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A multi-criteria procedure in new product development using different qualitative scales

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Abstract

In this paper, a new multi-criteria procedure is devised for new product development decision-making made from survey data. Groups of panelists evaluate several product categories regarding different criteria, each one through a specific qualitative scale, which ultimately will guide decision-makers to develop a new product in a specific category. These qualitative scales are equipped with ordinal proximity measures that collect the perceptions about the proximities between the terms of the scales by means of ordinal degrees of proximity. The linguistic assessments provided by panelists are compared with the highest terms of the corresponding qualitative scales. In order to aggregate the obtained ordinal degrees of proximity, a homogenization process is provided. It avoids any cardinalization procedure in the ordinal proximity measures associated with the ordered qualitative scales used for assessing the alternatives regarding different

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criteria. Products categories are ranked taking into account the medians of the homogenized ordinal degrees of proximity.

Keywords: multi-criteria decision-making; qualitative scales; ordinal proximity measures; market research; marketing strategy; new product development; customer purchase.

1. Introduction

The last few years have witnessed an increase in the dynamism of business environments, in particular because of global competition, the high level of technology change, the subsequent product life cycle shortening and the increase of new product and brands introduced in the market (see La Rocca et al. [18]).

We define dynamism of business environments as "the rate and unpredictability of environmental change" (see Mikalef et al. [24, p. 266]). Organizations run in these dynamic environments, and such they usually find it difficult to decode the cues from environment, which may hinder the management's skill to foresee the outcomes stemmed from their decisions (see Mena et al. [23]). Dynamic environments usually are related with uncertainty, specially when there is or lack of historical data on a specific situation, i.e. COVID-19 pandemic.

Managers may be given to delay or avoid certain strategic decisions under dynamic and uncertain environments, precisely because the lack of clarity about the possible outcome which leads to insecurity and decision-making paralysis, ultimately constraining responses to constantly evolving customer needs (see Jayachandran et al. [16]). This has led firms to face a crucial challenge to seduce customers, since they are considered a source of value creation for firms (see Kumar and Shah [17]).

Thus, delivering a better customer experience than competitors is a current leading management objective (see Leeflang et al. [19]).

Customer experience is an iterative and dynamic process with a firm throughout time during the purchase cycle (see Lemon and Verhoef [20]). One strategy to deliver a better customer experience in dynamic contexts, is new product development (see Miller and Swaddling [25]), which extensively requires market research, not just to foresee its acceptance by customers, but also as an input to the product's design (see Cooper [5]). Thus, market research can provide useful information to improve new product success, which ultimately enables new product development performance (see Nijssen and Frambach [27]), by identifying evolving customer needs and isolating potentially valuable market segments increases.

An exhaustive discussion of the role of marketing research in new product development is beyond the scope of this paper, so inspired in Weijters et al. proposal [30], we intend to explore deeply the tools used in marketing research to get to know about consumers: the questionnaire data. When creating questionnaires, researchers face several design-related choices. One such choice concerns the format of qualitative responses used in rating scales.

Ordered qualitative scales are frequently used not only in Marketing, but also in Economics, Psychology, Sensory Analysis, Sociology, etc., because they are more appropriate than numerical scales for dealing with the vagueness and imprecision of human beings when evaluating different issues (see Zimmer [33, 34] and Windschitl and Wells [31], among others).

The issue of appropriate response labels has been concerned principally with constructing instruments which contain intervals of equally increasing degrees of intensity. In this regard, several studies have been undertaken throughout years by marketers to assign scale qualitative values to adverbs and adjectives so that equal interval scales can be developed. Early researchers, such as Myers and Gregory [26], compiled scale values for 50 adjectives into two parallel response categories: one formal with five response categories, {'extremely poor', 'reasonably poor', 'neutral', 'good', 'remarkably good'}, and one colloquial, comprised also by five response categories, {'horrible', 'bad', 'moderately poor', 'neutral', 'pleasant', 'delightful', 'fantastic'}.

Brown et al. [3] used a product evaluation scale with five response categories, {'poor', 'fair', 'good', 'very good', 'extremely good', 'excellent'}, which has been widely used by general foods companies. Other early researchers such as Bartram et al. [2] used adverbial modifiers in their response categories such as {'slightly', 'fairly', 'extremely'} and they also put attention into the adjectives used to set the negative pole of the scale, i.e. {'terrible', 'awful', 'horrible', 'very poor'}.

Recent researchers, such as Zarantonello et al. [32] offered four categories of response to rate items on overall hate toward the brand: {'I hate this brand', 'I extremely dislike this brand' , 'I really detest this brand', 'I feel hostile to this brand'}.

In a different line of research, Grace et al. [14] have worked in a brand fidelity scale development using five categories responses to rate different items of the construct definition: {'not at all representative', 'minimally representative', 'moderately representative', 'very representative', 'completely representative'}.

In a topical line of research in marketing such as brand engagement, Obilo et al. [28] narrow down the categories response to three, in order to rate different items related to the representativeness of the concept. These categories of response are: {'not being representative', 'somewhat representative', 'very representative'}.

These examples illustrate the importance that the choice for a particular ordered qualitative scale format has in marketing, and specifically when designing a survey in market research. Generally speaking, the key choices when designing a survey can be broken down into two major components: the number of response categories to be offered, including the choice for an odd or even number of categories, and the labeling of response categories. These two components have received very little attention in Marketing research (see Weijters et al. [30]).

Although the rating scale format might affect the quality of questionnaire data (see Greenleaf [15] and Lietz [21]), specific evidence of the internal mechanism on how rating scale format affect quality of questionnaire data, has been almost ignored in the market research literature. An important reason for this gap is that most research on response styles has adopted a single approach, taking for granted equal perceptual distance between different qualitative categories.

In the examples presented before, some ordered qualitative scales can be considered as uniform, in the sense that the psychological proximity between each pair of consecutive terms of the scale is the same, e.g. Myers and Gregory's [26] scale used for evaluating products or advertisements {'extremely poor', 'reasonably poor', 'neutral', 'good', 'remarkably good}. However, not all ordered qualitative scales are uniform. For instance, the Brown et al. [3] scale used for evaluating products evaluation: {'poor', 'fair', 'good', 'very good', 'extremely good', 'excellent'} cannot be considered as uniform if one may think that 'fair' is closer to 'good' than to 'poor' (or if 'good' is closer to 'very good' than to 'fair', etc.).

In order to manage non-uniform ordered qualitative scales in a purely ordinal way, the notion of ordinal proximity measure was introduced by García-Lapresta and Pérez-Román [10]. Ordinal proximity measures collect the information about how individuals perceive the proximities between the linguistic terms of ordered qualitative scales through non-numerical degrees of proximity. The authors also provide some applications to consensus analysis and clustering in the context of non-uniform ordered qualitative scales.

García-Lapresta and Pérez-Román [11] propose a group decision-making procedure in the setting of non-uniform ordered qualitative scales and an extension to multi-criteria problems. These procedures are based on ordinal proximity measures.

García-Lapresta et al. [9] introduce the notion of metrizable ordinal proximity measure and provide a method for generating metrizable ordinal proximity measures through suitable sequences of questions for the case of ordered qualitative scales with four linguistic terms. They also introduce an aggregation procedure of metrizable ordinal proximity measures based on weighted metrics.

García-Lapresta and Pérez-Román [12] propose a method for generating metrizable ordinal proximity measures for the case of ordered qualitative scales with more than four linguistic terms.

García-Lapresta and González del Pozo [8] extend the multi-criteria decision-making procedure of García-Lapresta and Pérez-Román [11, Sect. 5] to the case where agents hesitate between two consecutive linguistic terms when assessing alternatives, and they apply the new procedure to a real wine tasting.

González del Pozo et al. [13] provide a multi-criteria decision-making procedure where agents evaluate a set of alternatives regarding different criteria through different ordered qualitative scales equipped with its corresponding metrizable ordinal proximity measures. They provide suitable mappings of such measures into a cardinal scale after a homogenization process based on the compensation between advantages and disadvantages of each alternative in comparison with its opponents.

The present paper shares with [13] the same framework, but avoiding the use of cardinal scales. In fact, the main novelty of this paper derives from the normalization process (Subsection 3.1). It avoids any cardinalization procedure in the ordinal proximity measures associated with the ordered qualitative scales used for assessing the alternatives regarding different criteria. The homogenization process is now devised in the sets of ordinal degrees of proximity. Once the metrizable ordinal proximity measures that represent the perceptions about the ordered qualitative scales for all the criteria have been fixed, we introduce a normalized set of ordinal degrees of proximity in such a way that each initial set of ordinal degrees of proximity is embedded into the normalized set of ordinal degrees of proximity.

The multi-criteria decision-making procedure is divided in different steps.

The assessments given by the panelists to the alternatives regarding all the criteria are replicated taking into account the importance of each criterion. Then, the ordinal degree of proximity between each linguistic assessment and the highest possible assessment in the corresponding scale is calculated. These ordinal degrees of proximity are normalized following the homogenization process. Then, the alternatives are ranked from the medians of the normalized ordinal degrees of proximity taking into account an appropriate linear order on the set of feasible medians. The procedure ends with a sequential tie-breaking method that provides the final ranking of the alternatives.

The new procedure is applied to a real decision-making process in a new product development context, outlined by the Spain's third-largest international exporter company in the food and beverage sector. The decision problem consist in which juice category should the company introduce their next product in the market, underpinning the decision on the responses collected from consumers about four Key Performance Indicators proposed by TNS Kantar[1]: purchase intention, uniqueness, price perception, and likeability.

The rest of the paper is organized as follows. Section 2 includes a short review of metrizable ordinal proximity measures. Section 3 contains the procedure that rank-order a set of alternatives from the qualitative assessments provided by a set of panelists to a set of alternatives regarding several criteria. Section 4 includes the real case study. Finally, Section 5 shows some concluding remarks.

2. Metrizable ordinal proximity measures

We consider that each individual of a group of panelists assigns a linguistic term to every alternative in each criterion. These linguistic terms belong to an *ordered qualitative scale* (**OQS**) $\mathcal{L} = \{l_1, \ldots, l_g\}$, arranged from worst to best, $l_1 \prec \cdots \prec l_g$, with $g \geq 3$.

The notion of ordinal proximity measure was introduced by García-Lapresta and Pérez-Román [10]. It is a mapping that assigns an ordinal degree of proximity to each pair of linguistic terms of an ordered qualitative scale $\mathcal{L}$. These ordinal degrees of proximity belong to a linear order $\Delta = \{\delta_1, \ldots, \delta_h\}$, with $\delta_1 \succ \cdots \succ \delta_h$, being δ_1 and δ_h the maximum and minimum degrees of prox-

[1]TNS Kantar is a world leader in market research, global market information and business analysis. Kantar provides market research insight across all industry and business sectors (see [29].

imity, respectively. It is important emphasizing that the elements of Δ are not numbers, but abstract objects that only represent different degrees of proximity.

As usual in the setting of linear orders, $\delta_r \succeq \delta_s$ means $\delta_r \succ \delta_s$ or $\delta_r = \delta_s$; and $\delta_r \prec \delta_s$ means $\delta_s \succ \delta_r$.

Definition 1. *([10]) An* ordinal proximity measure (**OPM**) on $\mathcal{L}$ with values in Δ *is a mapping* $\pi : \mathcal{L} \times \mathcal{L} \longrightarrow \Delta$, *where* $\pi(l_r, l_s) = \pi_{rs}$ *represents the degree of proximity between* l_r *and* l_s*, satisfying the following conditions:*

1. Exhaustiveness*: For every* $\delta \in \Delta$*, there exist* $l_r, l_s \in \mathcal{L}$ *such that* $\delta = \pi_{rs}$*.*
2. Symmetry*:* $\pi_{sr} = \pi_{rs}$*, for all* $r, s \in \{1, \dots, g\}$*.*
3. Maximum proximity*:* $\pi_{rs} = \delta_1 \Leftrightarrow r = s$*, for all* $r, s \in \{1, \dots, g\}$*.*
4. Monotonicity*:* $\pi_{rs} \succ \pi_{rt}$ *and* $\pi_{st} \succ \pi_{rt}$*, for all* $r, s, t \in \{1, \dots, g\}$ *such that* $r < s < t$*.*

The first condition requires that all the ordinal degrees of Δ should be used at least once, i.e., the function π is exhaustive. The second condition means that the ordinal degree of proximity between two linguistic terms does not depend on the order of the comparison, i.e., the function π is symmetric. The third condition says that the maximum degree of proximity is only reached when comparing a linguistic term with itself. The fourth condition requires that, given three linguistic terms arranged from the lowest to the highest, the ordinal proximity between the first and the second is higher than the ordinal proximity between the first and the third, and the ordinal proximity between the second and the third is higher than the ordinal proximity between the first and the third.

We say that an OPM $\pi : \mathcal{L} \times \mathcal{L} \longrightarrow \Delta$ is *uniform* if $\pi_{r(r+1)} = \pi_{s(s+1)}$ for all $r, s \in \{1, \dots, g-1\}$, and *totally uniform* if $\pi_{r(r+t)} = \pi_{s(s+t)}$ for all $r, s, t \in \{1, \dots, g-1\}$ such that $r + t, s + t \leq g$.

Every OPM $\pi : \mathcal{L} \times \mathcal{L} \longrightarrow \Delta$ is represented by a $g \times g$ symmetric matrix with coefficients in Δ, being the elements in the main diagonal $\pi_{rr} = \delta_1,\ r = 1, \dots, g$:

$$\begin{pmatrix} \pi_{11} & \cdots & \pi_{1s} & \cdots & \pi_{1g} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \pi_{r1} & \cdots & \pi_{rs} & \cdots & \pi_{rg} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \pi_{g1} & \cdots & \pi_{gs} & \cdots & \pi_{gg} \end{pmatrix}.$$

This matrix will be called *proximity matrix associated with* π.

If we consider the conditions appearing in Definition 1, we would only need to show the upper half proximity matrix

$$\begin{pmatrix} \delta_1 & \pi_{12} & \pi_{13} & \cdots & \pi_{1(g-1)} & \pi_{1g} \\ & \delta_1 & \pi_{23} & \cdots & \pi_{2(g-1)} & \pi_{2g} \\ & & & \cdots & \cdots & \cdots \\ & & & & \delta_1 & \pi_{(g-1)g} \\ & & & & & \delta_1 \end{pmatrix}.$$

We note that the minimum proximity between linguistic terms is only reached when comparing the extreme linguistic terms: $\pi_{rs} = \delta_h \Leftrightarrow (r,s) \in \{(1,g),(g,1)\}$ (see García-Lapresta and Pérez-Román [10, Prop. 2]).

A relevant family of OPMs, introduced by García-Lapresta et al. [9], is the one of metrizable OPMs which is based on linear metrics on OQSs.

Definition 2. *([9]). A* linear metric *on $\mathcal{L}$ is a mapping $d : \mathcal{L} \times \mathcal{L} \longrightarrow \mathbb{R}$ satisfying the following conditions for all $r, s, t \in \{1, \ldots, g\}$:*

1. Positiveness*: $d(l_r, l_s) \geq 0$.*
2. Identity of indiscernibles*: $d(l_r, l_s) = 0 \Leftrightarrow l_r = l_s$.*
3. Symmetry*: $d(l_s, l_r) = d(l_r, l_s)$.*
4. Linearity*: $d(l_r, l_t) = d(l_r, l_s) + d(l_s, l_t)$, if $r < s < t$.*

Definition 3. *([9]). An OPM $\pi : \mathcal{L} \times \mathcal{L} \longrightarrow \Delta$ is* metrizable *if there exists a linear metric $d : \mathcal{L} \times \mathcal{L} \longrightarrow \mathbb{R}$ such that $\pi_{rs} \succ \pi_{tu} \Leftrightarrow d(l_r, l_s) < d(l_t, l_u)$, for all $r, s, t, u \in \{1, \ldots, g\}$. We say that π is generated by d.*

Thus, if the perceptions of an individual about the ordinal proximities between the linguistic terms of an OQS can be described in a metrizable OPM, then this individual behaves as if he/she had in mind a linear metric on the OQS when comparing the proximities between the linguistic terms of the OQS.

If several experts perceive an OQS in a different way, it could be convenient to aggregate their perceptions in order to generate a collective metrizable OPM on the OQS. García-Lapresta et al. [9, Sect. 4] propose a distance-based procedure to solve that problem.

3. The procedure

A set of m panelists $P = \{p_1, \ldots, p_m\}$ evaluate a set of n alternatives $X = \{x_1, \ldots, x_n\}$ regarding a set of q criteria $C = \{c_1, \ldots, c_q\}$ through q OQSs $\mathcal{L}^k = \left\{l_1^k, \ldots, l_{g_k}^k\right\}$ equipped with metrizable OPMs $\pi^k : \mathcal{L}^k \times \mathcal{L}^k \longrightarrow \Delta^k$, where $\Delta^k = \left\{\delta_1^k, \ldots, \delta_{h_k}^k\right\}$ and $k = 1, \ldots, q$.

3.1. Normalization

Since criteria may be assessed through different OQSs equipped with the corresponding OPMs, a normalization process is needed. We consider two possible scenarios:

1. If $h_1 = \cdots = h_q = h$, then, $\Delta^* = \Delta^1 = \cdots = \Delta^q = \{\delta_1, \ldots, \delta_h\}$.
2. Otherwise, let $\Delta^* = \left\{\delta_1^*, \ldots, \delta_{h_*}^*\right\}$ be the normalized set of ordinal degrees of proximity. Each Δ^k can be embedded into Δ^* through the mapping $\Gamma_k : \Delta^k \longrightarrow \Delta^*$ defined as $\Gamma_k\left(\delta_r^k\right) = \delta_{\gamma_k(r)}^*$, with $\gamma_k(r) = 1 + d_k \cdot (r - 1)$ such that $\gamma_k(h_k) = h_*$. Thus, $\gamma_k(1) = 1, \gamma_k(2), \ldots, \gamma_k(h_k)$ are in arithmetic progression of difference $d_k,\ k = 1, \ldots, q$.

   We now show how this normalization process works for the cases $q = 2, 3$.

   - If $q = 2$, then $\gamma_1(h_1) = 1 + d_1 \cdot (h_1 - 1) = \gamma_2(h_2) = 1 + d_2 \cdot (h_2 - 1) = h_*$. Thus, $d_1 \cdot (h_1 - 1) = d_2 \cdot (h_2 - 1)$ and we take $d_1 = h_2 - 1$ and $d_2 = h_1 - 1$.

     For instance, if $\Delta^1 = \left\{\delta_1^1, \ldots, \delta_4^1\right\}$ and $\Delta^2 = \left\{\delta_1^2, \ldots, \delta_6^2\right\}$, then $d_1 = 4,\ d_2 = 3$ and $\Delta^* = \{\delta_1^*, \ldots, \delta_{16}^*\}$. Table 1 contains the values of $\gamma_k(r)$.

$\gamma_1(r) = 1 + 4(r-1)$	$\gamma_2(r) = 1 + 3(r-1)$
$\gamma_1(1) = 1$	$\gamma_2(1) = 1$
$\gamma_1(2) = 6$	$\gamma_2(2) = 4$
$\gamma_1(3) = 11$	$\gamma_2(3) = 7$
$\gamma_1(4) = 16$	$\gamma_2(4) = 10$
	$\gamma_2(5) = 13$
	$\gamma_2(6) = 16$

Table 1: Values of $\gamma_k(r)$.

     Taking into account Table 1, in Table 2 the mappings Γ_1 and Γ_2 are shown.

   - If $q = 3$, then $\gamma_1(h_1) = 1 + d_1 \cdot (h_1 - 1) = \gamma_2(h_2) = 1 + d_2 \cdot (h_2 - 1) = \gamma_3(h_3) = 1 + d_3 \cdot (h_3 - 1) = h_*$. Thus, $d_1 \cdot (h_1 - 1) = d_2 \cdot (h_2 - 1) =$

$$
\begin{array}{rcl}
\Gamma_1 : \Delta^1 & \longrightarrow & \Delta^* \\
\delta_1^1 & \mapsto & \delta_1^* \\
\delta_2^1 & \mapsto & \delta_6^* \\
\delta_3^1 & \mapsto & \delta_{11}^* \\
\delta_4^1 & \mapsto & \delta_{16}^*
\end{array}
\qquad
\begin{array}{rcl}
\Gamma_2 : \Delta^2 & \longrightarrow & \Delta^* \\
\delta_1^2 & \mapsto & \delta_1^* \\
\delta_2^2 & \mapsto & \delta_4^* \\
\delta_3^2 & \mapsto & \delta_7^* \\
\delta_4^2 & \mapsto & \delta_{10}^* \\
\delta_5^2 & \mapsto & \delta_{13}^* \\
\delta_6^2 & \mapsto & \delta_{16}^*
\end{array}
$$

Table 2: Mappings Γ_1 and Γ_2.

$d_3 \cdot (h_3 - 1)$. We take

$$d_1 = \frac{(h_2-1)\cdot(h_3-1)}{\gcd((h_2-1)\cdot(h_3-1),(h_1-1)\cdot(h_3-1),(h_1-1)\cdot(h_2-1))},$$

$$d_2 = \frac{(h_1-1)\cdot(h_3-1)}{\gcd((h_2-1)\cdot(h_3-1),(h_1-1)\cdot(h_3-1),(h_1-1)\cdot(h_2-1))},$$

$$d_3 = \frac{(h_1-1)\cdot(h_2-1)}{\gcd((h_2-1)\cdot(h_3-1),(h_1-1)\cdot(h_3-1),(h_1-1)\cdot(h_2-1))},$$

where gcd is the greatest common divisor.

For instance, if $\Delta^1 = \left\{\delta_1^1, \ldots, \delta_4^1\right\}$, $\Delta^2 = \left\{\delta_1^2, \ldots, \delta_5^2\right\}$ and $\Delta^3 = \left\{\delta_1^1, \ldots, \delta_7^1\right\}$, then $d_1 = 4$, $d_2 = 3$, $d_3 = 2$ and $\Delta^* = \{\delta_1^*, \ldots, \delta_{13}^*\}$. Table 3 contains the values of $\gamma_k(r)$.

Taking into account Table 3, in Table 4 the mappings Γ_1, Γ_2 and Γ_3 are shown.

3.2. *Criteria weights*

The opinions of all panelists over all alternatives regarding the criterion $c_k \in C$ are collected in a *profile* V^k, that is a matrix of m rows and n columns

$\gamma_1(r) = 1 + 4(r-1)$	$\gamma_2(r) = 1 + 3(r-1)$	$\gamma_3(r) = 1 + 2(r-1)$
$\gamma_1(1) = 1$	$\gamma_2(1) = 1$	$\gamma_3(1) = 1$
$\gamma_1(2) = 5$	$\gamma_2(2) = 4$	$\gamma_3(2) = 3$
$\gamma_1(3) = 9$	$\gamma_2(3) = 7$	$\gamma_3(3) = 5$
$\gamma_1(4) = 13$	$\gamma_2(4) = 10$	$\gamma_3(4) = 7$
	$\gamma_2(5) = 13$	$\gamma_3(5) = 9$
		$\gamma_3(6) = 11$
		$\gamma_3(7) = 13$

Table 3: Values of $\gamma_k(r)$.

$\Gamma_1 : \Delta^1$	$\longrightarrow$	Δ^*	$\Gamma_2 : \Delta^2$	$\longrightarrow$	Δ^*	$\Gamma_3 : \Delta^3$	$\longrightarrow$	Δ^*
δ_1^1	$\mapsto$	δ_1^*	δ_1^2	$\mapsto$	δ_1^*	δ_1^3	$\mapsto$	δ_1^*
δ_2^1	$\mapsto$	δ_5^*	δ_2^2	$\mapsto$	δ_4^*	δ_2^3	$\mapsto$	δ_3^*
δ_3^1	$\mapsto$	δ_9^*	δ_3^2	$\mapsto$	δ_7^*	δ_3^3	$\mapsto$	δ_5^*
δ_4^1	$\mapsto$	δ_{13}^*	δ_4^2	$\mapsto$	δ_{10}^*	δ_4^3	$\mapsto$	δ_7^*
			δ_5^2	$\mapsto$	δ_{13}^*	δ_5^3	$\mapsto$	δ_9^*
						δ_6^3	$\mapsto$	δ_{11}^*
						δ_7^3	$\mapsto$	δ_{13}^*

Table 4: Mappings Γ_1, Γ_2 and Γ_3.

with coefficients in $\mathcal{L}^k$:

$$V^k = \begin{pmatrix} v_1^{1,k} & \cdots & v_i^{1,k} & \cdots & v_n^{1,k} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ v_1^{p,k} & \cdots & v_i^{p,k} & \cdots & v_n^{p,k} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ v_1^{m,k} & \cdots & v_i^{m,k} & \cdots & v_n^{m,k} \end{pmatrix},$$

where $v_i^{p,k}$ is the assessment given by the panelist p to the alternative x_i with respect to the criterion c_k.

Criteria involved in multi-criteria decision-making processes may have different importance. Usually, a numerical weight is assigned to each criterion. Since the linguistic assessments given by panelists cannot be multiplied by numbers, we propose to replicate these linguistic assessments obtained for each alternative in each criterion as many times as necessary until these replications reflect the proportions among weights (see Balinski and Laraki [1, Sect. 21.3], García-Lapresta and González del Pozo [7] and García-Lapresta and Pérez-Román [11, Sect. 5]).

In a semi-democratic context, Franceschini and García-Lapresta [6] consider the possibility of assigning numerical weights to experts when their importance is not the same. Experts' opinions are replicated following the same pattern of the papers mentioned above. Nevertheless, in the present paper the opinions of all panelists have the same importance.

We consider a weighting vector $(w_1, \ldots, w_q) \in [0,1]^q$, with $w_1 + \cdots + w_q = 1$, where w_k is the weight assigned to criterion c_k, $k = 1, \ldots, q$. For practical reasons, we assume that these weights have at most two decimals, i.e., the percentages $100 \cdot w_1, \ldots, 100 \cdot w_q$ are integer numbers.

3.3. Ranking alternatives

To rank the alternatives, the procedure is divided in the following steps:

- *Step 1.* Gather the assessments given by the panelists in the corresponding profiles $V^1, \ldots, V^q$.

- *Step 2.* Replicate the previous profiles, taking into account the corresponding percentages $100 \cdot w_1, \ldots, 100 \cdot w_q$. In practice, calculate the greatest common divisor of percentages associated with the weights, and divide each percentage by the gcd. Thus, the minimum number of replications of each profile is:

$$t_k = \frac{100 \cdot w_k}{\gcd(100 \cdot w_1, \ldots, 100 \cdot w_q)}\,, \quad k = 1, \ldots, q. \tag{1}$$

  For instance, if $q = 3$, $w_1 = 0.5$, $w_2 = 0.2$, and $w_3 = 0.3$, then the profiles V^1, V^2 and V^3 should be replicated $t_1 = 5$, $t_2 = 2$ and $t_3 = 3$ times, respectively (note that $\gcd(50, 20, 30) = 10$).

- *Step 3.* For each alternative $x_i \in X$ and each criterion $c_k \in C$, calculate the ordinal proximities between the obtained assessments (taking into account the corresponding replications) and $l_{g_k} \in \mathcal{L}^k$, $k = 1, \ldots, q$:

$$\pi\Big(v_i^{1,1}, l_{g_1}^1\Big), \ldots, \pi\Big(v_i^{m,1}, l_{g_1}^1\Big), \ldots, \pi\Big(v_i^{1,q}, l_{g_q}^q\Big), \ldots, \pi\Big(v_i^{m,q}, l_{g_q}^q\Big) \in \Delta^*.$$

  Following the normalization process included in Subsection 3.1, if $h_1 =$

$\cdots = h_q = h$, then, $\Delta^* = \Delta^1 = \cdots = \Delta^q = \{\delta_1, \ldots, \delta_h\}$. Otherwise, $\Delta^* = \{\delta_1^*, \ldots, \delta_{h_*}^*\}$.

- *Step 4.* For each alternative $x_i \in X$, arrange the previous ordinal degrees of proximity in a decreasing fashion.

- *Step 5.* For each alternative $x_i \in X$, select the medians of the previous ordinal degrees of proximity in the following way:

  1. If the number of ordinal degrees of proximity listed in the previous step is even, then consider the two medians: $M_i = (\delta_r^*, \delta_s^*)$ for some $\delta_r^*, \delta_s^* \in \Delta^*$ such that $r \leq s$.
  2. If the number of ordinal degrees of proximity listed in the previous step is odd, then duplicate the median: $M_i = (\delta_r^*, \delta_r^*)$ for some $\delta_r^* \in \Delta^*$.

  Thus, $M_i \in \Delta_2^*$, where Δ_2^* is the *set of feasible medians*:

$$\Delta_2^* = \{(\delta_r^*, \delta_s^*) \in \Delta^* \times \Delta^* \mid r \leq s\}.$$

- *Step 6.* To order the medians of ordinal proximities obtained by different alternatives in the previous step, consider the linear order $\succeq$ on Δ_2^* defined as

$$(\delta_r^*, \delta_s^*) \succeq (\delta_t^*, \delta_u^*) \;\Leftrightarrow\; \begin{cases} r + s < t + u \\ \text{or} \\ r + s = t + u \;\text{ and }\; s - r \leq u - t, \end{cases} \tag{2}$$

  for all $(\delta_r^*, \delta_s^*), (\delta_t^*, \delta_u^*) \in \Delta_2^*$.

- *Step 7.* Finally, the alternatives are ranked according to the weak order $\succcurlyeq$ on X defined as $x_i \succcurlyeq x_j \;\Leftrightarrow\; M_i \succeq M_j$.

It is possible that two or more alternatives share the same medians. In that case, we propose to use the tie-breaking method introduced by García-Lapresta and Pérez-Román [11, Subsect. 3.2]. It consists of dropping the medians of the alternatives that are in a tie, and then select the new medians of the remaining ordinal degrees of proximity for the corresponding alternatives and applying the steps 6 and 7 of the procedure until the ties are broken.

Figure 1 contains a flowchart of the procedure.

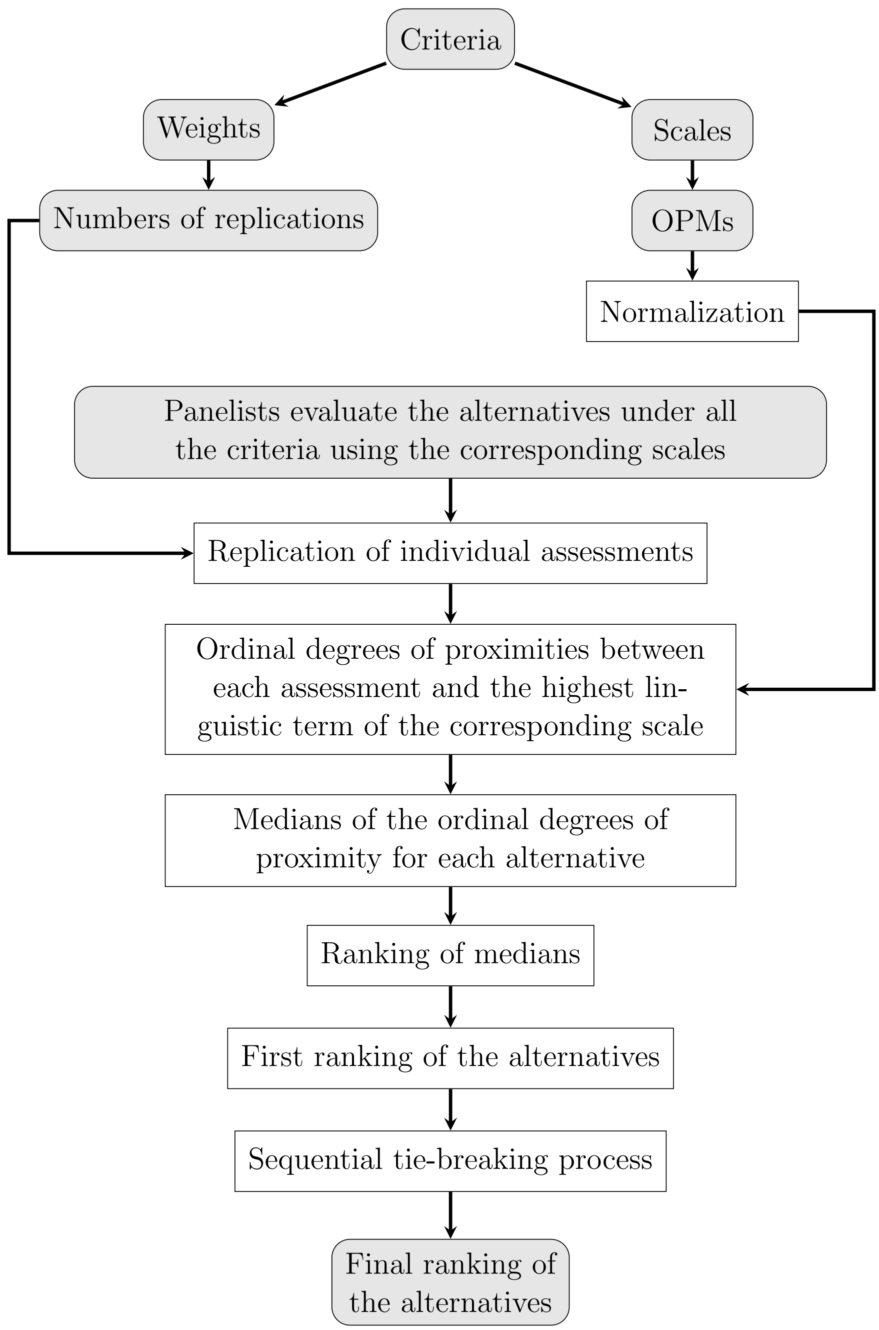

Figure 1: Flowchart of the procedure.

4. Case study

Our case study is based on the Spain's third-largest international exporter in the food and beverage sector who is very well known in FMCG (Fast Moving Consumer Goods) manufacturing industry worldwide. The company has a scientific-technical unit dedicated to Research & Development (R&D), comprised of more than 150 researchers and technologists. Its purpose is to analyze, anticipate, and predict intrinsic consumer needs using the most advanced technologies in order to develop new innovative, healthy, and nutritious drinks internationally. To this end, it specializes in basic research and research related to new product development. In their path to growth, they have focused on monitoring new products performance in international markets. They have exclusive agreements with retailers worldwide by which they collaborate in new product development projects based on the analysis of consumers' needs. Their next challenge in this field, is getting to improve the knowledge of the consumer experience in different contexts, taking into account the lack of prior market performance information inherent to new products in different stages of the customer journey.

To illustrate this challenge, we bring a real and current decision-making case. Nowadays it is very difficult to succeed in new product development. According to Buffoni et al. [4], 50% of new products in the market don't hit their targets, but any company looking to boost revenue growth needs to develop new products. More than 25% of total revenue and profits across industries comes from new product development. This is why the employment of development of validated Key Performance Indicator (KPI) in the market and a rigorous and discriminating analysis of the results, are key for management's decision-making.

Specifically, the company has to make a decision about which type of new product introduces in different markets worldwide. These types of products are: juices with added vitamins, juices 100% natural (nothing added), organic juices, and juices with probiotics. To make the decision on which of the four types of juices to introduce a new product, they set up a questionnaire in which they include questions on, among other variables, four relevant drivers of product purchase: purchase intention, product attraction, uniqueness, and perceived price value.

In addition to their importance in the academic literature, these variables have been chosen because they are used by Kantar Concept eValuate (eValuate is their validated model for testing innovations, see Martin [22]). Purchase intention summarizes the potential of the concept and the other variables (product attractiveness, uniqueness and perceived price value) allow them to determine the reasons for this potential. The platform designed by Kantar enables screening product concepts at each step of the customer journey.

The responses of these four variables are coded in four qualitative categories, two located in the negative end and two located in the positive end. Subsequently, they collect the data through Cint, the world's largest sample exchange platform. It was founded in 1998 in Stockholm and it enables an efficient data collection by seamlessly and rapidly connecting sample buyers to panel owners worldwide. The panel comprises more than 100M registered panelists in more than 150 countries.

Once a frequency analysis of the data has been carried out, the decision to introduce a new product, within one of the four juices types, is made on the basis of the "top 2 tier responses", i.e. the frequencies observed for the first two category responses located at the positive end of the qualitative scale.

On other occasions, the decision of new product development within the company has been made relying on the "top 1 tier response" criterion, i.e. in the frequency observed for the category response located at the first position of the positive end of the qualitative scale. In the decision to expand or reduce the range of the number of categories selected in the positive pole to establish a ranking for a new product development decision, some other external set of variables are taken into account, such as market niche the product is targeted to, consumers' purchasing power within the niche, country culture towards healthy habits, life style, etc. In this paper, we have focused in the real multi-criteria decision-making procedure the company carried out in the case study presented.

4.1. Description

A questionnaire survey was chosen as research method. The questionnaire allowed us to collect many responses in a short period of time using a closed format. Data was collected by the company using Cint consumer panel in Germany, Spain and United Kingdom. The samples were gathered in the time interval from June to August 2020. lt comprises a nationally representative sample of consumers who evaluate the product concepts present to them. Quality control procedures are used to ensure correct panel data capture and panel continuity.

The four alternatives included in Table 5 were assessed regarding the four criteria shown in Table 6 by 2028 panelists (825 in Germany, 800 in Spain and

403 in United Kingdom). Each criterion had a specific OQS formed by four linguistic terms (see Tables 10, 11, 12 and 13).

Alternatives	Meaning
x_1	Juices with added vitamins
x_2	Juices 100% natural (nothing added)
x_3	Organic juices
x_4	Juices with probiotics

Table 5: Alternatives.

Criteria	Meaning
c_1	Purchase intention
c_2	Uniqueness
c_3	Price perception
c_4	Likeability

Table 6: Criteria.

Since the four criteria included in Table 6 may have different importance, we addressed a survey to 26 company managers. They had to evaluate the importance of these criteria through a numerical scale {1, 2, 3, 4, 5}, being 1 and 5 the minimum and the maximum levels of importance, respectively. The number of times that each criterion obtains the numerical terms of the scale is included in Table 7 and, additionally, the corresponding means and medians.

Criteria	1	2	3	4	5	Mean	Median
c_1	0	0	1	2	23	4.846	5
c_2	1	2	6	10	7	3.769	4
c_3	1	1	5	11	8	3.923	4
c_4	0	5	4	10	7	3.730	4

Table 7: Criteria importance.

Taking into account the outcomes of Table 7, a weight is assigned to each criterion in Table 8. For instance, the mean weight of c_1 is $4.846/(4.846+3.769+3.923+3.730) = 0.297$. In turn, the median weight of c_1 is $5/(5+4+4+4) = 0.294$. The final weight for each criterion has been obtained by rounded the corresponding mean weights.

Criteria	Mean weight	Median weight	Rounded weight
c_1	$w_1 = 0.297$	$w_1 = 0.294$	$w_1 = 0.30$
c_2	$w_2 = 0.231$	$w_2 = 0.235$	$w_2 = 0.23$
c_3	$w_3 = 0.241$	$w_3 = 0.235$	$w_3 = 0.24$
c_4	$w_4 = 0.229$	$w_4 = 0.235$	$w_4 = 0.23$

Table 8: Criteria weights.

Thus, the opinions of panelists about the alternatives regarding the criteria c_1, c_2, c_3 and c_4 will be replicated 30, 23, 24 and 23 times, respectively.

The questions addressed to panelists are included in Table 9.

Criteria	Question
c_1	Assuming this product was available at a price that you consider satisfactory, how likely would you be to buy it for you or your household?
c_2	Which of these phrases best describe how new and different you think this product is from other juice products available?
c_3	From what you have seen, how would you expect this product to be priced in comparison to other juice products that are currently available?
c_4	How attractive are these products for you or your household?

Table 9: Questions.

Term	Meaning
l_1^1	I would definitely not buy it
l_2^1	I probably would not buy it
l_3^1	I would probably buy it
l_4^1	I would definitely buy it

Table 10: OQS $\mathcal{L}^1$ used for assessing the purchase intention (criterion c_1).

Term	Meaning
l_1^2	Not at all new and different
l_2^2	Slightly new and different
l_3^2	Very new and different
l_4^2	Extremely new and different

Table 11: OQS $\mathcal{L}^2$ used for assessing uniqueness (criterion c_2).

Term	Meaning
l_1^3	A lot less
l_2^3	Slightly less
l_3^3	Slightly more
l_4^3	Much more

Table 12: OQS $\mathcal{L}^3$ used for assessing price perception (criterion c_3).

Term	Meaning
l_1^4	Dislike it extremely
l_2^4	Dislike it moderately
l_3^4	Like it moderately
l_4^4	Like it extremely

Table 13: OQS $\mathcal{L}^4$ used for assessing likeability (criterion c_4).

The OQSs included in Tables 10, 11, 12 and 13 for evaluating the alternatives (see Table 5) regarding the four criteria (see Table 6) have been equipped with the OPMs associated with the proximity matrices A_{232} and A_{233} in different ways[2]:

[2]The subindices of the matrices A's correspond to the subindices of the δ's appearing in the coefficients just over the main diagonal, π_{12}, π_{23} and π_{34}, i.e., the ordinal degrees of proximity between the pairs of consecutive linguistic terms.

$$A_{232} = \begin{pmatrix} \delta_1 & \delta_2 & \delta_4 & \delta_5 \\ & \delta_1 & \delta_3 & \delta_4 \\ & & \delta_1 & \delta_2 \\ & & & \delta_1 \end{pmatrix}, \quad A_{233} = \begin{pmatrix} \delta_1 & \delta_2 & \delta_4 & \delta_6 \\ & \delta_1 & \delta_3 & \delta_5 \\ & & \delta_1 & \delta_3 \\ & & & \delta_1 \end{pmatrix}.$$

These OPMs can be visualized in Figures 2 and 3.

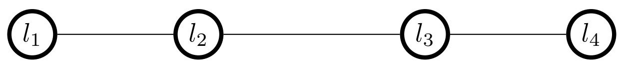

Figure 2: OPM with associated proximity matrix A_{232}.

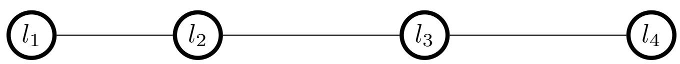

Figure 3: OPM with associated proximity matrix A_{233}.

4.2. Results

Table 14 includes the rankings of the alternatives (see Table 5) in each country when the OQSs of Tables 10, 11, 12 and 13 are equipped with the OPMs with associated proximity matrices appearing in the first four columns.

In the first case, all the OQSs have been equipped with the OPM associated with the proximity matrix A_{232}.

In the second case, the OQS of Table 13 has been equipped with the OPM associated with the proximity matrix A_{233}. The rankings are different to the previous case, but x_2 remains the winning alternative.

In the third case, the OQS of Table 10 has been equipped with the OPM associated with the proximity matrix A_{233}. Again, the rankings are different to the previous cases, and x_2 remains the winning alternative.

In the fourth case, the OQSs of Tables 11 and 13 have been equipped with the OPM associated with the proximity matrix A_{233}. Now the rankings are totally different and x_2 is the third position in all the countries.

We note that Germany and Spain have obtained the same rankings in all the cases.

Based on the procedure“top 2 tier responses”, we have obtained the results included in Table 15.

	$\mathcal{L}^1$	$\mathcal{L}^2$	$\mathcal{L}^3$	$\mathcal{L}^4$	Germany	Spain	United Kingdom
Case 1	A_{232}	A_{232}	A_{232}	A_{232}	x_2	x_2	x_2
					x_3	x_3	x_4
					x_4	x_4	x_1
					x_1	x_1	x_3
Case 2	A_{232}	A_{232}	A_{232}	A_{233}	x_2	x_2	x_2
					x_3	x_3	x_1
					x_1	x_1	x_3
					x_4	x_4	x_4
Case 3	A_{233}	A_{232}	A_{232}	A_{232}	x_2	x_2	x_2
					x_3	x_3	x_4
					x_4	x_4	x_3
					x_1	x_1	x_1
Case 4	A_{232}	A_{233}	A_{232}	A_{233}	x_3	x_3	x_1
					x_1	x_1	x_3
					x_2	x_2	x_2
					x_4	x_4	x_4

Table 14: Results.

Germany	Spain	United Kingdom
x_2	x_2	x_4
x_3	x_3	x_1
x_4	x_4	x_2
x_1	x_1	x_3

Table 15: Top 2 tier results.

Note that similar to the procedure described in this research, the ranking is the same for Spain and Germany, and differs from the ones in United Kingdom. In the case of Germany and Spain, there is a coincidence with cases 1 and 3 presented in Table 14, meanwhile in the case of the United Kingdom it presents a completely different ranking from that of the four cases presented.

It seems clear that following the usual procedure in the company, the decision to develop a new product targeted to German and Spanish consumers, it would be within the category of juices 100% natural (nothing added) (x_2), while in the

United Kingdom it would be a juice within the category of juices with probiotics (x_4).

The novelty in the multi-criteria decision-making procedure based on ordinal proximity measures, provides a wider point of view from the very own perceptions of consumers, thus enriching the contribution of data. Therefore, it is plausible to conjecture that a valid option in relation to decide which new juice develop in Germany and Spain, it could be the one matching case 4, thus introducing a new juice within the category of organic juices (x_3), and within the category of juices with added vitamins (x_1) in the United Kingdom. Moreover, these two products would generate a greater added value to the company than products within the juices 100% natural (nothing added) category (x_2).

Remark 1. The data has been processed through R2017b Matlab language, available in `https://bit.ly/33SL3qG`. Since 2028 panelists evaluated the four alternatives under four criteria and their assessments were replicated 100 times (30, 23, 24 and 23 times in the criteria c_1, c_2, c_3 and c_4, respectively, see Table 8), a total of 811200 data were managed for obtaining the corresponding pairs of medians. The tie-breaking process required additional computations for generating the rankings of alternatives in each of the four cases analyzed (see Table 14).

5. Concluding remarks

In this paper, we have introduced a new multi-criteria procedure to guide the decision-making process for new product development. We have considered that the criteria under which the alternatives are evaluated by the agents have specific OQSs and also that the ordinal proximities between their linguistic terms may be different.

We have provided a normalization procedure for combining assessments coming from several OQSs. This is one of the most important contributions of the paper.

Since the importance of the criteria may be different, a group of experts allocated weights to the criteria based on the importance they perceive regarding the multi-criteria decision-making case. Taking into account the information provided by the experts, we have associated a normalized weight with each criterion within the unit interval. Subsequently, we have considered a procedure that generates the number of replications of the agents' assessments, in each of the criteria, that are necessary to reflect the normalized criteria weights. It is important emphasizing that all the steps of the procedure (see Figure 1) have been managed in a purely ordinal way.

We have relied on a real case carried out by Spain's third-largest international exporter in the food and beverage sector. In the current dynamic context of great uncertainty for companies, and with the aim of adding value to their current and potential consumers, the company resorted to carrying out a market research in order to find out the preferences of German, Spanish and British consumers, in relation to four categories of juice: juices with added vitamins, juices 100% natural (nothing added), organic juices, and juices with probiotics. With the results obtained, the company seeks to better target the introduction of their new juice in these countries.

With this company's objective in mind, which inherently implies establishing a ranking of the different categories of juices, we consider there are plentiful differences between the multi-criteria decision-making procedure presented in this paper and the decision-making procedure employed by the company, known as "top 2 tier responses" procedure. The latter procedure uses fewer steps to establish a final ranking of alternatives and the method used to establish the ranking from the consumers' responses, is based on a very basic statistics, avoiding valuable information, that nevertheless our novel procedure does integrate. And that is where the importance lies now the company can choose between one procedure or another. Using our procedure, different rankings on the set of alternatives can be reached, depending on the OPMs we associate to the OQSs, which leads to a more refined solution. While by using the "top 2 tier responses" procedure, we arrive to a single case, in which no other possibilities are even considered, due in part to the simplicity of this procedure.

By proposing this new procedure to multi-criteria decision-making applied in this case, we have opened the spectrum of choices when it comes to establishing a ranking of alternatives based on consumers' preferences. The critical importance of this ranking of alternatives stems from being a key valuable resource used by managers, among other internal and external analysis, to produce the final new product development decision. We thus have dig out new scenarios which matches more accurately the company offerings with consumer's needs. Ultimately, we have risen a better multi-criteria procedure to new product development.

These findings, however, needs further exploration in business and management cases.

Also as stated before, in Section 4, we have equipped the OQSs (used for assessing the alternatives regarding the corresponding criteria) with specific OPMs. Obviously, other OPMs could be considered. We note that different perceptions about an OQS can be aggregated in order to obtain an OPM that represents those perceptions in a global way. This can be done following the mechanism provided by García-Lapresta et al. [9, Sect. 4].

Sometimes panelists may hesitate on which linguistic term best fits their opinions. In these situations, the procedure provided by García-Lapresta and González del Pozo [8] can be applied.

In this paper, we have considered that the opinions of all panelists have the same importance. It is possible to extend the procedure to a scenario where panelists may have different expertise. Franceschini and García-Lapresta [6] provide three paradigms to deal with that problem.

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