrm{W}_{QC} \sum_{i=1}^{m-1} P_{QC}^{i} - \\ & W_{RM(2)} \sum_{i=1}^{m} P_{RM(2)}^{i} - W_{RM(1)} \sum_{i=1}^{m} P_{RM(1)}^{i} - W_{CM} \sum_{i=1}^{m-1} P_{CM}^{i} - W_{PM}\, \mathrm{P}_{PM} - W_I \end{aligned} \tag{22}$$

And,

$$\begin{aligned} E[T] = {} & \sum_{i=1}^{m} T_0^{\,i} + \sum_{i=1}^{m} T_1^{\,i} + Z_{RM(1)} \sum_{i=1}^{m} P_{RM(1)}^{i} + Z_{RM(2)} \sum_{i=1}^{m} P_{RM(2)}^{i} + Z_{CM} \sum_{i=1}^{m-1} P_{CM}^{i} \\ & + Z_{PM} P_{PM} + Z_I \end{aligned} \tag{23}$$

Maintenance Model

In this model, it is assumed that only maintenance planning is conducted on the system and there is no sampling inspection. The system starts its operation at the zero-age time while it is in-control. After passing t_m time units from the start of operation, the maintenance inspection is conducted on the system. If this inspection denotes that one or two units of the system is in State 1, RM (1) or RM (2) is conducted on the system, respectively. On the other hand, if this inspection indicates that the system still is in-control, preventive maintenance is performed. Note that in this model, if the system shifts to the out-of-control state before t_m, it continues its operation until t_m.

Based on these assumptions and considering the notations of Section 5, the following equations are obtained for E[P] and E[T] in the maintenance model:

$$E[P]=[\overline{F}(t_m)]^2\left[R_0 t_m - W_{PM}\right] \tag{24}$$
$$+\left(1-\left[\overline{F}(t_m)\right]^2\right)\left(R_0\int_0^{t_m} tg(t\,|\,t<t_m)dt + R_1(t_m - \int_0^{t_m} tg(t\,|\,t<t_m)dt\right)$$
$$-W_{RM(1)}\times 2\overline{F}(t_m)F(t_m) - W_{RM(2)}[\mathrm{F}(\mathrm{t_m})]^2 + W_I$$

$$E[\mathrm{T}] = \mathrm{t_m} + Z_{\mathrm{PM}}[\overline{\mathrm{F}}(t_m)]^2 + Z_{RM(1)}\times 2\overline{F}(t_m)F(t_m) + Z_{RM(2)}[\mathrm{F}(\mathrm{t_m})]^2 + Z_I \tag{25}$$

Finally the expected profit per time unit, EPT, for this model is obtained using equation 21.

Numerical Example and Sensitivity Analysis

This section is classified into two subsections. In the first subsection, the application of the models for a specific state is discussed. In the second subsection, a numerical analysis and a comparison study are conducted. Then, using a factorial design, sensitivity analyses are performed.

Application of the Model for a Specific State

For the numerical analysis conducted, it is assumed that $\bar{x}$ control chart is applied for the system monitoring. A single quality characteristic of product denoted as X is used for the system monitoring. If the system operates in the in-control state, it is assumed that X follows a normal distribution with mean μ_0 and standard deviation σ. In the out-of-control state, the mean of X, shifts from μ_0 to $\mu_1 = \mu_0 \pm \delta\sigma$, but this shift does not affect the system standard deviation. δ denotes the magnitude of the shift, and it is assumed to be constant. At the specific time points $(t_1,t_2,\ldots,t_{m-1})$, n units of the produced items are randomly selected as a sample and the quality characteristic of product ,X, is measured. Based on the information obtained from this sample, the mean of the sample, $\bar{x}$, is calculated and plotted on a $\overline{x}$ chart whit the following control limits: $\mu_0 \pm K\frac{\sigma}{\sqrt{n}}$. K denotes the width of the control limits, and it is a decision variable of the integrated model.

If $\phi(\bullet)$ is denoted as the cumulative distribution function (c.d.f) of the normal distribution, it is easy to show that in the $\bar{x}$ control chart, α and β are equal to:

$$\alpha = 2\phi(-k) \ \ and \ \ \beta = \phi(k - \delta\sqrt{n}) - \phi(-k - \delta\sqrt{n}) \tag{26}$$

From a theoretical point of view, the inspection time points, t_i, can be any arbitrary value. However, in practice, the inspection frequency should be based on a simple rule such that it could be applied in practice. For example, fixed sampling period and constant hazard policy are tow commonly applied rules in practice for determining inspection times. For the numerical analysis of this section, fixed sampling period is applied. It is assumed that the deterioration of each unit in the system follows a Weibull distribution.

Example, Comparison Study and Sensitivity Analyses

The values of the input parameters of an example are shown in Table 2.

Table 2.The Parameters of the Example

R_1	R_0	C_f	C_v	W_{PM}	W_{CM}	$W_{RM(1)}$	$W_{RM(2)}$	W_I	δ
100	500	5	1	1000	700	1500	2000	100	1

Z_{PM}	Z_{CM}	$Z_{RM(1)}$	$Z_{RM(2)}$	Z_I	Z_{QC}	μ
1.5	1	2	3	0.5	0.05	14

C_f and C_v are the fixed and variable sampling costs, respectively. Hence, the sampling inspection cost, W_{QC} for n units is: $C_f + C_v \times n$. The mean of the Weibull distribution, as denoted in Table 2, is 14. The results of optimizing the two models, for different values of shape parameter (v) of Weibull distribution, are illustrated in Table 3 and Figure 3. By discretizing the continuous variables (k, t_1) in the reasonable ranges, it is used as an exhaustive search to determine the decision variables. The programs for optimizing these models are coded in MATLAB software and are available from authors upon request.

Table 3.Result of Optimization of the Example for Different Values of the Shape Parameter in the Weibull Distribution

	v=1		v=2		v=3		v=4	
	IM[1]	MM[2]	IM	MM	IM	MM	IM	MM
EPT	170	124	238	219	267	262	286	286
t_1	1.9	-	2	-	2.9	-	10	-
k	2.9	-	2.5	-	2.4	-	-	-
n	19	-	17	-	15	-	-	-
m	50	-	9	-	5	-	2	
t_m	93.1	13.7	16	9.7	11.6	9.9	10	10.3

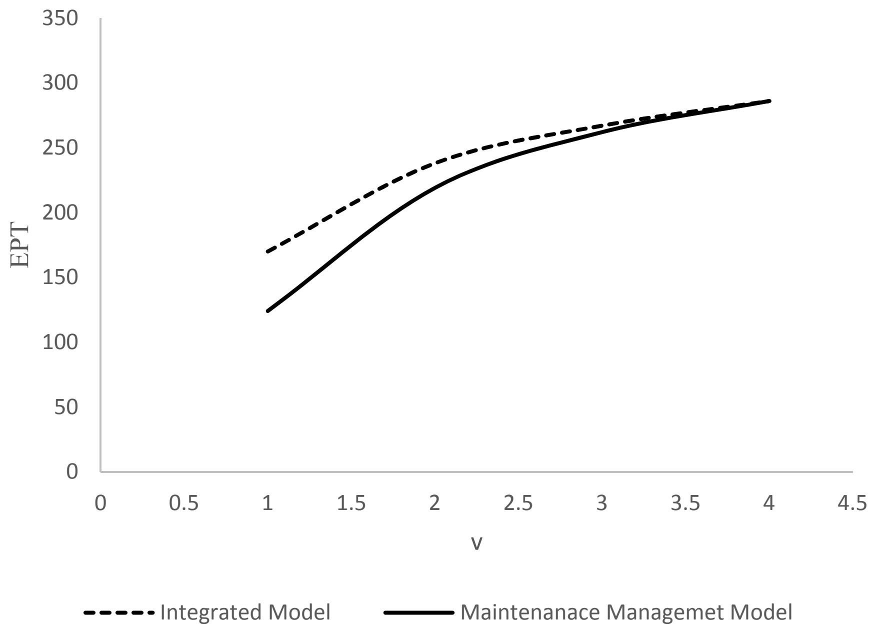


Figure 3. Effect of shape parameter (v) of the Weibull distribution on the values of EPT

In the next step of our analyses, the parameters impacting on the performance of the integrated model are studied. For this purpose, a

1. Integrated model
2. Maintenance model

technique of experimental design, that is Plakett-Burman design, is applied. The integrated model has 17 factors and an experiment with 36 runs is applied. The high and low levels for each factor are illustrated in Table 4.

The results of the experiment design are summarized in Table 5. In this table, the factors are the parameters of the integrated model, and the response variables are the decision variables of the integrated model. The signs in each column indicate the effect of that factor on the decision variable. The positive sign indicates that increasing that factor leads to an increase in the response variable, while the effect of the negative sign is vice versa. The blank entry means that the factor has no meaningful effect on the response variable.

Table 4.The High and Low Level for Each Parameter in the Factorial Design

Factor	δ	V	μ	R_0	R_1	C_f	Cv	W_I	W_{CM}	W_{PM}	$W_{RM(1)}$	$W_{RM(2)}$
Low level(-)	0.5	2	10	300	0	1	0.2	50	300	800	1200	2200
High level(+)	2	4	20	500	100	5	1	100	700	1200	2000	3200

Factor	Z_I	Z_{CM}	Z_{PM}	$Z_{RM(1)}$	$Z_{RM(2)}$
Low level(-)	0	0.5	1	1	2
High level(+)	0.5	1	2	2	3

Table 5. The Results of Factorial Design

Factor / Response variable	δ	V	μ	R_0	R_1	C_v	Wi	W_{CM}	W_{PM}	$W_{RM(1)}$	$W_{RM(2)}$	$Z_{RM(1)}$
EPT		+	+	+			-			-		
t_1				-	+			+				
K	+			-	+			+		-		
n	-			+							-	
m	+	-			-	-			+	-		-
t_m												

Discussion

To coordinate the decision associated with MM and SPC an integrated mathematical model is developed. The model optimally determines the parameters of the control chart and maintenance actions so that the profit of the system would be maximized. Using a technique of experimental design, the effect of each parameter of the system on the decision variables and the objective function is analyzed. The results of these analyses are shown in Table 5. According to the sensitivity analyses, a factor may have an increasing effect on a specific variable, while its effect on another variable is decreasing.

For example, based on Table 5, increasing the value of shape parameter in the Weibull distribution, v, leads to an increase in the value of EPT, while increasing v has a decreasing effect on the value of m. This behavior can be justified because by increasing v in the Weibull distribution, the distribution variance decreases, and consequently prediction of failure time is easier. Some results of Table 5 are intuitive to some extent. For example, increasing the magnitude of the shift, δ_1 , leads to an increase in the value of K and a decrease in the value of n. That is because, for the larger values of the shift, the control chart has more power in detection of the shift. Thus, in the larger value of δ, K becomes larger and n becomes smaller.

The performance of the integrated model is compared with a stand-alone maintenance model with respect to the value of EPT. The results of this comparison are illustrated in Table 3. Accordion to this table, the integrated model leads to a better performance and can improve the profit of the system. As it is shown in Table 3 and Figure 3, for v=1,2,3 the integrated model leads to the larger values of EPT compared to the maintenance model. Also, the difference between the values of EPT of the two models decreases by increasing the value of v, such that in the case v=1 there is the largest difference between EPT in these two models, while the EPT of both models is equal in the v=4. Thus, it is concluded that as the failure time becomes more unpredictable using the integrated model is more conducive. The findings of this section are comparable with the results of the research of Panagiotidou and Tagaras (2012). They reached the similar conclusions about a production system consisting of two operational states and a complete failure state.

Conclusions

A series production system consisting of similar units is investigated. To optimize the profit of the system, the decisions associated with MM and SPC are coordinated through an integrated mathematical model. The model optimally determines the parameters of the control chart and maintenance actions so that the profit of the system can be optimized. Using a technique of factorial design, sensitivity analyses are conducted, and thorough investigation is performed on the model. To evaluate the performance of the integrated model, a stand-alone maintenance model is also presented. Results of the numerical example clarify that, compared with the maintenance model, the integrated model has a better performance. The main novelty of this paper is in two aspects: (1) Development of an integrated model for SPC and MM, while no restrictive assumption is considered about the deterioration mechanism of the units of the system, except that it is continuous with non-decreasing failure rate; and (2) the model can be applied to different types of inspection policies such as constant hazard policy or fixed sampling period policy. Hence, the developed model has a wider application domain with respect to the previous integrated models of MM and SPC.

Access to the real data of the production system is the main limitation of the research. Integration of MM and SPC for more complex systems, development of the models for a system with complete failure state, and application of multivariate control charts for the system monitoring are directions to develop this research.

Appendix 1.

Consider y as a random variable that denotes the time of the shift to the out-of-control state. Process operates in the out-of-control state if at least one of the units operates in the out-of-control state. If the state of the system is in-control at the start of the period (t_{i-1},t_i), then the following equation is derived:

$$\overline{G}(t \mid t > t_{i-1}) = \frac{P(y > t, y > t_{i-1})}{P(y > t_{i-1})}$$

$$= \frac{P(y > t)}{P(y > t_{i-1})} = \frac{\left[1 - F(t)\right]^2}{\left[1 - F(t_{i-1})\right]^2} = \frac{[\overline{F}(t)]^2}{[\overline{F}(t_{i-1})]^2}$$

Hence,

$$G(t \mid t > t_{i-1}) = 1 - \frac{[\overline{F}(t)]^2}{[\overline{F}(t_{i-1})]^2}$$

Differentiating this equation with respect to t leads to the following equation:

$$g(t \mid t > t_{i-1}) = \frac{2f(t)\overline{F}(t)}{\left[\overline{F}(t_{i-1})\right]^2}$$

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Dynamics of Risk Perception Towards Mutual Fund Investment Decisions

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Abstract

The present paper measures the risk perception of the bank employees in respect of investment in mutual fund and to identify the factors affecting risk perception. The paper also attempts to find out the impact of these factors on overall risk perception. The study is based on primary data collected by using questionnaire from the bank employees in Tripura state of India. For the analysis of data, Cronbach's alpha, factor analysis, binary logistic regression, mean and standard deviation, and etcetera are used. It is found that bank employees' overall level of risk perception is moderate. There are three factors that affect the overall risk perception namely fear psychosis, lack of knowledge, and lack of confidence and these three factors have impact on the investment decision employees are making with regard to investment in mutual fund. The study is the first of its kind and hence original in nature.

Keywords

Bank employees, risk perception, investment behavior, factor analysis.

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Introduction

Mutual fund collects the savings of a large number of small investors and invests the same in the capital market and transfers the benefits to the investors (Kumar, 2011). Since it is managed by the expert fund managers, investors do not need to monitor the market (Sindhu & Kumar, 2014). However, it is not risk-free. The return from mutual fund is subject to market risk. Out of several factors identified by the researchers affecting the investment in mutual fund, one such trait is risk perception (Weber & Milliman, 1997**).** The impact of risk perception of investors on their investment behaviour is a rising issue in research (Singh & Bhowal, 2010a).

Risk perception is the approach of the investors to have an understanding and feeling, on the basis of their experience, of the risk inherent in an asset (Singh & Bhowal, 2008), and it plays a vital role in making decision in risky situations (Sindhu & Kumar, 2014).

Background of the Research

Risk is probability of deviation of actual return from expected return. Risk is playing a key role in influencing investors' investment decisions (Yang & Qiu, 2005). Of late, investors are seen to have a large number of choices for making investments (Kida et al., 2010). It is seen that investors are used to switch their investment from one type of investment or from one fund to another. The decision to switch their investment is affected by investor's perception of risk (Lenard et al., 2003).

Fischhoff (1994) stated that mental interpretation is one of the processes of building an internal model of environment and therefore, perception is considered to be the psychological understanding of physical feelings given by the stimulus from the external world. The term risk perception is a subjective judgment. It is related to the understanding of the people about the uniqueness and rigorousness of a risk. It assesses the views of people about the dangerous activities, stuffs, and know-how (Slovic, 1987). It plays a vital function in decision making of people. It is on the basis of risk perception, different people either move towards or stay away from different alternatives supposed as risky or otherwise (Weber & Milliman, 1997).

Literature Review

Impact of Risk Perception on Investment Behaviour

Singh and Bhowal (2009) found that risk perception level of individuals affect their investment in equity shares. Chancy decision-making behaviour is prejudiced by risk perceptions (Sitkin & Weingart, 1995; Sitkin & Pablo, 1992; Riaz et al., 2012). Investors' expected return is also governed by the level of his/her risk perception (Yang & Qiu, 2005). Investors' perceptions display important altering over the path of the catastrophe, with risk perceptions being less unstable than return outlook (Hoffmann, Post, & Pennings, 2013). The decision to switch funds among different avenues is affected by investor's attitude towards risk (Lenard et al., 2003). Moreover, high gain with a low level of risk, safety and liquidity are important considerations for investment in mutual fund by a small investor (Rathnamani, 2013).

While investing in risky assets such as mutual fund, people attempt to establish a balance between risks and return (Fischer & Jordan, 2006). Besides, people try to avoid risk for the same level of return (Kahneman & Tversky, 1979). Understanding about mutual fund investment by the people is very complex. Even the experienced investors make mistake in assessing the mutual fund and equity shares (Kida et al., 2010). The level of risk perception of individuals influences their investment in equity shares (Singh & Bhowal, 2009). Investment in mutual fund is an indirect investment in equity shares. Hence, it is expected that investment in mutual fund is also affected due to the risk perception of the people. Singh and Bhowal (2010a) found that mutual funds are perceived as relatively less risky than equity shares. Singh (2009) found that mutual funds are preferred more among the employee investors than the direct investment in equity shares. From the above literature, it is clear that risk perception of investors have influenced their behaviour with respect to investment in mutual fund. Therefore, in this study, impact of risk perception on mutual fund investment is considered to be studied.

Rationale of Studying Risk Perception

Risk perception is a vital constituent in several assessments and hence, psychologists are continuously attempting to find out one best way of measuring risk perception. Singh and Bhowal (2008) established that risk perception of an individual can be controlled provided a person is aware of the different aspects of his/her risk perception as well as the reason for the given risk perception and therefore, authorities entrusted with the job of framing policies should strive to measure the risk perception of individuals to manage it and implement several policies (Bhowal & Singh, 2006).

Reason for Choosing Bank Employees

Bank employees are considered to possess relatively higher degree of financial literacy than any other member of the society. Recently, most of the banks have started their own asset management companies and thus, they are promoting mutual funds under their own brand name. Such mutual funds are not only perceived to be relatively less risky but also more preferred over other mutual funds by the bank employees (Singh & Bhowal, 2010a).

Therefore, risk perception of bank employees towards mutual fund is an emerging area of research. The investment decision of an investor, which is influenced by unavoidable psychological and emotional factors, is also affected by their outlook towards risk. With the changing level of risk perception, the investment decisions of individual investors also keep on changing. Therefore, the present paper attempts to study the influence of risk perception of bank employees towards their investments in mutual funds.

Measuring Risk Perception Related to Investment

It is already established that risk perception needs to be measured in order to manage it. Various authors attempted to measure the risk perception. MacCrimmon and Wehrung (1990) have measured the risk propensity. Sitkin and Pablo (1992) and Sitkin and Weingart (1995) re-conceptualized and highlighted the determinants of risk perceptions. Powers (2009) established association connecting risk and return. Doff (2008) investigated risk measurement methods. Singh and Bhowal (2011), Deb and Singh (2016), and Singh (2012) have measured risk perception in financial securities. From the above review of literature, it is evident that there is little research done to assess risk perception level of bank employees with respect to their investment in mutual funds, who are directly dealing with financial product and expected to be financially literate.

In the present study, the risk perception of the bank employees has been assessed in respect of mutual fund. Risk perception is measured using the tool developed by Singh and Bhowal, (2011) and Singh (2012). In the present study, several characteristics of mutual funds are considered and respondents' perception towards them are attempted to be taken in order to assess their level of risk perception as a latent variable.

Research Objectives and Questions

Objectives of the Study

The objectives of the present study are as follows:

a) To ascertain the level of risk perception of bank employees in Tripura of India in respect of their investment in mutual fund;
b) To find out the impact of risk perception on their investment in mutual funds;
c) To identify the factors affecting their risk perceptions towards mutual fund;
d) To find out the impact of identified factors of risk perception towards mutual fund on their investment in mutual funds.

Hypotheses of the Study

Singh and Bhowal (2009) have found that equity share investment is influenced by the risk perception of the investors. Mutual fund is also indirectly investing in equity shares. Singh (2009) reveals that employees prefer to invest in equity shares through that indirect route of mutual fund. Deb and Singh (2016) found that risk perception towards mutual fund and investment in mutual funds are inversely related. This has given the drive to structure the following hypotheses:

The null hypotheses formulated for the study is given below:

H_{01}: There is no significant association between risk perception and investment in mutual fund by the bank employees in Tripura, India.

H_{02}: There is no significant association between factors affecting risk perception of individual investors and their investment decision towards mutual fund.

Research Questions

a) What is the bank employees' overall level of risk perception in Tripura?

b) What are the factors that affect the risk perception of bank employees towards mutual fund?

Research Methodology

The following points are given to highlight the research methodology used in the study:

Population of the Study

The population of the study is the total numbers of bank employees in Tripura who are employees of a bank which is having an own sponsored mutual fund. The total numbers of such employees as on 1st July, 2015 are 815.

Sampling Unit and Sample Size

A sample size of 262 employees (a bank employee is the sampling unit in this study) from different banks in Tripura that have their own sponsored mutual funds is chosen using simple random sampling from the population of 815 employees (as on 31st October, 2015) at 95% confidence level and at 5% confidence interval.

Data Collection

Primary data were collected using a well-structured questionnaire. For secondary data, journals, magazines and newspapers were consulted.

Development of Questionnaire

Based on the study made by Singh and Bhowal (2011), Deb and Singh (2016), and Singh (2012), several items were identified to measure risk perception of bank employees towards mutual fund. Some of the items were reframed; some of the items were added or dropped after having a discussion with the experts in the area and pilot study. Finally, 18 items were considered to assess the risk perception of the employees. A copy of the questionnaire is given in Appendix 1:

Data Analysis

For identifying the factors of risk perception, factor analysis is used, and to ascertain the impact of the factors on investment decision, binary logistic regression analysis has been used. Cronbach's alpha is used to test the reliability of questionnaire. Mean, standard deviation, ratios and so on are also used to draw meaningful conclusion from the study.

Analysis and Findings

The following paragraphs deal with the analysis and findings of the study.

Reliability of the Tool

Table 1.Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.901	0.939	18

Source: Compiled from questionnaire

Cronbach's alpha was used to ascertain the reliability of the scale which was 0.901 and since it is more than 0.70, there is a high degree of reliability of the considered scale. It also reflects that the statements were highly correlated (Nunnaly, 1978).

Measuring Risk Perception: Item Statistics

The item statistics for the risk perception of bank employees to the various items considered for the study is presented in Table 2.

Table 2.Item Statistics

Particulars	Mean	Std. Deviation
Idea about the investment in mutual fund.	3.2786	1.11187
Certainty of income	3.1641	0.97859
Steadiness of income	3.2710	0.96641
Difficulty of calculating income from mutual fund investment	3.2176	1.00687
Understanding the complex rules and regulations of mutual fund investment	3.1450	1.01424
Understanding the NAV fixation mechanism related to mutual fund	3.1527	1.04293
Confidence of time and NAV of buying and selling mutual funds	3.1641	1.00942
De-motivation due to pattern of change in the NAV of mutual fund	3.2137	3.31028
Difficulty of tracking the daily NAV movement of mutual funds	3.0000	1.11761
Education required for investment in mutual fund	2.9695	1.10338
Others' view about the riskiness of mutual fund	3.0649	0.99788
Seeing others to suffer loss in mutual fund investment	3.0076	0.97475
Doubt on the integrity of the local agents	3.0305	1.02040
Awareness of place for grievance redressal	3.0076	1.06491
Complexity of investment in mutual fund	3.0038	1.03390
Selecting a particular mutual fund for investment	2.8893	1.04641
Fear due to reporting of mutual fund related scandals in newspapers	2.8779	1.02477
Likelihood of becoming a victim of fraud committed by others	2.7137	1.03859

Source: Compiled from questionnaire

Scale Statistics

Table 3.Scale Statistics

Mean	Variance	Std. Deviation	N of items
55.1718	195.262	13.97360	18

Source: Compiled from questionnaire

The scale chosen to assess risk perception of investors consists of 18 items which is converted into statements and the respondents were asked to rate them according to their understanding on a five-point Likert Scale. A score of 5, 4, 3, 2, 1 were given to each statement for the responses strongly agree, agree, neutral, disagree and strongly disagree respectively. Then, a total score for risk perception was found by adding the scores of all the statements related to risk perception. Maximum possible score of risk perception was 90 (18x5) and minimum possible score of risk perception was 18 (18x1). The difference between maximum and minimum possible scores was 72.

In order to ascertain the risk perception at five levels, this range was divided by 5. It was found 14.54. Adding 14.4 to 18 (lowest possible score), the very low level of risk perception range (18-32.4) was obtained. Similarly, adding 14.4 to the subsequent value, next higher range was obtained. In the following table, risk perception score is interpreted.

Table 4. Interpretation of Risk Perception Score

Scale value	Interpretation of scale value
18-32.5	Very low level
32.5-46.8	Low level
46.8-61.2	Moderate level
61.2-75.6	High level
75.6-90	Very high level

Source: Compiled from questionnaire

In Table 3 of scale statistics, it is seen that mean score is 55.1718 which falls in the moderate level. Thus, it can be concluded that bank employees of Tripura have moderate level of risk perception regarding their investment in mutual fund.

Overall risk perception of the entire respondents is calculated by adding their scores in the Likert scale. Then, its value is interpreted using Table 4. The overall level of risk perception is presented in Table 5.

Table 5.Overall Risk Perception

Level of risk perception	Frequency	Percent
Very High	11	4.2
High	97	37.0
Moderate	60	22.9
Low	77	29.4
Very low	17	6.5
Total	262	100.0

Source: Compiled from questionnaire

Table 5 shows that majority of bank employees in Tripura are having high level of risk perception.

Identification of Factors Affecting Risk Perception of the Investors

Factor analysis has been done to extract the factors affecting risk perception of the bank employees in Tripura with respect to their investment in mutual fund. For this purpose, Eigen value criteria (greater than one) and Varimax Rotation criteria have been used respectively. Sample adequacy has been checked using KMO and Bartlett's test which is found to be highly satisfactory as the value of KMO is 0.937 and Bartlett's Test of Sphericity is also found to be significant. Table 6 shows the summary of the sample adequacy results.

Table 6. Result of KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.937
Bartlett's Test of Sphericity	Approx. Chi-Square	2797.514
	D.F	153
	Significance	.000

Source: Compiled from questionnaire

Table 7. Total Variance Explained

Component	Initial Eigen values			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9.015	50.084	50.084	9.015	50.084	50.084	4.792	26.621	26.621
2	1.172	6.510	56.595	1.172	6.510	56.595	4.040	22.444	49.065
3	1.004	5.577	62.172	1.004	5.577	62.172	2.359	13.107	62.172
4	.862	4.790	66.961						
5	.796	4.424	71.386						
6	.654	3.634	75.020						
7	.550	3.054	78.074						
8	.541	3.008	81.082						
9	.507	2.818	83.900						
10	.496	2.755	86.655						
11	.414	2.300	88.955						
12	.392	2.180	91.135						
13	.379	2.106	93.242						
14	.315	1.753	94.994						
15	.278	1.542	96.536						
16	.239	1.327	97.863						
17	.222	1.233	99.096						
18	.163	.904	100.000						

Source: Compiled from questionnaire

In the second step, it is found that three factors are loaded and with the help of these three factors, 62.172% variations can be explained. Detailed descriptions about the variables loaded in different factors are presented in Table 7.

In Table 8, the results of rotated component matrix are shown. In this case, the variables are loaded under three factors and on the basis of the arrangement, factors are named as fear psychosis, investor's lack of knowledge, and investor's lack of confidence.

Table 8.Varimax Rotated Loading

Factors affecting risk perception towards mutual fund investemnt	Factor1	Factor 2	Factor3
Investors' fear psychosis			
Complexity of investment in mutual fund	.487		
Likelihood of becoming a victim of fraud committed by others	.596		
Education required for investment in mutual fund	.529		
Others view about the riskiness of mutual fund	.657		
Fear due to reporting of mutual fund related scandals in news papers	.762		
Seeing others to suffer loss in mutual fund investment	.727		
Doubt on the integrity of the local agents	.707		
Awareness of place for grievance redressal	.80		
Investor's lack of knowledge			
Idea about the investment in mutual fund.		.437	
Certainty of income		.830	
Steadiness of income		.859	
Difficulty of calculating income from mutual fund investment		.682	
Selecting a particular mutual fund for investment		.534	
Understanding the NAV fixation mechanism related to mutual fund		.552	
Investors' lack of confidence			
Understanding the complex rules and regulations of mutual fund investment			.510
Confidence of time and NAV of buying and selling mutual funds			.499
De-motivation due to pattern of change in the NAV of mutual fund			.785
Difficulty of tracking the daily NAV movement of mutual funds			.471

Source: Compiled from questionnaire

Impact of Identified Factors Affecting Risk Perception on Investment Decision in Mutual Fund

To ascertain the impact of factors affecting risk perception of bank employees on the investment decision of employees with respect to investment in mutual fund, binary logistic regression is used. Investment in mutual fund is considered as the dependent variable and three factors affecting risk perception as calculated in Table 8 are the predictor variable. The dependent variable is mutual fund investment at present that is Y=0 (invested in mutual fund) and Y=1 (not invested in mutual fund). Predictor variables are identified factors affecting risk perception of bank employees. These are Factor 1 (fear psychosis of investors), Factor 2 (Investor's lack of knowledge) and Factor 3 (Investor's lack of confidence)

As dependent variable is on nominal scale and dichotomous, linear regression model cannot be used as a good model in order to find the impact of identified factors affecting risk perception on investment in mutual fund. In linear regression model, dependent variable is metric scale (interval or ratio) (Hair et al., 2009). So, binary logistic regression is suitable for this case. Moreover, it does not required normality assumption. Thus, the model is explained as follows:

P(Y=1) is the probability of not investing in mutual fund.

P(Y=0) is the probability of investing in mutual fund.

$P(Y=1)=1-P(Y=0)$

Here $P(Y=1)$ must lie between 0 and 1.

Regression model that will be predicting the logit, is given below:

Ln(ODD)=ln{P(Y=1)/(1-P(Y=1)}= a +b1(fear psychosis of investors) +b2(Investor's lack of knowledge) +b3(Investor's lack of confidence)

Table 9.Omnibus Tests of Model Coefficients

	Chi-square	Df	Sig.
Step	76.532	3	.000
Block	76.532	3	.000
Model	76.532	3	.000

Source: Compiled from questionnaire

From Table 9, it is evident that Omnibus test of model coefficients is significant as p-value is less than 0.05. This indicates that adding variables like fear psychosis of investors, investor's lack of knowledge and investor's lack of confidence to the model have significantly increased the ability of the model to predict the decisions made by investors.

Table 10.Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	283.235[a]	0.253	0.339

Source: Compiled from questionnaire

From Table 10, the Cox and Snell R^2 value for the fitted binomial logistic regression is 0.253 which does indicate a good fit.

Table 11.Variables in the Equation

Factors of risk perception	B	S.E.	Wald	Df	Sig.	Exp(B)
Fear psychosis of investors	1.037	.166	38.798	1	.000*	2.820
Investor's lack of knowledge	.490	.153	10.286	1	.001*	1.632
Investor's lack of confidence	.629	.187	11.313	1	.001*	1.875
Constant	.294	.146	4.061	1	.044*	1.342

Source: Compiled from questionnaire

The variables in the equation output show us that the regression equation is:

ln(ODD)=ln{P(Y=1)/(1-P(Y=1)}=0.294+1.036(fear psychosis of investors) +0.490(Investor's lack of knowledge) +0.629(Investor's lack of confidence)

Table 11 investigates the estimated parameters. These are the ordered log-odds (logit) regression coefficients. It indicates that one unit increase in factors of risk perception, the dependent variable is expected to change from yes to no by its respective regression coefficient in the ordered log-odds scale while the other variables in the model are held constant.

It is seen that all the factors of risk perception (fear psychosis of investors, investor's lack of knowledge and investor's lack of confidence) have significant impact on investment decision in mutual fund at 5% level of significance. Investors' investment in mutual fund is influenced by three factors. Among these three factors, fear psychosis of investors is playing the highest role followed by investor's lack of confidence and investor's lack of knowledge based on their respective beta values which are mentioned in Table 11.

Policy Implications and Conclusion

It is seen that overall risk perception of bank employees of Tripura towards investment in mutual fund is in moderate level. Overall level of risk perception is affected by three factors namely fear psychosis of employees to invest in mutual fund, their lack of knowledge and lack of confidence to invest in mutual fund. Out of these three factors, the impact of fear psychosis is relatively the highest on mutual fund investment decision.

So, in order to reduce the impact of these three factors of risk perception on mutual fund investment decision, awareness programs of mutual fund should be arranged for the bank employees. This also need adoption of adequate marketing strategy for the mutual funds (Singh & Bhowal, 2011; Singh & Bhowal, 2010b; Singh, 2011). So, policy makers should focus on designing suitable policies to improve the knowledge and confidence of employees so that they can fearlessly invest in mutual fund and in the long run the investment habit of employees towards mutual fund will change. Ramanathan and Meenakshisundaram (2015) suggested that awareness programs have to be conducted to educate the bank employees towards capital market investment and in this regard employer should take a leading role while imparting investment education to their employees (Singh & Bhowal, 2010c). By conducting these awareness programs, the climate of investment would definitely become very friendly and attractive.

Scope of Future Research

This study is conducted only on the bank employees in Tripura. In order to generalize the findings for the whole country more such cross-sectional and longitudinal studies are required. A cross-sectional and longitudinal studies can also be undertaken by considering the investment in gold, equity shares, Unit Linked Insurance Plan and so on.

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Appendix 1

Investment in Mutual Fund: Please (√) the appropriate option

1. Do you invest in mutual fund?

Yes

No

2. In respect of the following statements tick in the appropriate alternatives,

SA: Strongly Agree, A: Agree, N: Neutral, D: Disagree, SD: Strongly Disagree

Sl. No.	Statements	SA	A	N	D	SD
1.	I have very little idea about the investment in mutual fund.					
2	There is no certainty of income					
3	There is no steady income					
4	It is difficult to calculate income from investment from mutual fund					
5	I do not understand the complex rules and regulations of mutual fund investments					
6	Investment in mutual fund is very complex					
7	It is very much likely to become a victim of fraud committed by others.					
8	It is difficult to select type of mutual fund for investment.					
9	It is difficult to understand the NAV fixation mechanism related to mutual fund					
10	I feel less confident regarding time and NAV at which mutual fund are to be bought and sold for a best bargain.					
11	Pattern of change in the NAV of mutual fund de-motivates me in regard to the investment in in mutual Fund.					
12	It is very difficult to track the daily NAV movement of mutual fund of the companies					
13	I do not have sufficient education required for investment in mutual fund					
14	Others told me that investment in mutual fund is risky					
15	Very often mutual fund related scandals are reported in papers and I am afraid of investing in mutual fund					
16	I have seen others to suffer loss in mutual fund investment rather than amassing huge money.					
17	I doubt the integrity of the local agents.					
18	In case of grievances, I am not sure where I should register my protest and get my grievances redressed					