Risk and Ambiguity in Information Seeking: Eye Gaze Patterns Reveal Contextual Behaviour in Dealing with Uncertainty

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Abstract

Information foraging connects optimal foraging theory in ecology with how humans search for information. The theory suggests that, following an information scent, the information seeker must optimize the tradeoff between exploration by repeated steps in the search space vs. exploitation, using the resources encountered. We conjecture that this tradeoff characterizes how a user deals with uncertainty and its two aspects, risk and ambiguity in economic theory. Risk is related to the perceived quality of the actually visited patch of information, and can be reduced by exploiting and understanding the patch to a better extent. Ambiguity, on the other hand, is the opportunity cost of having higher quality patches elsewhere in the search space. The aforementioned tradeoff depends on many attributes, including traits of the user: at the two extreme ends of the spectrum, analytic and wholistic searchers employ entirely different strategies. The former type focuses on exploitation first, interspersed with bouts of exploration, whereas the latter type prefers to explore the search space first and consume later. Based on an eye-tracking study of experts’ interactions with novel search interfaces in the biomedical domain, we demonstrate that perceived risk shifts the balance between exploration and exploitation in either type of users, tilting it against vs. in favour of ambiguity minimization. Since the pattern of behaviour in information foraging is quintessentially sequential, risk and ambiguity minimization cannot happen simultaneously, leading to a fundamental limit on how
good such a tradeoff can be. This in turn connects information seeking with the emergent field of quantum decision theory.

1 Introduction

Searching for food is a common pattern of behaviour: humans and animals share dedicated cognitive mechanisms to find resources in the environment. Such resources are distributed in spatially localized patches where the task is to maximize one’s intake, that is, knowing when to exploit a local patch versus when it is time to move on and explore one’s broader surroundings.

In humans, the underlying neuropsychological mechanisms result in cognitive searches, such as recalling words from memory [1, 2]. As part of users’ information seeking behaviour, the concept of information foraging describes the above quest by a similar strategy [3].

Key to the understanding of decisions by a consumer of information is that they are subject to uncertainty: his or her knowledge of the environment is incomplete, so the resulting decisions must go back to perceptions and certain heuristics. By turning to classical works in economy, we can identify two facets of this uncertainty, namely risk and ambiguity [4, 5]. Their interpretation according to the foraging scenario is in place here.

Briefly, risk is the quality of the current patch and our fragmented perception of it. Is the place of good quality? Should one stay here or move on? Since we are already at the preselected location, we do have prior information about it. A risk-minimizing behaviour will favour exploitation over exploration, staying longer at individual locations, potentially losing out if outstanding patches remain unvisited.

The above immediately have anthropological overtones. Foraging behaviour seems to apply to a much larger domain than just looking for food, such as the optimization of upper and lower extremities of pleasure and pain, gain and loss, benefit and cost, reward and punishment, joy and sorrow. Seeking one while avoiding the other is the subject of risk analysis, where the nature of risk is hesitation. It is obvious that if we are too quick or too slow, we lose a positive option by gaining a negative score somewhere else without even having noticed.

Ambiguity, on the other hand, is related to opportunity cost, the price of not foraging elsewhere. “Elsewhere” refers to the rest of the unknown distribution which is not observed at the moment. A human forager who wants to reduce ambiguity first will jump around different patches and explore more, learning as much as possible about the information distribution while reducing the associated uncertainty. This behaviour will not stop at the first good enough patch.

To continue the anthropological implications, ambiguity would also mean that all of the above are the essence of situations, of problem solving in general, but by decisions (and the crucial belief that we have resolved the problem) we create a new situation by trying to escape it. So in a sense, risk would belong to the surface layer and ambiguity to the deep layer of any decision situation. If
the above hold, we could identify many more scenarios relevant from psychology to decision theory and from cognitive science to the stock exchange.

Resonating with the aforementioned, our working hypothesis below will be that if animal foraging is subject to uncertainty, and information seeking is an essentially identical activity in a different context, then a limit to simultaneous risk and ambiguity minimization must apply to information foraging as well. This limit emerges from the sequential and incompatible nature of the decisions made to minimize these two aspects of uncertainty. The incompatible decisions are similar to measurements in quantum mechanics where they give rise to the uncertainty principle; thus our work connects information foraging and information seeking behaviour to the thriving field of quantum decision theory [6, 7, 8, 9, 10]. We will demonstrate our point on eye tracking studies data in our study of user interactions with novel search interfaces for biomedical information search.

The structure of the article is as follows: in Section 2 we discuss the origins and application areas of uncertainty, including foraging decisions and information seeking as examples. In Section 3, a preliminary analysis of search behaviour based on eye tracking data is offered, with Section 4 listing our results and discussing them. Section 5 brings us to our conclusions and plans for future work.

2 Background

2.1 The origins and application areas of uncertainty

A decision in the presence of uncertainty means that the outcome cannot be fully predicted before the decision is made. Multiple possible outcomes can occur, and our knowledge of the probability distribution only allows for a limited characterization of uncertainty. Following Refs. [4] and [5, 11], we can distinguish between two fundamental aspects of uncertainty, aforementioned ambiguity and risk. The simple definition of risk is uncertainty with known probabilities, a certain a priori probability for a given outcome. Ambiguity is also probabilistic but less well defined, generally associated with events that the decision maker has even less information about than the risk of outcomes. The two aspects are also called expected and unexpected uncertainty. Dealing with unexpected uncertainty involves a more subjective evaluation of probabilities. In the case of ambiguity, less information is available, and expected utility is harder to estimate. Not knowing crucial information, such as the probability distribution of the outcomes, is a frightening prospect which explains why most people are ambiguity-averse [5]. The two forms of uncertainty are so different that dealing with risk and ambiguity are supported by distinct neural mechanisms in humans [12].

Apart from this probabilistic nature of decisions in an uncertain environment, there is an even deeper form of uncertainty: the kind we normally refer to in the context of quantum mechanics. Some measurements on a quantum
system are simply incompatible: measuring one aspect of the system prevents us from learning more about another aspect thereof, explored by a different measurement.

As stated by Ref. [13] in what constitutes the basis of this brief overview, “There are various mathematical aspects of the uncertainty principle, including Heisenberg’s inequality and its variants, local uncertainty inequalities, logarithmic uncertainty inequalities, results relating to Wigner distributions, qualitative uncertainty principles, theorems on approximate concentration, and decompositions of phase space” [13]. It is partly a description of a characteristic feature of quantum mechanical systems, partly a statement about the limitations of one’s ability to perform measurements on a system without disturbing it, and partly a meta-theorem in harmonic analysis that can be summed up as follows: “A nonzero function and its Fourier transform cannot both be sharply localized.” Therefore the principle leads to mathematical formulations of the physical ideas first developed in Heisenberg’s seminal paper of 1927 [14], explored from many angles afterwards.

Initially this rule was carved in stone for a particular case only – that we cannot simultaneously learn the position and the velocity (momentum) of a quantum particle with arbitrary precision. Namely Heisenberg’s uncertainty principle states that the standard deviation of such measurement outcomes on these two complementary aspects of the system cannot be simultaneously minimized:

$$\sigma_X \sigma_P \geq \frac{\hbar}{2}$$

where $\sigma_X$ is the standard deviation on the measurement of the position, $\sigma_P$ is the standard deviation on the measurement of the momentum, and $\hbar$ is the reduced Planck’s constant or Dirac constant.

This principle was later generalized to arbitrary pairs of incompatible measurements, and expressed by many other mathematical concepts different from standard deviation. Incompatible measurements mean that certain observations on a system do not commute: by making an observation, we are making a second one in the context created by the first. In other words, incompatibility, noncommutativity, and contextuality are closely related concepts.

Noncommutativity allows the definition of an alternative event algebra or logic, which in turn leads to applications in decision theory [7, 9]. This line of research is part of a broader trend of applying the mathematical framework of quantum mechanics in domains outside physics [8].

2.2 Uncertainty and foraging decisions

We are especially interested in how risk and ambiguity appear in sequential decisions. Simultaneous or coordinated decision making, on the other hand, is more complex, being less common among animals because it involves comparative evaluation. Pointing at a major difference between the animal kingdom vs. man, Ref. [15] showed that humans are able to choose between these two models
in uncertain environments. A foraging scenario is a good example of sequential decision making: food resources are available in patches, and a forager must find an optimal strategy to consume the resources. There is a cost associated with switching from one patch to another. Uncertainty relates to the quality of the current patch, the quality of background options – the opportunity cost of not foraging elsewhere – and the environment is also subject to changes. The forager has to minimize the tradeoff between exploitation of a patch versus exploration of background options. The pattern is not restricted to food consumption: for instance, it pertains to mate selection, retrieving memories, and consumer decisions. In fact, the same neural mechanism can serve these different functions [16].

Optimal foraging theory gives the strategy to follow if the probabilities can be estimated and updated by the forager [17, 18]. Ambiguity alters the behaviour: for example, unexpected forms of uncertainty may trigger more exploration [19]. We would like to see how ambiguity and risk can be minimized in sequential decisions, and how that affects exploration and exploitation.

Many decisions require an exploration of alternatives before committing to one and exploiting the consequences thereof. This is known as foraging in animals that face an environment in which food resources are available in patches: the forager explores the environment looking for high-quality patches, eventually exploiting a few of them only. The decisions take place in an uncertain environment: ambiguity about the quality of patches and the risk of not foraging at better patches force the forager to accept a tradeoff.

Risk-sensitive foraging is not exclusive to animals, human subjects also show similar behavioural patterns [20, 21]. An optimal solution between exploration and exploitation is generally not known, except in cases with strong assumptions about both the environment and the decision maker [19]. The tradeoff between exploration and exploitation is also known as the partial-feedback paradigm, linking the decision model to the description–experience gap [22]: people perceive the risk of a rare event differently if the probability distribution is known (decision from description) vs. when they have to rely on more uncertain information (decision from experience).

### 2.3 Information seeking as foraging

To take the next step in our working hypothesis, below we shall look at a scenario where seeking was exercised by gaze fixation at segments of user interfaces with significant elements of content, and show that underlying the seemingly random walks of eye gaze on the screen, there is order in the patterned data inasmuch as a certain typology of user behaviour applies to them.

The information foraging nature of the data was recognized by eye tracking analysis, based on the concept of information scent, operationalized as “the proportion of participants who correctly identified the location of the task answer from looking at upper branches in the tree” in a study of user interactions with visualization of large tree structures [23]. Ref. [24] provided further theoretical accounts for scanpaths from cognitive perspectives in which users were
able to find information more quickly when strong information scent was detected. Ref. [25] built a computational model for user information needs and search behavior based on information scent, and the model and algorithm were evaluated by simulated studies. More recently, the modeling of user search behavior using eye tracking techniques has focused on levels of domain knowledge, user interests, types of search task and relevance judgments in search processes [26, 27, 28, 29, 30]. However, there is still limited understanding of the effect of individual differences and user perceptions of search tasks on eye gaze patterns in information search. Ref. [31, 32] provided a review of information foraging and user interactions with search systems.

The eye gaze patterns, an indicator of user attention and cognitive processes have been extensively studied for designing user interfaces, such as the functional grouping of interface menu [33, 34], faceted search interface [35, 36] and comparison of interface layouts [37]. Information retrieval researchers have been concerned with users’ attention to the ranking position of documents and different components of search engine results page (SERP) [38, 39, 40, 41, 42]. These studies generally suggest that there is no significant difference in users’ eye gaze patterns on comparisons of search interface layouts, and users’ attention to elements of interfaces depends on the length and quality of snippets on SERPs, as well as the displayed position of search results.

3 User Experiment

This study was designed to investigate user gaze and search behaviour in biomedical search tasks, with particular reference to the user’s attention to and use of the document surrogates (i.e., Medical Subject Headings (MeSH) terms, title, authors, and abstract). A total of 32 biomedical experts participated in the controlled user experiment, performing searches on clinical information for patients. The participants were mostly students with search engine experience and some academic background in the biomedical domain.

We used a $4 \times 4 \times 2$ factorial design with four search interfaces, controlled search topic pairs and cognitive styles. A $4 \times 4$ Graeco-Latin square design was used [43] to arrange the experimental conditions. Each user was assigned 8 topics in total, with a 7-minute limit for each topic, and the experiment took about 90 minutes in total.

3.1 Search interfaces

Participants searched on four different search interfaces, with a single search system behind the scenes. The four search interfaces were distinguished by whether MeSH terms were presented and how the displayed MeSH terms were generated:

Interface “A” mimicked web search and other search systems with no controlled vocabulary. This interface had a brief task description at top; a
Imagine that you are 65-year-old female with urinary retention. You would like to find information about urinary retention, differential diagnosis. You have not saved any documents. When you are done, you can move to the next task.

Your search for urinary retention after menopause returned 1 results.

(a) Screenshot of Interface “B”, suggestions per-query and displayed at top.

(b) Screenshot of Interface “C”, suggestions per-query and displayed at top.

(c) Screenshot of Interface “D”, suggestions per-document and displayed with the document.

Figure 1: Three of the four search interfaces in the study.
Imagine that you are 63-year-old male with acute renal failure probably 2nd to aminoglycosides/contrast dye. You would like to find information about acute tubular necrosis due to aminoglycosides, contrast dye, outcome and treatment.

Figure 2: An example OHSUMED search topic, reworded for the participants.

conventional search box and button; and each result was represented with its title, authors, publication details, and abstract where available.

Full text was not available, so the results were not clickable. Users judged their success on the titles and abstracts alone.

**Interface “B”** (Figure 1(a)) added MeSH terms to the interface. After the user’s query was run, MeSH terms from all results were collated; the ten most frequent were displayed at the top of the screen. This mimics the per-query suggestions produced by systems like ProQuest.

MeSH terms were introduced with “Try:” and were clickable: if a user clicked a term, his or her query was refined to include the MeSH term and then re-run. It was hoped that the label, and the fact they work as links, would encourage users to interact with them.

**Interface “C”** (Figure 1(b)) used the same MeSH terms as “B” but displayed them alongside each document, where they may have been more (or less) visible. It is a hybrid of interfaces “B” and “D”.

**Interface “D”** mimicked EBSCOhost and similar systems that provide indexing terms alongside each document. As well as the standard elements from interface “A”, interface “D” displayed the MeSH terms associated with each document, as part of that document’s surrogate (Figure 1(c)).

Again, terms were introduced with “Try:” and were clickable.

Each interface was labelled with a simple figure: a square, circle, diamond, or triangle, which was referred to in the exit questionnaire. A save icon alongside each retrieved document was provided to collect user perceived relevant documents.

### 3.2 Search topics

Search topics used here were a subset of the clinical topics from OHSUMED [44], originally created for information retrieval system evaluation. The topics were slightly rewritten so they read as instructions to the participants (see Figure 2 for an example). Topics were selected to cover a range of difficulties.

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1. For example, see [http://www.proquest.co.uk/en-UK/products/brands/pl_pq.shtml](http://www.proquest.co.uk/en-UK/products/brands/pl_pq.shtml)
2. [http://www.ebscohost.com/](http://www.ebscohost.com/)
3.3 Procedure

Participants were given brief instructions about the search task and system features, followed by a practice topic and then the searches proper. They were informed that the test collection is incomplete and out-of-date since the OHSUMED test collection [44] was used, with MEDLINE data from 1987 to 1991. User interaction data recorded included: all queries, mouse clicks, retrieved and saved documents, time spent, and eye movements. Electroencephalogram (EEG) readings were also captured.

Background and exit questionnaires collected demographic information and asked participants about their perception of the search process. Participants’ opinions of the tasks and the interfaces was sought. Finally, information on participants’ cognitive styles was collected by a computerised test [45, 46], which took a further 15 minutes to complete.

3.4 Hardware and software

The search system was built on Solr\(^3\), with the search results ranked by default relevance score. The MeSH terms were not specifically weighted.

Eye gaze data was recorded from two Sony VFCB-EX480B infrared (IR) cameras which were controlled by Seeing Machines FaceLab 4.5 software\(^4\) and attached to a dedicated machine running Windows 7. At the same time, EyeWorks Design and EyeWorks Record\(^5\) were used to present instructions for the corresponding search tasks during the experiment. Gaze points were recorded at 60 Hz, and the eye gaze data included the \(x\) and \(y\) coordinates of where the eye was looking on the screen, as well as the time that gaze point is recorded. EEG data was recorded with an Emotiv headset\(^6\) to monitor emotional variation throughout the search session. A Windows 7 computer was dedicated to the cognitive styles test.

3.5 Data analysis

Recordings were analysed to see how often there were fixations in different parts of document surrogates (i.e., different elements of the interfaces), and therefore how often people looked at each part.

Four common areas of interest (AOI) were specified: title, author, abstract and MeSH (except for Interface A, without MeSH) to investigate which elements received attention. EyeWorks Analyze\(^7\) was used to specify the AOI, and fixations were specified as gazes within a 5-pixel radius which lasted at least 75 ms [47].

\(^3\)http://lucene.apache.org/solr/
\(^4\)http://www.seeingmachines.com/product/facelab/
\(^5\)http://www.eyetracking.com/Software/EyeWorks
\(^6\)http://www.emotiv.com/
\(^7\)http://www.eyetracking.com/Software/EyeWorks
In the study a post-search questionnaire was used to assess user perceptions about the search processes, in which search task difficulty was also identified as important moderator of eye gaze behaviour [48].

4 Results of search behaviour and eye gaze

Overall, our results support the hypothesis that search interfaces have significant effects on eye gaze behaviour in terms of proportion of fixations in reading time. This in turn translates to different strategies in dealing with risk and ambiguity.

4.1 Search task difficulty and eye gaze

Table 1 reveals that there was a statistically significant negative relationship between user perception of search task difficulty and proportion of fixations in reading time on all elements in documents. Further analysis indicates a significant interaction effect of interface and task difficulty on the fixations time spent in title (F(3, 248) = 3.72, p < .05) and MeSH terms (F(3, 248) = 3.71, p < .05), but it is not the case for the element of author (F(3, 248) = 1.69, p > .05) and abstract (F(3, 248) = 1.55, p > .05). These results suggest that perceived the search task as difficult, they did not attend to all elements in the documents.

| Areas of Interest | CutPoint (Mean) | Odds Ratio | Log Odds | Stand. Error | t Value | Signif. |
|-------------------|----------------|------------|----------|--------------|---------|---------|
| Title             | 24.33          | 0.06       | -2.73    | 0.71         | -3.86   | Yes     |
| Author            | 12.53          | 0.12       | -2.13    | 0.70         | -3.02   | Yes     |
| Abstract          | 45.81          | 0.13       | -2.05    | 0.71         | -2.90   | Yes     |
| MeSH              | 17.34          | 0.07       | -2.72    | 0.70         | -3.87   | Yes     |

Table 1: Summary of the relationship between search task difficulty and eye gaze (N search task difficulty = 256, N eye gaze = 256; statistical significance at 95 %)

4.2 Search task difficulty, cognitive style and eye gaze

In the study the E-CSA-WA (Extended Cognitive Style Analysis–Wholistic Analytic) test was used to determine user’s cognitive style. A Wholistic Analytic ratio (WA ratio) for each participant was produced [45]. The results suggest that there was no significant relationship between the users’ cognitive style and eye gaze across all elements in documents in terms of proportion of fixations in reading time.

Further analysis of the effects of search task difficulty, search interface and cognitive style and their interactions on eye gaze indicates significant interaction effects of difficulty and cognitive style (F(1, 240) = 4.54, p < .05), and cognitive style vs. search interface (F(3, 240) = 2.89, p < .05) in terms of fixation time on the element of abstract. We found significant interaction effects between
search task difficulty and search interface (F(3, 240) = 4.19, p < .01), and search interface and cognitive style (F(1, 240) = 4.24, p < .01) for the element of MeSH terms. These results suggest that searchers with different cognitive styles may use different search strategies under an environment with uncertainty perceived as difficult and observed by their eye gaze behaviour.

4.3 Search task difficulty and search behaviour

Table 2 shows that when search tasks were perceived difficult, users tended to spend less time searching, issued less queries or typed queries, saved fewer documents and had fewer mouse clicks, but there was no difference in the number of MeSH queries issued and the number of pages viewed.

Overall, the results indicate that searchers made less mental effort when the search tasks were difficult, and they tended to optimise limited resources in information seeking, demonstrated both by eye gaze (Table 1) and search behaviour (Table 2). Search behaviour associated with expending mental efforts like issuing MeSH terms and viewing SERPs has not changed according to the uncertainty within the environment, such as perceived search task difficulty.

| Search behaviour          | CutPoint (Mean) | Odds Ratio | Log Odds | Stand. Error | t–value | Stat. Signif. |
|--------------------------|----------------|------------|----------|--------------|---------|---------------|
| Time spent               | 185.7          | 0.11       | -2.25    | 0.70         | -3.20   | Yes           |
| Number of queries issued | 3.80           | 0.12       | -2.13    | 0.72         | -2.98   | Yes           |
| Number of MeSH queries issued | 0.33   | 0.30       | -1.19    | 0.74         | -1.60   | No            |
| Number of typed queries issued | 3.48  | 0.18       | -1.73    | 0.74         | -2.33   | Yes           |
| Number of pages viewed   | 5.04           | 0.23       | -1.47    | 0.76         | -1.94   | No            |
| Number of saved documents| 3.63           | 0.10       | -2.33    | 0.71         | -3.26   | Yes           |
| Number of mouse clicks   | 4.88           | 0.09       | -2.42    | 0.72         | -3.37   | Yes           |

Table 2: Summary of the relationship between search task difficulty and search behaviour (N search task difficulty = 256, N eye gaze = 256; statistical significance at 95 %)

4.4 Search behaviour and eye gaze in information search

Number of queries issued. Table 3 shows that there was a statistically significant connection between the number of queries issued and the area of interest (AOI) of MeSH terms. That is, when users issued more queries, they paid they paid significantly more attention.

Number of MeSH queries issued. Table 4 reveals that there was a statistically significant relation between the number of MeSH queries issued and the element of abstract negatively. That is, when users issued more MeSH queries, they paid significantly less attention to the abstract section of documents.

Number of mouse clicks. Table 5 indicates that there was a statistically significant inverse relationship between the number of mouse clicks and the title element of documents visited. That is, users who clicked the mouse more often were less likely to pay attention to titles.
| Areas of Interest | CutPoint (Mean) | Odds Ratio | Log Odds | Stand. Error | t−Value | Stat. Signif. |
|------------------|----------------|-----------|----------|--------------|---------|--------------|
| Title            | 24.33          | 0.76      | -0.27    | 0.25         | -1.09   | No           |
| Author           | 12.53          | 0.93      | -0.07    | 0.25         | -0.28   | No           |
| Abstract         | 45.81          | 0.92      | -0.09    | 0.25         | -0.34   | No           |
| MeSH             | 17.34          | 1.67      | 0.51     | 0.25         | 2.04    | Yes          |

Table 3: Summary of the relationship between number of queries issued and gaze (N number of queries issued = 256, N eye gaze = 256; statistical significance at 95 %)

| Areas of Interest | CutPoint (Mean) | Odds Ratio | Log Odds | Stand. Error | t−Value | Stat. Signif. |
|------------------|----------------|-----------|----------|--------------|---------|--------------|
| Title            | 24.33          | 1.39      | 0.33     | 0.37         | 0.89    | No           |
| Author           | 12.53          | 1.01      | 0.01     | 0.37         | 0.03    | No           |
| Abstract         | 45.81          | 0.45      | -0.80    | 0.39         | -2.02   | Yes          |
| MeSH             | 17.34          | 1.77      | 0.57     | 0.38         | 1.50    | No           |

Table 4: Summary of the relationship between number of MeSH queries issued and gaze (N number of MeSH queries issued = 256, N eye gaze = 256; statistical significance at 95 %)

| Areas of Interest | CutPoint (Mean) | Odds Ratio | Log Odds | Stand. Error | t−Value | Stat. Signif. |
|------------------|----------------|-----------|----------|--------------|---------|--------------|
| Title            | 24.33          | 0.46      | -0.77    | 0.26         | -3.00   | Yes          |
| Author           | 12.53          | 0.95      | -0.05    | 0.25         | -0.21   | No           |
| Abstract         | 45.81          | 1.21      | 0.19     | 0.25         | 0.76    | No           |
| MeSH             | 17.34          | 1.19      | 0.17     | 0.25         | 0.68    | No           |

Table 5: Summary of the relationship between number of mouse clicks and gaze (N number of mouse clicks = 256, N eye gaze = 256; statistical significance at 95 %)
**Number of pages viewed.** Table 6 brings evidence for the same inverse relationship between the number of pages viewed vs. titles inspected.

| Areas of Interest | CutPoint (Mean) | Odds Ratio | Log Odds | Stand. Error | t-Value | Stat. Signif. |
|-------------------|----------------|------------|----------|--------------|---------|--------------|
| Title             | 24.33          | 0.47       | -0.75    | 0.27         | -2.82   | Yes          |
| Author            | 12.53          | 0.61       | -0.49    | 0.26         | -1.85   | No           |
| Abstract          | 45.81          | 1.40       | 0.34     | 0.26         | 1.31    | No           |
| MeSH              | 17.34          | 1.54       | 0.43     | 0.26         | 1.65    | No           |

Table 6: Summary of the relationship between number of pages viewed and gaze (N number of pages viewed = 256, N eye gaze = 256; statistical significance at 95 %)

**Number of documents saved.** Table 7 reveals that there was a statistically significant relationship as regards the number of documents saved vs. abstracts and MeSH terms as document segments inspected. That is, when users saved more documents, they paid significantly more attention to the element of abstract, but less attention to the MeSH.

| Areas of Interest | CutPoint (Mean) | Odds Ratio | Log Odds | Stand. Error | t-Value | Stat. Signif. |
|-------------------|----------------|------------|----------|--------------|---------|--------------|
| Title             | 24.33          | 1.09       | 0.08     | 0.25         | 0.32    | No           |
| Author            | 12.53          | 1.32       | 0.28     | 0.26         | 1.08    | No           |
| Abstract          | 45.81          | 1.72       | 0.54     | 0.26         | 2.10    | Yes          |
| MeSH              | 17.34          | 0.38       | -0.97    | 0.26         | -3.70   | Yes          |

Table 7: Summary of the relationship between number of documents saved and gaze (N number of documents saved = 256, N eye gaze = 256; statistical significance at 95 %)

**Summary of search behaviour and gaze pattern types** Table 8 provides a summary of search behaviours and gaze patterns. These results clearly show that types of searching behaviour, such as issuing queries with MeSH terms that imply notable mental effort and strive at the exploitation of resources, are correlated with changes in eye gaze patterns.

## 5 Results and discussion

We summarize the main findings in the data as follows:

- When users perceived their search tasks as difficult, they did not attend to all content elements in documents.
- Searchers with different cognitive styles may use different search strategies under an environment with uncertainty they perceive as difficult.
Table 8: Summary of the relationship between search behaviour and gaze patterns

|            | # of queries issued | # of MeSH queries issued | # of mouse clicks | # of pages viewed | # of documents saved |
|------------|---------------------|--------------------------|-------------------|------------------|---------------------|
| Title      | -                   | -                        | -                 | -                | -                   |
| Author     | -                   | -                        | -                 | -                | -                   |
| Abstract   | -                   | -                        | -                 | -                | -                   |
| MeSH       | ●                   | ○                        | -                 | -                | ●                   |

Note. The relationship is not statistically significant (—), positively significant (●), or negatively significant (○).

- Search behaviour associated with expanding mental efforts like issuing MeSH terms and viewing SERPs has not changed according to the uncertainty within the environment, such as perceived search task difficulty.

- Certain search behaviour types, such as issuing queries and MeSH terms that involve notable mental efforts and exploitation of resources, are correlated with changes in eye gaze patterns.

These findings indicate distinct strategies in dealing with uncertainty, possibly changing from preferring exploration to exploitation and vice versa, and therefore corroborate our hypothesis that the corresponding observations do not commute (Section 5.1). This in turn enables us to frame information foraging as a form of quantum-like behaviour (Section 5.2).

5.1 Different strategies and noncommuting observations

In the above eye tracking study, the document surrogates and the four layouts characterize different perceptions of risk of information patches, gazing time being a good figure of merit for exploitation. Exploration is the jumping gaze combined with a repeated query as these reduce overall ambiguity. There is evidence that wholistic users prefer to get an overview of tasks before drilling down to detail, whereas analytic users look for specific information. These two extreme user behaviours rely on the two measurement operators, namely risk- vs. ambiguity reduction, in different order, proving noncommutativity. Unfortunately, at this point there is no significant relationship between the users’ cognitive style and the AOIs.

However, if we also change the perceived risk by varying the search interface, the picture changes. The effect of cognitive styles, interfaces and their interactions on the AOI of MeSH terms (excluding Interface A) is statistically significant in terms of cognitive style and interface interactions, and weakly significant in terms of cognitive style ($F(1,188) = 2.79, p < .01$). Interfaces make a statistically significant difference for the wholistic style ($F(2, 111) = 6.58, p < .001$), and cognitive styles make a statistically significant difference in Interface B ($F(1, 62) = 5.11, p < .05$). The results indicate that wholistic users’ attention to the MeSH terms is more affected by search interfaces than that of
analytic users, and this interaction effect is significant when interacting with Interface B. Thus noncommutative measurements emerge.

5.2 Information seeking is quantum-like

To sum up, uncertainty as a composite of risk and ambiguity drives information seeking behaviour in a complex way, with successive decisions attempting to minimize both components at the same time. However, to find their joint optimum is not possible, because risk-prone and ambiguity-prone behaviour manifest two versions of foraging attitude, called the “consume first and worry later” (exploitation) vs. the “worry first and consume later” (exploration) types. Whichever option taken, it becomes the context of the opposite alternative, so that ambiguity minimization dependent on risk minimization vs. risk minimization dependent on ambiguity minimization yield different sets of retrieved items, i.e. the outcome of information seeking as a process is non-commutative.

For every case where this joint optimum seeking mentality influences the results, plus the decision making process that has led to a particular outcome must be preserved for future reconstruction, our findings are relevant. However, there is more to the implications of the above.

In this study we have seen that two types of information seeking behaviour emerged from interaction between the cognitive apparatus and the phenomenon observed, i.e. information. This is reminiscent of the the Copenhagen interpretation of quantum mechanics, where interaction between the measurement apparatus and the observable cannot be reduced to zero, and the measured value is a result of (or is not independant from) interaction; again in the words of Ref. [13], “the values of a pair of canonically conjugate observables such as position and momentum cannot both be precisely determined in any quantum state.” Further, we have found that the above two types of behaviour go back to the application of two operators, risk- and ambiguity-aversion, so that by applying now this, then the other first, their sequential application leads to different results, called non-commutativity.

Moreover, as much as risk and ambiguity are two sides of the same coin, non-commutativity is an essential feature of the uncertainty principle core to quantum mechanics. Given this, our current finding hints at something potentially fundamental about the nature of browsing. At the same time, since Ref. [49] proposed to treat precision and recall as complementary operators regulating the surface of effectiveness in information retrieval, whereas Ref. [50] argued that relevance is an operator on Hilbert space and as such is part of the quantum measurement process, neither was our insight totally unexpected. Rather, connected to the uncertainty principle, we see noncommuting measurements to surface also in information seeking as another link to quantum decision theory [51, 52, 53].
6 Conclusions and future research

We interpreted risk and ambiguity as two types of measurement on an uncertain environment, arguing that in an information foraging scenario, these measurements are sequential and do not commute, that is, reversing their order yields different outcomes. We demonstrated this by analyzing user behaviour in interacting with different designs of search results, specifically, by tracking the gaze of users. Depending on the degree of uncertainty involved, qualitatively different types of information seeking behaviour emerged, agreeing with our hypothesis.

We have reason to believe that similar data, such as clickstreams, will show similar patternedness as evidence of non-commutative user behaviour manifesting the same cognitive types in a different setting. In a broader context, non-commuting measurements are standard tools in quantum mechanics, and they are being explored in quantum decision theory for modelling decision problems and known fallacies – our work connects information seeking to this line of research.

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