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Knowledge-Based Open Performance Measurement System (KBO-PMS) for a Garment Product Development Process in Big Data Environment

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ABSTRACT Globally, customers are getting increasingly demanding in terms of personalization of products and are asking for shorter product development periods with more predictable product performance, especially in fashion industry. Current market pressures drive firms to adapt new design process in product development (PD) processes. Nevertheless, choosing the effective PD process is a challenging, complex decision. There is a critical need to develop a performance measurements system (PMS) for choosing appropriate product development (PD) processes in garment design to support product mangers to effectively respond to market. This paper presents a knowledge-based open performance measurement system (KBO-PMS) in big data environment, in order to support complex industrial decision-making for new product development. Its dynamic and flexible structure enables the whole system to be more adapted to knowledge sharing of product managers and processing of various time-varying data. The proposed KBO-PMS is composed of an interactive structure, capable of both integrating new KPIs from the open resource and tracking the evolution of the KBO-PMS components with time. The proposed KBO-PMS has been validated by realizing the performance evaluation of product development (PD) in fashion industry. It can be regarded as an application of open-resource based dynamic group decision-making in fashion big data environment.

INDEX TERMS Dynamic key performance indicators, dynamic group decision-making, knowledge-based system, fashion big data, open system.

I. INTRODUCTION

Data explosion is occurring at an unprecedented rate in fashion industry. These data come from fashion blogs, social networks, fashion retailers (online and classical fashion shops) and enterprise information systems [1]. As digital data in fashion companies can be created and stored very quickly, operational decisions should be made within a tight schedule. Driven by this mandatory requirement and the wish of the company for business success, these massive quantities of data (known as 'fashion big data') should be exploited for supporting a wide range of decision-making in fashion industry. The existing examples in the literature demonstrated that fashion big data are very large and complex so that they are difficult (or impossible) to be managed with traditional data processing methods. For example, Min developed a fashion retailing forecasting system based on data with large demand trend slope [2]. Kota took a big-data approach to study social influence in a real world and online social network specialized in fashion, which could be further applied to investigate fashion trend [3]. Tsan-Ming proposed an intelligent sales forecasting algorithm using data with large seasonal cycle's variance [4]. These examples show that fashion big data are overwhelming due to its increasing volume, gradually

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diversified data types, and high speed. Current research on fashion big data focuses on applications of predictive analytics for data exploration and utilization. Although big data analytics has shown its effectiveness in fashion trend analysis, consumer behavior analytics and fashion marketing and sales forecast based on literature, their implication in fashion business and operational management has not been well investigated.

Our research work focuses on business and operational management. Especially, we study the product development (PD) process and related PMS in fashion big data environment because PD generally plays a very important role in each fashion company. Garment product development is the creation and realization of a garment product from its initial design concept of designer to its sale to consumers. The garment product development consists of a comprehensive process, which starts from design, modeling/prototyping for realizing the demonstration products at fashion fairs, detailed engineering, material sourcing and then ends with production and distribution [5]. As an important section in the product life cycle, PD processes will influence enterprise management. In the same time, the user experience of a consumer, such as the consumer's satisfaction and loyalty, will also be largely affected by product and service provided, which is strongly related to the PD process chosen. For a fashion enterprise, the business model, planning strategies and other activities can be modified by the structures and contents of different PD processes. The process control and performance track of the product life cycle are also influenced by PD processes. These considerations aggravate the complexity for decision-makers of the company (product managers) to choose an appropriate PD process [6]. In this situation, an efficient Performance Measurement System (PMS) evaluating different PD processes enables to provide a powerful decision-making support to product managers by determining the most appropriate PD process.

A Performance Measurement System (PMS) plays an important role in industrial decision-making at different aspects (strategy, tactics, operational management). Usually, a PMS includes several evaluation criteria (such as *infrastructure*, *cost*, ...) and KPIs (such as *Activated workflow number, Material cost, ...*) [7], [8]. There are three tasks in designing an appropriate PMS: (1) modeling of the PMS framework based on the desirable characteristics, (2) determination of the PMS components, including related evaluation criteria and their corresponding KPIs and (3) definition of respective weights of the PMS components. The previous studies have demonstrated that each PMS follows a hierarchical structure in which the general objectives can be found on the root, the evaluation criteria on the branches, and the indicators on the leaves [9], [10]. In the existing work, they mainly concern the adaptation of different mathematical models for simulating the desired PMS. For example, Steven X. Ding developed a data-driven scheme on the prediction of key performance indicators (KPIs), which is widely recognized in industry [11]. Marco Alemanni developed a set of KPIs for the adoption of a Product Lifecycle Management [7]. However, the KPIs of a specific PMS usually refer to more than one criterion, and these criteria are often in conflict with each other [12]. Mutual influences among different KPIs in the hierarchical structure of the PMS are not considered either. This fact usually leads to a reduction of accuracy in the weights of the PMS components. In this situation, based on the classical hierarchical structure, a PMS with a network structure fully considering the independence of components is considered as more efficient.

A performance indicator can be described as ''a variable that quantitatively expresses the effectiveness or efficiency, or both, of a part of, or a whole process, or system, against a given norm or target'' [13]. Strongly related to data collected or computed from any process or activity of an enterprise, it is a number or value, which can reflect the critical success factors of its organization. The historic evolution of PMSs can be divided into two phases. In the first phase, PMS mainly focused on financial and productivity performance measures. In the second phase, since 1980s, PMS turned into a multidimensional set of performance evaluation criteria, mainly including non-financial metrics. Currently, the increasing complexity of PMS requires that its structure should be flexible enough, capable of dynamically integrating new evaluation criteria and indicators in order to deal with the changing environment and process concerning evolutionary fashion data [14]. Also, a PMS must be aligned with the organization's strategies and should be reviewed periodically. However, the existing PMSs are still static systems with fixed structures and components, and rarely process the influences of big data on the performance measurement of a company.

In order to overcome the limitations of the current PMSs, we developed a new dynamic PMS with a network structure, capable of integrating and processing time-varying data of different types. In comparison with the traditional PMS, the proposed KBO-PMS enables to update the KPIs by introducing new indicators or modifying the existing ones according to the performance evaluation of the PMS. Using this method, the evolution of KPI with time can be used to further identify business trends. In our study, the Fuzzy Analytic Network Process (FANP) is used to determine the PMS structure, in which the independence of the PMS components can be preserved, leading to a more simplified representation of the involved decision problem. The proposed KBO-PMS is a group decision-making support system, in which the operational knowledge about PD can be shared among different decision-makers (product managers). Moreover, as various data types are involved in different KPIs, it is necessary to aggregate them to make a global decision when evaluating different PD processes. In this situation, the Fuzzy Technique for Order Preference by Similarity to Ideal Solution (Fuzzy TOPSIS) is used in the evaluation process.

The rest of the paper is organized as follows. Section 2 describes related literature review on performance measurement system (PMS). In Section 3, the general framework of the proposed KBO-PMS, integrating both FANP model and Fuzzy TOPSIS model is outlined. The related concepts and formulation are also given in this section. In Section 4, the working process of the proposed KBO-PMS is presented. The algorithm of dynamically integrating a new KPI is also explained. Section 5 presents an empirical study using the proposed KBO-PMS for dealing with personalized garment design. The related experiments and data are discussed in order to demonstrate and validate the effectiveness of the proposed KBO-PMS. Section 6 concludes the paper.

II. LITERATURE REVIEW ON PERFORMANCE MEASUREMENT SYSTEM (PMS)

During the past decades, studies on the design of Performance Measurement Systems (PMS) have proliferated hugely. These studies have highlighted several applications of PMS design to industrial decision-making such as management accounting (MA) [15], supply chain management [16], and business strategy [17]. For example, David explored the decision-facilitating role of performance measurement systems in firms attempting to translate competence ambidexterity (i.e., the simultaneous pursuit of exploration and exploitation) into innovation ambidexterity outcomes. A. Jääskeläinen and O. Thitz investigated prerequisites for supply chain performance measurement systems (see among others, [15]–[40]).

A PMS contains several evaluation criteria (such as infrastructure, cost, ...) and their related KPIs (such as Activated workflow number, Material cost, ...) [28]. Current studies related to performance measurement systems have highlighted the structure and content for PMS design, such as the modeling of the PMS framework based on the desirable characteristics, determination of the PMS components, and definition of respective weights of the PMS components [29]. Based on these studies, it can be concluded that a PMS follows a hierarchical structure, in which the general objectives can be found on the root, the evaluation criteria on the branches, and the indicators on the leaves [9], [10]. In existing studies, the development of different PMS is realized by mathematical simulation with the adaptation of different mathematical models (see among others, [12], [41]). Normally a hierarchical structure is applied to such sumilation. One problem faced by these PMSs is that, the KPIs involved in a specific PMS usually refer to more than one criterion, and it is quite common that these criteria are in conflict with each other [12]. Mutual influences among different KPIs in the hierarchical structure of the PMS are not well considered, which results in the reduction of accuracy in the weights of the PMS components [30]. A network structure usually considers the independence of components. It is therefore more suitable to use network structure to simulate PMS, compared with classical hierarchical structure.

From the application perspective, globally industrial decision-making to be solved by PMSs are rather evolutionary and dynamically changing, which is affected by a lot of factors [31]. For example, the PMS designed for government decision-making, such as inequality, poverty, corruption and migration, as well as climate change, loss of habitat and the ageing society, should be able to ensure open assets, open services and open engagement [36]. In this condition, there are increasing demand about the interaction, flexibility, experimentation, and engagement participation for PMS [37]. In respond to such demand, it is important to design PMS as open system, which are supposed to receive input from other subsystems or open resource and conveniently modeled as open systems [35]. Informally an open system is a dynamical system that receive inputs from other systems. There are several formal models of open systems starting with collections of vector fields that depend on parameters. For example, in [32] the input-state-output model is used.

However, existing PMSs which are found in literatures are all still static systems with fixed structures and components, and rarely process the influences of big data on the performance measurement of a company [34]. Since a PMS is generally designed by a set of KPIs, in order to design a PMS as open system, it is essential to ensure a PMS to be able to update the KPIs by introducing new indicators or modifying the existing ones according to the performance evaluation of the PMS [16], [27].

Based on literature, there are two limitations in existing PMS design, the first is that PMSs designed with hierarchical structure are not able to process mutual influences among different KPIs inside these PMSs, and the second is that, existing PMSs are all static systems with fixed structures and components which is not able to introduce new indicators or modify existing KPIs. In this research, we propose a new dynamic PMS with a network structure, capable of integrating and processing time-varying data of different types. Compared with the traditional PMS, the proposed KBO-PMS is able to update the KPIs by introducing new indicators or modifying the existing ones according to the performance evaluation of the PMS.

III. GENERAL PRINCIPLE OF THE PROPOSED KBO-PMS USING FANP AND FUZZY TOPSIS

In this study, we set up a PD processes-oriented and open resource-based KBO-PMS by implementing a series of experiments on human evaluation. In these experiments, relevant perceptual data on successful product development processes are extracted through interactions with a number of decision-makers (product managers). Fuzzy ANP is applied to model the interactive framework of the decision-making problem. Under this model, different evaluation criteria and their KPIs are defined in order to evaluate alternative garment PD processes by experts and determine their corresponding weights. Also, Fuzzy TOPSIS method is used to rank all the PD processes in order to recommend the most appropriate one, which conforms to the structure of the fashion company. The combination of Fuzzy ANP and Fuzzy TOPSIS using a knowledge-based subjective evaluation procedure constitutes the main methodology of the proposed recommendation system.

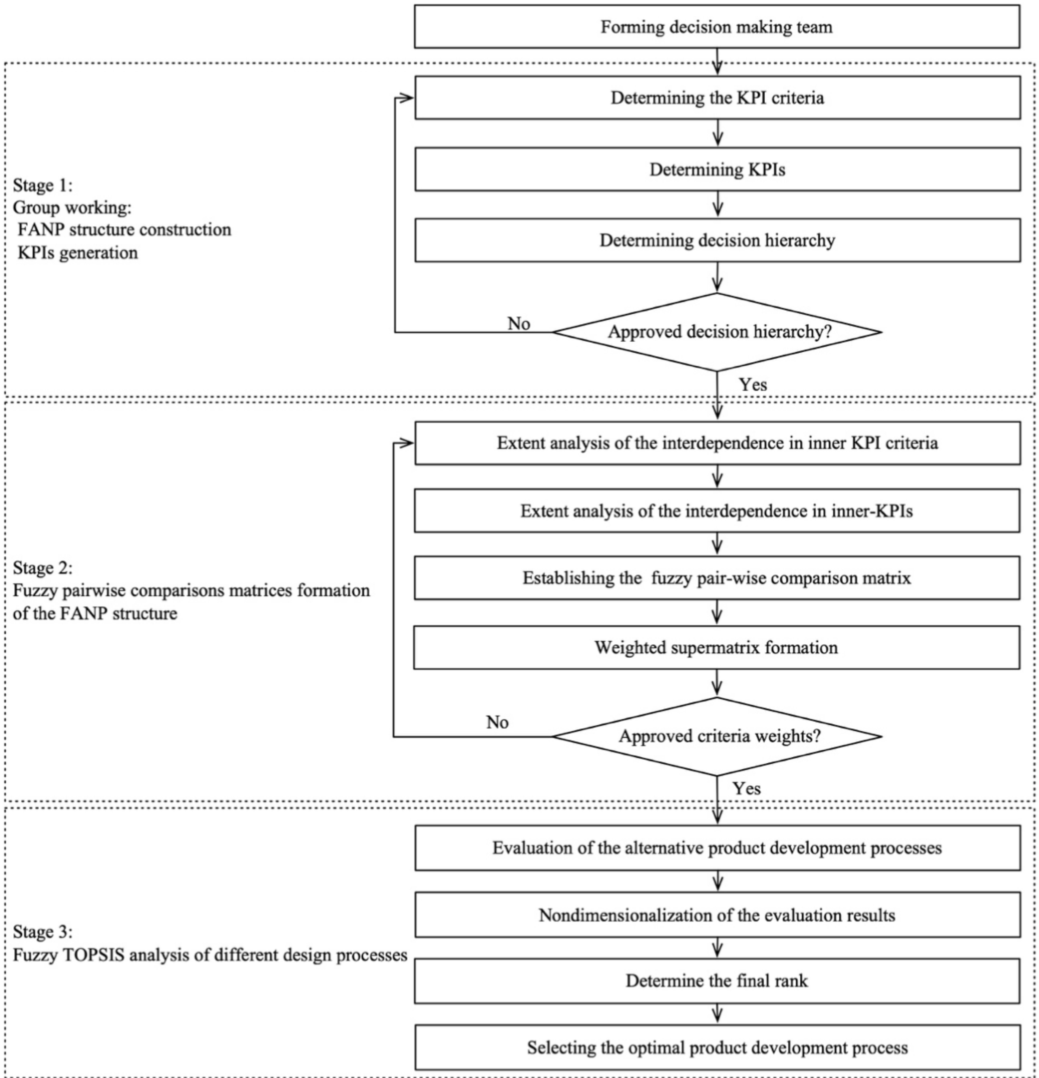

FIGURE 1. The flow charts for the algorithm in this study.

The construction of the proposed KBO-PMS consists of three stages: (1) identification of the evaluation criteria and their KPIs, (2) computations of the relative weights of the KPIs using Fuzzy ANP model, (3) evaluation of alternative PD processes regarding the proposed KPIs, evaluation data process using Fuzzy TOPSIS and determination of the final ranking list. The flow chart of this procedure is shown in Figure 1.

A. CONSTRUCTION OF THE FANP FRAMEWORK OF THE PROPOSED KBO-PMS: STEPS, FORMULAS AND CALCULATION PROCESSES

Analytic Hierarchy Process (AHP) is a classical method widely used in multi-criteria decision-making (MCDM) to overcome the restriction of hierarchical structure [42]. Unlike AHP, the Analytic Network Process (ANP) method is capable of establishing an evaluation framework with interdependent criteria [6]. By using the FANP method, all the information of the involved decision makers (product managers) can be collected and will be fully contributed to the final decision-making. All the evaluators are required to have a clear understanding on the evaluation criteria and their KPIs, ensuring the collection of useful information and necessary data. Also, during the proposed evaluation procedure, the decision makers can further understand their own requirements and duty in their position, permitting to improve the working efficiency of the company.

1) IDENTIFICATION OF THE KBO-PMS STRUCTURE AND COMPONENTS USING FANP

In this study, the networked hierarchical process is set up by performing an advanced interview with product managers for collecting PMS components. This procedure will help to understand the perception of the decision-makers about the

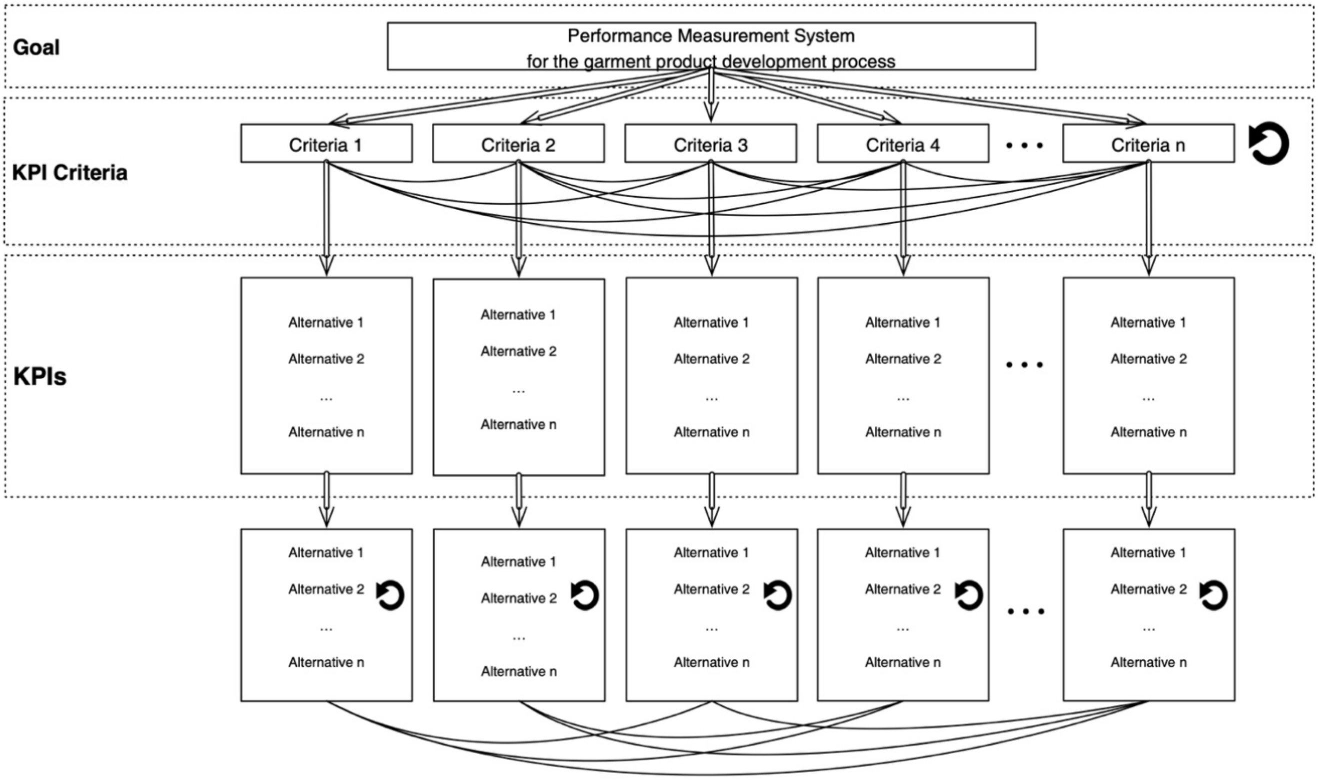

FIGURE 2. **The FANP framework of the KBO-PMS for product development process.**

interdependence of the structure and content of the proposed KBO-PMS [43]. The proposed FANP model is depicted in Figure 2.

2) DETERMINING THE FUZZY LINGUISTIC DEGREE OF THE EVALUATION CRITERIA AND THEIR RELATED KPIs IN A FANP MODEL

Fuzzy set theory was developed to model and analyze complicated and vague problems [44]. Fuzzy theory enables decision makers to tackle the ambiguities involved in the process of the linguistic assessment of the data, generally characterizing the human judgment by linguistic terms, like 'equal', 'moderately', 'strongly', 'very strongly', 'extremely', by defining the 'importance degree' of indicators [45], [46].

Evaluation performed using linguistic terms can be converted into fuzzy numbers. These fuzzy numbers are then used to build a pairwise comparison matrix offering the weights of PMS components at each level. We assume that decision makers use the linguistic terms from the linguistic rating scale *{extremely less important, strongly less important, moderately important, equal, moderately more important, strongly more important, extremely more important}*, for evaluating the relative importance of different evaluation criteria and their KPIs of the proposed KBO-PMS. The fuzzy linguistic rating scale is illustrated in Figure 3. Using this scale, the previous linguistic terms can be quantified into Triangular Fuzzy Numbers (TFNs).

A Triangular Fuzzy Number (TFN) is one of the most commonly used fuzzy sets (see Figure 4) [47]. A Triangular Fuzzy Number (TFN), M, can be denoted using n-tuples formalism as $M = (l,\ m,\ u)$ *or* $M = (l/m,\ m/u)$. The parameters l, m and u are used to describe the fuzzy event, which denote the smallest possible value, the most promising value, and the largest possible value respectively.

Each TFN has linear representations on its left and right side, such that its membership function can be defined as:

$$\mu_m(x) = \begin{cases} 0, & x \in [-\infty, l] \\ \dfrac{x-l}{m-l}, & x \in [l, m] \\ \dfrac{x-u}{m-u}, & x \in [m, u] \\ 0, & x \in [u, +\infty] \end{cases} \tag{1}$$

If $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ are two TFNs, the operation laws between them can be defined as:

$$M_1 \oplus M_2 = (l_1 + l_2, m_1 + m_2, u_1+) \tag{2}$$

$$M_1 \odot M_2 = (l_1 l_2, m_1 m_2, u_1) \tag{3}$$

$$\lambda \odot M_1 = (\lambda l_1, \lambda m_1, \lambda u_1)\,, \quad \lambda \in R \tag{4}$$

$$(l_1, m_1, u_1)^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\right). \tag{5}$$

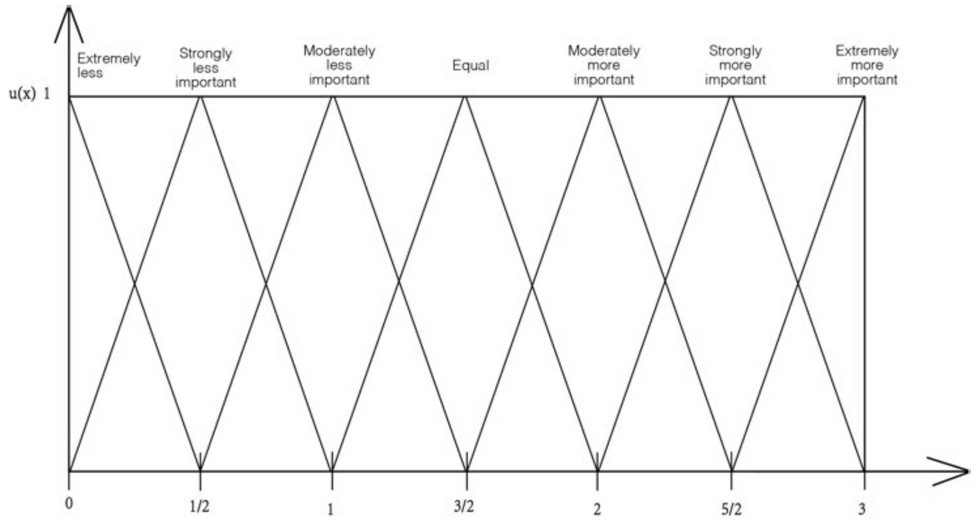

FIGURE 3. The fuzzy linguistic rating scale of the importance for the PMS.

TABLE 1. Linguistic rating scale of the relevant importance and corresponding fuzzy numbers.

Linguistic values	TFNs
Extremely high (EH)	(2.5,3,3)
Strongly high (S)	(2,2.5,3)
Moderately high (MH)	(1.5,2,2.5)
Average (A)	(1,1.5,2)
Moderately low (ML)	(0.5,1,1.5)
Strongly low (SL)	(0,0.5,1.5)
Extremely low (EL)	(0,0,0.5)

3) FUZZY PAIRWISE COMPARISONS MATRICES BETWEEN EVALUATION CRITERIA AND THEIR KPIs OF THE PMS IN A FANP MODEL

In this step, decision-makers were asked to respond to a series of comparisons for all pairs of PMS components at each level, with respect to the final goal. For example, if we assume there are k evaluation criteria (V_1, V_2, $\ldots V_K$) of the proposed KBO-PMS, the question asked to the decision makers is "what is the relative importance of evaluation criteria $V_i(i = 1, 2, \ldots, k)$ in comparison with $V_j(j = 1, 2, \ldots, k)$ in the garment PD process?" After that, fuzzy pairwise comparisons results can be transferred into a set of linguistic terms. Using fuzzy set theory, these linguistic terms can be quantified into TFNs, as presented in Table 1.

Thus, if we denote these TFN evaluation results as a_{ij}, fuzzy comparisons matrices of the relative independence can be denoted as $\widetilde{\mathrm{A}}$.

$$\widetilde{\mathrm{A}} = \begin{array}{c} \\ V_1 \\ V_2 \\ V_3 \\ V_4 \\ V_5 \end{array} \begin{pmatrix} V_1 & V_2 & V_3 & V_4 & V_5 \\ 1 & a_{12} & a_{13} & a_{14} & a_{15} \\ a_{21} & 1 & a_{23} & a_{24} & a_{25} \\ a_{31} & a_{32} & 1 & a_{34} & a_{35} \\ a_{41} & a_{42} & a_{43} & 1 & a_{45} \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 \end{pmatrix} \quad where\ a_{ij} = \frac{1}{a_{ji}}$$

Using the rules given by Equations 2, 3, 4, the evaluation scores given by each evaluator e_h are denoted as $\{a_{ijh}/i = 1, \ldots, 5, j = 1, \ldots, 5, h = 1, \ldots, m\}$, where a_{ijh} represents the number of the evaluators who choose one certain degree. Therefore

$$\mathrm{a_{ij}} = (\frac{1}{\mathrm{m}} \sum\nolimits_{\mathrm{j=1}}^{1} \mathrm{a_{ijh}t_1}, \frac{1}{\mathrm{m}} \sum\nolimits_{\mathrm{j=1}}^{1} \mathrm{a_{ijh}t_2}, \frac{1}{\mathrm{m}} \sum\nolimits_{\mathrm{j=1}}^{1} \mathrm{a_{ijh}t_3}) \tag{6}$$

where t_1, t_2 and t_3 correspond to the values of the triangular fuzzy numbers, defined according to the scale in Figure 3.

The extent analysis values are denoted:

$$\mathrm{M_{E_i}^1}, \mathrm{M_{E_i}^2}, \ldots \mathrm{M_{E_i}^m}, \quad i = 1, 2, \ldots, n$$

where $\mathrm{M_{E_i}^1}$ $(i = 1, 2, \ldots, n)$ are all TFNs. The value of fuzzy synthetic extent with respect to the i-th object is defined as:

$$\mathrm{S_i} = \sum\nolimits_{\mathrm{j=1}}^{\mathrm{m}} \mathrm{M_{E_i}^j} \odot \left[\sum\nolimits_{\mathrm{i=1}}^{\mathrm{n}} \sum\nolimits_{\mathrm{j=1}}^{\mathrm{m}} \mathrm{M_{E_i}^j}\right]^{-1} \tag{7}$$

Let $A = (a_{ij})_{n\times m}$ be a fuzzy analytical matrix, where $a_{ij} = (l_{ij}, m_{ij}, u_{ij})$ are defined by the calculated values:

$$l_{ij} = \frac{1}{u_{ij}}; \quad m_{ij} = \frac{1}{m_{ij}}; \quad u_{ij} = \frac{1}{l_{ij}}.$$

If $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ are two triangular fuzzy numbers, the degree of possibility of $M_2 = (l_2, m_2 u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined-by:

$$V\ (M_2 \geq M_1) = SUP_{y\geq x}\left[min\left(\mu_{M_1}(x), \mu_{M_2}(y)\right)\right] \tag{8}$$

and can be expressed as follows:

$$V\ (M_2 \geq M_1) = hgt\ (M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & if\ m_2 \geq m_1 \\ 0, & if\ l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & otherwise \end{cases}$$

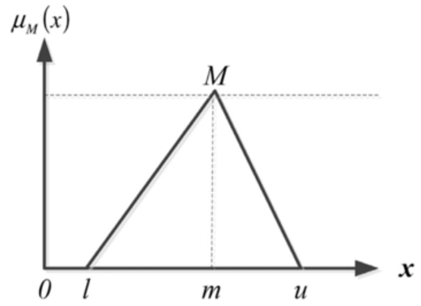

FIGURE 4. The triangular fuzzy number.

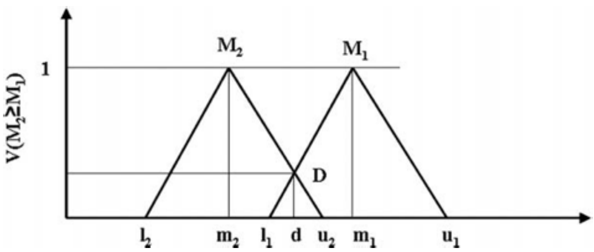

FIGURE 5. The intersection between M_1 and M_2.

(9)

Figure 5 illustrates Equation (9), where 'd' is the ordinate of the highest intersection point between μ_{M_1} and μ_{M_2}. To compare M_1 and M_2, we need both the values of $V(M_2 \geqslant M_I)$ and $V(M_I \geqslant M_2)$. The degree possibility for a convex fuzzy number to be greater than the k convex fuzzy $M_i (i = 1, 2, \ldots, k)$ numbers can be defined as:

$$\begin{aligned} &V(M \geq M_1, M_2, \ldots, M_k) \\ &\quad = V[(M \geq M_1 \text{ and } M \geq M_2 \text{ and } \ldots M \geq M_k) \\ &\quad = \min V(M \geq M_i), \quad \mathrm{i} = 1, 2, 3, \ldots, \mathrm{k}. \end{aligned} \tag{10}$$

Assuming that $d(A_i) = minV(S_i \geq S_k)$ for $k = 1, 2, \ldots, n; k \neq i$. Then, weight vector will be given by

$$\mathrm{W}' = \left(\mathrm{d}'(\mathrm{A}_1), \mathrm{d}'(\mathrm{A}_2), \ldots \mathrm{d}'(\mathrm{A}_\mathrm{n})\right)^{\mathrm{T}} \tag{11}$$

where $\mathrm{A_i}$ and $i = 1, 2, \ldots, n$ denote in i- th element and n number of elements respectively.

A fuzzy number is a convex, normalized fuzzy set $\widetilde{\mathrm{A} \subseteq \mathcal{R}}$ whose membership function is at least segmentally continuous and has the functional value $\mu_{\tilde{\mathrm{A}}}(x) = 1$ at precisely on the element. Using the classical normalization operation, the normalized weight vectors are given as follows.

$$\mathrm{W} = (\mathrm{d}(\mathrm{A}_1), \mathrm{d}(\mathrm{A}_2), \ldots \mathrm{d}(\mathrm{A}_\mathrm{n}))^{\mathrm{T}} \tag{12}$$

where W is a non-fuzzy number.

4) FORMALIZATION OF THE IMPORTANCE LEVEL OF THE KPIs

Let $K = \{k_1, k_2, \ldots, k_n\}$ be a set of selected KPIs, where n is the number of the selected KPIs, the importance level of a specific KPI k_i can be calculated as follows:

$$L_i = \frac{M_i \times D_i}{\sum_{i=1}^{n} M_i \times D_i}, \quad i = 1, 2, 3, \ldots, n \tag{13}$$

where L_i is the normalized importance level (normalized KPI index) of this KPI, M_i is the normalized relative importance degree of the KPIs, D_i is the normalized relative importance degree of the evaluation criteria which is related to this KPI. M_i and D_i are obtained from the FANP method as described before. Using the proposed FANP method, we can draw from the decision-makers' preferences the weight of each KPI in the ANP hierarchy, ranging between 0 and 1.

B. EVALUTION OF DIFFERENT PD PROCESSES USING FUZZY TOPSIS: STEPS, FORMULAS AND CALCULATION PROCESSES

TOPSIS is an aggregation method that compares a set of alternatives by identifying weights for each criterion in multi-criteria decision analysis [48]. The evaluation scores will be normalized and calculate the geometric distance between each alternative and the ideal alternative. The principle of TOPSIS is that the chosen alternative should have the shortest geometric distance from the positive ideal solution (PIS) and the longest geometric distance from the negative ideal solution (NIS) [49]. Fuzzy set theory was introduced to TOPSIS by Chen [47] to solve the problem of uncertainty in the evaluations and judgments in the multi-criteria decision-making process. In this research, a nondimensionalization process is first introduced into TOPSIS method, which ensures the same dimension of experiment data of incongruous evaluation criteria.

As the evaluation result regarding KPIs refer to various data types: real number, interval number, TFN, there are incongruous evaluation criteria among evaluation data. In order to evaluate the performance of different PD processes according to the proposed KPIs, a nondimensionalization process is required. In general, the experimental data can be classified into two groups, one group is qualitative indicators and another group is quantitative indicators.

For quantitative indicators, we introduce a denormalization method into the TOPSIS process to deal with the problem of multi-dimensions exist in the parameters or criteria of multi-criteria problems. We denote the assessment result value of PD process j according to KPI i as $\widetilde{x_{iJ}} = \left(a_{ij}, b_{ij}, c_{ij}\right)$, where $a_{ij} \leq b_{ij} \leq c_{ij}$. The positive ideal solution (PIS) allows minimizing the cost attributes and maximizing the benefit attributes. On the contrary, the negative ideal solution (NIS) performs to maximize the cost attributes and minimize the benefit attributes. The normalization of $\tilde{x_{ij}}$ can be defined as:

$$\tilde{r}_{iJ} = \frac{\tilde{x_{iJ}} - \min\left(a_{ij}\right)}{\max\left(c_{ij}\right) - \min\left(a_{ij}\right)} \quad \text{when } i \text{ is a positive-ideal solution,} \tag{14}$$

$$\tilde{r}_{lJ} = \frac{\max\left(c_{ij}\right) - \widetilde{x_{lJ}}}{\max\left(c_{ij}\right) - \min\left(a_{ij}\right)} \quad \text{when } i \text{ is a negative-ideal solution.} \tag{15}$$

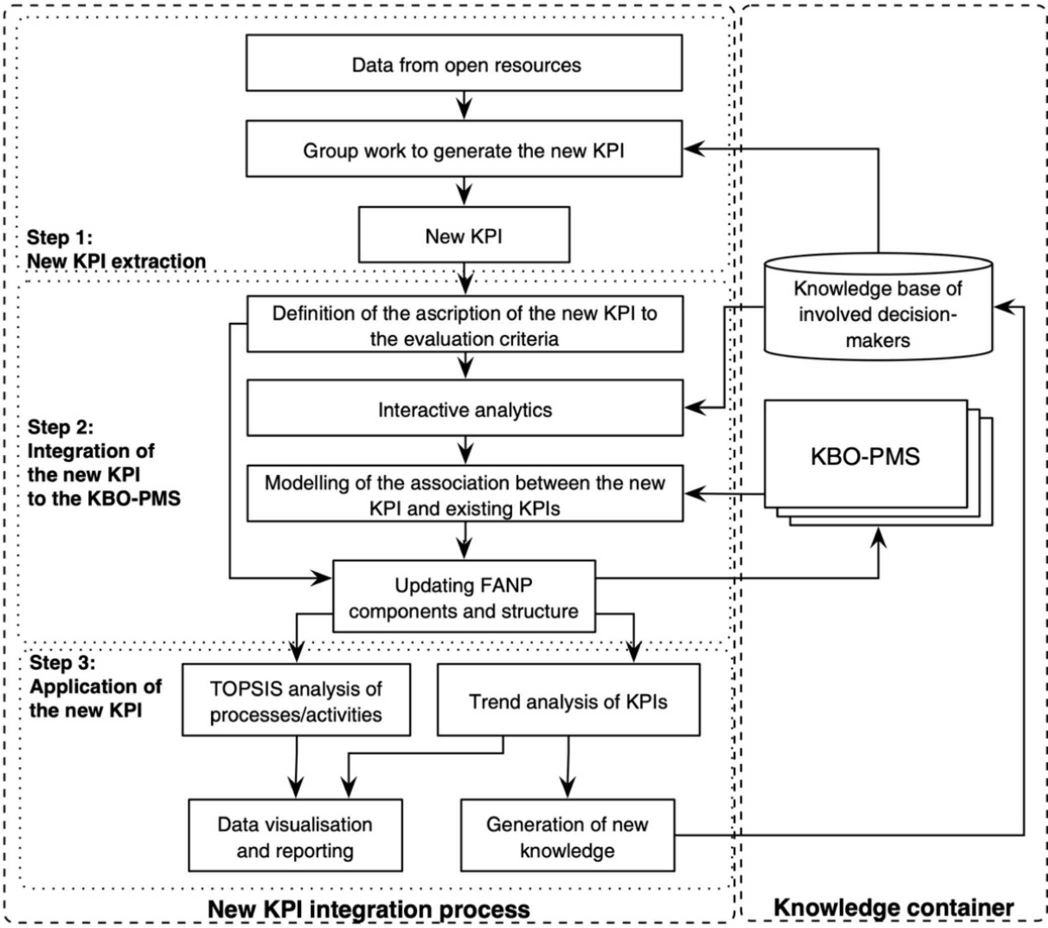

FIGURE 6. **Integration of a new KPI into the proposed PD processes-oriented and open resource-based PMS in big data environment.**

After that the obtained weight of these indicators are fuzzy numbers in the interval of [0,1]. If the value of the indicator of certain solution is closer to 1, the performance of this solution is better in terms of this indicator. Using this method, all the quantitative indicators will be in the same dimension, which ensures further comparison using TOPSIS.

For qualitative indicators, knowledge-based subjective evaluation will be applied together with a fuzzy linguistic scale in Figure 3. Each of the alternative processes will be evaluated regarding the KPIs. Then, fuzzy linguistic ratings of an option given by decision-makers will be converted into TFNs. Also, the obtained weights of these indicators are fuzzy numbers in the interval of [0,1]. If the value of the indicator of certain solution is closer to 1, the performance of this solution is better in terms of this indicator.

The ranking of the alternative options can be generated according to the values of closeness coefficients. The best alternative for the decision-making will be the farthest to the FNIs and the closest to the FPIs.

C. INTEGRATION OF A NEW KPI INTO THE PROPOSED KBO-PMS

The proposed KBO-PMS is a dynamic and open resource-based system, which can integrate new PMS components. There are three phases for integrating a new KPI (See Figure 6). First, a new KPI is extracted by the concerned decision-makers through the real PD process. Next, the extracted KPI is integrated into the existing PMS through an interactive analytics process. Finally, the new KPI will be applied together with the existing components of the PMS in order to perform the performance evaluation of the PMS related activities or processes, trend analysis of the KPIs and generation of new knowledge related to business and operations.

1) DATA ACQUISITION AND NEW KPI EXTRACTION

For an industrial company, a KPI is extracted from the data on the concerned activities and processes as well as new trends in business and operational management. Any modification on business model and strategy will enable to generate

KPI-related data. Also, the KPI extracted from data should conform to the knowledge of the involved decision-makers. Only the KPI approved by all of them can be authorized to be integrated into the existing PMS.

2) INTEGRATION OF THE NEW KPI TO THE PROPOSED KBO-PMS

The integration of the approved KPI into the existing PMS is realized thorough an interactive analytic process, with participation of the involved decision-makers. Associations between the new KPI and existing KPIs will be evaluated by the involved decision-makers using a set of linguistic terms such as "related" and "not related". Let $E = \{e_1, e_2, e_3, \ldots, e_m\}$ be a set of decision-makers in the decision-making team. Let $W = (w_1, w_2, w_3, \ldots, w_n)$ be a set of linguistic terms describing the association between the new KPI and existing KPIs. Each of the decision-makers e_m is invited to evaluate this association by using the linguistic terms in W. The evaluation process is performed based on the professional knowledge and experience of the involved decision-makers. In this study, W is defined as (*Not related, A little related, Related, Rather related, Extremely related),* corresponding to (w_1, w_2, w_3, …, w_n), where $n = 5$. These linguistic terms will be further quantified into numerical equivalence values, as presented in Table 2.

TABLE 2. **Linguistic rating scale of the relevance degrees and the corresponding fuzzy numbers.**

Linguistic values	Numerical equivalence values
Extremely related (ER)	1
Rather related (RR)	0.75
Related (R)	0.5
A little related (AR)	0.25
Not related (NR)	0

As defined in Section 2.1.5, let $K = (k_1, k_2, \ldots, k_m)$ be a set of selected KPIs existing in the PMS, and $L = (l_1, l_2, l_3, \ldots, l_m)$ be the vector of the normalized KPI index of K, where n is the number of the existing KPIs in a PMS.

Let R be a fuzzy evaluation matrix for the associations between the new KPI k_{m+1} with other existing KPIs of K, and

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{bmatrix}$$

where $r_{ij}(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$ is the membership function of the ith KPI k_i regarding the jth linguistic term w_j.

For the ith KPI k_i, if there are n decision-makers choose w_n, *then for* $i = 1, 2, \ldots, m, j = 1, 2, \ldots, n$

$$r_{ij} = \frac{w_{ij}}{\sum_{i=1}^{n} w_{ij}} \tag{16}$$

Using Equation 6, all the evaluation results of the involved decision-makers can be aggregated.

After that, the KPI index of the new KPI k_{m+1} can be obtained through a fuzzy relations composition method. Let l'_{n+1} be the vector of index of the new KPI $k_{m+1,}$

$$l'_{n+1} = L \bigcirc R = (p_1, p_2, \ldots, p_n) \tag{17}$$

$$\text{and} \quad p_n = max\left\{min\left(a_i, r_{ij}\right)\right\}, \tag{18}$$

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

Let $L'' = \left(l''_1, l''_2, \ldots l''_n, l''_{n+1}\right)$ be the vector of the normalized KPI index of the new KPI set,. we have

$$l''_i = \frac{l'_i}{\sum_1^{n+1} l'_i}, \quad i = 1, 2, 3, \ldots, n, n+1 \tag{19}$$

The new KPI and newly calculated normalized importance levels of all the KPIs will be stored in the PMS.

3) APPLICATION OF THE NEW KPI

The updated PMS with integration of the new KPI will be further applied to evaluate the performances of the activities and/or processes using the Fuzzy TOPSIS method. The operational trend can also be obtained by visually analyzing the new normalized importance levels of the KPIs. A report about the evaluation results and trend analysis will be generated to support decision-making of the company. New knowledge related to the KPI trend will also be generated to provide reference when generating a new KPI and enhance the success of the PMS.

IV. A CASE STUDY

We take the real case of a famous made-to-measure garment design and production company in Paris for the validation of the effectiveness of the proposed KES. This case study focuses on personalized garment PD process. It aims at the identification of the most appropriate garment PD process and performing related analysis for personalized garment design. There are four assignments of this case study: (1) identification of components of the proposed personalized garment PD processes-oriented KBO-PMS; (2) determination of the normalized KPI index; (3) performance evaluation of three alternative personalized garment PD processes; (4) presentation of the integration of a new KPI for the proposed system. In order to realize these assignments, four experiments are proposed.

A. EXPERIMENT I: IDENTIFYING PMS COMPONENTS OF PERSONALIZED GARMENT PD PROCESS: EVALUATION CRITERIA AND THEIR KPIs

The collection of the raw data has been carried out in two steps. In the first step, a group of product managers were selected and assigned as decision-makers. In the second step, the assigned decision-makers performed the evaluation criteria and KPI generation process through deep interview.

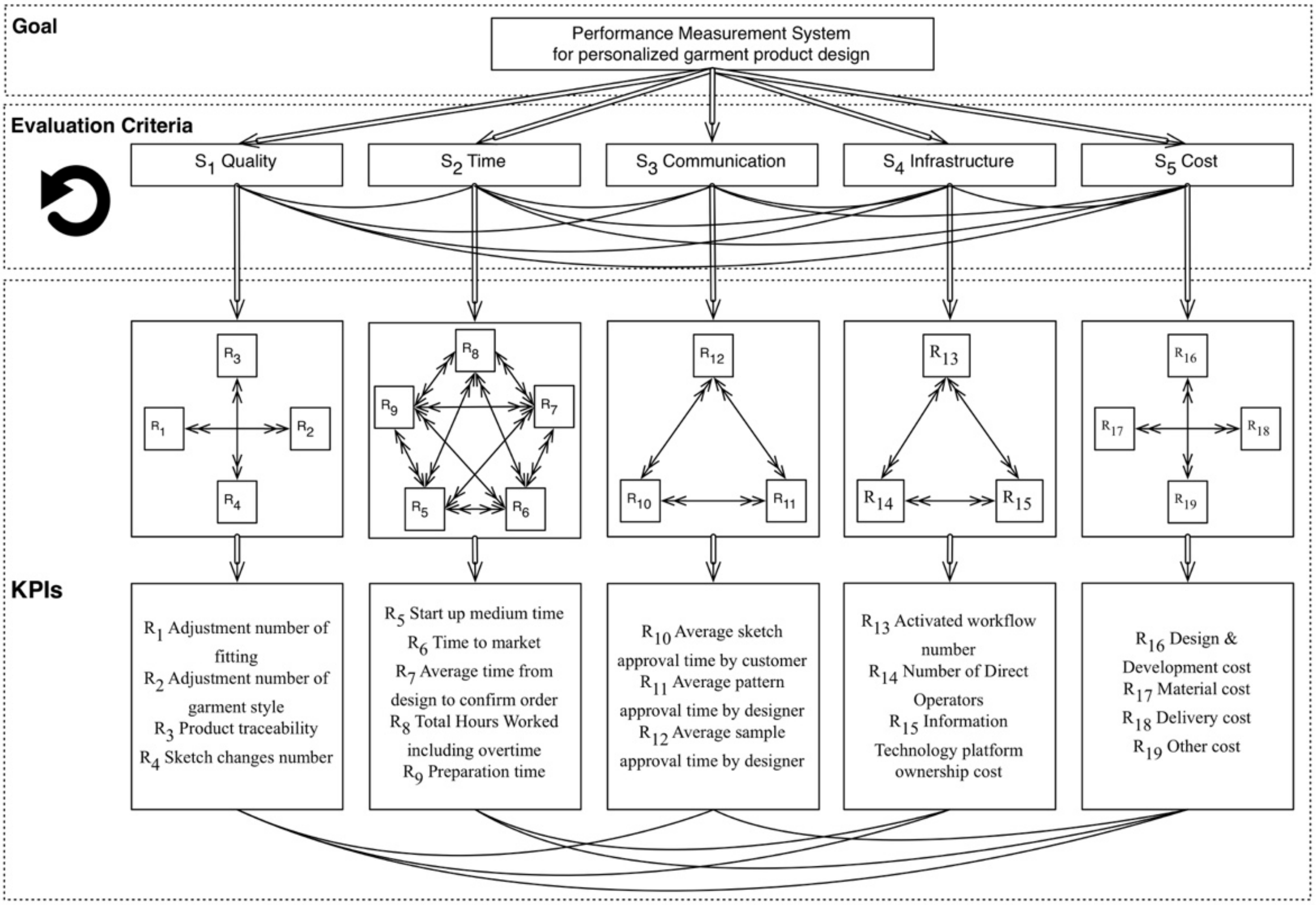

FIGURE 7. The FANP decision structure of the KBO-PMS for personalized garment PD process.

1) SELECTION AND ASSIGNMENT OF DECISION-MAKERS (STEP I)

19 product managers were selected to participate in the interview with a predefined questionnaire according to the following three conditions: (1) they have more than 10 years' working experience; (2) they belong to the high-level managers of the company and understand the strategy of the company; (3) they are familiar with new product design and development planning.

2) PMS COMPONENTS DETERMINATION AND ASSIGNMENT OF THEIR QUANTITATIVE/QUALITATIVE PROPERTIES (STEP II)

At the beginning of this step, a training section was carried out in order to avoid cognitive confusions and obtain a better understanding on the purpose of the human evaluation. First, each of the invited evaluator was asked to provide an exhaustive list of the relevant criteria and KPIs about the personalized garment development process according to their professional knowledge and experience. The selected KPIs should satisfy the following conditions including: (1) they are the key issues for the success of the company [50]; (2) only the quantifiable (measurable) KPIs should be selected; (3) the definition and measurements of the selected KPIs must be stable; (4) the goals for a specific KPI should be flexible and easy to the change. [51].

The cited evaluation criteria represent the essential requirements for selecting the most appropriate indicators and building an effective PMS [52]. These criteria are also applicable to the measurement of the personalized garment PD process. Secondly, a screening was performed by a "round table" discussion among all the invited product managers, to select the most appropriate evaluation criteria and KPIs. Finally, a set of 5 evaluation criteria and 19 KPIs were selected, as presented in Figure 7.

After that, a clear definition of quantitative/qualitative and positive/negative properties of different KPIs were performed after the ANP structure construction (See Table 3). These properties have been further applied in the Fuzzy TOPSIS process. The quantitative/qualitative property determines the data type and the positive/negative property defines PIS and NIS, as mentioned in Section 2.2.

B. EXPERIMENT II: DETERMINATION OF THE INDEXES OF THE KBO-PMS COMPONENTS (EVALUATION CRITERIA AND THEIR KPIs)

To measure the relative importance of the different evaluation criteria, the managers were asked to evaluate the

TABLE 3. Components of personalized garment PD process-based PMS and their properties.

KPI evaluation criteria	KPIs	Quantitative/Qualitative	Positive/Negative
R_1 **Cost**	R_1 Design & Development cost	Quantitative	Negative
	R_2 Material cost	Quantitative	Negative
	R_3 Delivery cost	Quantitative	Negative
	R_4 Other costs	Quantitative	Negative
R_2 **Time**	R_5 Startup medium time	Quantitative	Negative
	R_6 Time to market	Quantitative	Negative
	R_7 Average time from design to confirm order	Quantitative	Negative
	R_8 Total Hours Worked including overtime	Quantitative	Negative
	R_9 Preparation time	Quantitative	Negative
R_3 **Communication**	R_{10} Average sketch approval time by customer	Quantitative	Negative
	R_{11} Average pattern approval time by designer	Quantitative	Negative
	R_{12} Difficulty degree of the communications	Qualitative	Negative
R_4 **Infrastructure**	R_{13} Activated workflow number	Quantitative	Negative
	R_{14} Number of Direct Operators	Quantitative	Negative
	R_{15} Information Technology platforms ownership cost	Quantitative	Negative
R_5 **Quality**	R_{16} Adjustment number of fitting	Quantitative	Negative
	R_{17} Consumer satisfaction of the service	Qualitative	Positive
	R_{18} Product traceability	Qualitative	Positive
	R_{19} Sketch changes number	Quantitative	Negative

TABLE 4. The fuzzy comparisons matrix of the evaluation criteria.

	R_1	R_2	R_3	R_4	R_5
R_1	(2,2.5,3)	(3,3.5,4)	(0.5,1,1.5)	(2,2.5,3)	(2,2.5,3)
R_2	(1,1.5,2)	(2,2.5,3)	(3.5,4,4.5)	(3,3.5,4)	(2,2.5,3)
R_3	(3.5,4,4.5)	(0.5,1,1.5)	(2,2.5,3)	(0.5,1,1.5)	(0.5,1,1.5)
R_4	(2,2.5,3)	(1,1.5,2)	(3.5,4,4.5)	(2,2.5,3)	(2,2.5,3)
R_5	(2,2.5,3)	(2,2.5,3)	(3.5,4,4.5)	(2,2.5,3)	(2,2.5,3)

relative degree of importance between different evaluation criteria, by using the linguistic scales defined in Figure 3. Through the fuzzy arithmetic operation by using Equation 6, the fuzzy pairwise comparisons matrices were constructed based on the data collected from the 19 decision-makers. Further, the degree of importance of the evaluation criteria was obtained by the procedure of extent analysis approach. The analysis outcomes are shown in Table 4.

First, by applying Equation 2, we can calculate the fuzzy number as shown below

$$R_{R_1} = \sum\nolimits_{j=1}^{n} \widetilde{a_1}_j = (2, \quad 2.5, \quad 3) \oplus (3, 3.5, 4) \oplus (0.5, 1, 1.5) \oplus (2, 2.5, 3) \oplus (2, 2.5, 3) = (9.5, 12, 14.5)$$

$$R_{R_2} = \sum\nolimits_{j=1}^{n} \widetilde{a_{2}}_j = (1, \quad 1.5, \quad 2) \oplus (2, 2.5, 3) \oplus (3.5, 4, 4.5) \oplus (3, 3.5, 4) \oplus (2, 2.5, 3) = (11.5, 14, 16.5)$$

$$R_{R_3} = \sum\nolimits_{j=1}^{n} \widetilde{a_{3}}_j = (3.5, 4, 4.5) \oplus (0.5, 1.1.5) \oplus (2, 2.5, 3) \oplus (0.5, 1, 1.5) \oplus (0.5, 1, 1.5) = (7, 9.5, 1, 2)$$

$$R_{R_4} = \sum\nolimits_{j=1}^{n} \widetilde{a}_{4\,j} = (2, 2.5, 3) \oplus (1, 1.5, 2) \oplus (3.5, 4, 4.5) \oplus (2, 2.5, 3) \oplus (2, 2.5, 3) = (10.5, 13, 15.5)$$

$$R_{R_5} = \sum\nolimits_{j=1}^{n} \widetilde{a}_{5\,j} = (2, 2.5, 3) \oplus (2, 2.5, 3) \oplus (3.5, 4, 4.5) \oplus (2, 2.5, 3) \oplus (2, 2.5, 3) = (11.5, 14, 16.5)$$

$$R_{R_1} \oplus R_{R_2} \oplus R_{R_3} \oplus R_{R_4} \oplus R_{R_5} = (50, 62.5, 75)$$

Using Equation (7):

$$\tilde{S}_1 = R_{R_1} \odot \left[R_{R_1} \oplus R_{R_2} \oplus R_{R_3} \oplus R_{R_4} \oplus R_{R_5}\right]^{-1} = (9.5, 12, 14.5) \odot \left(\frac{1}{75}, \frac{1}{62.5}, \frac{1}{50}\right) = (0.1267, 0.192, 0.29)$$

$$\tilde{S}_2 = R_{R_2} \odot \left[R_{R_1} \oplus R_{R_2} \oplus R_{R_3} \oplus R_{R_4} \oplus R_{R_5}\right]^{-1} = (11.5, 14, 16.5) \odot \left(\frac{1}{75}, \frac{1}{62.5}, \frac{1}{50}\right) = (0.1533, 0.224, 0.33)$$

$$\tilde{S}_3 = R_{R_3} \odot \left[R_{R_1} \oplus R_{R_2} \oplus R_{R_3} \oplus R_{R_4} \oplus R_{R_5}\right]^{-1} = (7, 9.5, 12) \odot \left(\frac{1}{75}, \frac{1}{62.5}, \frac{1}{50}\right) = (0.0933, 0.152, 0.24)$$

$$\tilde{S}_4 = R_{R_4} \odot \left[R_{R_1} \oplus R_{R_2} \oplus R_{R_3} \oplus R_{R_4} \oplus R_{R_5}\right]^{-1} = (10.5, 13, 15.5) \odot \left(\frac{1}{75}, \frac{1}{62.5}, \frac{1}{50}\right) = (0.14, 0.208, 0.31)$$

TABLE 5. The whole indices of the KBO-PMS for personalized garment PD process.

KPI evaluation criteria	Relevant importance of evaluation criteria (D_i)	KPIs	KPI Weights (M_i)	Normalized KPI index (L_i)	Normalized evaluation criteria index (L_i)
	0.1902	Design & Development cost	0.0765	0,0700	
S_1 Quality	0.1902	Material cost	0.0404	0,0370	0,2428
	0.1902	Delivery cost	0.0554	0,0507	
	0.1902	Other cost	0.0705	0,0645	
	0.2347	Startup medium time	0.0424	0,0479	
	0.2347	Time to market	0.0548	0,0619	
S_2 Time	0.2347	Average time from design to confirm order	0.0749	0,0846	0,2739
	0.2347	Total Hours Worked including overtime	0.0515	0,0581	
	0.2347	Preparation time	0.0503	0,0568	
	0.1282	Average sketch approval time by customer	0.0395	0,0244	
S_3 Communication	0.1282	Average pattern approval time by designer	0.0402	0,0248	0,1201
	0.1282	Difficulty degree of the communications	0.0404	0,0249	
	0.2121	Activated workflow number	0.0482	0,0492	
S_4 Infrastructure	0.2121	Number of Direct Operators	0.0417	0,0425	0,1424
	0.2121	Information Technology platform ownership cost	0.0525	0,0536	
	0.2347	Adjustment number of fitting	0.0482	0,0544	
S_5 Cost	0.2347	Consumer satisfaction of the service	0.0793	0,0895	0,2209
	0.2347	Product traceability	0.059	0,0666	
	0.2347	Sketch changes number	0.0344	0,0388	

$$\widetilde{S}_5 = R_{R_5} \odot \left[R_{R_1} \oplus R_{R_2} \oplus R_{R_3} \oplus R_{R_4} \oplus R_{R_5}\right]^{-1}$$
$$= (11.5, 14, 16.5) \odot \left(\frac{1}{75}, \frac{1}{62.5}, \frac{1}{50}\right)$$
$$= (0.1533, 0.224, 0.33)$$

Using Equation (9):

$$V\left(\widetilde{S}_1 \geq \widetilde{S}_2\right) = 0.8103,\ V\left(\widetilde{S}_2 \geq \widetilde{S}_1\right) = 1;\ V\left(\widetilde{S}_1 \geq \widetilde{S}_3\right) = 1,$$
$$V\left(\widetilde{S}_3 \geq \widetilde{S}_1\right) = 0.739;\ V\left(\widetilde{S}_1 \geq \widetilde{S}_4\right) = 0.9036,$$
$$V\left(\widetilde{S}_4 \geq \widetilde{S}_1\right) = 1;\ V\left(\widetilde{S}_1 \geq \widetilde{S}_5\right) = 0.8103,\ V\left(\widetilde{S}_5 \geq \widetilde{S}_1\right) = 1;$$
$$V\left(\widetilde{S}_2 \geq \widetilde{S}_3\right) = 1,\ \left(\widetilde{S}_3 \geq \widetilde{S}_2\right) = 0.5463;\ V\left(\widetilde{S}_2 \geq \widetilde{S}_4\right) = 1$$
$$V\left(\widetilde{S}_4 \geq \widetilde{S}_2\right) = 0.9073;\ V\left(\widetilde{S}_2 \geq \widetilde{S}_5\right) = 1,\ V\left(\widetilde{S}_5 \geq \widetilde{S}_2\right) = 1;$$
$$V\left(\widetilde{S}_3 \geq \widetilde{S}_4\right) = 0.641;\ V\left(\widetilde{S}_4 \geq \widetilde{S}_3\right) = 1;$$
$$V\left(\widetilde{S}_3 \geq \widetilde{S}_5\right) = 0.5463,\ V\left(\widetilde{S}_5 \geq \widetilde{S}_3\right) = 1;$$
$$V\left(\widetilde{S}_4 \geq \widetilde{S}_5\right) = 0.9073,\ V\left(\widetilde{S}_5 \geq \widetilde{S}_4\right) = 1.$$

Thus, according to Equation (10), the numerical values of the evaluation criteria were obtained as:

$$d\,(\mathrm{R}_1) = V\left(\widetilde{S}_1 \geq \widetilde{S}_2, \widetilde{S}_3, \widetilde{S}_4, \widetilde{S}_5\right)$$
$$= \mathrm{MIN}\{0.8103, 0.9036, 0.8103\} = 0.8103,$$
$$d\,(\mathrm{R}_2) = V\left(\widetilde{S}_2 \geq \widetilde{S}_1, \widetilde{S}_3, \widetilde{S}_4, \widetilde{S}_5\right) = \mathrm{MIN}\{1, 1, 1, 1\} = 1,$$
$$d\,(\mathrm{R}_3) = V\left(\widetilde{S}_3 \geq \widetilde{S}_1, \widetilde{S}_2, \widetilde{S}_4, \widetilde{S}_5\right)$$
$$= \mathrm{MIN}\{0.739, 0.5463, 0.641, 0.5463\} = 0.5463,$$
$$d\,(\mathrm{R}_4) = V\left(\widetilde{S}_4 \geq \widetilde{S}_1, \widetilde{S}_2, \widetilde{S}_3, \widetilde{S}_5\right)$$
$$= \mathrm{MIN}\{1, 0.9037, 1, 0.9037\} = 0.9037,$$
$$d\,(\mathrm{R}_5) = V\left(\widetilde{S}_5 \geq \widetilde{S}_1, \widetilde{S}_2, \widetilde{S}_3, \widetilde{S}_4\right) = \mathrm{MIN}\{1, 1, 1, 1\} = 1.$$

Then, according to Equation (11), the ordering vector, W'_R *of* R_1, R_2, R_3, R_4, R_5 were obtained as $W'_R = (0.8103, 1, 0.5463, 0.9037, \quad 1)$. Using classic normalization operations (Equation (12), the normalized weight vector W_R can be defined as W_R = *(0.1902, 0.2347, 0.1282, 0.2121, 0.2347)*. Using the fuzzy arithmetic operations (Equation (9)), the fuzzy pairwise comparisons–matrix based on the KPIs established by the 19 managers can be synthesized. The normalized weight vector W_A can also be obtained, and in the particular example is the following: W_A= *(0.0765, 0.0404, 0.554, 0.0705, 0.424, 0.0548, 0.0749, 0.0515, 0.0503, 0.0395, 0.0402, 0.0404, 0.0482, 0.0417, 0.0525, 0.0482, 0.0793, 0.059, 0.0344)*.

By performing a classic normalization operation, using Equation (12), the normalized KPI index can be obtained. The summary of results for the hierarchy network is shown in Table 5. The values in Table 5 shows that the overall performance of the personalized garment PD process can be evaluated. Further, the performances of the different processes (2D-to-3D and 3D-to-2D) need to be compared, for understanding their performances, thus helping the decision makers to choose the right process.

TABLE 6. **Experimental data of different PD processes regarding the different KPIs.**

Quantitative KPIs	Classic 2D-to-3D	Virtual 2D-to-3D	Virtual 3D-to-2D
Adjustment number of fitting	6.2	5.5	2.9
Sketch changes number	4.2	3.4	3.3
Startup medium time	13.1h	8.3h	6.2h
Time to market	17.6h	15.4h	10.5h
Average time from design to confirm order	2.3h	1.9h	1.7h
Total Hours Worked including overtime	16.4h	14.6h	8.3h
Preparation time	1.5h	2.6h	1.8h
Average sketch approval time by customer	3.2	2.5	1.8
Average pattern approval time by designer	4.3	1.8	3.5
Activated workflow number	7	6	4
Number of Direct Operators	4	4	1
Information Technology platforms ownership cost	0	20 Euro	24 Euro
Design & Development cost	5.4 Euro	3.9 Euro	2.8 Euro
Material cost	18.1 Euro	15.7 Euro	12.9 Euro
Delivery cost	15.6 Euro	13.9 Euro	13.6 Euro
Other costs	2.4 Euro	1.7 Euro	1.4 Euro

Qualitative KPIs	Classic 2D-to-3D				Virtual 2D-to-3D				Virtual 3D-to-2D			
	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4	D_1	D_2	D_3	D_4
Consumer satisfaction of the service	A	MH	ML	MH	A	S	MH	S	S	MH	S	MH
Product traceability	SL	SL	ML	ML	A	MH	A	MH	S	MH	MH	S
Difficulty degree of the communications	EH	S	MH	MH	MH	A	MH	A	ML	SL	ML	ML

C. EXPERIMENT III: PERFORMANCE ANALYSIS OF DIFFERENT PD PROCESSES FOR PERSONALIZED GARMENT DESIGN AND FUZZY TOPSIS COMPUTATION

Nine personalized shirts (three garments for each process) for the same consumer were designed and produced using three alternative PD processes: Classic 2D-to-3D, Virtual 2D-to-3D and Virtual 3D-to-2D. Several experienced fashion designers, pattern makers and product managers were invited to perform this design and produce process. Experiments data were collected regarding different KPIs of the proposed system. The three sets of experiments were carried out in the same working environment (equipment and software), under the same working pressure. There was a training session about the involved PD processes, equipment and software for all involved designers, pattern makers and sewers before the experiments. The three sets of experiment were carried out after the involved people were familiar with the required skills (PD process, equipment and software).

For each set of experiment, experiments of two different categories were performed regarding quantitative or qualitative attribution in Table 3. For quantitative KPI related data, the involved designers and pattern designers performed different PD processes. Averaged values of experimental data were collected. For qualitative KPI related data, product managers gave subject evaluations, using different linguistic terms in Table 1, based on the experiment performed by designers and pattern designers. All the raw experimental data were collected in Table 6.

For raw experimental data obtained from quantitative KPIs were processed by a nondimensionalization procedure using Equation (14) and (15). All the experiment data in the form of real number were processed into TFNs, which ensures a data calculation in the same dimension. For raw experimental data obtained from qualitative KPIs, using Table 1, fuzzy linguistic terms were transferred into TFNs also, as described in Table 7. After that, a normalization operation was performed to process these data.

Using data in Table 7 and following the positive/negative properties of each KPI from Table 3, the classic Fuzzy TOPSIS were performed. The separation distances and closeness coefficients (CCs) for all the alternative fabrics are summarized in Table 8.

D. EXPERIMENT IV: INTEGRATION OF A NEW KPI TO THE PROPOSED SYSTEM

Experiment IV is designed to investigate how is a new KPI integrated into a PMS. Although product design and development is recognized as creativity-intensive work, impact of the creativity sharing among designers is always ignored in the product development performance. "Creativity sharing" refers to knowledge and idea sharing among designers in a collaborative design project. In this situation, a new indicator "Creativity sharing" is considered to be essential to the proposed KBO-PMS regarding the evaluation criteria "R_3 *Communication*". The new KPI is defined as R_{20}, which is regarded to be sharing. As explained in Section 3, each member of the decision-making team (19 product managers) is assigned to define the relevance degree of R_{20} regarding the other 19 KPIs in the proposed KBO-PMS using linguistic

TABLE 7. Aggregated fuzzy decision matrix after nondimensionalization.

KPIs	Aggregated fuzzy decision matrix after nondimensionalization		
	Classic 2D-to-3D	Virtual 2D-to-3D	Virtual 3D-to-2D
R_1	(0,0,0)	(0.21,0.21,0.21)	(1,1,1)
R_4	(0,0,0)	(0.9,0. 9,0. 9)	(1,1,1)
R_5	(0,0,0)	(0.7,0.7,0.7)	(1,1,1)
R_6	(0,0,0)	(0.31,0.31,0.31)	(1,1,1)
R_7	(0,0,0)	(0.67,0.67,0.67)	(1,1,1)
R_8	(0,0,0)	(0.22,0.22,0.22)	(1,1,1)
R_9	(1,1,1)	(0,0,0)	(0.72,0.72,0.72)
R_{10}	(0,0,0)	(0.5,0.5,0.5)	(1,1,1)
R_{11}	(0,0,0)	(1,1,1)	(0.32,0.32,0.32)
R_{13}	(0,0,0)	(0.33,0.33,0.33)	(1,1,1)
R_{14}	(0,0,0)	(0,0,0)	(1,1,1)
R_{15}	(1,1,1)	(0.17,0.17,0.17)	(0,0,0)
R_{16}	(0,0,0)	(0.58,0.58,0.58)	(1,1,1)
R_{17}	(0,0,0)	(0.47,0.47,0.47)	(1,1,1)
R_{18}	(0,0,0)	(0.85,0.85,0.85)	(1,1,1)
R_{19}	(0,0,0)	(0.7,0.7,0.7)	(1,1,1)
R_2	(2.13,2.63,3.13)	(2.63,3,13,3.63)	(2.75,3.25,3.75)
R_3	(1.25,1.75,2.25)	(2.25,2.75,3.25)	(2.75,3.25,3.75)
R_{12}	(2.88,3.38,3.88)	(2.25,2.75,3.25)	(1,38,1,88,2,38)

TABLE 8. Relative closeness coefficients (CCs).

	Classic 2D-to-3D	Virtual 2D-to-3D	Virtual 3D-to-2D
$CC_i = \frac{(d_i^-)}{(d_i^+ + d_i^-)}$	0,108378871	0,126593807	0,146763902

terms in Table 2. This procedure is performed based on knowledge and experience of involved decision-makers.

Using Equation 16 and 17, evaluation results of all decision-makers about the association between the new KPI R_{20} and all existing KPIs in the system, can be aggregated and normalized as *R = (0.0699, 0.0393, 0.0568, 0.0655, 0.0655, 0.0742, 0.0655, 0.0393, 0.048, 0.0524, 0.0393, 0.0655, 0.0786, 0.0611, 0.0611, 0.0524, 0.0306, 0.0175, 0.0175)*. Referring to Table 5, *L = (0.007, 0.037, 0.0507, 0.0645, 0.0479, 0.0619, 0.0846, 0.0581, 0.0568, 0.0244, 0.0248, 0.0249, 0.0492, 0.0425, 0.0536, 0.0544, 0.0895, 0.0666, 0.0388)*. Then, using Equation (17), the index of the new KPI R_{20} can be determined as $l'_{n+1} = L \bigcirc R$ = *max {min(0.0699, 0.007), min(0.0393, 0.037), min(0.0568, 0.0507), min(0.0655, 0.0645), min(0.065, 0.0479), min(0.0742, 0.0619), min(0.0655, 0.0846), min(0.0393, 0.0581), min(0.048, 0.0568), min(0.0524, 0.0244), min(0.0393, 0.0248), min(0.6555, 0.0249), min(0.0786, 0.0492), min(0.0611, 0.0425), min(0.0611, 0.0536), min(0.0524, 0.0544), min(0.03065, 0.0895), min(0.0175, 0.0666), min(0.0175, 0.0388)} = 0.0699*.

Then, a normalization process will be performed with the integration of the new KPI R_{20}. By using Equation 19, the normalized KPI index of the new KPI set can be determined as L'' = *(0.0654, 0.0345, 0.0474, 0.0603, 0.0447, 0.0578, 0.0790, 0.0543, 0.0531, 0.0228, 0.0232, 0.0233, 0.0460, 0.0398, 0.0501, 0.0509, 0.0837, 0.0623, 0.0363, 0.0653)*, where the normalized index of the new KPI is *0.0653*.

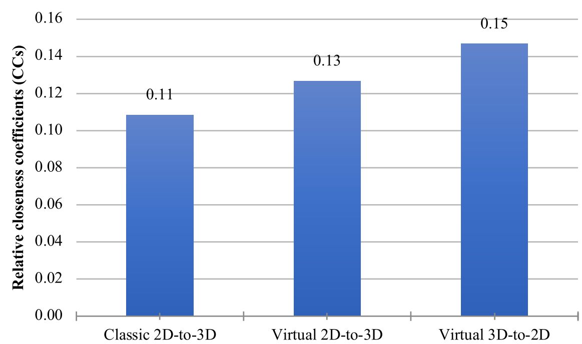

FIGURE 8. Closeness coefficients for all alternative PD processes.

E. RESULT DISCUSSION AND SUGGESTION

1) DISCUSSION ON DIFFERENT PD PROCESSES FOR PERSONALIZED GARMENT PD

Figure 8 shows all closeness coefficients of all alternative PD processes for personalization garment design. Based on CCj values, the ranking of the alternative PD processes in descending order are Virtual 3D-to-2D method (Closeness coefficients value 0.147), Virtual 2D-to-3D method (Closeness coefficients value 0.127), and Classic 2D-to-3D method (Closeness coefficients value 0.108). Results obtained from the proposed KBO-PMS indicate that Virtual 3D-to-2D method is the best alternative with closeness coefficients value of 0. 0.147.

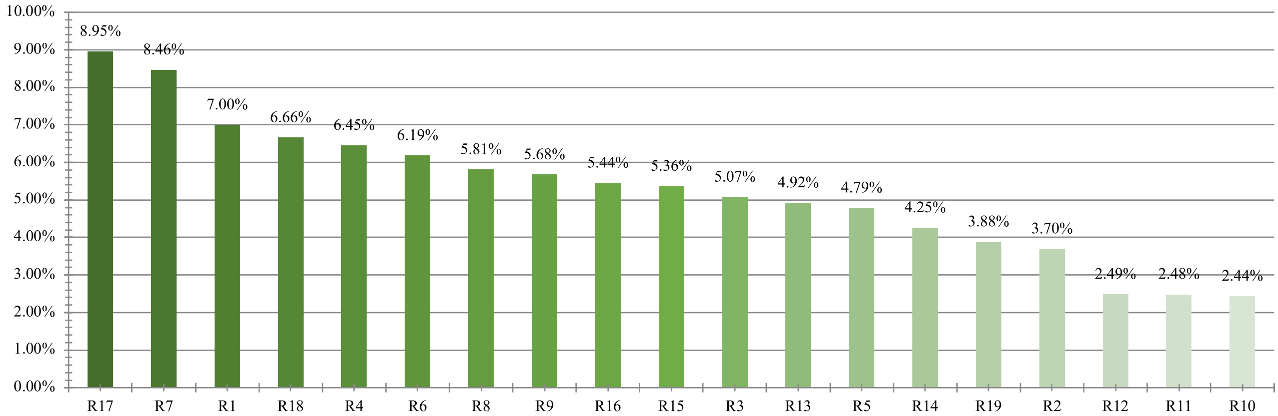

FIGURE 9. Normalized KPI index of the first 19 KPIs of the proposed KBO-PMS.

Due to the application of virtual technology, virtual PD processes (Virtual 3D-to-2D and Virtual 2D-to-3D) has obvious advantages than the classic process (Classic 2D-to-3D) [53]. Virtual Reality technology has been applied successfully in fashion industry, including using Virtual Reality software for building virtual fashion stores, displaying fashion show in Second Life, and creating 3D fashion portfolio [54], [55]. Using Virtual Reality oriented 3D avatars (virtual humans) to help with clothes design is the new channel for the application of Virtual Reality technology in fashion industry.

The virtual 3D-to-2D approach is a 3D virtual garment design method, permitting one to realize and validate design ideas and principles within a very short time [56], [57]. It speeds up the product development process and shortens the time from design and production to the market of fashion products [58]. Using Virtual Reality technology, a collaborative PD process based on the Virtual 3D-to-2D method can be realized [54]. During the collaborative PD process, the garment design technical space and perceptual space of the finished garments can be fully controlled, so that a desired personalized garment design effect can easily be satisfied by the adjustment of technical parameters [55].

2) TREND ANALYSIS OF KPIs

Figure 9 presents the respective ranking of the first 19 KPI of the proposed personalized garment PD process-based KBO-PMS regarding the normalized KPI index. For the normalized KPI index, higher index values mean more important, vice versa. Based on the normalized KPI index, the ranking of the KPIs in descending order are: R_{17} *Consumer satisfaction of the service,* R_7 *Average time from design to confirm order,* R_1 *Design & Development cost,* R_{18} *Product traceability,* R_4 *Other costs,* R_6 *Time to market,* R_8 *Total Hours Worked including overtime,* R_9 *Preparation time,* R_{16} *Adjustment number of fitting,* R_{15} *Information Technology platforms ownership cost,* R_3 *Delivery cost,* R_{13} *Activated workflow number,* R_5 *Startup medium time,* R_{14} *Number of Direct Operators,* R_{19} *Sketch changes number,* R_2 *Material cost,* R_{12} *Difficulty degree of the communications,* R_{11} *Average pattern approval time by designer,* and R_{10} Average sketch approval time by customer. Results obtained from the proposed KBO-PMS indicate that "R_{17} *Consumer satisfaction of the service",* is the most important KPI with the index value of 0.0895.

As mentioned previously, "R_{17} *Consumer satisfaction of the service*" obtained the highest normalized KPD index. It indicates that, for personalized garment PD, improving consumer's satisfaction is regarded as the most important principle. From the perception of the product managers, compared with other fashion products categories, personalized garment PD is a service, which is expected to provide good consumer experience [59]. Customer service has proved itself to be a key element for achieving good results in fashion industry, especially for personalized garment design service area. Consumers expect to be able to complete transactions about their requirements about the desired product correctly, in order to receive personalized attention, have the product delivered on time, their emails answered quickly and have access to information. Specifically, the highlight of "R_7 *Average time from design to confirm order"*(with the normalized index value of 0.0846) is also a reflection of these requirements. Consumer's satisfaction not only reflects the perceived quality of the consumer, but also influences on consumer loyalty and retention of the fashion brands [60].

Based on the understanding of the product managers, "R_1 *Design & Development cost*" is considered as the third most important indicator with the normalized index value of 0.07. "R_1 *Design & Development cost*" in personalized garment design refers to: (1) the regular design & development cost, such as the payment for the involved actors (designer, pattern designers, sewers, ...), and (2) facility investment, such as the digitalized garment design platform construction, body scanning machine and related software, which are rather expensive. These facilities ensure a digital media intermediary to provide better service to improve consumers' satisfaction. These facilities are one-time investment for the PD process. However, this kind of investment is rather expensive.

Product managers have doubts that if the investment of the new facilities can ensure the success of the brand.

Product traceability is also considered as a very important in personalized garment PD process. This aspect is also strongly related to the nature of the personalized garment design, which is service. Making the PD process traceability ensures customer's engagement across the design service and communication channels with designers (fashion designers and pattern designers), and consistent answers to customer questions or inconsistent offers. A common agreement between designers and consumers can be reached more easily subsequently. Also, consumers can easily supervise the carry out of the designers, which will improve the consumer experience. A clear traceability of PD process will help brands to build up the brand image of trust, limit losses and reduce costs. For example, in the personalized garment PD process, if customers have to repeat their requirements to a agent brand and check the design progress with repeated times, it can leave them feeling like the brand doesn't want to understand them and doesn't care about them. Making the PD process traceable can greatly avoid this problem.

In evaluating which of the KPIs has the lowest importance, "R_{10} *Average sketch approval time by customer*", "R_{11} *Average pattern approval time by designer*," and "R_{12} *Difficulty degree of the communications*" are selected. In general, it can be concluded that, fashion brands, which provides personalized garment design services, are aware of the importance of improving service quality of personalization. These brands are willing to accept the fact that working complexity among actors (designers, pattern designers, sewers, ...) in the PD process will be increased.

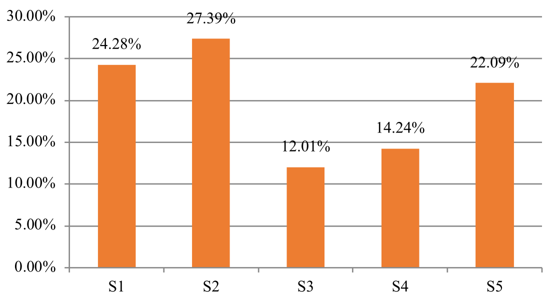

FIGURE 10. Normalized evaluation criteria index of the proposed KBO-PMS.

Figure 10 presents the index values of the 5 evaluation criteria. Based on the results obtained, the ranking of the evaluation criteria, in descending order, are: S_2 *Time,* S_1 *Cost,* S_5 *Quality,* S_4 *Infrastructure,* and S_3 *Communication.* Results obtained from the proposed KBO-PMS indicate that "S_2 *Time",* is the most important evaluation criteria with the index value of 0.2739. From this result, it can be concluded that, in personalized garment design process, time is concerned as the most important aspect for the success of the service. Shorter time to deliver the product to the consumer will increase his/her satisfaction and loyalty to the brand. On the other hand, shorter delivering time will help to reduce the complexity of the management of the PD process and to obtain a higher benefit. "S_1 *Cost*" is regarded as the second most important evaluation criteria because it is also an efficient way to increase the benefit. Lower costs entail a cut in investments for the new system, which could influence the price of the customized product that is being offered to clients. "S_5 *Quality*" is the third main concern for the product managers. Quality is always considered in the personalized garment design as one of the main evaluation criteria because it is a key element of consumer perceived value and experience. Thus, reducing time and costs and improving the quality of the final product are the most important aspects for the product managers in the context of the new PD process.

"S_4 *Infrastructure"* and "S_3 *Communication"* are not as important as S_1, S_2 and S_5 because they do not reflect the direct relationship with the consumer or the consumer's degree of satisfaction; these criteria deal mainly with internal management issues. Both infrastructure and communication can be improved by taking appropriate measures and by training the involved staff. All these corrective steps and equitable assessments can lead to the improvement or even optimization of the PD process that is a very dynamic at its core.

Figure 11 presents the respective ranking of the 20 KPIs of the updated personalized garment PD process-based KBO-PMS with the integration of "R_{20} *Creativity sharing"*, regarding the normalized KPI index. "R_{20} *Creativity sharing"* appears to be the fourth of the ranking of the KPIs in descending order based on the normalized KPI index.

Fashion industry, as an art and business combined area, creativity and knowledge is the most essential factor concerned by product managers. A fashion personalization brand should be knowledgeable about a customer's history and understanding of their specific requirements. One of the most important requirements is their emotional need. The reason a consumer chooses personalization service is that through personalization their emotional needs can be recognized. One of the key success factors to satisfy these emotional needs is that the understanding level of a fashion brand and corresponding design proposal is greater than other competitors. For personalized fashion design, creativity of designers is the insurance of consumer satisfaction and presentation of brand value.

3) SUGGESTION FOR COMPANIES

A reasonable PMS is able to effectively support the management of an organization, which is crucial to the success of a firm. This study is devoted to investigating KPIs facing personalized garment PD for the establishment of a successful PMS to support the management of fashion brands.

(1) Virtual Reality technology is validated to be able to support the PD for fashion industry in a large extent [61]. As an advanced method, Virtual Reality supported 3D-to-2D garment design and production method (Virtual 3D-to-2D method) can effectively improve the working efficiency and consumer satisfaction of personalized garment design service. Except for the virtual PD process, Virtual Reality

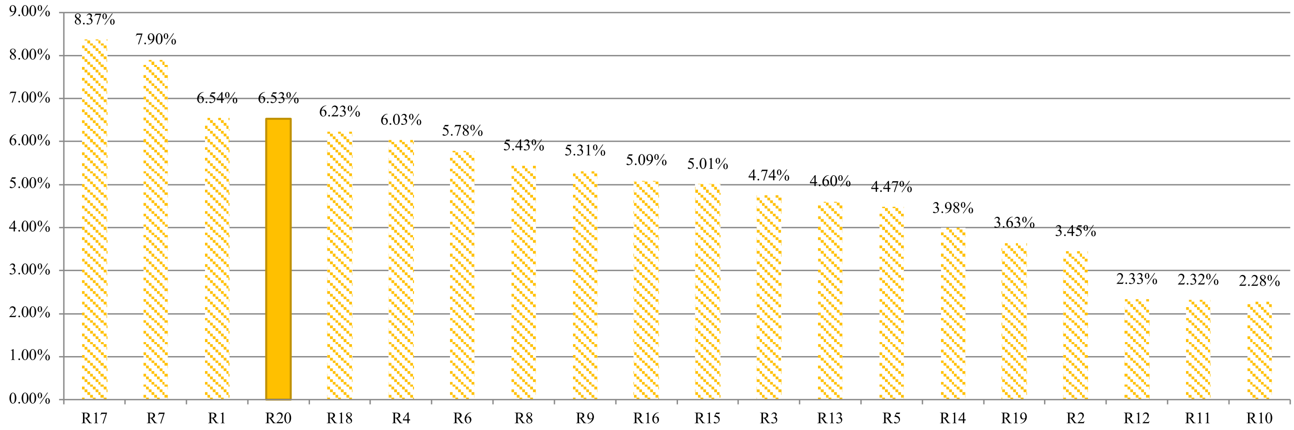

FIGURE 11. Updated KBO-PMS with the integration of R_{20}.

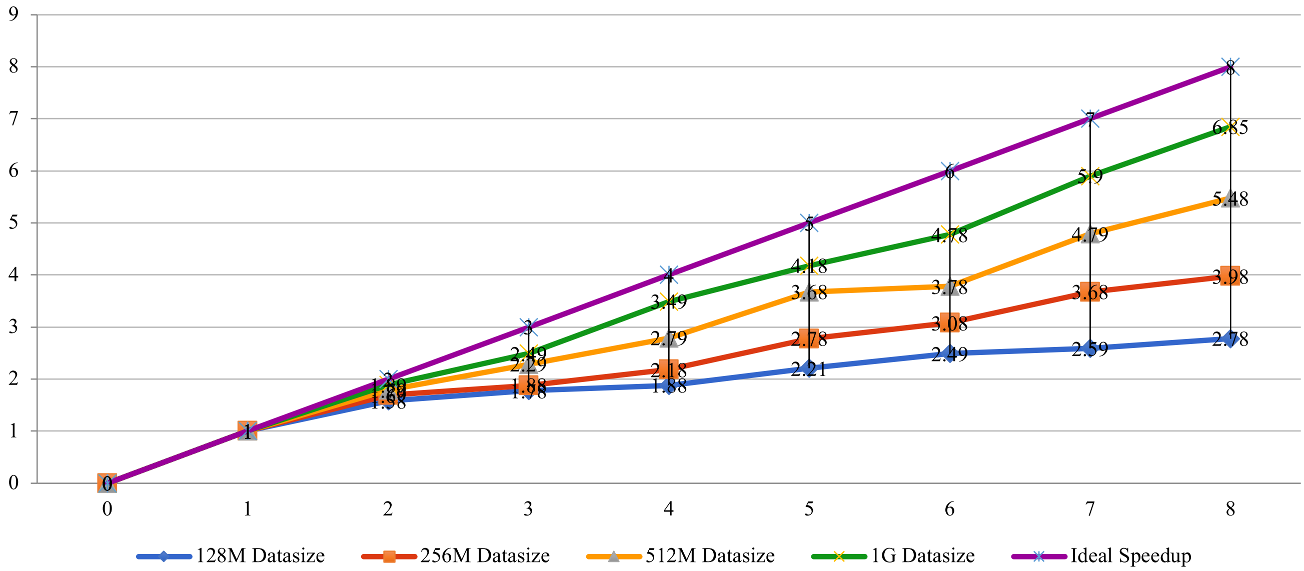

FIGURE 12. Speedup of the proposed KBO-PMS.

technology can also provide other technical solutions, like building virtual fashion stores, Second Life fashion show and 3D fashion portfolio design. Product managers and other decision-makers of a fashion brand should fully consider introducing necessary Virtual Reality technology supported software and platform in order to increase their competitive strength.

(2) "Consumer satisfaction of the service" is the most important indicator for the performance of an appropriate PD process. Virtual 3D-to-2D are the main factor that can largely improve consumer satisfaction. Besides, establishing measurement systems for measuring customer satisfaction, improving customer relationship management for building customer loyalty, tracking and monitoring of social media is also an important strategy to improve customer satisfaction that the product managers should also carefully consider. Besides, tracking and monitoring of social media is also an important strategy to improve customer satisfaction.

(3) As a supply chain management concept, "Product traceability" is also considered to be critical to an appropriate PD process. In other words, tracking product workflow is also very important work in the management procedure. Understanding workflows in the process under monitoring provides the key for efficient operation and a less stressful working environment.

(4) Creativity and knowledge sharing among designers is very important to the success of fashion brands. Informatics design platform, which is widely concerned by modern research related to fashion technology should be considered to be adapted to personalized fashion design.

V. EVALUATION OF SCALABILITY OF THE PROPOSED KBO-PMS REGARDING ITS PERFORMANCE ON THE BIG DATA ENVIRONMENT

Speedup is a well-accepted scalability metric, which has been used to measure the performance of an algorithm regarding the scalability [62]. Speedup is defined as follows:

$$S_p = \frac{T_1}{T_p} \tag{20}$$

where p is the number of processors, T_1 is the sequential execution time, T_p is the parallel execution time with p processors [63].

When the number of processors increases, if the memory capacity and network bandwidth also increase, it means this algorithm is considered scalable [63]. For a fixed data size, the memory capacity and network bandwidth of an algorithm is represented by Speedup. If the Speedup has a linear relation with the number of processors, the algorithm is regarded as having good scalability [64]. When the data size increase, if this kind of linear relation tends to be more obvious, this algorithm has better scalability.

To verify the scalability of the proposed KBO-PMS, a set of experiments were carried out. At the beginning of the Speedup evaluation, a data simulator is firstly developed to create a set of random raw data. The created data are developed based on Table 3-8, which fully match the data characteristic of real data. Due to the time horizon of the system, we processed all the collected data into four synthetic datasets of different sizes (128M, 256M, 512M and 1G). For each of the synthetic datasets of different sizes, experiments were carried out using processors ranging from 1 to 8 respectively. Figure 12 presents the speedup of the proposed KBO-PMS.

From Figure 12, it can be found that, with the growth of the number of nodes, the speedup of the proposed KBO-PMS algorithm increases relative linearly. Meanwhile, the dataset with a larger size tends to obtain a better speedup. Specifically, when the data size is 1G and the number of nodes is 8, the speedup value reaches 6.85, which is 85.6% (6.85/8 = 85.6%) of the ideal speedup. The Speedup evaluation shows that the proposed KBO-PMS has good scalability and performs better with larger datasets. It can be concluded the proposed system is applicable in the big data environment.

VI. CONCLUSION

In this research, a PD processes-oriented and open resource-based PMS in big data environment, to support complex decision-making problems, is proposed. New KPIs can be generated from the open source and integrated to the proposed KBO-PMS. The proposed KBO-PMS is based on an FANP and Fuzzy TOPSIS integrated algorithm. Efficiency of the proposed KBO-PMS is validated through an application case for performance evaluation facing personalized garment product development. The scalability which indicates the efficiency of the proposed KBO-PMS to be performed in big data environment has been validated by a Speedup test. The proposed KBO-PMS is realized by setting up an analysis hierarchy process to identify the evaluation criteria and their corresponding KPIs. Fuzzy numbers are introduced to quantify linguistic variables that consider the subjective judgment of evaluators. The analytical network process is applied to clarify the interrelations of intertwined sub-criteria in the complex structural hierarchy of personalized garment product design and production process selection problems. The Fuzzy TOPSIS method is used to evaluate the alternative PD processes based on the KPIs obtained from the ANP process and give final total ranking of the involved PD processes, which can effectively process both positive and negative evaluation criteria. Using FANP method, the interactions and mutual influence among KPI evaluation criteria and KPIs of the personalized garment PD process is fully considered and proved. The entire information of the all decision makers can be well collected to contribute to the final decision. The proposed KBO-PMS will enhance the chances of success of the company by suggestions in order to make appropriate decisions in the PD during the new product planning stage. Future work regarding this paper will be about the improvement of the accuracy of the algorithm used in this paper.

APPENDIX

Appendixes, if needed, appear before the acknowledgment.

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(Yan Hong and Tianyu Wu contributed equally to this work.)

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