A Self-regulating Information Acquisition Algorithm for Preventing Choice Regret in Multi-perspective Decision Making

A novel information acquisition algorithm based on the value that information has when preventing a decision maker from regretting his or her current decision. In a self-regulation mechanism, the model accounts for different risk attitudes and the ability to assess projects or products defined by multiple characteristics.

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1 Introduction

Information is an essential input into any decision process. For example, there is evidence of a positive correlation between business performance and the practice of decision-making (Mackie et al. 2007). Moreover, the quantity and quality of information available to DMs in business organizations is correlated with the quality of their decisions (O'Reilly 1982). In this regard, many project managers tend to believe that their decision-making capabilities are above average (Massey et al. 2006), and as a result do not consider improving their quality (Goodwin and Wright 2004). This attitude affects their criteria when acquiring information and may potentially result in wrong judgments that could have been prevented. At the managerial level, the acquisition of information is a strategic process that must be shared between managers and information specialists to be fully exploited (Xianzhong et al. 2002). In this sense, managers with access to large amounts of information must become selective in favor of the information they consider to be most useful (Mintzberg 1978; Williams et al. 2009).

1.1 Motivation

The value assigned to a piece of information by a decision maker (DM) as well as its effect on the resulting information acquisition and decision processes differ significantly among the branches of the academic literature dealing with sequential search structures. Economists (Ponssard 1976), operational researchers (Medhurst et al. 2009; Bakir and Klutke 2011) and psychologists (Schepanski and Uecker 1984; Kahneman and Tversky 2000) each adapt the concept of value of information to their respective environments and define it according to their particular needs. Most of these approaches concentrate on the systemic differences arising from variations in the amount of information provided.

Finally, following (Lancaster 1966), choice objects on which information is acquired should be defined by multiple characteristics that must be considered by the DM before deciding whether or not to shift from one object to another. The information acquisition process should therefore be defined through a sequential algorithmic structure, a point already recognized by economists and operational researchers (McCall and McCall 2007; Ulu and Smith 2009; Smith and Ulu 2012). However, these disciplines tend to concentrate on the importance of search costs in the information acquisition process of DMs while dealing with objects defined by a unique characteristic. As a result, their focus on information acquisition costs leaves aside the strategic interactions that may arise from multidimensional settings, such as the display of product characteristics based on the incentives resulting from the information acquisition process of DMs.

The approach followed in the current paper considers the properties of the information acquisition process outlined above, where DMs value information insomuch as it prevents them from making a suboptimal choice that they may regret afterwards.

1.2 Contribution

The current paper derives the optimal information acquisition strategy of a DM in a setting where the decision regret is minimized when acquiring information sequentially from a set of products defined by multiple characteristics. We introduce a new idea of value of information that relates to the regret that may arise from the potential choices made by a DM. Information will be considered valuable if it prevents the DM from making the choice that she would be willing to make given her current available information. This regret-based definition of value of information will provide the dynamic incentives for the DM to both acquire additional information and stop acquiring it when its potential value is exhausted.

The current regret-based approach differs from that of the literature with respect to the Value of Information concept in information acquisition environments, where the value of information is defined as the difference between the expected value of the best alternative based on the information available and the expected value of the best alternative after acquiring additional information and using a Bayesian approach to update the corresponding probability distributions (Delquie 2008; Frazier and Powell 2010; Vilkkumaa et al. 2014). This standard concept and the resulting framework are applicable as an extension of an alternative version of the current information acquisition environment where signals and Bayesian updating processes are allowed on behalf of the DMs, who are however constrained in the number of observations that they may acquire (Di Caprio et al. 2013).

We assume that DMs try to prevent regretting a choice before actually making it and information becomes therefore valuable when it serves this purpose, i.e., DMs try to anticipate regret when making sequential decisions (Sarangee et al. 2013). In this regard, a DM may not only regret a choice if a better object could be immediately found but also if she accepts [rejects] the current object when it should actually be rejected [accepted]. As a result, the DMs modeled in this paper look forward before making a choice, which is always compared to the potential choices that follow from the next piece of information.

We emphasize the importance of the multidimensional aspect of the choice objects while ignoring information acquisition costs when analyzing the sequential search process that is derived from our definitions of value of information and regret.

Since no information acquisition costs are assumed, it seems natural to ask whether there is a limit to the quantity of information acquired by DMs. Given that economists and operational researchers tend to consider mainly risk-neutral DMs, how is this limit affected by the risk attitudes of the DMs? Given the multiple characteristics defining an object, how does the information already acquired on a given object affect the subsequent behavior of the DMs? If there are endogenous incentives to stop acquiring information at some point, then there must exist some incentive for the information senders to be observed as soon as possible by the DMs. This is particularly true when analyzing sequential information acquisition processes in an online environment, characterized by very low information acquisition costs but with a large amount of information available (Carr 2011). Thus, some kind of queuing mechanism should follow from our analysis.

We show that DMs have an incentive to continue acquiring information until observing an object whose choice cannot be reversed, a situation that may only take place for sufficiently high values of the characteristics observed. If the characteristics observed from a given object have consistently low values, DMs will at some point have an incentive to start acquiring information on a new object. Moreover, whenever faced with the choice between acquiring information on any of the objects previously observed and abandoning or starting with a new one, DMs will always choose the latter option.

The information acquisition structure that results from our model is similar to the one defining the information acquisition and decision algorithms employed by the operational research literature (Shepherd and Levesque 2002; Ulu and Smith 2009). However, the current algorithm presents significant differences with respect to this branch of the literature. More precisely, we do not need to impose information acquisition costs or limited memory capacity constraints in order for DMs to stop the search process at a given point in time or discard the objects previously observed. In our setting, DMs stop acquiring information after observing an object whose characteristics provide a utility such that the choice of this object cannot be reversed by a new observation on either the same object or a new one.

The remainder of the paper is organized in two parts. The first part, composed by Sects. 2 to 5, provides a formal analysis characterizing our information acquisition structure. The second part, consisting of Sect. 6, presents several numerical illustrations of the main formal results. Section 7 concludes and suggests possible extensions.

2 Main Assumptions

The notations and initial assumptions we refer to when constructing our model build on those of Di Caprio and Santos-Arteaga (2009). However, for the sake of completeness, this section partially reproduces some formal definitions and related comments already described in Sect. 2 (Preliminaries and basic notations) and Sect. 3 (Main assumptions) of Di Caprio and Santos-Arteaga (2009).

Let Γ denote the set of all choice objects (projects or products). The generic element of Γ will be denoted by G_k. Each object G_k will be represented by a finite tuple of $n \geq 2$ characteristics, that is, $(x_1^k \ldots, x_n^k)$. For every $i \leq n$, X_i denotes the set of all possible values for the i-th characteristic x_i^k of the generic object G_k.

Definition 2.1 For every $i \leq n$, X_i will be called the i-th characteristic factor. The Cartesian product $X = \prod_{i \leq n} X_i$ will be referred to as the *characteristic space*.

We assume that the enumeration of the factor spaces reflects the order of preference assigned by the DM. That is, the first characteristic is preferred by the DM to the second characteristic, while the second characteristic is preferred to the third characteristic, and so on.

Recall that (Mas-Colell et al. 1995) a *preference relation* on a nonempty set A is a binary relation on A satisfying reflexivity, completeness and transitivity, and it is said to be representable by a *utility function* if there exists a real-valued order-preserving function from A to $\Re$.

Assumption 1 For every $i \leq n$, X_i is a compact real interval of the form $[\alpha_i, \omega_i]$, the preference relation on X_i is the standard linear order $>$ of $\Re$, and $u_i : X_i \to \Re$ is a bounded continuous utility function on X_i, that is,

$$\forall x_i,\ y_i \in X_i \quad \text{with } x_i \neq y_i \\ x_i > y_i \quad \Leftrightarrow \quad u_i(x_i) > u_i(y_i) \tag{1}$$

Assumption 2 X is endowed with the additive preference relation $\succsim$ defined as follows:

$$(x_1, \ldots, x_n) \succsim (y_1, \ldots, y_n) \\ \overset{def}{\Leftrightarrow} \quad \sum_{i \leq n} u_i(x_i) \geq \sum_{i \leq n} u_i(y_i) \tag{2}$$

For more on additive preference relations see Wakker (1989).

Note that the preference relation $\succsim$ is not strict. Indeed, two different tuples of characteristics, $(x_1, \ldots, x_n)$ and $(y_1, \ldots, y_n)$, may deliver the same utility even if each u_i is strictly increasing.

Further, we assume the DM to be endowed with a subjective probability (density) function over each characteristic factor X_i (each X_i can be considered a random variable).

Assumption 3 For every $i \leq n$, $\mu_i : X_i \to [0, 1]$ is a non-atomic probability density function if X_i is absolutely continuous, and a non-degenerate probability function if X_i is discrete.

For every $i \leq n$, we will denote by E_i the expected value of $u_i(x_i)$, where x_i is the realization from a random variable X_i endowed with a probability function μ_i, that is:

$$E_i = \begin{cases} \int_{X_i} \mu_i(x_i) u_i(x_i) dx_i \\ \quad \text{if } X_i \text{ is absolutely continuous} \\ \sum_{x_i \in X_i} \mu_i(x_i) u_i(x_i) \\ \quad \text{if } X_i \text{ is discrete} \end{cases} \tag{3}$$

The functions $\mu_1, \ldots, \mu_n$ represent the subjective "beliefs" of the DM. That is, given $i \leq n$ and $Y_i \subseteq X_i$, $\mu_i(Y_i)$ is the subjective probability that a randomly observed object from Γ displays an element of Y_i as its i-th characteristic.

Definition 2.2 (Mas-Colell et al. 1995) Let $i \leq n$. The *certainty equivalent of* μ_i *and* u_i, denoted by c_i, is a characteristic in X_i that the DM is indifferent to accept in place of the expected one to be obtained through μ_i and u_i. That is, c_i is an element of X_i whose utility $u_i(c_i)$ equals the expected value E_i.

Since each u_i has been assumed strictly increasing and continuous on X_i, c_i is the unique element of X_i such that is, $c_i = u_i^{-1}(E_i)$. Any object *randomly chosen* from Γ can be described by $(c_1, c_2, \ldots, c_n)$. Thus, if a list of known characteristics $(x_1, x_2, \ldots, x_i)$, where $i \leq n$, delivers a higher [lower] utility than the corresponding list of certainty equivalent values $(c_1, c_2, \ldots, c_i)$, the DM prefers the object defined by the former list to a randomly chosen one (a randomly chosen object to the one defined by the former list).

Assumption 4 The DM is allowed to collect a maximum of θ observations, with $\theta \geq 2$.

We analyze the sequential information acquisition behavior of a DM based on the following criteria:

- after retrieving a given observation, the DM decides whether to continue acquiring information on the same object or shifting to a different one;
- the DM does not acquire any further information on an object after shifting to a different one;
- the objects on which the DM stops acquiring information are not in the final choice set.

Without loss of generality, we can assume the enumeration of the objects in Γ to coincide with the order in which the DM observes the objects through the information acquisition process.

3 Sequential Information Acquisition

Suppose that, after having checked $q - 1$ pieces of information out of the θ allowed, the DM is in the situation represented in **Fig. 1**. That is, the DM has checked the first m_1 characteristics of G_1, then the first m_2 characteristics of G_2, and so on until the first m_k characteristics of G_k. In particular, we have $q - 1 = \sum_{i=1}^{k} m_i$.

If $\theta = q - 1 = \sum_{i=1}^{k} m_i$, that is, if the DM exhausts the amount of information available to collect, then the DM has no other option than stopping:

- $Opt(STOP)$ = "DM stops collecting information".

If $\theta > q - 1 = \sum_{i=1}^{k} m_i$, then the following two cases are possible.

(**a**) **Suppose** that $n = m_k$, that is, all the characteristics of object G_k have been observed by the DM. The DM can either stop or check the value of the first characteristic of object G_{k_1+1} (hence, *start with the next object*):

- $Opt(STOP)$ = "DM stops collecting information".
- $Opt(G_{k+1}; 1)$ = "DM checks the value of the 1-st characteristic of G_{k+1}".

(**b**) **Suppose** that $n > m_k$, that is, there are more characteristics of object G_k to check. The DM can check either the value of the next characteristic of G_k (hence, *continue with the same object*) or the value of the first characteristic of G_{k+1} (hence, *start with the next object*):

- $Opt(G_k; m_k + 1)$ = "DM checks the value of the $(m_k + 1)$-th characteristic of G_k".
- $Opt(G_{k+1}; 1)$ = "DM checks the value of the 1-st characteristic of G_{k+1}".

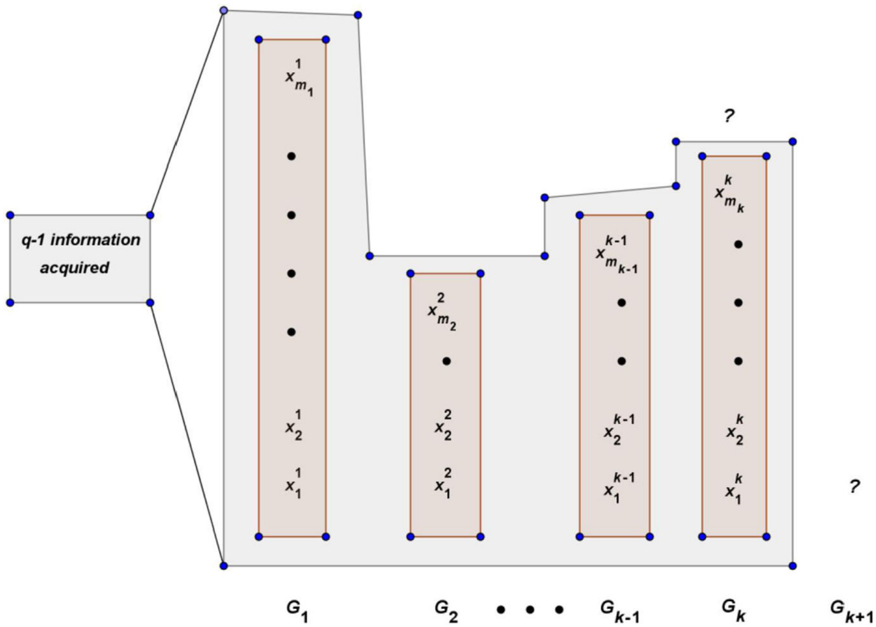
As a consequence, we need to define a suitable rule/criterion allowing the DM to decide between $Opt(STOP)$ and $Opt(G_{k+1}; 1)$ or between $Opt(G_k; m_k + 1)$ and $Opt(G_{k+1}; 1)$.

Figure 2 shows the options the DM is presented with in the case when $\theta = 5$ and $n = 2$.

4 Value of Information

The criterion we define to be followed by the DM when deciding how to proceed through the information acquisition process is based on the concepts of value of information and choice regret. Intuitively, acquiring information on a given object will be assumed to be valuable if the potential choice expected to be made by the DM is reversed after the next observation is acquired. Consequently, we are assuming that information has an expected value in itself, this value being

Fig. 1 Possible scenario faced by the DM after $q-1=\sum_{i=1}^{k} m_i$ observations have been acquired



strictly related to a non-regrettable choice induced by it.

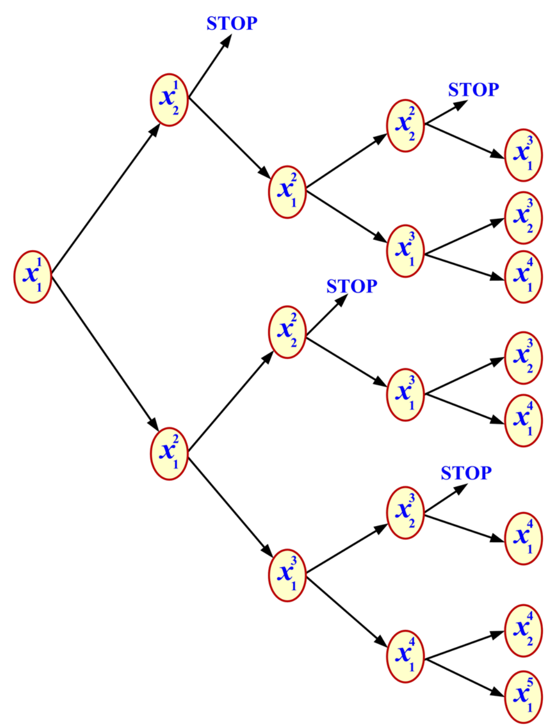
Assumption 5 Information is valuable if it induces a reversal in the DM's potential final choice.

Therefore, the information to be acquired at each step of the algorithm is the one providing the DM with the highest expected value derived from reversing the final choice she would make otherwise. Note that, should the information exhaust its value, the DM has the option to stop acquiring information.

More precisely, suppose again that the DM has collected $q-1=\sum_{i=1}^{k} m_i$ observations and finds herself in the situation represented by **Fig. 1**.

- Assume $\sum_{i=1}^{m_k} u_i(\alpha_i) \leq \sum_{i=1}^{m_k} u_i(x_i^k) < \sum_{i=1}^{m_k} E_i$, where α_i is the minimum value of X_i. If an additional piece of information cannot be acquired, the DM would choose any object in Γ randomly. Suppose that an additional piece of information can be acquired. In order for this information to have some value, the DM would have to consider either G_k or G_{k+1} as potential final choices instead of a random object. For this to be the case, either the (m_k+1)-th characteristic $x_{m_k+1}^k$ of G_k should be such that $\sum_{i=1}^{m_k+1} u_i(x_i^k) > \sum_{i=1}^{m_k+1} E_i$ or the first characteristic x_1^{k+1} of G_{k+1} should be such that $u_1(x_1^{k+1}) > E_1$.
- Assume $\sum_{i=1}^{m_k} E_i \leq \sum_{i=1}^{m_k} u_i(x_i^k) < \sum_{i=1}^{m_k} u_i(\omega_i)$, where ω_i is the maximum value of X_i. If an additional piece of information cannot be acquired, the DM would choose G_k. Suppose that an additional piece of information can be acquired. In order for this information to have a value, the DM would have to consider either a random object or G_{k+1} as potential final choices instead of G_k. For this to be the case, either the (m_k+1)-th characteristic $x_{m_k+1}^k$ of G_k should be such that $\sum_{i=1}^{m_k+1} u_i(x_i^k) < \sum_{i=1}^{m_k+1} E_i$ or the first characteristic x_1^{k+1} of G_{k+1} should be such that $u_1(x_1^{k+1}) + \sum_{i=2}^{m_k} E_i > \sum_{i=1}^{m_k} u_i(x_i^k)$.
- Assume $\sum_{i=1}^{m_k} u_i(x_i^k) = \sum_{i=1}^{m_k} u_i(\omega_i)$. If an additional piece of information cannot be acquired, the DM would choose G_k. Suppose that an additional piece of information can be acquired. In this case, the first characteristic x_1^{k+1} of G_{k+1} cannot satisfy $u_1(x_1^{k+1}) + \sum_{i=2}^{m_k} E_i > \sum_{i=1}^{m_k} u_i(x_i^k)$. Hence, the new information has some value only

Fig. 2 Potential information acquisition paths for the DM when $\theta = 5$ and $n = 2$



if the (m_k+1)-th characteristic $x^k_{m_k+1}$ of G_k is such that $\sum_{i=1}^{m_k+1} u_i(x_i^k) < \sum_{i=1}^{m_k+1} E_i$. If this happens, the potential final choice considered by the DM would be represented by a random object instead of G_k.

The above reasoning leads to the following novel definition of valuable information.

Definition 4.1 Suppose that after acquiring $q-1$ pieces of information, the DM has reached object G_k and knows the values of its first m_k characteristics, $x_1^k, \ldots, x_{m_k}^k$ (refer to **Fig. 1**). *The value of continuing acquiring information* on G_k, that is, the value of acquiring $x^k_{m_k+1}$ given that $x_1^k, \ldots, x_{m_k}^k$ are known, is defined as follows:

$$val\big(x^k_{m_k+1}|x_1^k,\ldots,x^k_{m_k}\big) = \begin{cases} \max\{0, \sum_{i=1}^{m_k+1} u_i(x_i^k) - \sum_{i=1}^{m_k+1} E_i\} \\ \quad \text{if } \sum_{i=1}^{m_k} u_i(\alpha_i) \le \sum_{i=1}^{m_k} u_i(x_i^k) \\ \qquad < \sum_{i=1}^{m_k} E_i \\ \max\{0, \sum_{i=1}^{m_k+1} E_i - \sum_{i=1}^{m_k+1} u_i(x_i^k)\} \\ \quad \text{if } \sum_{i=1}^{m_k} E_i \le \sum_{i=1}^{m_k} u_i(x_i^k) \\ \qquad \le \sum_{i=1}^{m_k} u_i(\omega_i) \end{cases} \tag{4}$$

The value of starting acquiring information on G_{k+1}, that is, the value of acquiring x_1^{k+1} given that $x_1^k, \ldots, x^k_{m_k}$, are known, is defined as follows:

$$val\big(x_1^{k+1}|x_1^k,\ldots,x^k_{m_k}\big) = \begin{cases} \max\{0, u_1(x_1^{k+1}) - E_1\} \\ \quad \text{if } \sum_{i=1}^{m_k} u_i(\alpha_i) \le \sum_{i=1}^{m_k} u_i(x_i^k) \\ \qquad < \sum_{i=1}^{m_k} E_i \\ \max\{0, u_1(x_1^{k+1}) + \sum_{i=2}^{m_k} E_i \\ \qquad - \sum_{i=1}^{m_k} u_i(x_i^k)\} \\ \quad \text{if } \sum_{i=1}^{m_k} E_i \le \sum_{i=1}^{m_k} u_i(x_i^k) \\ \qquad < \sum_{i=1}^{m_k} u_i(\omega_i) \\ 0 \quad \text{if } \sum_{i=1}^{m_k} u_i(x_i^k) \\ \qquad = \sum_{i=1}^{m_k} u_i(\omega_i) \end{cases} \tag{5}$$

The next definition introduces two subsets (one of X_{m_k+1} and one of X_1) consisting of valuable information for the DM, that is, information whose value, in the sense of Definition 4.1, is positive.

Definition 4.2 Suppose that after acquiring $q-1$ pieces of information, the DM has reached object G_k and knows the values of its first m_k characteristics, $x_1^k, \ldots, x_{m_k}^k$ (refer to **Fig. 1**). Let

$$CT\big(x_1^k,\ldots,x^k_{m_k}\big) = \big\{x_{m_k+1} \in X_{m_k+1}: val(x_{m_k+1}|x_1^k,\ldots,x^k_{m_k}) > 0\big\} \tag{6}$$

and

$$ST\big(x_1^k,\ldots,x^k_{m_k}\big) = \big\{x_1 \in X_1 : val\big(x_1|x_1^k,\ldots,x^k_{m_k}\big) > 0\big\}. \tag{7}$$

By (4), it follows that:

$$CT\big(x_1^k,\ldots,x^k_{m_k}\big) = \begin{cases} (A, \omega_{m_k+1}] \\ \quad \text{if } \sum_{i=1}^{m_k} u_i(\alpha_i) \le \sum_{i=1}^{m_k} u_i(x_i^k) \\ \qquad < \sum_{i=1}^{m_k} E_i \\ [\alpha_{m_k+1}, A) \\ \quad \text{if } \sum_{i=1}^{m_k} E_i \le \sum_{i=1}^{m_k} u_i(x_i^k) \\ \qquad < \sum_{i=1}^{m_k} u_i(\omega_i) \end{cases} \tag{8}$$

where A is the value that the next characteristic of G_k should take to satisfy $u_{m_k+1}(A) + \sum_{i=1}^{m_k} u_i(x_i^k) = \sum_{i=1}^{m_k+1} E_i$. Similarly, (5) implies that:

$$ST\big(x_1^k,\ldots,x^k_{m_k}\big) = (B, \omega_1] \tag{9}$$

where B is the value that the first characteristic of the next object G_{k+1} should take to satisfy

$$u_1(B) + \sum_{i=2}^{m_k} E_i = \max\left\{\sum_{i=1}^{m} u_i\big(x_i^k\big), \sum_{i=1}^{m_k} E_i\right\}$$

5 Implementing Valuable Information

In order to model the behavior of the DM at a generic step of the algorithm, we need to define suitable functions expressing the expected value of the information still to be acquired.

Suppose that $q-1$ characteristics have been checked and that the DM is in the situation described in **Fig. 1**. If $\theta = q-1$, the DM must stop collecting information. If $\theta > q-1$, there are two possibilities: either $n > m_k$ or $n = m_k$.

Suppose: $n > m_k$. Then, DM needs a criterion to compare $Opt(G_k; m_k+1)$ with $Opt(G_{k+1}; 1)$.

Following Assumption 5 and Definitions 4.1 and 4.2, we propose the following definition for the expected value derived from continuing to check G_k, that is, collecting $x^k_{m_k+1}$ as the q-th piece of information.

$$EV_{CT}\big(G_k|x_1^k, x_2^k,\ldots,x^k_{m_k}\big) = \int_{CT(x_1^k,x_2^k,\ldots,x^k_{m_k})} \mu_{m_k+1}(x_{m_k+1}) \times val\big(x_{m_k+1}|x_1^k,x_2^k,\ldots,x^k_{m_k}\big) \times dx_{m_k+1} \tag{10}$$

Similarly, the expected value derived from starting to check G_{k+1} , that is, collecting x_1^{k+1} as the q-th piece of information, is defined as follows:

$$EV_{ST}\big(G_{k+1}|x_1^k, x_2^k,\ldots,x^k_{m_k}\big) = \int_{ST(x_1^k,x_2^k,\ldots,x^k_{m_k})} \mu_1(x_1) \times val\big(x_1|x_1^k,x_2^k,\ldots,x^k_{m_k}\big)dx_1 \tag{11}$$

Therefore, the following criterion can be applied.

Criterion (when $n > m_k$). Acquiring $x^k_{m_k+1}$ is more valuable than acquiring x_1^{k+1} if and only if $EV_{CT}(G_k|x_1^k, x_2^k, \ldots, x^k_{m_k}) \ge EV_{ST}(G_{k+1}|x_1^k, x_2^k, \ldots, x^k_{m_k})$.

Note that this criterion assumes that, whenever $EV_{CT}(G_k|x_1^k, x_2^k, \ldots, x^k_{m_k}) = EV_{ST}(G_{k+1}|x_1^k, x_2^k, \ldots, x^k_{m_k})$, the DM prefers by default to remain acquiring information on the object at hand. Intuitively, this can be justified by assuming an infinitesimal but positive disutility faced by the DM when switching between objects while being indifferent with respect to information values.

Suppose: $n > m_k$. Then, DM needs a criterion to compare $Opt(STOP)$ with $Opt(G_{k+1}; 1)$.

The expected value derived from collecting x_1^{k+1} is still given by $EV_{ST}(G_{k+1}|$

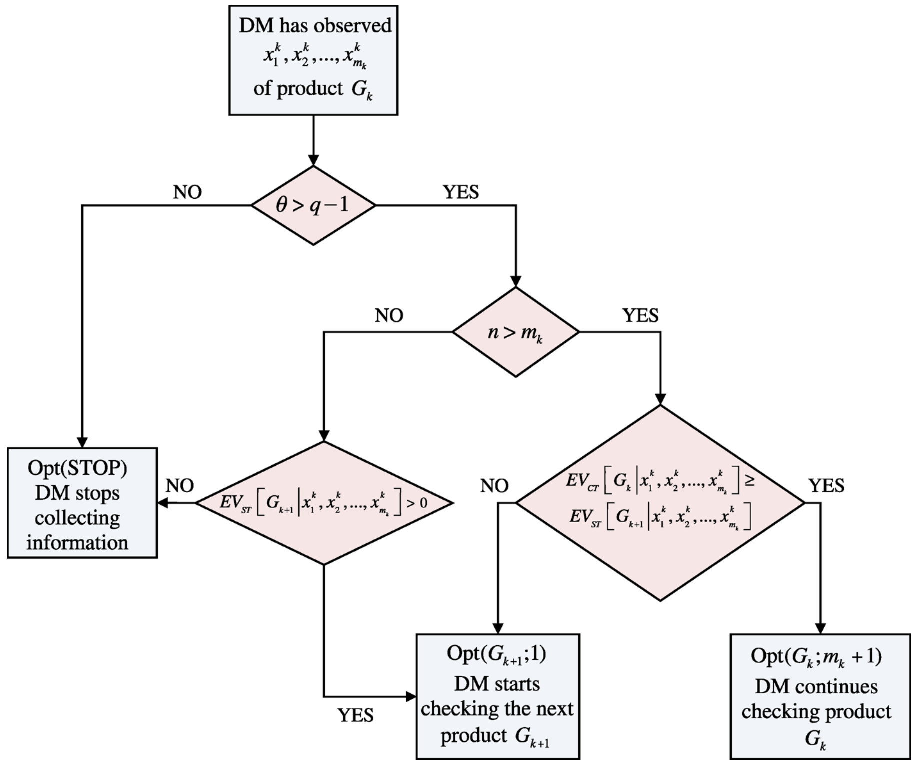


Fig. 3 Decision criteria after $q-1=\sum_{i=1}^{k} m_i$ observations have been collected

$x_1^k, x_2^k, \ldots, x_{m_k}^k$), but this time this value must be compared with the value zero. Indeed, if there are no more characteristics to check from object G_k, then $Opt(STOP)$ does not have value in terms of new information. At the same time, $EV_{ST}(G_{k+1}|x_1^k, x_2^k, \ldots, x_{m_k}^k)$ is either positive or zero depending on whether the new information acquired adds value or not. Hence, $Opt(G_{k+1};1)$ turns out to be preferable to $Opt(STOP)$ if and only if $EV_{ST}(G_{k+1}|x_1^k, x_2^k, \ldots, x_{m_k}^k) > 0$.

Therefore, the following criterion can be applied.

Criterion (when $n = m_k$). Acquiring x_1^{k+1} is more valuable than stopping if and only if $EV_{ST}(G_{k+1}|x_1^k, x_2^k, \ldots, x_{m_k}^k) > 0$. Equivalently, the stopping option is chosen over starting to check G_{k+1} if and only if $EV_{ST}(G_{k+1}|x_1^k, x_2^k, \ldots, x_{m_k}^k) = 0$.

The criteria obtained above can be schematized as follows.

Decision Criteria after $q-1=\sum_{i=1}^{k} m_i$ observations have been collected:
DM has observed the first m_k characteristics of G_k, that is, $x_1^k, x_2^k, \ldots, x_{m_k}^k$.
If $\theta = q-1$:
$Opt(STOP)$
If $\theta > q-1$ and $n = m_k$:

- *Aim*:
  Deciding whether obtaining x_1^{k+1} is still valuable compared to stopping.
- *Criterion*:
  $Opt(STOP)$ is chosen over $Opt(G_{k+1};1) \Leftrightarrow EV_{ST}(G_{k+1}|x_1^k, x_2^k, \ldots, x_{m_k}^k) = 0$.

If $\theta > q-1$ and $n > m_k$:

- *Aim*:
  Deciding which information is more valuable to obtain between $x_{m_k+1}^k$ and x_1^{k+1}.
- *Criterion*:
  $Opt(G_k;m_k+1)$ is chosen over $Opt(G_{k+1};1) \Leftrightarrow EV_{CT}(G_k|x_1^k, x_2^k, \ldots, x_{m_k}^k) \geq EV_{ST}(G_{k+1}|x_1^k, x_2^k, \ldots, x_{m_k}^k)$.

The flowchart illustrated in **Fig. 3** provides a graphical description of this generic step of the algorithm.

6 Numerical Simulations

We introduce several numerical simulations that illustrate the behavior followed by the DM when considering the expected value of information as the mechanism defining her information acquisition process. We consider objects defined by tuples of four characteristics distributed uniformly over their respective domains. The numerical domains on which the characteristics of an object are defined have been chosen to describe increments in the expected utility received by the DM as functions of the spread of their probability functions. That is, the first characteristic will be uniformly distributed over $X_1=[15,20]$, the second one over $X_2=[10,20]$, the third one over $X_3=[5,20]$ and the fourth one over $X_4=[0,20]$. Thus, preferred characteristics lead to higher expected values and their domains are contained within those of the less preferred characteristics while sharing the upper limit. Assuming uniform probability functions on the factor spaces X_i provides a suitable approach in terms of maximal information entropy to the complete uncertainty faced by DMs (Srikanth et al. 2003, p. 240).

In all the figures introduced through this section, the horizontal axis describes realizations of the corresponding x_i^1, $i=1,2,3$, while the vertical one accounts for the expected value obtained from acquiring an additional piece of information. Clearly, we are assuming that the DM starts acquiring information on the first object G_1. Finally, in order to make the figures more tractable, we will use a simplified version of the notation introduced in the body of the paper. The sub-indexes CT and ST will be omitted and further notational changes will be described as we introduce them.

6.1 Acquiring the Second Observation

We start by analyzing the acquisition of the second piece of information. This case is presented in **Fig. 4**. As already stated, the first and second characteristics are uniformly defined on the intervals $X_1 = [15, 20]$ and $X_2 = [10, 20]$, respectively. Thus, the expected utility values are $E_1 = 17.5$ and $E_2 = 15$, which coincide with the respective certainty equivalents within the risk-neutral setting, where $u_i(x_i) = x_i$.

As described in Sect. 5, $EV(G_1|x_1^1)$ represents the expected value derived from continuing with G_1 and collecting x_2^1 as the second piece of information. $EV(G_1|x_1^1)$ is defined by two functions determined by the value of c_1, which are denoted by $EV(G_1|x_1^1 < c_1)$ and $EV(G_1|x_1^1 \geq c_1)$. Note that $EV(G_1|x_1^1)$ attains the highest value at c_1, since the certainty equivalent allows for the widest variability in terms of the potential realizations of the characteristics of the object being observed. The value of information, in the sense of Definition 4.1, decreases progressively when moving away from c_1 through realizations located either above or below the certainty equivalent value.

$EV(G_2|x_1^1)$ represents the expected value derived from starting with G_2 and collecting x_1^2 as the second piece of information. $EV(G_2|x_1^1)$ follows a logic similar to $EV(G_1|x_1^1)$ in terms of reference points but its behavior is clearly different from that of $EV(G_1|x_1^1)$. Realizations below c_1 provide a constant value of information based on expected improvements upon the certainty equivalent. This part of the function is denoted by $EV(G_2|x_1^1 < c_1)$. At the same time, as the realizations of x_1^1 exceed c_1, the value derived from starting acquiring information on a new object decreases, since this new object becomes progressively less probable to be improved upon. This part of the function is denoted by $EV(G_2|x_1^1 \geq c_1)$.

The graphs of the functions $EV(G_1|x_1^1)$ and $EV(G_2|x_1^1)$, and their possible crossing points, determine *continuation intervals* and *starting intervals*, that is, subintervals of X_1 where the former graph is respectively above or below that of the latter one. Thus, the DM has an incentive to continue acquiring information on the object observed for realizations of x_1^1 belonging to the interval [16.0355, 20], see **Table 1**. This will tend to bias the information acquisition process of the DM towards the first object observed.

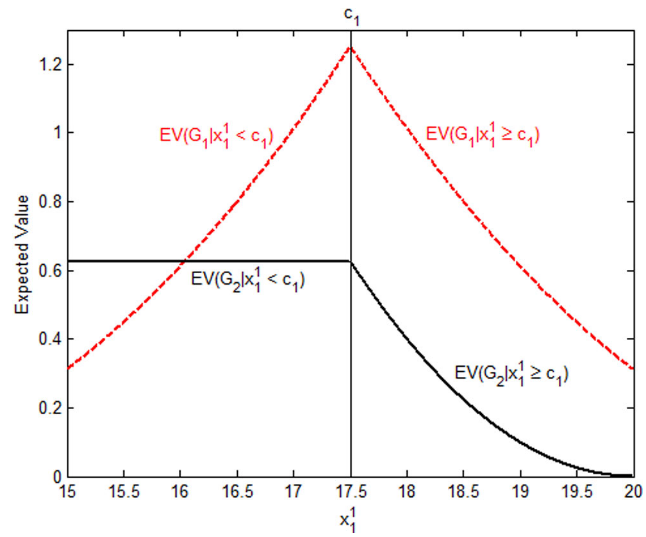


Fig. 4 Acquiring the second observation under uniformity and risk-neutrality

Table 1 Crossing values: risk-neutral case, $u_i(x_i) = x_i$

Second observation	Third observation		Fourth observation			
16.0355	$x_1^1 = 16$	$x_1^1 = 19$	$x_1^1 = 16$	$x_1^1 = 16$	$x_1^1 = 19$	$x_1^1 = 19$
	13.3301	10.3301	$x_2^1 = 12$	$x_2^1 = 18$	$x_2^1 = 12$	$x_2^1 = 18$
			12	6	9	No cut

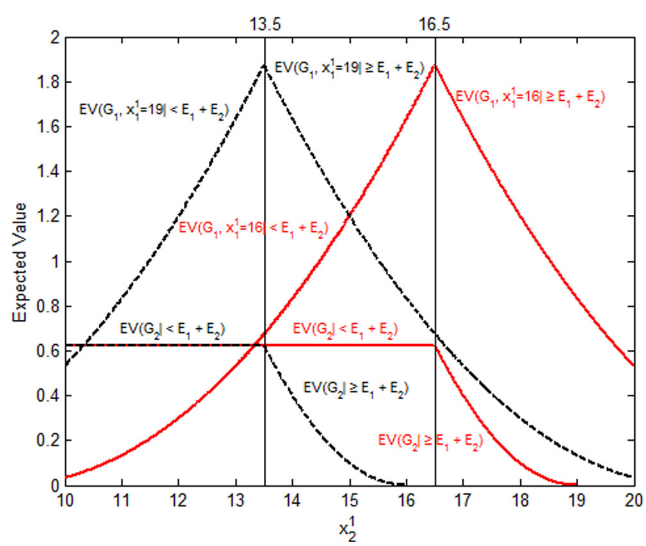


Fig. 5 Acquiring the third observation under uniformity and risk-neutrality

6.2 Acquiring the Third Observation

Figure 5 describes the information acquisition incentives of the DM after having already observed two characteristics from the first object, i.e. x_1^1 and x_2^1. We take the value of the first characteristic x_1^1 as given and analyze two cases: $x_1^1 = 16$ and $x_1^1 = 19$. The first value is below c_1 while the second is above c_1. **Figure 5** illustrates the expected information value for all possible realizations of x_2^1 when combined with the fixed value of x_1^1. The red functions correspond to the case where $x_1^1 = 16$ while the black ones to the case where $x_1^1 = 19$.

Since $E_1 = 17.5$ and $E_2 = 15$, we have $E_1 + E_2 = 32.5$. Thus, when $x_1^1 = 16$

[resp. $x_1^1 = 19$], for the sum of the utilities of both realizations to equate $E_1 + E_2$, the value of the second characteristic must be 16.5 [resp. 13.5]. Consequently, the value $x_2^1 = 16.5$ [resp. $x_2^1 = 13.5$] is the value at which $EV(G_1|x_1^1, x_2^1)$ and $EV(G_2|x_1^1, x_2^1)$ split in two functions. The functions in which $EV(G_1|x_1^1, x_2^1)$ is divided describe the expected value of information when the DM continues acquiring information on the object observed and the sum of the utility provided by the first two observations is above or below $E_1 + E_2$. In **Fig. 5**, these functions are denoted by $EV(G_1, x_1^1 = \cdot| \geq E_1 + E_2)$ and $EV(G_1, x_1^1 = \cdot| < E_1 + E_2)$, respectively. The corresponding functions of $EV(G_2|x_1^1, x_2^1)$ are denoted by $EV(G_2| \geq E_1 + E_2)$ and $EV(G_2| < E_1 + E_2)$.

The intuition behind both the case $x_1^1 = 16$ (functions in red) and the case $x_1^1 = 19$ (functions in black) is identical to the one described in the second observation acquisition setting of **Fig. 4**. However, comparing the crossing point of the functions in red with the crossing point of the functions in black, an interesting result follows from the current risk-neutral uniform setting. The crossing points are obtained respectively at 13.3301 (functions in red) and 10.3301 (functions in black), see **Table 1**. Thus, the increment of three units in the realization of x_1^1, from 16 to 19, leads to a decrement of three units when moving from one crossing point to the other.

We will provide further insight about this fact and the resulting exchangeability of information values among characteristics when analyzing the four observations setting below.

6.3 Acquiring the Fourth Observation

Figures 6, 7 and **8** analyze the acquisition of the fourth observation after three characteristics from the first object have been observed, i.e. x_1^1, x_2^1 and x_3^1. The values of x_1^1 and x_2^1 are taken as given. The reference case against which we draw comparisons is given by $x_1^1 = 16$ and $x_2^1 = 12$, both values being below their respective certainty equivalents. The notation for the functions $EV(G_1|x_1^1, x_2^1, x_3^1)$ and $EV(G_2|x_1^1, x_2^1, x_3^1)$ has been further simplified in these figures, since it is clear when they refer to the case $\geq E_1 + E_2 + E_3$ or the case $< E_1 + E_2 + E_3$.

These figures illustrate how any increment in the value of any of the previous characteristics, either the first or the second, leads to a leftward shift of the crossing point between $EV(G_1|x_1^1, x_2^1, x_3^1)$ and $EV(G_2|x_1^1, x_2^1, x_3^1)$. This result is expected, as increasing the value of any of the characteristics of the object observed will lead to an increase in the value of the information acquired about this object relative to a new one.

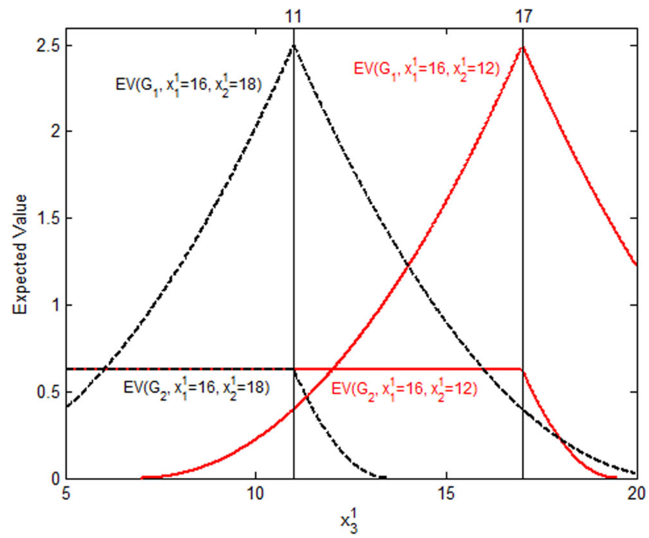


Fig. 6 Acquiring the fourth observation under uniformity and risk-neutrality

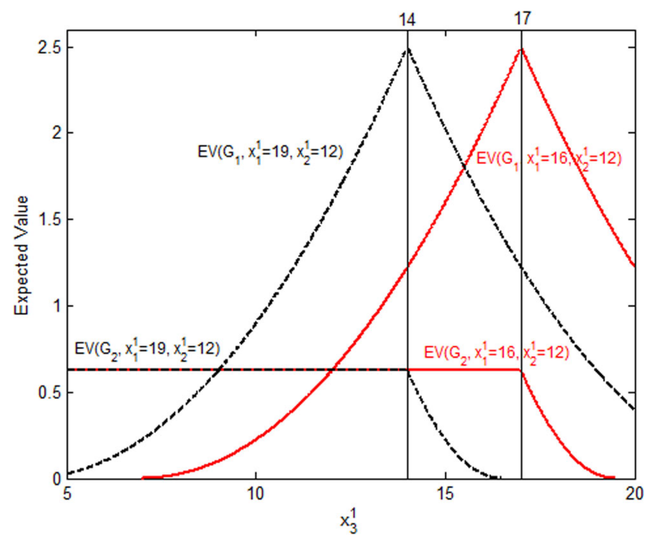


Fig. 7 Acquiring the fourth observation under uniformity and risk-neutrality

Figure 6 illustrates the shift of the crossing point when the value of the second characteristic observed increases from $x_2^1 = 12$ to $x_2^1 = 18$, while the value of the first one remains fixed at 16. The increment of six units in the realization of x_2^1 leads to a decrement of six units when moving from one crossing point to the other, that is, from $x_3^1 = 12$ to $x_3^1 = 6$; see **Table 1**.

Similarly, **Fig. 7** describes the case when the value of the first characteristic observed increases from $x_1^1 = 16$ to $x_1^1 = 19$, while the value of x_2^1 remains fixed at 12. The crossing point shifts from $x_3^1 = 12$ to $x_3^1 = 9$; see **Table 1**.

Remark Note that the crossing points between the functions $EV(G_1, x_1^1 = \cdot, x_2^1 = \cdot)$ and $EV(G_2, x_1^1 = \cdot, x_2^1 = \cdot)$ in **Figs. 6** and **7** shift by the amount of the increment applied to one of the observed characteristics regardless of whether the characteristic improved is the first or the second one; see again **Table 1**. We are aware of the fact that the risk-neutrality assumption plays an important role in this result, which can be distorted by moving to a risk-averse setting, see **Table 2**. However, this substitutability result is quite important from a strategic perspective. For example, even if a producer

Table 2 Crossing values: risk-averse case, $u_i(x_i) = \sqrt{x_i}$

Second observation	Third observation		Fourth observation			
15.8222	$x_1^1 = 16$	$x_1^1 = 19$	$x_1^1 = 16$	$x_1^1 = 16$	$x_1^1 = 19$	$x_1^1 = 19$
	12.6115	10.1912	$x_2^1 = 12$	$x_2^1 = 18$	$x_2^1 = 12$	$x_2^1 = 18$
			9.9189	5.6211	7.7870	No cut

cannot compete in terms of the most preferred characteristics of a given set of products, he may capture a given market through improvements in the second most preferred ones.

Finally, **Fig. 8** presents the effect of both previous increments combined. More precisely, if the values of $x_1^1 = 16$ and $x_2^1 = 12$ increase to $x_1^1 = 19$ and $x_2^1 = 18$, respectively, then the crossing point disappears, since $EV(G_1, x_1^1 = \cdot, x_2^1 = \cdot)$ dominates $EV(G_2, x_1^1 = \cdot, x_2^1 = \cdot)$ over the entire domain X_3. This figure also shows how whenever the characteristics observed are sufficiently high, the value of information becomes zero and the DM stops acquiring information; refer to the graphs of $EV(G_1, x_1^1 = 19, x_2^1 = 18)$ and $EV(G_2, x_1^1 = 19, x_2^1 = 18)$.

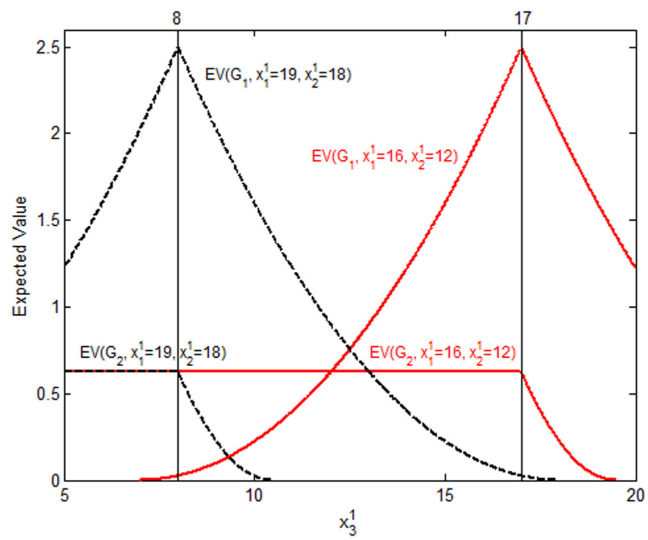


Fig. 8 Acquiring the fourth observation under uniformity and risk-neutrality

6.4 On the Algorithm Induced Value Gains

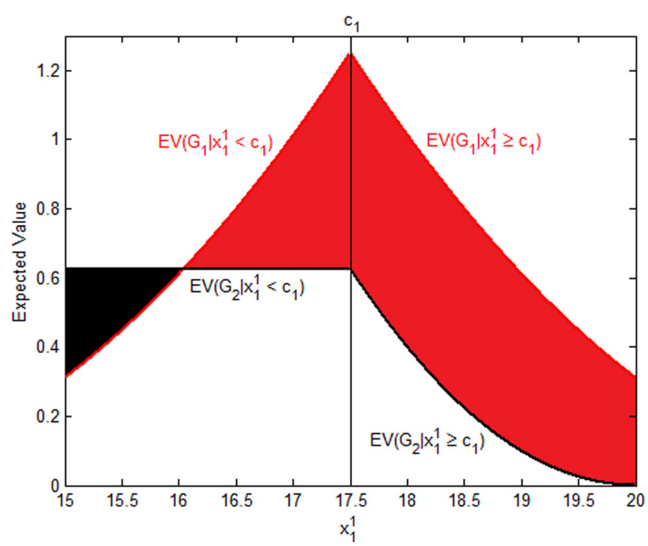


Fig. 9 Expected value gain from continuing relative to starting with a new randomly chosen product

The numerical setting described in the previous subsection allows us to compute the expected value gains obtained when DMs follow the current information acquisition process relative to heuristic mechanisms such as starting acquiring information on a new product randomly after observing a characteristic from a given product. These gains are illustrated in **Fig. 9**, where the second observation case has been used as a basic setting. The value gain from continuing acquiring information on a product over starting with a new one chosen randomly is given by the red area in this figure. At the same time, the black area accounts for the value gained from starting with a new product over continuing with the one being observed. The difference between the red and black areas defines the value gain from continuing over starting with a new random product. Clearly, the same calculations can be applied in all remaining figures. In the second observation case, the expected value gain within the risk neutral setting is given by 1.5625. The corresponding values have been calculated for the case where the third observation is being acquired when $x_1^1 = 19$, which equals 5.9445. Moreover, we have also calculated the gain when the fourth observation is acquired for $x_1^1 = 19$ and $x_2^1 = 12$, which is equal to 9.9792 and for $x_1^1 = 19$ and $x_2^1 = 18$, which generates 11.4125. Note that it is the sequential cumulative nature of the information process, together with the regret-based value of information environment what determines the increasing expected value gains as the process proceeds through a given product. Note also that this affect relates directly to the self-regulating nature of the information acquisition algorithm.

Consider now the case where the DM observes the characteristics defining the certainty equivalent product, that is, $x_1^1 = 17.5$, $x_2^1 = 15$ and $x_3^1 = 12.5$. It may intuitively seem that, in this case, the value from acquiring information on the product observed is equivalent to starting

Abstract

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A Self-regulating Information Acquisition Algorithm for Preventing Choice Regret in Multi-perspective Decision Making

In a world filled with an increasing number of choices people must carefully select the information they acquire in order to make sound decisions that they will not regret in the future. This ranges from everyday life decisions to those made by experts in the business world. The authors introduce a novel information acquisition algorithm based on the value that information has when preventing a decision maker from regretting his or her current decision. The main features of the model include the capacity to account for different risk attitudes of the decision maker as well as his or her forward-looking behavior, the ability to assess choice objects (projects or products) defined by multiple characteristics and a self-regulation mechanism for the information acquisition process, even in the absence of information acquisition costs. The main properties of the algorithm are examined numerically.

Keywords: Sequential information acquisition, Value of information, Choice regret, Utility theory

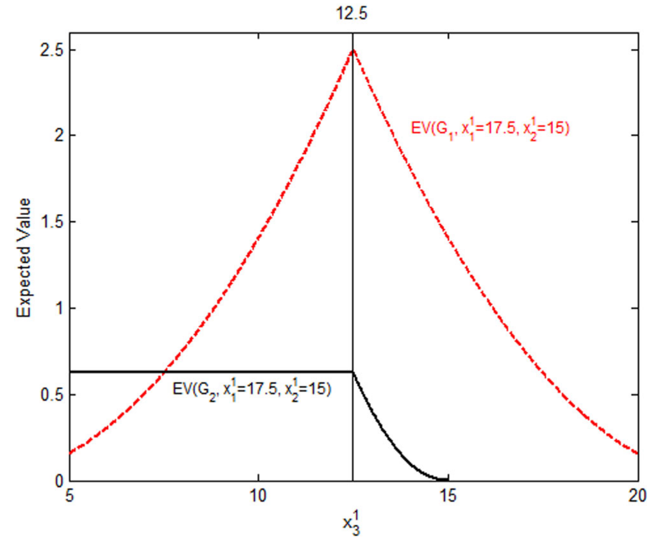

Fig. 10 Acquiring the fourth observation under uniformity and risk-neutrality: the certainty equivalent product case

acquiring information on a new random product. However, as already stated in Sect. 6.1, the certainty equivalent realizations are precisely those allowing for the widest variability in terms of the potential realizations of the characteristics of the object being observed. Given the sequential cumulative nature of the value of information, the corresponding crossing values within a risk neutral environment are given by 16.0355, 11.8301, and 7.5 for the second, third and fourth observation cases, respectively. **Figure 10** illustrates the fourth observation scenario. At the same time, the expected value gain from continuing over starting acquiring information on a new randomly chosen product when the third observation is acquired is given by 5.3820, while the fourth observation setting generates 11.1980. When comparing these values with those obtained in the previous paragraph we can observe an increment in the expected value of information as the realizations of the products increase, which may seem to indicate a decrease in the regret experienced by the DM. This is due to the fact that, as better products are observed, it is less plausible that the DM ends up regretting the choice made.

6.5 The Effect of Risk Aversion

We assume now that the i-th utility function of the DM is defined by $u_i(x_i) = \sqrt{x_i}$. The general form of the functions $EV(G_1, \ldots)$ and $EV(G_2, \ldots)$ is almost identical to that obtained in the risk-neutral case. However, the values of the crossing points as well as the effect derived from increments in the values of the characteristics of the object differ. In particular, the crossing points are obtained for lower values of x_1^1 and x_2^1 given identical uniform distributions, see **Table 2**. Moreover, an increment of x_1^1 from 16 to 19 leads to a decrease of 2.4203 units in the value of x_2^1 determining the crossing point; such a decrease is lower than the one obtained in the risk-neutral case, see **Tables 1** and **2**. The same patterns can be observed in the fourth observation acquisition setting when comparing **Tables 1** and **2**. Thus, risk-averse DMs will tend to continue acquiring information on the object being observed with more probability than risk-neutral ones, but improvements on the characteristics of the object will have a relatively smaller effect than in the risk-neutral setting.

7 Conclusions and Future Research Directions

The current paper has derived the optimal information acquisition strategy of a DM in a setting where the decision regret is minimized when acquiring information sequentially from a set of products defined by multiple characteristics. The novel information acquisition structure introduced allows for the definition of different levels of risk aversion among DMs and heterogeneous beliefs regarding the distribution of the characteristics of the objects being considered. These are both important determinants of the information acquisition process of DMs (Abbas et al. 2013).

The model also illustrates how DMs may voluntarily stop acquiring information when searching for a product absent information acquisition costs. This type of model is suitable to study environments with a substantial amount of information and almost negligible acquisition costs. The overload of cheap information has important effects on the information acquisition and choice behavior of DMs (Chen et al. 2009).

Moreover, factors such as trust and credibility of firms could also be accounted for (Gefen et al. 2008). In this regard, our model introduces a clear strategic component to the information acquisition behavior of DMs, currently obviated by the economic and management literatures (Citroen 2011; Di Caprio and Santos-Arteaga 2011).

The rejection probability of an object by a DM can be easily calculated following our model. As a result, our model provides a formal framework to analyze different types of competitive scenarios and their effect on the product introduction strategies of firms. This allows for a direct link with the evidence relating changes in the demand side of the market triggered by different information structures and their effect on the supply (Clemons 2008).

Finally, additional extensions of our model may be considered in environments where decisions must be taken after having gathered the information required while minimizing any posterior regret. This is particularly the case in areas of the literature dealing with health-related scenarios (de Bekker-Grob and Chorus 2013) and the strategic expansion of political and economic alliances (Sandler 1993).

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