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Risk information processing and rational ignoring in the health context☆

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ABSTRACT

Findings about the desire for health-risk information are heterogeneous and sometimes contradictory. In particular, they seem to be at variance with established psychological theories of information-seeking behavior.

The present paper posits the *decision* about treating illness with medicine as the causal determinant for the expected net value of information, and attempts to explain idiosyncrasies in information-seeking behavior by using the notion of decision sensitivity to incoming information.

Furthermore, active information avoidance is explained by modeling the expected emotional distress potentially brought about by "bad news" as a disutility factor in pay-off maximization.

In this context two notions of uncertainty are distinguished: an epistemic uncertainty related to the prognostic probability assigned to the risk, and an emotional uncertainty related to the expected damage. Health-risk information can both reduce epistemic and increase emotional uncertainty, giving rise to idiosyncratic processing strategies.

1. Introduction

Information-seeking behavior has been explained in cognitive accounts mainly through reference to two concepts: uncertainty and search cost. In general, it is supposed that individuals seek information when they are uncertain and the cost of information does not exceed the benefit expected from uncertainty reduction.

In many empirical analyses, the focus on uncertainty reduction has ended up with obscuring the main point of the decision-theoretic approach: i.e., that the perceived value of additional information mainly depends on whether it is expected to make a difference by changing the preference over alternatives considered in the choice (decision sensitivity to incoming information). Empirical findings about information-seeking behavior are difficult to explain adequately (especially in the health context) because this fundamental aspect is overlooked.

Within the Bayesian approach to information value, decision sensitivity to incoming information is a *sine qua non* for information to have any value at all. Consequently, uncertainty is not sufficient per se to trigger information search. Instead, the expected value of additional information is formalized as a function of both information relevance and decision sensitivity to it.

Whereas consumer research and Bounded Rationality theory explain deviations from rational learning in terms of cost/effectiveness optimization, and socio-psychological accounts of health-risk information processing relate them to perceived control over risk and the ability to cope with the situation and to process related information (efficacy and self-efficacy), this paper affirms that decision sensitivity to additional information is the principal determinant of whether or not information will be sought and processed. It is assumed that information-seeking behavior is a function of the expected net gain of decision-relevant information. This implies that information is sought not because the cost for acquiring it is counterbalanced by uncertainty reduction, but, more precisely, because it is outweighed by the reward difference between the choice made with and without the incoming information.

☆ The article posits the decision about treating illness with medicine and the concept of decision sensitivity to incoming information as central notions for the analysis of information seeking behavior in the health context. Its main contribution lies in providing a comprehensive and parsimonious account for apparent contradictory findings observed in the empirical literature devoted to health risk information search behavior by drawing on the notions of decision sensitivity to incoming information and of expected emotional costs of information.

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Furthermore, a distinction between *epistemic* and *emotional uncertainty* is made, and the emotional distress brought about by health-risk information is incorporated in the decision utility function.

In sum, information-seeking behavior is explained not only in terms of knowledge *gap* and acquisition/processing *costs*, but also in terms of:

i. Decision *sensitivity* to additional information.
ii. *Anticipated emotional* distress deriving from new information.

The implicit assumption is that the normative paradigm of the expected value of information is sufficient to explain the behavioral effects observed in economic, cognitive and socio-psychological accounts of health-information search and processing when the emotional cost of information acquisition is taken into account.

2. Health-risk information processing

The cost/benefit framework adopted so far in the research literature, in order to explain information-seeking behavior seems unable to explain information-seeking behavior in the health context. On the one hand, risk information is considered highly relevant; on the other, a perceived knowledge gap (uncertainty) is not invariably accompanied by active information search. For example, information about side effects is generally considered very important among drug consumers: when asked, 90% of patients express the desire to receive information on side effects, which they consider the most important aspect of drug information (McGavock, 1998). Furthermore, information about adverse drug reaction ranks very highly compared with other therapy-related information (Van Grootheest et al., 2004; Laaksonen et al., 2002; Bouvy et al., 2002; Åstrom et al., 2000; Howard et al., 1999; Vigilante and Wogalter, 1997). Moreover, risk issues are the most recurring concerns when evaluating drugs (Kare et al., 1996).[1] It has also emerged from a national survey carried out in the UK that 70% of respondents wanted more information than they were given (Gibbs and George, 1990).

And yet, more detailed analysis shows that information is not always welcome. A study carried out by Duggan and Bates (2000) has identified "Intrinsic Desire for Information" as a construct to describe the extent to which patients perceive the need for further information. In this study, health-related topics were identified through a series of semi-structured interviews and then used as a survey tool. Principal component analysis subsequently identified a 'knowledge requirement' factor. One important result of the study was that satisfaction about received information was also shown to be dependent on the patient's desire to receive it: providing information about medicines to patients who desire it makes them feel more satisfied and empowered, whereas providing the same information to those who do not want it makes them feel more anxious and less empowered.

A subsequent study of the same group (Åstrom et al., 2000) further distinguished the IDI factor from inhibition in expressing it and combined the dichotomized factor scores (low/high level of IDI; low/high level of inhibition in expressing information desire) with interview data (qualitative analysis). Table 1 shows the matrix that results from combining factor 1 (Intrinsic Desire of Information) and the three subnodes associated with factor 2 (Type of Desired Information).[2] High IDI scorers tend to express desire for factual information in order to make an autonomous judgment, whereas low scorers tend to seek reassuring information or to avoid information, and instead delegate decision-making to the health professional.

In general, low scorers were more concerned with benefit information, whereas high scorers wanted to know about the risk associated with the treatment and possible alternatives (pp. 161–162).

Laaksonen et al., 2002 have also found that low scorers tend to take medicine out of duty and have no information need: "I just don't know if knowing will help ... I mean, a bad effect is a bad effect." Moreover, low scorers were evasive about adverse drug reactions and unsure about their being correlated with the drug, while high scorers were aware not only of side effects but also of the drug being helpful: "It's about a balance between the good and bad effects".

This paper outlines a model of information-seeking behavior which accounts for the apparently contradictory findings observed in empirical studies of health-information seeking behavior and clarifies why the received view fails to explain them fully.

3. Information processing

Information-seeking behavior has generally been explained using a least-effort paradigm. Information-seeking behavior is thought to optimize the costs and benefits expected from incoming information: information is sought provided that the economic/cognitive cost of acquiring it does not exceed its estimated benefit.

The main point is thus how benefit is modeled. In the expected utility paradigm, benefit is modeled in terms of expected reward in changing the decision: information is valued in terms of uncertainty reduction but only on condition that it is able to reverse the options ranking (the expected value of information depends on decision sensitivity to it). However, since information search was initially studied in the context of information economics, information benefit coincided with reduction of uncertainty about price dispersion. As a result, information benefit was identified with uncertainty reduction and the decision sensitivity component was neglected. Only recently has the concept of decision sensitivity to incoming information again been emphasized and recognized as a fundamental dimension of information benefit and consequently of information-seeking behavior (Berg and Hoffrage, 2008; Delquié, 2008).

By relying more or less implicitly on the cost/benefit approach championed by information economics, the cognitive literature on information processing has inherited a restricted concept of information benefit in which information benefit is straightforwardly identified with uncertainty reduction and takes no account of decision sensitivity to it.

Bounded Rationality theory – also based on a cost/benefit approach – has related information-seeking behavior to the decision at hand, but has preferred to focus on *cost optimization* strategies.

The socio-psychological account of coping strategies such as cognitive dissonance (Festinger, 1957; Steckelberg, 2005; Steckelberg et al., 2007) and reappraisal (Preuss, 1996) tends

[1] Satisfaction with the received information has been found to affect patient compliance (O'Brien et al., 1990; Coulter et al., 1999). Indeed, discontinuation of drug treatment as a reaction to the development of side-effects occurs particularly in cases where no information on side-effects has been given by the practitioner (Enlund et al., 1991). This seems to imply that confidence in the treatment and consequently in the health professional's prescription is not shaken when the drug consumer has been previously informed about possible side effects and has accepted them as "part of the bargain". Furthermore, awareness that the doctor knows about side-effects might imply that the user believes they are under control.

[2] "What kind of information about your medicines do you want?": 1. No expressed desire for information; 2. Desire for further information, but no expressed purpose; 3. Desire for further information and expressed purpose.

Table 1
Intrinsic Desire for Information and types of information required.

	No expressed desire for information	A desire for information, but no expressed purpose	A desire for information, and an expressed purpose
High score	No real interest in further information	Specific interest in side effects, expected benefits and interactions with other drugs.	Specific interest in side effects, safety issues and general effects of drugs, including benefits. Desire to keep control of my 'body'. Wanted choices and information about alternatives.
Low score	Lack of interest in information; information provokes anxiety; rather trust decision of HPs.	Main interest in reason for drug and how to take it. Want reassurance on benefit if drug, but willing to put trust in HPs. Decisions	Want reasons for drug choice and reassurance of benefit. Feel they should know what they are taking.

The two rows refer to the subgroups of high scorers and low scorers in the parameter Intrinsic Desire for Information (IDI); the columns present the most recurrent topics addressed in the two groups as for *type* of information required. High scorers tend to require factual information and information for decision, whereas low scorers tend to avoid information, delegate the choice and to look for reassuring information (Åstrom et al., 2000: 162).

instead to neglect cost/benefit considerations and focus on the effect of *emotion* on information processing, especially in "bad news" contexts.

The aim of this paper is to adopt the normative model of the expected value of information in order to provide a framework that can explain health information-seeking behavior while also factoring in the anticipated emotional cost attached to information as an explanatory antecedent for seemingly irrational search behavior.

In sum, the following two points are added to the existing picture in the information search literature:

1. The benefit brought about by additional information should be considered in relation to the decision at hand and its sensitivity to that information, i.e., the extent to which the information is able to *change* the decision (to make a difference).
2. Emotional as well as economic and cognitive costs should be considered in explanations of information-seeking behavior.

4. Information benefit as uncertainty reduction

In the cognitive literature, benefit has generally been modeled in terms of uncertainty reduction, where uncertainty is usually defined as the perceived knowledge gap between the desired and actual level of knowledge. For instance, the principle of sufficiency (Chaiken et al., 1996) assumes that individuals assess their actual level of confidence (AC) and the desired level of confidence (sufficiency threshold: ST): the gap between the two motivates the search for further information (Fig. 1).

In this model 'confidence' is opposed to 'uncertainty'. Uncertainty motivates the search for additional information and determines the level of processing accuracy: "people will exert whatever efforts are required to attain a 'sufficient' degree of confidence, that they have accomplished their processing goals" (Eagly and Chaiken, 1993: 330).

Therefore, according to this paradigm:

1. A perceived knowledge gap should trigger active information seeking,
2. with the ultimate purpose of reducing uncertainty.

Absence of information search in the presence of a knowledge gap has been explained in the cognitive literature through reference to processing costs. The effort invested in seeking and processing information depends not only on perceived information benefit (in terms of gap-bridging), but also on cost/effectiveness considerations (Johnson and Payne, 1985). This means that the benefit of becoming more knowledgeable should override or at least be equal to the cognitive/economic cost of acquiring the new information. In general, incoming information will be processed cursorily and by resorting to cues and rules of thumb whenever this proves sufficient for acquiring the desired amount of data.

The effort-accuracy trade-off paradigm models the compromise between accuracy and effort spent in information search strategy as an indifference curve based on the agent's goal (Fig. 2).

Depending on the accuracy they want to attain, and the effort they are prepared to make, agents will choose a processing strategy along the curve closer to its upper or lower end.

In the heuristic-systematic model of information processing, the effort-accuracy trade-off is modeled dichotomously and the default

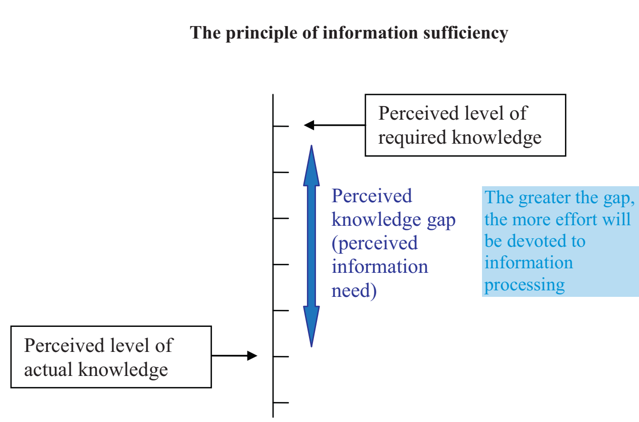

Fig. 1. The principle of information sufficiency. Sufficiency principle: information seeking and accuracy of processing as a result of the perceived gap between actual level of knowledge and the perceived level of required knowledge.

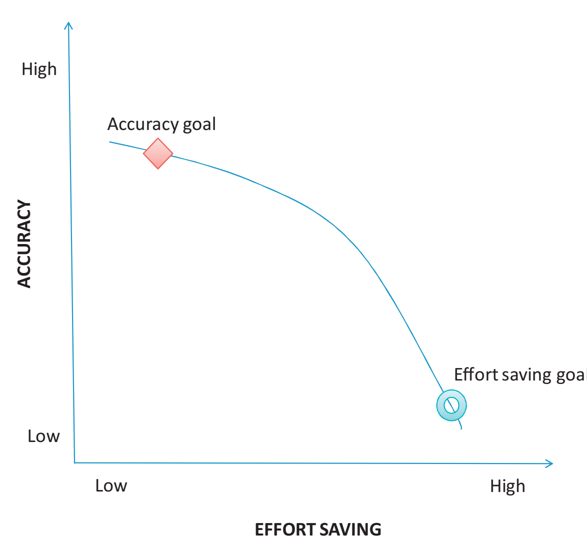

Fig. 2. Effort-accuracy trade-off model.
Adapted from Payne (1982).

mode is the heuristic one, whereas systematic information processing is triggered only in particular cases (Chaiken et al., 1996, 1989; Trumbo, 1999; Griffin et al., 2002; Kahlor et al., 2003). Though individuals may switch back and forth between the two modes within the same task, they will tend to gravitate towards one or the other depending on their capacity to deal with the information, their motivation to invest energy, and time constraints (Trumbo, 1999: 392; Kahlor et al., 2003: 356; Griffin et al., 2002: 706).

4.1. Cost moderators: efficacy, self-efficacy, choice delegation

The information-search strategy literature has identified two main moderators of information search costs: efficacy (expertise, familiarity with the task) and self-efficacy (perceived capacity to deal with the information).

Dougherty et al. (2003) have singled out unfamiliarity of the task as a variable that tends to generate an analytical strategy (systematic processing), whereas expertise is associated with cost-efficient processing shortcuts.[3]

Expertise is associated with a better accuracy-cost trade-off (see Beach, 1990; Kuo et al., 2004; Hammond et al., 1987; Mitchell and Beach, 1990; Staggers and Norcio, 1993). Kuo et al. (2004) also assume that experts can be distinguished from non-experts because they attain a high level of accuracy *regardless* of effort (in terms of time spent in the search), while non-experts calibrate their effort to the required level of accuracy (Kuo et al., 2004: 338).

Self-efficacy is related to efficacy but should be distinguished from it. Self-efficacy is a psychological construct: "People's *beliefs* about their capabilities to produce designated levels of performance that exercise influence over events that affect their lives. Self-efficacy beliefs determine how people feel, think, motivate *themselves* and behave" (Bandura, 1994: 71; my italics). Griffin et al. (2002) found a negative correlation between systematic information processing and self-efficacy. It seems that a certain degree of self-confidence in dealing with the topic predicts the use of heuristics (moderated by lower motivation) rather than systematic processing (see also Trumbo, 1999).

In general, self-efficacy moderates the effect of the effort-accuracy trade-off (when measured in terms of time spent) in the sense that the effort-accuracy trade-off is non-operative in high self-efficacy subjects (Smith et al., 1985).

Another important proxy variable for insensitivity to information and low search is lack of motivation owing to choice delegation (to a fiduciary person or to an expert: see recently Lanzi and Mathis (2008), and related literature). This is a key parameter that calls for more thorough investigation, especially in relation to health choices, because they are often the outcome of a consensual procedure or shared decision-making in a context of marked information asymmetry. Other things being equal, choice delegation should lead to reduced information processing.

5. Ecological accounts of information processing: Bounded Rationality theory

The least-effort principle has found a specific implementation in the so-called Bounded Rationality theory.

In the wake of studies that emphasized the inability of non-experts to deal with probabilistic information and focused on judgment biases (Kahneman et al., 1982; Bar-Hillel, 1980; Tversky and Kahneman, 1974), Bounded Rationality theory has proposed an explanatory model for fallacies in probabilistic updating. Many of these apparent inconsistencies are explained as the result of optimizing processing efforts and heuristic modes of information processing in general (Payne et al., 1993; Gigerenzer, 1998, 1996, 1994; Gigerenzer and Hoffrage, 1995; Gigerenzer et al., 1999; Cosmides and Tooby, 1996; Kleiter, 1994; Kohler, 1996; Girotto and Gonzales, 2001; Reyna et al., 2003). Within this paradigm, focus on effort optimization is justified not only by the fact that human processing capacities are not unlimited, but also, and most importantly, that it is precisely these limits that make for cognitive efficiency. Memory limits are believed to generate the "fast and frugal heuristics" which in the daily context can provide more efficient information use than systematic, exhaustive processing.

The term "Bounded Rationality" was first coined by Herbert Simon, whose main concern was to revise the concept of economic rationality and the Subjective Expected Utility paradigm by stressing that deviations from it neither necessarily nor straightforwardly mean irrationality (Simon, 1955). Simon distinguishes between two different strategies: "optimizing" and "satisficing". Optimizing is the "rational" computation of optimal sample size: the correct point at which to terminate information seeking is found by equating marginal costs of search with expected marginal improvement of alternatives.

Satisficing occurs when alternatives are encountered sequentially. It is rather a cost-effective strategy than an optimal one, in that it has a less rigid search-termination rule: search terminates when the best offer exceeds an aspiration level that itself adjusts gradually to the value of the offers received so far (Simon, 1988: 67, 69). Bounded Rationality theory has focused on identifying the "fast and frugal" heuristics commonly used to cope with different decision tasks. In accomplishing this task, a special emphasis has been given to the algorithms which are successfully adopted as an alternative to the expected utility paradigm.[4] Rules of thumb are the basis of choice among options (recognition heuristic, priority heuristic, etc.), rather than the complex computation of probabilities and preferences envisaged by the classical Bayesian theory of utility maximization.

More distinctively, the Bounded Rationality paradigm claims to be an ecologic approach to information-processing in that identified heuristics and processing strategies are considered to be the result of the agent's adaptation to the environment.

For the purposes of this paper, however, the kinds of heuristics BRT theory has identified is less important than the fact that it uses the decision paradigm as a basic frame within which information processing should be investigated and explained. This is fundamentally different from the "sufficiency principle" paradigm because cost/benefit analysis of the perceived knowledge gap and the processing mode ultimately follows from decision-theoretic parameters such as task, stakes involved, decision type, time and other pragmatic constraints.[5]

[3] The general hypothesis underlying the model is that accumulated memories of similar decision problems result in automatic, associative problem-solving, while new situations require deliberative evaluation and an analytic breakdown of the decision. Experience in a specific domain might lead to a shift from rule-based to memory-based (pre-stored) solutions. This is also thought to explain why expertise is not generally linked to systematic analysis prior to decision but rather to idiosyncratic heuristics: experts are better at attending to relevant information rather than engaging in an undifferentiated encoding of all available data.

[4] Connolly (1980), Cosmides and Tooby (1996), Gigerenzer (1994, 1996, 1998), Gigerenzer and Hoffrage (1995), Gigerenzer et al. (1999), Girotto and Gonzales (2001), Kleiter (1994), Kohler (1996), and Pachur and Hertwig (2006).

[5] See for instance Kahlor et al. (2003), Reyna et al. (2003), Dougherty et al. (2003), Martignon and Krauss (2003), Schneider and Shanteau (2003), Griffin et al. (2002), Slovic and McMackin (2000), Gigerenzer et al. (1999), and Trumbo (1999).

6. Emotional costs of information and coping strategies

"Irrational" (again, in the sense of not following expected utility rules) information-seeking behavior has been explained in socio-psychological research through reference to coping strategies typically associated with risk and "bad news" contexts, and to their related emotional burdens.

In studies of emotion and decision-making, emotions are credited with performing four main functions (Pfister and Böhm, 2008):

1. *Providing information* about pleasure and pain for *preference construction*. Feelings such as joy and distress, or regret and disappointment may have an important role in the "How do I feel about it heuristic" (Hanoch, 2002, 14; see also van Gelder et al., 2008). People anticipate future scenarios and inspect their feelings about each of them in order to evaluate targets (Böhm and Pfister, 2008). Damasio also speaks of somatic markers, i.e., emotion which automatically attaches to a future prospect and acts as an alarm signal: "Beware of danger ahead of you" (Damasio, 1994: 174).[6]
2. *Filtering*: emotions restrict the range of options considered by focusing on certain variables, and by initiating and terminating the evaluation process (working as a satisficing mechanism). Cognitive load is also reduced by ignoring parameters associated with low emotional values (Hanoch, 2002: 7, 15, ff.; see also Janis and Mann, 1977, and Bealneaves and Long, 1999).
3. In *emergencies*, specific emotions such as fear divert *attention* to something in the environment which needs immediate attention, triggering rapid responses and fast choices. Heuristic-systematic processing theory associates affect and cognition with automatic and controlled processing respectively (see Gelder et al., 2008; Slovic et al., 2005): if incoming information is "indexed" with an emotional tag such as "danger", "quick and dirty" rather than systematic processing will follow.
4. Generating *commitment* to morally and socially significant decisions (Pfister and Böhm, 2008).

In all these approaches, emotion is studied as a source of information management. However, none of them analyzes the possible role of the *anticipated* emotional cost associated with a piece of information.

The extensive literature on the effects of emotion on information processing (see, for example, Bealneaves and Long, 1999; Janis and Terwilliger, 1962; and references in Hanoch, 2002, and Gelder et al., 2008) also ignores the role of emotion as a motivator/deterrent with respect to information search. The literature on coping strategies indirectly considers the anticipated emotional effect of incoming information as a determinant of the information search strategy. Coping strategies are represented as divergent behavioral responses to risk information and as a way of coping with threatening information. Coping strategies are generally divided into three main groups[7]:

1. Information avoidance.
2. Situation reappraisal.
3. Search for counterbalancing, reassuring information.

1. Researchers have been puzzled by active information avoidance in the face of decision-relevant information: "it has been reported that 57% of individuals with hereditary risk of colon cancer declined an offer for genetic testing".[8] The usual explanation is that avoiding relevant information can be a reasonable strategy when the information is considered too stressful, or when it is perceived as unhelpful: "sometimes the perception arises that more information does not resolve the problem".[9]
2. Reappraisal is a common phenomenon in situations where risk is characterized by lack of control.[10] The impossibility of acting against it induces the subject to act on his emotions and reevaluate the threatening source, thereby reducing its perceived danger. As a consequence, risk perception decreases *as well as perceived information need*.[11]

   Witte (1998) assumes that this head-in-the-sand policy is a consequence of low efficacy (perceived ability to face and solve a problem) in relation to the threat. In this sort of situation the subject "*ignores the threat* and recommended responses and instead engages in coping responses to *reduce fear*" (my italics).[12] This "perceptual defense" typically means that individuals "distort or ignore any incoming information about a threat".[13]

   Active information seeking may also be biased by the cognitive dissonance phenomenon, a kind of selection bias that leads the reader to seek information that confirms his opinion or wishful thinking while neglecting data which might contradict his beliefs or hopes.[14]

   In general, reappraisal and cognitive dissonance are thought to lessen perceived outcome value (in this case outcome disutility), to decrease the desired level of confidence, and to reinterpret uncertainty so as to abort the information-seeking process.[15]
3. If the head-in-the-sand policy leads to uncertainty ignorance, the perceived importance of health information counteracts this tendency and enhances *need for control*: a proactive information-seeking attitude has been found to be correlated with either need for control and/or *need for reassurance* (Morris and Aikin, 2001).

Whereas ecological accounts of information-processing behavior underlie cost/benefit optimization strategies and identify the knowledge-gap as a motivating factor for information search, socio-psychological accounts emphasize the feed-back between emotional effects produced by such information and information-seeking behavior (cognitive dissonance, reappraisal and coping strategies in general). In the first approach, information is *sought* to the extent that its expected benefit in terms of uncertainty reduction does not exceed the economic/cognitive costs of acquiring it. In the second paradigm, information is *avoided* or selectively filtered to the extent that it produces anxiety and increases the perceived risk, i.e., uncertainty. In what follows, the distinction between epistemic and decision relevance of incoming information (through the concept of decision sensitivity), in conjunction with the distinction between emotional and epistemic uncertainty, will help us

[6] The importance of emotion in outcomes ranking is demonstrated by subjects with lesions to the frontal lobe, who are emotionally flat. In addition to losing the capacity to experience emotion, these subjects have been observed to lose their decision-making capabilities. A possible explanation is that they do not attach any emotional value to future outcomes, which renders the outcomes meaningless (Damasio, 1994).

[7] Afifi and Weiner (2004: 181).

[8] Lerman et al. (1999). Research on the framing effect has also shown that behaviors that serve to *detect* risk rather than *preventing* it are perceived as risky, in the sense that they involve the *risk of discovering the disease!* (Rothman et al., 1993, 2006).

[9] Babrow (2001: 563): "Many uncertainties cannot be resolved by more information", cited in Afifi and Weiner (2004).

[10] See Preuss (1986: 74 ff).

[11] Afifi and Weiner (2004: 181 ff).

[12] Witte (1998: 437), cited in Afifi and Weiner (2004: 182).

[13] Witte (1998: 438), cited in Afifi and Weiner (2004: 182).

[14] The role of this phenomenon in health-risk information processing has been empirically observed by Steckelberg, 2005, Steckelberg et al., 2007.

[15] Afifi and Weiner (2004: 183).

to demonstrate that information search, and avoidance or biased filtering, are part of one and the same strategy.

7. Epistemic vs. decision relevance (uncertainty and indecision)

In a seminal paper published in 1961, George Stigler introduced the theory of Economics of Information (EOI Theory), which attempted to show how information and uncertainty influence the behavior of buyers and sellers in the marketplace (Stigler, 1961). As a corollary of the cost/benefit framework adopted in his theoretical perspective, information search is taken to be positively correlated to price dispersion (uncertainty) and to be inversely related to search costs.

In Stigler's model, information search is remunerative to the extent that price dispersion is large and search costs are low: the optimum amount of search is such that the marginal cost of search equals the expected increase in receipts. Receipts are given by the amount saved through paying a lower price than would have been the case without search.[16]

Since it applies only to choices among homogeneous commodities and to price information, Stigler's model cannot be generalized and straightforwardly applied to compensatory decision sets, i.e., where the agent's preference ranking is determined not only by price, but also by multidimensional commodities. In Stigler's model, uncertainty reduction is *immediately* related to price lowering for buyers, and therefore to economic reward, though it is acknowledged that, in general, conditional learning does not invariably lead to decision improvement. Change in the ranking of options does not follow straightforwardly from a change in the probabilistic distribution of relevant states: it depends on the extent to which the epistemic change outdoes the preference ranking. The closer to indifference the choice among alternatives is, the more sensitive to incoming information the decision will be. Conversely, the wider apart the different options are, the less likely it is that new information will induce a decision change, even if it modifies the probability distribution of the states partition.

Whereas classical Bayesian analysis has explicitly incorporated this aspect of decision-making in the concept of expected net gain of information through the notion of decision sensitivity to incoming information, economic analyses of information search have only hinted at the distinction between epistemic and decision relevance (decision sensitivity to incoming information).

Outside the field of information economics, Stigler's cost/benefit framework has been further developed in consumer and marketing research. The hypothesis of a causal connection between dispersion (uncertainty) and search has been studied empirically, leading to mixed results (see Urbany, 1986: 258 for literature).

However, awareness of the distinction between choice uncertainty and knowledge uncertainty has gradually found its way into the information economics literature, although this distinction has never been explicitly associated with the influence of the decision sensitivity component.

Following Berg et al. (1978) and Wilton and Myers (1986) distinguish between a *conceptual* and an *instructional* use of information. Information is used for conceptual purposes when the individual is thought to gain some understanding of the issue or to acquire knowledge for its own sake. By contrast, the instructional use of information concerns decision tasks, i.e., contexts where the information should prescribe or recommend a specific behavior. In their study they demonstrate that individuals who use information for conceptual (exploratory) purposes perceive *greater utility* and show greater use of information than individuals who use information for instrumental purposes. This might be an indirect confirmation that, in instrumental contexts, relevant information does not invariably produce benefits in terms of decision improvement, and therefore, from this point of view, it is considered of lower value.

Urbany (1986) found that the relationship between search cost and dispersion does not always apply, but it is moderated by the *kind* of uncertainty faced by decision-makers. In the group which received only dispersion range information, there was a significant dispersion-cost interaction, whereas the group which also received the dealers' ranking positions was affected neither by the dispersion-search relationship, nor by the inverted cost-search relationship. Urbany's conclusion is that, in decision-making, information principally serves the purpose of ranking the available alternatives; when they are already ranked, additional information is likely to be *valuable only insofar as it may change the ranking*.

This empirical work has pushed research further in the direction of a distinction between mere epistemic vs. decision relevance.

Urbany et al. (1989) make a distinction between knowledge uncertainty (KU, uncertainty regarding information about each alternative) and choice uncertainty (CU, uncertainty about which alternative to choose). Their study shows that, given a taxonomy of high or low KU and high or low CU subjects, the highest search level is not predicted by the high KU/high CU cell, but by the low KU/high CU one. This is explained by relating low knowledge uncertainty to expertise, and therefore to reduced search cost and increased search. However the CU category is unambiguously related to information search. Both high CU groups are in the upper bound of the search scale: "consumers can be high in knowledge uncertainty yet low in choice uncertainty (and vice versa, in the case of an expert who cannot decide between several equally attractive alternatives)" (213). Choice uncertainty – and not necessarily knowledge uncertainty – leads to information search.

On the basis of this study, Moorthy et al. (1997) distinguish between relative brand uncertainty (uncertainty among brands), and brand uncertainty (deficiency or lack of information about any single brand).[17] In their model, the value of information depends on relative brand uncertainty, defined as the degree of overlap between brand utility functions: "The more the distributions overlap, the less certain is the consumer about which brand is the better choice, and the more likely it is that she will search. Relative brand uncertainty is thus related to the concept of *choice uncertainty*" (266: my italics). The probability that search is remunerative increases when utility functions get closer to each other stochastically: the amount of search depends both on the epistemic relevance of the information *and* on the relative uncertainty among the distributions. There is an interactive effect between the two: "the goal of search is to help identify the best brand, and if search is not going to change that identification, there is no point in searching" (267), i.e., if information is not expected to change the decision, it will not be processed even if relevant from an epistemic perspective. This confirms the hypothesis that information search is mainly related to indecision and not necessarily to epistemic uncertainty.

All these studies help to make a clear distinction between choice indecision and epistemic uncertainty about each available alternative.

Classical decision theory developed the concept of decision sensitivity to account for state-relevant information which has no

[16] This account is the basis of the cost/benefit approaches to information search mentioned in Section 3, although in most studies the economic model is adopted without explicit acknowledgement.

[17] Relative uncertainty about brands relates to uncertainty about which brand is the best, whereas individual uncertainty concerns the individual characteristics of each brand: "relative brand uncertainty can be non-zero even if brand uncertainty is non-zero. The need for search arises only when relative brand uncertainty is non-zero" (Moorthy et al., 1997: 275).

effect on the decision because of its incapacity to reverse the ranking between the available options.

In general, the value of information is defined as the difference between the expected utility of the act that would be chosen with the information, and the expected utility of the act that would be chosen without it. If the information does not change the act, the difference is zero, i.e., its value is zero, and therefore it is perfectly rational to ignore it in a decision context.

Strangely enough, only recent studies have incorporated decision sensitivity as a predictor of information-seeking behavior and have provided an explanatory model for *rational ignoring*.

7.1. Decision insensitivity to state-relevant information and rational ignoring

The concept of decision sensitivity to incoming information is not new to decision analysis. However, its implications for the analysis of information search have only recently been made explicit and formalized.

As mentioned in the previous section, the main cause for this neglect is that information value and uncertainty reduction have coalesced in information economics studies, which identify uncertainty with price dispersion.

Similarly, the identification of information benefit with uncertainty reduction has also been taken up by the cognitive approach to information-seeking behavior, as illustrated above.

Neglect of the decision sensitivity component, and exclusive focus on uncertainty reduction as a measure of information value, has generated sets of apparently incongruent data in the cognitive literature and other fields (Gould, 1974; Hilton, 1981; Eeckhoudt and Godfroid, 2000; Eeckhoudt et al., 1984). The notion of decision sensitivity may provide an intuitive explanation for these contradictory findings in that it explains information search in terms of its capacity to change options ranking, beyond and independently of its potential to reduce uncertainty. Information may well reduce uncertainty or change the probability distribution among relevant states in general, and yet be incapable of changing options ranking. This can happen when the change is insufficient to counterbalance the strength of preference for the first ranked option.

Notwithstanding the importance of decision sensitivity to incoming information in the estimation of information value, and therefore as a possible predictor of information search, this aspect has never been explicitly considered in cognitive analyses of information-seeking behavior. Instead of taking into account decision insensitivity as a possible explanation of information ignorance, lack of information search has generally been studied as an instance of Bounded Rationality, biased reasoning, cognitive dissonance or perceptual reappraisal.

Berg and Hoffrage (2008) emphasize that Bounded Rationality, biases, non-linear probability weightings and other departures from expected utility theory are not necessary to explain information ignorance. Information ignorance is perfectly plausible within an expected utility maximization paradigm when the joint structure of information *and* pay-offs is considered. Behavioral insensitivity to objectively predictive information is perfectly rational when probabilities and pay-offs are inversely related and the effects of conditioning disappear on average (i.e., under the expectation operator) even though they produce non-trivial effects on pay-offs and probabilities considered in isolation (i.e., before integrating).

In classic decision analysis the expected value of information is measured as the difference between the expected reward of choosing the act that would presumably be chosen on the basis of the expected information, and of the act that would be chosen under the state of knowledge prior to information acquisition. When the act is the same, the difference is zero, as is the value of the information under consideration. Drawing on this formalization, Berg and Hoffrage identify the determinants for rational ignoring in a straightforward manner. Considering, for instance, a two-states × two-actions decision matrix and a binary signal, when the difference between the rewards of the two actions are of the same sign under both signal results, the information is insufficient to change the act ranking, even though it changes the probability distribution of the states:

	Expected utility given signal = 1	**Expected utility given signal = 0**
	P (state of the system = A/signal = 1) = P_1 P (state = B/ signal = 1) = 1 – P_1	P (state = A/signal = 0) = P_0 P (state = B/ signal = 0) = 1 – P_0
act T	$P_1\ (u_{T/A}) + (1 - P_1)(u_{T/B})$	$P_0\ (u_{T/A}) + (1 - P_0)(u_{T/B})$
act H	$P_1\ (u_{H/A}) + (1 - P_1)(u_{H/B})$	$P_0\ (u_{H/A}) + (1 - P_0)(u_{H/B})$

where P_1 stands for the probability that the system is in state A, given that signal 1 has been received, and P_0 is the same probability, given that signal 0 has been received; u_T/A stands for the utility of act T under state A, and so on.

If the difference between the expected utilities of the different acts for each signal (Δ_0 and Δ_1) are of the same sign, i.e., if

$$\Delta_1 = [P_1(u_{T/A}) + (1 - P_1)(u_{T/B})] - [P_1(u_{H/A}) + (1 - P_1)(U_{H/B})] > 0$$

and

$$\Delta_0 = [P_0(u_{T/A}) + (1 - P_0)(u_{T/B})] - [P_0(u_{H/A}) + (1 - P_0)(U_{H/B})] > 0$$

then the optimal act is T if either signal 1 or 0 is given. In this case, the expected utility of act T is greater than the expected utility of act H regardless of the signal being 1 or 0. Conversely, if both Δ_0 and $\Delta_1 < 0$, then the optimal act is H independently of the realized value of the signal. This means that the signal has no practical effect on the decision.

Instead, if the differences have different signs, this means that under one realized value of the signal, it is more convenient to choose act T, while under the other, the optimal act is H. Only in this case is the decision sensitive to the signal. The formula $\Delta_1\Delta_0 < 0$ represents the constraint under which the decision is considered to be sensitive to the information. $\Delta_1\Delta_0 > 0$ constitutes instead a *subset* in the domain of state-relevant information, for which information ignoring is fully rational.

Following the same line of argument, Delquié (2008) shows that the value of information depends first and foremost on the strength of preference between choice alternatives, as measured by their difference in utilities. In his account, the expected value of information is traditionally derived as follows.

Suppose that option X is preferred to Y, and Z is a random variable whose observed values provide information on X (and Y); then

$$\mathrm{EUI} = E_z \max\left[\mathrm{Eu}\left(\frac{X}{Z}\right); \mathrm{Eu}\left(\frac{Y}{Z}\right)\right] - \mathrm{Eu}(X).$$

Since $\mathrm{Eu}(X) = E_z\,[\mathrm{Eu}(X/Z)]$

$$\begin{aligned}\mathrm{EUI} &= E_z \max[\mathrm{Eu}(X/Z);\ \mathrm{Eu}(Y/Z)] - E_z[\mathrm{Eu}(X/Z)].\\ &= E_z \max\{[\mathrm{Eu}(X/Z) - \mathrm{Eu}(X/Z)],\ [\mathrm{Eu}(Y/Z) - \mathrm{Eu}(X/Z)]\}\\ &= E_z \max\{0, [\mathrm{Eu}(Y/Z) - \mathrm{Eu}(X/Z)]\}.\end{aligned}$$

where $\mathrm{Eu}(X/Z)$ is the expected utility of choosing act X, given the information provided by Z; $\mathrm{Eu}(Y/Z)$ is the expected utility of choosing act Y, given the information provided by Z; and E_z refers to the expected conditional probability given the observed values of Z.

The formula implies that the information either reverses the options ranking (represented by $[\mathrm{Eu}(Y/Z) - \mathrm{Eu}(X/Z)] > 0$), in which case its value corresponds to the difference in expected utility as predicted by signal Z, or equals zero, because no change takes place.

An important corollary of this theory is that information value is maximal when the prior difference in expected utilities among available options is zero: i.e., when preference is accorded to more than one course of action with the same intensity prior to information acquisition. If we keep information impact (Z) fixed, and analyze the impact of change in prior expected utilities on EUI, we observe that, for instance, by progressively increasing the expected value of Y, the delta reward brought about by the additional information is expected to reach the highest level when *prior* expected utilities of X and Y intersect (i.e., are equal) because at this point the distance between the posterior expected utility and the prior expected utility is maximal (see Delquié, 2008: 7 ff for details).

Both Delquié (2008) and Berg and Hoffrage (2008) show that signals are expected to be ignored to the extent that they are weak *and* that payoffs are highly asymmetric, whereas indifference over which action to choose predicts high value of information. That zero value reflects information ignoring is a behavioral conclusion which needs to be validated, but it does cast some light on the idiosyncratic findings in the empirical literature on information search.

It should be noted that decision sensitivity to incoming information is a binary parameter: depending on the distance between the best pay-off and the other ones, further information will either be able to change the alternatives ranking or not: $C = \{1;0\}$. If the value of the parameter "decision sensitivity" is 1, then, the value of the information will depend on the expected change in reward (Δ reward). But if the value of the parameter "decision sensitivity" is 0, then the information is not expected to change the decision; even though it might provide more accurate knowledge of the state of affairs, its value to the decision will be 0, notwithstanding its uncertainty-reducing effect.

8. Epistemic vs. emotional uncertainty and information disutility

In general, both the economics literature on expected information value and the cognitive literature on information-seeking behavior have investigated uncertainty in the technical sense, without considering its emotional counterpart. This neglect may explain the puzzlement surrounding empirical studies which show that more knowledge increases rather than decreases uncertainty (Schuldt, 1992, 1998).

If we refer to the knowledge gap as "epistemic uncertainty" (uncertainty$_1$) and to the emotional distress related to anticipated bad news as "emotional uncertainty" (uncertainty$_2$), it becomes clear that additional information can reduce the knowledge gap while at the same time increasing the anxiety associated with health news. In the decision context, risk information can both increase and decrease anxiety (uncertainty$_2$) *independently* of the extent to which uncertainty$_1$ is reduced. The table shows that uncertainty$_1$ reduction means more confidence in risk occurrence and therefore presumably a higher level of uncertainty$_2$.

Risk information: damage probability	$0 \rightarrow .5 \leftarrow 1$		$0 \leftarrow .5 \rightarrow 1$	
Uncertainty$_1$ (epistemic)	Increase (+)		Decrease (−)	
Uncertainty$_2$ (emotional)	(+)	(−)	(−)	(+)

On a scale from 0 to 1, the highest uncertainty$_1$ is in the middle (.5): this is where you would not bet on either of the possibilities. At 1 you are *certain* that damage will happen. At 0 you are certain of the contrary. And emotional distress, or uncertainty$_2$, has its highest peak when the damage probability approaches 1.

When no benefit can be expected from further risk information because the decision would not be changed by it (decision insensitivity), information is perceived not only as useless, but even as less than useful. By either confirming or disconfirming previously held opinions, it certainly helps sharpen our knowledge of the state of affairs and therefore enhances our capability to adjust and optimize our decisions. However, with health decisions in particular, there could be cases where further information, though refining our beliefs, cannot help improve our choices because no room is left for alternative options. If this information is also emotionally distressful, then its only effect is to increase anxiety without any benefit on the final decision outcome. This accounts for active information avoidance or lack of information seeking even in the presence of a perceived knowledge gap (epistemic uncertainty).

The emotional cost attached to incoming information can be assessed in terms of marginal economic loss (or through other relevant measures) and will be capitalized in terms of outcome disutility.

9. An integrated model of health-risk information processing

The above considerations suggest that information-seeking behavior is predicted by decision sensitivity to incoming information (indecision) *and* the perceived information disutility in emotional terms (anticipated emotional distress), rather than explained by the knowledge gap (epistemic uncertainty) alone.

In this sense, Bayesian decision theory provides a "reductionist" model for information-seeking behavior and, more specifically, for information avoidance, in that the decision to avoid information is explained by the relatively *slight reward from acquiring new information when there is little hope that the information will make a difference.*

Ultimately it is the expected impact of information on decision change rather than its mere uncertainty decrease capacity which determines whether information will be valuable for the individual.

There is, however, an emotional cost, the emotional distress induced by the expected confirmation of "bad news". This is incorporated in the cost/benefit estimation through the integration of a negative factor in the utility function.

As a result, further information will be welcome only to the extent that it is expected to improve the decision. When this is not so, and the information is also thought to only produce emotional distress, then not only does its value tend to zero, but the anxiety that may be induced by it is considered a useless emotional *cost*.

The theoretical account advanced here proposes that the agent's information search optimizes the play-off between decision uncertainty and anticipated emotional distress, provided that the decision is information-sensitive. Information will be sought when it improves the decision and the emotional costs of acquiring it do not exceed the benefit derived from it. The expected value of additional information (EVI) can be roughly formalized in the following system of equations:

$$\mathrm{EVI} = \begin{cases} \Delta\mathrm{Reward} - \text{emotional cost} & \text{if ds} = 1 \\ 0 - \text{emotional cost} & \text{if ds} = 0 \end{cases}$$

where ds stands for decision sensitivity.

It is possible to avoid emotional distress by drawing on coping strategies such as reappraisal, cognitive dissonance, active avoidance or search for counterbalancing reassuring information. Coping strategies are therefore not solely the result of personality factors but ultimately depend on cost/benefit assessment based on expected net gain of information to decision (i.e., Δ reward – emotional cost).[18]

10. Empirical evidence

The theoretical model exposed in this paper has been stimulated by the data provided by an empirical study carried out in order to assess information processing behaviors of drug users with special reference to patient package leaflets (Osimani, 2007). Full account of the study will be given in a separate paper, suffice it to present the main results. The study was conducted on a sample of drug users who were asked among other to assess their level of information before and after reading the drug package leaflet accompanying their leaflet. The sample (n = 55) was restricted to people under treatment at the time of survey (real-time decision-making) and not hospitalized. No significant change in decision has been registered in the sample after reading the package leaflet (based on Wilcoxon signed ranks tests). Neither were the risk-benefit assessments greatly influenced by PL reading. Interestingly however, the perceived amount of information available significantly changed after reading the package leaflet. In the scale from 0 (no information at all) to 100 (I have no need of more information), the participants declared that their level of information reached an average point of 82.12 after having read the PL (sd 20.77, n = 54), whereas before the mean is attested at 65.74. (sd 27.7, n = 54). The means are significantly different: Z. −4013 (p = .000). Most importantly, the intention to further enquire about the drug is not invariably associated with the perceived lack of information.

The highest correlation is instead observed with the perceived relevance of the information to the decision: "Are you considering not taking the treatment because of eventual missing information?" (Kendall's tau-b .001; Spearman's Rho .001). This data supports our hypothesis that the relevance of the information to the decision can be considered a predictor of active information seeking, rather than the mere awareness of information lack.

Furthermore, while the benefit-risk assessment parameter is correlated with the information seeking variable (Kendall's tau-b .045; Spearman's Rho .05), this does not hold for the level of illness severity. The closer the drug benefit-risk assessment to the breakeven point (50–50), the stronger becomes the intention to look for further information. The expected value of additional information is low, *ceteris paribus*, when the expected benefit is considerably higher with respect to the expected damage (e.g. 90 vs. 10 in our survey); it is high when both benefit and risk tend to be equal (e.g. 55 vs. 45). This is precisely a case where the decision is highly sensitive to new information.

This hypothesis is also backed up by the inverse relationship between degree of confidence in the decision and information seeking (Kendall's tau-b .026; Spearman's Rho .021). The lower the confidence in the decision, the greater the intention to search for further information. Instead the illness severity per se does not invariably trigger a demand for information: high concern does not necessarily lead to information search.

The association between intention to seek for information and decision sensitivity to it is consistent with the findings delivered by a study on the relationship between risk judgment and heuristic vs. systematic processing (Trumbo, 1999). This study investigates information processing as an antecedent for risk judgment through structural equation modeling on the basis of observational data. The resulting model, which relates motivation, self-efficacy and information gap on one side, with heuristic vs. systematic processing on the other – is significantly more robust for the "uncertain group" as opposed to the high-concerned and low concerned participants.

As for the role played by the anticipated emotional cost of incoming information, indirect evidence is provided by Kahn and Luce (2003). In their study, planned compliance with future mammograms is ambiguously related to stress: in the subgroup with a false-positive history the association between stress and future compliance is negative, whereas in the subgroup with no false-positive history the same association is positive. This means that stress, and its emotional cost, is experienced in two opposite ways. When it follows a history of false-positive test results, it tends to be interpreted as the unnecessary cost caused by a false alarm, leading to lower compliance with future screening. But when no such history is present, perceived stress in the face of a possibly threatening event is perceived as "genuine" and functions as a motivator for alerting measures (such as risk prevention through surveillance).

Obviously, further and more systematic evidence is needed in order to validate the rational-ignoring model. However, these data encourage us to develop this integrated model of rational ignoring into a full-fledged theory of information seeking, where this is considered to follow from both decision sensitivity to information and the emotional cost of the information.

11. Summary and outlook

This paper has outlined major theories of information-seeking behavior with particular reference to their explanatory power in health information search. In the health context, it seems that stopping rules do not follow the pattern predicted by standard cost/benefit accounts of information-seeking behavior. Furthermore, contrary to the classical equation "information = uncertainty reduction", it seems that information tends to be avoided in certain contexts precisely because it is expected to increase rather than to decrease uncertainty.

Distinguishing between epistemic and decision uncertainty, by using the notion of decision sensitivity on the one hand, and between epistemic and emotional uncertainty on the other, has helped to provide a model of information search that explains these apparently contradictory phenomena. In this model, information is valued (and sought) to the extent that it helps improve the decision and that the anticipated emotional cost attached to it does not outweigh its benefit in terms of choice reward.

The model is supported by fragmentary and provisory evidence, and thus needs further confirmation, but it is theoretically plausible in that it is able to predict the observed phenomena of information search (reappraisal, information avoidance, etc.) in a comprehensive and pasimonious fashion, without resorting to external factors such as personality traits or socio-cultural determinants.

[18] Shani et al. (2007) demonstrated that the emotional cost of uncertainty is higher than the emotional cost of knowing negative information. Feelings of discomfort associated with exposure to personally relevant negative information follow a curvilinear function: they are low when the negative outcome is associated with a low probability; high when the event is certain; even higher when the event is highly probable but uncertain. The smaller the gap to certainty, the more motivated subjects are to seek information which might definitely confirm or disconfirm the hypothesis. This finding does not contradict the model presented here, however, as long as we distinguish between perfect and imperfect information. Definite knowledge is provided only by perfect information: in this case, knowing for sure that a negative event will occur has an emotional cost which does not exceed or is inferior to the emotional cost of uncertainty. By contrast, imperfect knowledge does not promise to eliminate uncertainty, but only to reduce it, and thereby even to augment the feeling of frustration associated with smaller knowledge gaps. Information to which the decision is insensitive, but which promises certainty might still be preferred to uncertainty. However, this does not necessarily hold for information which is expected to reduce but not eliminate uncertainty.

Although the theoretical account presented in this study obviously needs further empirical validation (and more exact mathematical formalization), it provides a good starting-point for further research on health information-seeking behavior. Furthermore, the model could be validated and tested for different typologies of risk information: health vs. monetary or other risks, individual vs. collective choice, and individual vs. n-players game.

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