Article:

Perkovic, S orcid.org/0000-0003-0488-3755, Bown, NJ orcid.org/0000-0001-5510-2053 and Kaptan, G orcid.org/0000-0002-3219-9347 (2018) Systematicity of Search Index: A new measure for exploring information search patterns. Journal of Behavioral Decision Making, 31 (5). pp. 673-685. ISSN 0894-3257

https://doi.org/10.1002/bdm.2082

Systematicity of Search Index: A New Measure for Exploring Information Search Patterns

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Acknowledgments

The authors thank Christopher Ball, Moshe Glickman, Thomas Hills, Jacob L. Orquin, Sajid Siraj, Michael Schulte-Mecklenbeck and Dirk Wulff for their helpful comments. The authors also thank Martin P. Bagger and Marko Perkovic for their assistance with the experimental setup in PsychoPy.

Word count: 9904

Abstract

Many studies on information search in multi-attribute decision-making rely on the analysis of transitions from one piece of information to the next. One challenge is to categorize information search that includes an equal amount of alternative- and attribute-wise transitions. We propose a measure, the Systematicity of Search Index (SSI), for exploring information search based on sequences of either alternative- or attribute-wise transitions. The SSI explores information search in terms of systematicity or the proportion of non-random search, i.e. search that is alternative- or attribute-wise corrected for chance. Our experiment confirms the validity of the SSI and shows that the SSI can shed light on processes not captured by the measures analysing single transitions, such as Payne's Search Index.

Keywords: information search; systematicity; Search Index; multi-attribute decision-making; eye tracking

Systematicity of Search Index:

A New Measure for Describing Information Search Patterns

Cognitive processes underlying individual decision-making have been the centre of researchers' focus for several decades. Two methodologically distinct approaches have been used to study these processes: a structural approach and an information processing approach (Abelson & Levi, 1985; Ford, Schmitt, Schechtman, Hults, & Doherty, 1989; Newell & Simon, 1972; Payne, Braunstein, & Carroll, 1978; Westenberg & Koele, 1994). The structural approach is based on statistical models that describe the relation between information stimuli (input) and decision responses (outcomes) (Abelson & Levi, 1985). The information processing approach, on the other hand, stems from human problem solving research (Newell & Simon, 1972) and tries to understand which cognitive processes precede a response (Payne et al., 1978). Since this approach investigates cognitive processes more directly, it often produces more detailed explanatory models of decision-making behaviour (Harte, Westenberg, & van Someren, 1994; Payne, 1976; Payne et al., 1978). Overall, it has been argued that whenever possible, both approaches should be used in a complementary way because they contribute to explaining different aspects of the decision-making behaviour (Einhorn & Hogarth, 1981; Einhorn, Kleinmuntz, & Kleinmuntz, 1979; Riedl, Brandstätter, & Roithmayr, 2008; Wulff & van den Bos, 2017).

The methodology derived from the information processing approach, often referred to as process tracing, has been used to uncover the cognitive processes preceding the decision-maker's response (Payne et al., 1978). Several process tracing methods have been applied in decision-making research. They can loosely be classified into three groups: a) methods for tracing information acquisition (e.g. information boards, eye tracking and active information search), b) methods for tracing information integration and evaluation (e.g. thinking aloud and structured response elicitation), and c) methods for tracing physiological, neurological, and other accompanying cognitive processes (e.g. measurement of reaction time, galvanic skin conductance, pupil dilation and neuronal techniques of location) (for a review see Schulte-Mecklenbeck et al., in press).

Here we focus on methods for tracing information acquisition. Several measures have been developed to explore information acquisition behaviour such as the depth of search, the pattern of information search, the variability of search, the compensation index, the latency of search and the content of search, to name just a few (for a review see Harte & Koele, 2001; Riedl, Brandstätter, & Roithmayr, 2008). Of all the measures on information acquisition, measures for exploring the pattern of information search have received most attention so far, mainly due to Payne's seminal paper (1976) where he proposes a simple measure for detecting the pattern of information search.

Pattern of information search

Focusing on the pattern of information search when studying decision-making processes has also been labelled as "analysis of transitions" because it considers the change from one acquired piece of information to the next (Jacoby, Chestnut, Weigl, & Fisher, 1976). These processes have usually been studied in the context of multiattribute decision making, which includes a choice between two or more alternatives, each described by several attributes. There are four types of transitions which can be distinguished with respect to whether the sequence of information searched consists of transitions belonging to a different or the same alternative and a different or the same attribute (see Table 1). Type 1 transitions occur when a decision maker re-examines the same attribute within the same alternative; type 2 transitions occur when a decision maker examines different attributes within the same alternative; type 3 transitions occur when a decision maker examines the same attributes between different alternatives, and type 4 transitions occur when a decision maker examines different attributes between different alternatives. Out of these four types of transitions, type

2 and type 3 transitions are most often analysed in decision-making studies (Norman & Schulte-Mecklenbeck, 2009).

Table 1

Types of transitions during information search

Alternative	Attribute	
	Same	Different
Same	Type 1	Type 2
Different	Type 3	Type 4

Several measures have been proposed for analysing the pattern of information search based on type 2 and type 3 transitions. Since these types of transitions include the analysis of single-step transitions, they have been labelled as single-step transition measures (Ball, 1997). The number of citations suggests[1] that the most commonly used measure is the Search Index (SI) proposed by Payne (1976) which shows the proportion of alternative-wise (i.e. type 2) and attribute-wise (i.e. type 3) search. The measure is a ratio of the number of alternative-wise transitions minus the number of attribute-wise transitions over the sum of those two numbers:

$$\mathrm{SI} = \frac{N_{type\ 2} - N_{type\ 3}}{N_{type\ 2} + N_{type\ 3}} \tag{1}$$

It ranges from -1 to 1, -1 being a fully attribute-wise search and 1 being a fully alternative-wise search. In case there is an equal number of alternative-wise and attribute-wise transitions, the SI equals to zero. It is often assumed that alternative-wise search reflects compensatory strategies, i.e. a high value on one attribute can compensate for a low value on another, and that attribute-wise search reflects non-compensatory strategies, i.e. no trade-offs

[1] The number of citations of Payne's paper Task complexity and contingent processing in decision making: An information search and protocol analysis was 2190 on 24 October 2017. On the same date, Böckenholt and Hynan's paper Caveats on a process-tracing measure and a remedy and Van Raaij's paper Consumer information processing for different information structures and formats had 77 and 99 citations, respectively (obtained using Google Scholar).

between the attributes (Reisen, Hoffrage, & Mast, 2008). However, one should exercise caution when making these assumptions because some compensatory strategies could also rely either partially or entirely on attribute-wise search (Rieskamp & Hoffrage, 1999).

However, there has been much criticisms of the SI. For instance, Böckenholt and Hynan (1994) suggested that for an accurate categorization of information-acquisition strategies, one needs to consider characteristics of the task environment such as the number of presented alternatives and attributes. Specifically, the authors argue that the mean of the SI is zero only when the number of alternatives is equal to the number of attributes. Alternatively, when the number of attributes is higher than the number of alternatives, the SI points to an alternative-wise information search and when the number of alternatives is higher than the number of attributes, the SI points to an attribute-wise information search. The previous holds assuming a random selection strategy, i.e. every piece of information is equally likely to be selected with a probability $1/N_{alt} * N_{att}$, N_{alt} being the total number of alternatives and N_{att} being the total number of attributes. The SI may, therefore, lead to inaccurate classifications of information search because it ignores these characteristics of the task environment. Moreover, the measure's mean varies not only as a function of the number of alternatives and attributes, but also the number of transitions, when this number is small (for an argument see Böckenholt & Hynan, 1994). Therefore, the values of the SI observed in different sized matrices as well as the values within the same matrix, when the number of transitions is small, could not be compared directly (Bettman & Jacoby, 1976; Böckenholt & Hynan, 1994). In addition, extreme SI values may have a higher probability of occurrence than intermediate values assuming a random selection strategy (Böckenholt & Hynan, 1994). Böckenholt and Hynan, therefore, proposed a strategy measure (SM) which describes information search strategies as standardized deviations from random search patterns:

$$\mathrm{SM} = \frac{\sqrt{N}((AD/N)(r_a - r_d) - (D-A))}{\sqrt{A^2(D-1) + D^2(A-1)}} \qquad (2)$$

where N represents the total number of transitions, A represents the number of alternatives and D the number of attributes (dimensions) in an information matrix, r_a represents the frequency of alternative-wise transitions and r_d the frequency of attribute-wise transitions. However, Payne and Bettman (1994) argued that the limitation of the SM lies in its inability to provide consistent results when decision-makers make only one type of transitions (e.g. alternative- or attribute-wise). For instance, when a decision-maker repeatedly makes attribute-wise search patterns in different choice tasks which differ in length (i.e. different number of transitions), SM assigns different values to those patterns, even though they consist of only one type of transitions (i.e. attribute-wise). On the other hand, the SM delivers identical results when it should not, for instance, such as in a case of a search pattern consisting of only attribute-wise transitions versus a pattern consisting of a mixture of attribute- and alternative-wise transitions. Ball (1997) suggests that the distribution of SM values still varies with changes in the number of alternatives and attributes in a matrix as well as the total number of transitions performed. Furthermore, comparing the mean SM values for the same search strategy applied in different sized matrices yields mixed results, as the calculation of the mean is sensitive to extreme values.

A different line of thought has led Van Raaij (1977) to propose a measure which is based on the same input as the SI but compares the number of times alternative- and attribute-wise transitions occur in the first versus the second part of the search process. More specifically, the information search patterns may change over time due to the application of different decision strategies during different stages of a decision process. The analysis is, therefore, sometimes divided into a few equal parts which are analysed separately (Svenson, 1979). The Van Raaij index can be calculated using:

$$\frac{[N(type\ j)_1 - N(type\ j)_2]}{M-1} \qquad (3)$$

where N represents the number of observations for a particular type of transition, j represents the type of transition (type 2 or type 3), the subscripts 1 and 2 represent the first and second half of the decision-making process respectively and M represents the total number of information items searched for. This measure has been shown to be more sensitive in detecting strategies used in the first versus the second phase of the decision-making process than the SI (Stokmans, 1992). Furthermore, the measure is independent of the number of alternative- and attribute-wise transitions and the expected value is zero.

Overall, Ball (1997) nicely summarizes the three main limitations of measures that include the analysis of single-step transitions. First, since the analysis is restricted to single steps in the information search sequence, not all available information is used. Second, one does not actually learn about the search strategies used because the measures often restrict comparisons of search strategies to strict compensatory (e.g. weighted additive strategies) and non-compensatory strategies (e.g. lexicographic strategies). For instance, Ball argues that it is unclear how to classify strategies that include both types of transitions and, therefore, fall between these two extremes. This is a direct criticism of the SI and particularly noticeable in the example of strategies that include an equal amount of both types of transitions so the SI concentrates around zero. This issue has also been addressed by other scholars (e.g. Harte & Koele, 2001). Finally, the distributions of such measures seem to be dependent on the number of dimensions (i.e. alternatives and attributes) of a matrix. Ball, therefore, proposes the use of multiple-step transitions which overcomes these limitations by focusing on more complex and complete range of transitions.

Here we focus more closely on Ball's previously introduced remarks. Specifically, we are interested in shedding light on how to categorize information search when the SI is close to zero. Put differently, when it is close to zero, all that the SI conveys is that a decision-maker made approximately the same number of alternative- and attribute-wise transitions. However, does this mean that a decision-maker's information search should, thus, be, described as random or is it possible that this similar number of both types of transitions did not happen by chance?

To answer this question, we propose a new measure, the Systematicity of Search Index (SSI), which explains information search in terms of systematicity or the proportion of non-random search, i.e. search that is alternative- or attribute-wise, corrected for chance. In addition, the SSI is a measure based on multiple-step transitions. As we show later, the SSI can be used as an additional measure for exploring information search in terms of systematicity as well as a complementary measure to existing measures for exploring the pattern of information search, most specifically the SI. In the next section, we briefly outline how the SSI was developed (a detailed account is presented in the results section). We then discuss our expectations and report an experiment in which we test the validity of the SSI.

Development of Systematicity of Search Index

We develop the SSI in the following way. First, instead of focusing solely on single transitions such as in existing measures for exploring the pattern of information search, we propose focusing on alternative- and attribute-wise patterns, i.e. sequences of either alternative- or attribute-wise transitions of specific length. The reasoning behind this is an attempt to set the threshold higher in terms of what can be accepted as an indication of alternative- or attribute-wise processing. Second, we propose assessing whether the obtained patterns occur by chance by estimating the probability of a pattern occurring using Monte Carlo simulation. Third, to get the proportion of systematic search, we propose that the SSI should be a ratio of alternative- and attribute-wise patterns corrected for chance over all transitions made. The SSI ranges from 0 to 1, 0 representing a random or unsystematic search and 1 representing a non-random or systematic search. The SSI can, therefore, be calculated using the following equation:

$$\mathrm{SSI} = \frac{\sum_{i=1}^{n} l_i N_i \,(1 - p_i)}{l_{total}} \tag{4}$$

where l_i is the length of a pattern i, N_i is the frequency of a pattern i, p_i is the probability of a pattern i occurring by chance and l_{total} is the length of a total sequence of all transitions (i.e. string length).

Since the SSI aims to show the proportion of non-random search in overall search performed based on alternative- and attribute-wise patterns, we need to weight the systematicity of search by the length and the frequency of each identified pattern. The rationale behind this decision is to obtain the same number in the numerator and the denominator, in case the search performed is completely systematic (SSI = 1). In addition, we weight the systematicity of search by the probability of each pattern occurring by chance, i.e. assuming that each transition is uncorrelated to the previous transition and that it occurs with a probability of $1/N_{alt} * N_{att}$, N_{alt} being the total number of alternatives and N_{att} being the total number of attributes, because we expect that some patterns might occur due to chance. Since there is, to the best of our knowledge, no easy analytical solution, we compute the probability of the pattern occurring by chance using a Monte Carlo simulation.

Although we suspect that the SSI could be useful for determining the systematicity of the entire SI scale, it should be particularly useful in situations where decision makers make approximately the same amount of alternative- and attribute-wise transitions (SI ≈ 0). That said, we expect that the SSI can show whether these alternative- and attribute-wise transitions did or did not occur by chance. We also expect that the SSI is higher in environments where information is visually organised compared to environments where it is disorganised, because the context should encourage the level of systematic search. These expectations were tested in the validation experiment below.

Validation experiment

We test the SSI in a discrete choice experiment using eye tracking technology. We use four within-subjects conditions in which we present information in an organised or disorganised way to encourage either systematic or unsystematic search, respectively. As will be illustrated in the stimuli section below, in the conditions encouraging systematic search, the pieces of information are presented by either grouping alternatives (alternative array condition), grouping similar attributes (attribute array condition) or by presenting alternatives vertically in a matrix (matrix condition). In contrast, in the condition which encourages unsystematic search, all pieces of information belonging to each alternative are presented randomly in a matrix. The expected SI score for a random information search is zero only in the case of a symmetrical matrix, i.e. when the number of attributes is equal to the number of alternatives. Therefore, to answer our question whether the SSI is a useful complementary measure to the SI when SI is close to zero, we are most interested in the conditions with symmetrical matrix visual grouping.

Method

Participants. Thirty-five participants were recruited through a consumer panel provider. Three participants were excluded from the further analyses due to insufficient data quality resulting in a total sample of 32 participants. An a priori power analysis performed through a simulation in R indicated that to have 95.6% power for detecting a small-sized effect (d = .2; see Cohen, 1988), with an alpha level of .05 for a within-subjects design with four conditions and 100 trials per participant, a sample size of 28 participants is required. The participants ranged in age from 23 to 50 years (M = 29.59, SD = 6.36) with more female than male participants (18 women). Only participants with normal and full colour vision were included in the study. Each participant received approximately €10 for completing the study. All participants gave informed consent.

Design. In the discrete choice experiment, participants were instructed to select the most healthful out of the four alternatives. The experiment had four within-subjects conditions (i.e. alternative array, attribute array, matrix and random matrix) in which information was presented differently. Each condition had 25 trials resulting in a total of 100 trials per participant. Each trial had four alternatives named A, B, C and D. Each alternative had four attributes: brand, percentage of fat, grams of protein and grams of sugar. The attributes had four levels (see Table 2) all of which were present in each trial. In every trial participants were, therefore, presented with 16 pieces of information. Each trial was generated by randomly combining attribute levels without replacement. The order of conditions was randomized across participants.

Table 2

Attributes and attribute levels

Attribute			
Brand	Fat (%)	Protein (g)	Sugar (g)
Alpro	0.2	3	4
Cultura	1	6	8
Thise	1.5	9	12
Yoggi	3	12	16

Stimuli. One of the conditions (i.e. random matrix condition) required disorganised information presentation format which would encourage unsystematic search. To achieve this, we needed to spatially dissociate alternatives and attributes which raised the need for a method for identifying what attribute levels belong to which alternatives. The Gabor patch solves the problem by associating each attribute level to a specific alternative allowing us to position the attribute levels anywhere on the screen. Therefore, the sixteen pieces of information in each trial were presented with 32 Gabor patches (i.e. sinusoidal gratings typically with a Gaussian envelope) paired in the following way: each Gabor patch pair had a target Gabor and a distractor Gabor. Distractor Gabors had a rectangular envelope (5 cycles/deg, 3˚ x 3˚) and target Gabors had a circular envelope (5 cycles/deg, diameter 1˚). The distractor Gabors were oriented horizontally. The target Gabors were tilted either 20˚, 70˚, 110˚ or 160˚ clockwise from vertical. Each orientation of the target Gabor represented a different alternative. The Gabors tilted 20˚, 70˚, 110˚ and 160˚ belonged to alternatives A, B, C and D, respectively. A grey rectangle (2˚ x .7˚) was positioned in the centre of each target Gabor. An attribute level (text height = .5˚) was positioned within each rectangle.

Each condition had its own unique visual presentation. In the alternative array condition, all attributes belonging to an alternative were presented together in a group (see Fig. 1a). The spacing between Gabor pairs within groups was 1˚ and between groups 3˚ of a visual angle. The centres of the Gabor pair groups were located at the following coordinates: {(-5,5), (5,5), (-5,-5), (5,-5)}. The locations of target Gabors were randomized within groups across all trials. The attributes were randomly assigned to the four group locations. Additionally, the locations of attribute levels within groups were randomized. In the attribute array condition, similar attributes were presented together in groups, i.e. brand with brand, fat percentage with fat percentage and so on (see Fig. 1b). The spacing and the location of Gabor pairs were the same as in the alternative array condition. The locations of target Gabors were randomized between groups across all trials. The attributes were randomly assigned to the four group locations. Additionally, the locations of attribute levels within groups were randomized. In the matrix condition, alternatives and attributes were presented in a matrix, i.e. alternatives were presented vertically and attributes horizontally (see Fig. 1c). The locations of target Gabors and attribute levels were randomized column-wise and row-wise, respectively, across all trials. In the random matrix condition, alternatives and attributes were presented in a matrix as in the matrix condition; however, all pieces of information were presented independently (see Fig. 1d). The locations of target Gabors and attribute levels were randomized across all trials.

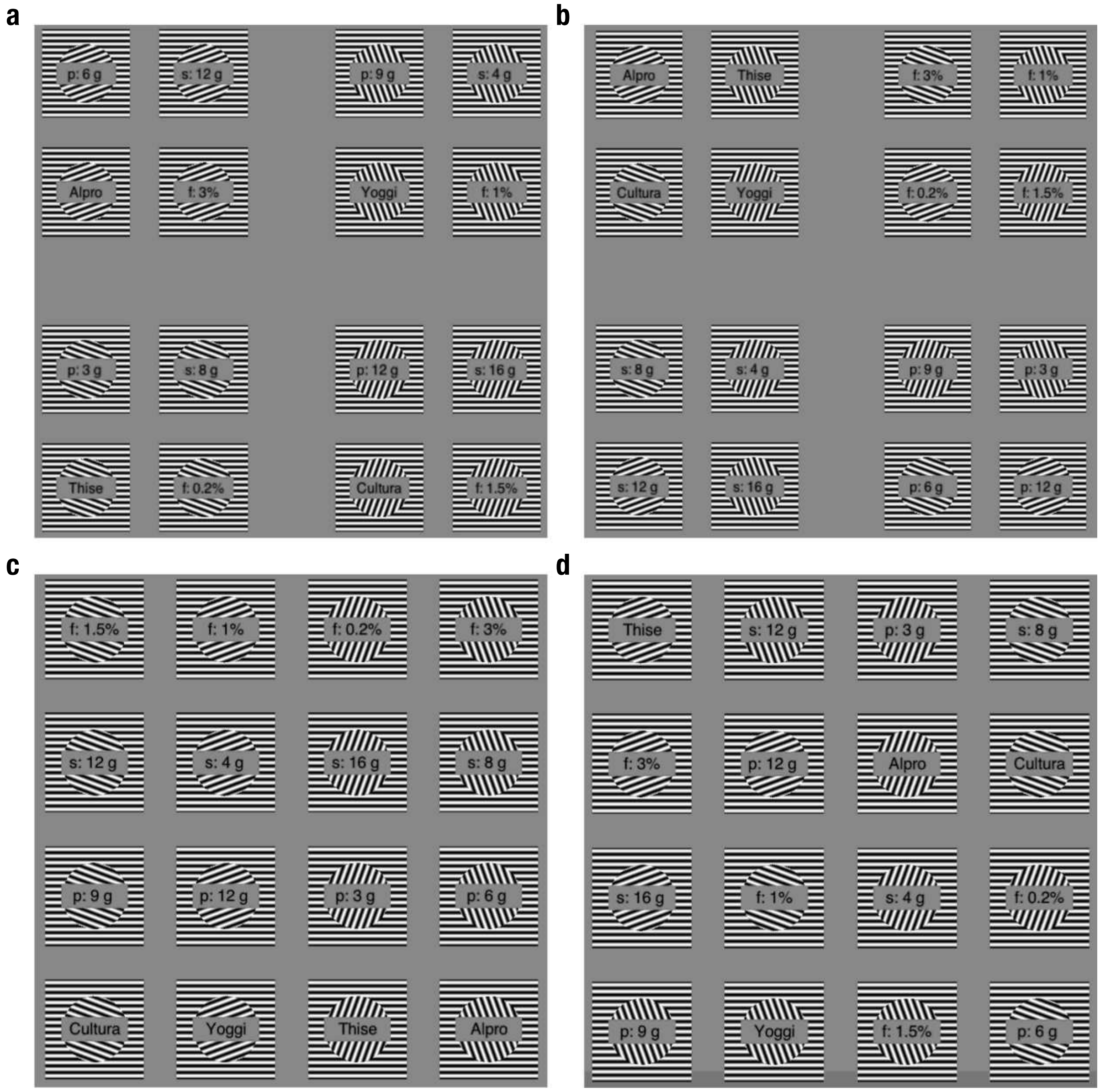

Figure 1. Visual array of each condition. a) alternative array condition: alternatives presented together (note the orientation of the lines in the circular Gabor Patch). b) attribute array condition: attribute levels belonging to the same attribute presented together. c) matrix condition: alternatives presented vertically and attributes horizontally. d) random matrix condition: all pieces of information presented independently.

Apparatus. The stimuli were created and presented using PsychoPy 1.84.2 (Peirce, 2007, 2009). Eye movements were recorded using a desk-mounted EyeLink 1000 eye tracker with a monocular sampling rate of 1000 Hz and a screen resolution of 1920x1200 pixels. The screen subtended a visual angle of 46.5˚ horizontally and 30.1˚ vertically. Average viewing distance was 60 cm from the screen. A chin rest was used to stabilize head position. Fixations were detected using a velocity, acceleration and motion-based algorithm with velocity, acceleration, and motion thresholds of 30˚/sec, 8,000 ˚/sec^2, and 0.15˚, respectively (Holmqvist et al., 2011; SR Research, 2008). To consider the inaccuracy in recording of eye fixation locations, an area of interest (AOI) was drawn around every distractor Gabor (Orquin, Ashby, & Clarke, 2016).

Procedure. The study was conducted in a light-controlled laboratory environment. Upon arrival to the laboratory, participants were greeted and asked to read the study information sheet and fill in the consent form. Immediately after, the experimenter explained the procedure, task and visual design of the experiment. Specifically, participants were presented with four possible target Gabors and were informed that each target Gabor represents a specific alternative throughout the experiment. Participants were then asked to memorize the four target Gabors. They were also shown a screenshot of each condition and asked to locate alternatives in each. After determining the dominant eye, participants were calibrated using a 9-point calibration procedure followed by a 9-point drift validation test. A calibration offset < 1.0° was considered acceptable. After the calibration, they were introduced to the experiment layout and instructions on the screen. To test whether participants had memorized the target Gabors, they practiced recognizing in up to 48 practice trials. Each target Gabor was presented randomly 12 times. Feedback was given after each practice trial. Participants proceeded to the next practice trial only by providing the correct answer. In case of 10 correct answers in a row, suggesting mastery of recognition, participants immediately proceeded to the experiment. Participants were instructed to select the healthiest among four alternatives by indicating their choice through a key press (i.e. A, B, C or D). They used as much time as needed to make their choices. No feedback was given between trials. To control the location of the first fixation, a fixation cross lasting 1000 ms appeared in the centre of the screen preceding each trial. Participants completed 25 trials per condition, resulting in a total of 100 trials. The experiment lasted 45 minutes on average.

Results

Calculating the Systematicity of Search Index. The analysis of participants' information search behaviour was divided into five steps. First, we determined which attributes participants fixated on and in which order. Eye fixations were, therefore, coded considering 16 possible combinations of four alternatives and four attribute levels (see Table 3) which resulted in a string length of 154,355 elements for all participants. Since we were only interested in whether participants fixated on an attribute at least once, subsequent fixations, i.e. two or more fixations in a row to the same attribute within an alternative, were deleted from the string which resulted in a total string length of 96,222 elements.

Table 3

Recoding of eye fixations depending on attribute-alternative combination

		Alternative			
		(1) 20°	(2) 70°	(3) 110°	(4) 160°
Attribute	Brand (b)	1b	2b	3b	4b
	Fat (f)	1f	2f	3f	4f
	Protein (p)	1p	2p	3p	4p
	Sugar (s)	1s	2s	3s	4s

Next, we determined alternative- and attribute-wise patterns in the string. The patterns were created for every participant on a trial level. We started by identifying the alternative- and attribute-wise substrings. A sequence was classified as an alternative-wise substring if at least two subsequent fixations belonged to different attributes within the same alternative. Then, we focused on the order and frequency of the elements within each such substring. Specifically, in each alternative-wise substring we ordered the elements alphabetically and deleted every repeating instance of an element. In other words, if a participant inspected three attributes within an alternative and then focused on the same three attributes, but in a different order in the next alternative, the attributes were coded as if they had been inspected in the same order. For example, a sequence sugar-protein-fat which is equal to fat-protein-sugar and protein-sugar-fat and so on, was then coded as fat-protein-sugar, i.e. 'fps'. Additionally, if a participant fixated on an attribute within an alternative several times, the additional fixations were deleted. For example, if a participant made a sequence sugar-protein-sugar-protein-sugar within an alternative, we coded it as protein-sugar, i.e. 'ps'.

After identifying and recoding all substrings, we concatenated the identical subsequent substrings which belonged to different alternatives. For example, if a participant fixated on sugar and protein levels twice in a row across two different alternatives, a pattern named 'psps' was produced. To be classified as an alternative-wise pattern, the same substring of a minimal length of two had to appear at least twice in a row. For this reason, a pattern length of four was the shortest possible alternative-wise pattern length. An example of the 10 alternative-wise patterns obtained can be found in Table 4 (column three). The maximum pattern length in this example is 12 (trial three).

A sequence was classified as an attribute-wise substring if at least four subsequent fixations belonged to the same attribute, but different alternatives within a trial. For example, if a participant fixated on a sugar level four times in a row across four different alternatives, an attribute-wise pattern named 'ssss' was produced. Since the shortest possible alternative-wise pattern was of length 'four', we considered only the attribute-wise patterns of length 'four' or greater. An example of the 10 attribute-wise patterns obtained can be found in Table 5 (column three). The maximum pattern length in this example is nine (trial 26). We then determined the frequency for every alternative- and attribute-wise pattern (see column four in Table 4 and Table 5).

After identifying patterns and their frequencies, we assessed whether the obtained patterns occurred by chance. We, therefore, used a Monte Carlo simulation and simulated 1,000 random observations for each trial with the string length of each trial being equal to the one in the original data set. An observation consisted of an alternative number (1 to 4) and an attribute initial (b, f, p and s). We analysed the random data sets in the same way as we analysed the original data set in terms of identifying alternative-wise and attribute-wise patterns and calculating their frequencies on a trial level. We then compared all the patterns and their frequencies from the original data set with the patterns and the associated frequencies (see column five in Table 4 and Table 5) in 1,000 random data sets on a trial level. Specifically, we looked at how frequently a pattern from the original data set occurred in that amount or more in 1,000 random data sets in a specific trial. For instance, if we observed that a pattern ‘ssss’ occurred one time in a trial in the alternative array condition, we looked at how many times this pattern occurred at least one time or more in that trial in the alternative array condition in 1,000 random data sets.

We then calculated the probabilities by dividing these pattern frequencies by the total number of iterations (1,000) (see column six in Table 4 and Table 5). Instead of selecting a significance level (e.g. .05) which would serve as a cut of value for determining whether a pattern occurred by chance, we used the probability complements. Specifically, we multiplied each pattern (frequency and length) from the original data set with its probability complement (see column seven in Table 4 and Table 5). This suggests that only if a probability of a pattern occurring by chance was one, would a probability complement be zero, which would then result in an automatic exclusion of this specific pattern from the further calculation of the SSI (see the numerator of the equation (4) below).

Table 4

First 10 alternative-wise patterns identified for one participant on a trial level

Condition	Trial	Pattern	Pattern Frequency	Pattern Frequency (Simulation)	Probability	Probability Complement
Alternative array	1	fpsfps	1	1	.001	.999
Alternative array	2	bfsbfs	1	3	.003	.997
Alternative array	3	bfpsbfpsbfps	1	0	0	1
Alternative array	3	fpsfps	1	4	.004	.996
Alternative array	4	fpsfps	2	0	0	1
Alternative array	5	bfpsbfps	2	0	0	1
Alternative array	6	bfpsbfps	1	2	.002	.998
Alternative array	6	bsbsbs	1	6	.006	.994
Alternative array	6	fpsfps	1	2	.002	.998
Alternative array	6	psps	1	59	.059	.941

Note. Attributes: b: brand, f: fat, p: protein, s: sugar.

Table 5

First 10 attribute-wise patterns identified for one participant on a trial level

Condition	Trial	Pattern	Pattern Frequency	Pattern Frequency (Simulation)	Probability	Probability Complement
Alternative array	8	ssssss	1	1	.001	.999
Alternative array	9	ssss	1	80	.080	.920
Alternative array	11	ssss	1	33	.033	.967
Alternative array	18	ssss	1	32	.032	.968
Attribute array	26	bbbbbb	1	1	.001	.999
Attribute array	26	ffffffff	1	1	0	1
Attribute array	26	fffffffff	1	1	0	1
Attribute array	26	ppppp	1	14	.014	.986
Attribute array	26	ssss	1	75	.075	.925
Attribute array	28	bbbb	1	53	.053	.947

Note. Attributes: b: brand, f: fat, p: protein, s: sugar.

We then applied the following, previously introduced, equation to calculate the systematicity of participants' information search within each condition on a trial level:

$$\text{SSI} = \frac{\sum_{i=1}^{n} l_i \, N_i \, (1 - p_i)}{l_{total}} \tag{4}$$

where l_i is the length of a pattern i, N_i is the frequency of a pattern i, p_i is the probability of a pattern i occurring by chance and l_{total} is the length of a total sequence of all transitions (i.e.

string length). We also calculated the direction of participants' information search within each condition and for each trial by calculating the SI using:

$$SI = \frac{N_{type\,2} - N_{type\,3}}{N_{type\,2} + N_{type\,3}} \tag{1}$$

where type 2 are transitions occurring within the same alternative but different attributes, and type 3 are transitions occurring within the same attribute but different alternatives. We present these results in the following section. The R script with all the previously described steps applied to our data set can be found at the following link: **https://github.com/sonjaPerkovic/SSIcode.**

Eye movement analysis. To test whether participants are being more systematic in the three visually organised conditions compared to a disorganised one, i.e. alternative array, attribute array, matrix and random matrix condition, respectively, we analysed the data by means of linear mixed-effects model. The model was fitted using the 'lme' function from 'nlme' package in R (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2017). We used the SSI as a dependent variable, condition as an independent variable and participant variable as a random effect. The analysis revealed that adding the fixed effect of condition to the model significantly improved the fit compared to the baseline model, $\chi^2(3) = 107.51$, $p < .001$. A Tukey post hoc test revealed that the SSI was significantly different between all conditions. There was a significant difference between the random matrix compared to the alternative array condition (b = - .13, p < .001, d = -.86), the random matrix compared to the attribute array condition (b = - .28, p < .001, d = -1.52), the random matrix compared to the matrix condition (b = - .21, p < .001, d = -1.11), the attribute array compared to the alternative array condition (b = .15, p < .001, d = .68), the matrix compared to the alternative array condition (b = .08, p < .001, d = .35) and the matrix compared to the attribute array condition (b = - .07, p < .01, d = -.29).

To test the direction of participants' information search across four conditions, again we applied linear mixed-effects model using the ‘lme’ function from ‘nlme’ package in R. We used the SI as a dependent variable, condition as an independent variable and participant variable as a random effect. Again, the analysis revealed that adding the fixed effect of condition to the model significantly improved the fit compared to the baseline model, $\chi^2(3) = 193.89$, $p < .001$. A Tukey post hoc test revealed that the direction of information search was significantly different between all conditions. There was a significant difference between the attribute array compared to the alternative array condition (b = - 1.09, $p < .001$, d = -3.10), the matrix compared to the alternative array condition (b = - .62, $p < .001$, d = -1.51), the random matrix compared to the alternative array condition (b = - .39, $p < .001$, d = -.98), the matrix compared to the attribute array condition (b = .47, $p < .001$, d = 1.18), the random matrix compared to the attribute array condition (b = .70, $p < .001$, d = 1.75) and the random matrix compared to the matrix condition (b = .22, $p < .001$, d = .50).

To better understand the relationship between the two indices, we plotted the SSI against SI across conditions (see Fig. 2.). Figure 2 shows that participants scored higher on the SSI in the alternative array condition, the attribute array condition, and the matrix condition compared to the random matrix condition. The SI, on the other hand, shows that participants on average made more alternative-wise transitions in the alternative array condition and more attribute-wise transitions in the attribute array condition. In the matrix condition, participants on average made approximately an equal amount of alternative- and attribute-wise transitions, while in the random matrix condition they on average made slightly more alternative- than attribute-wise transitions. This suggests that the information presentation format influenced the performance of both measures. Systematic information search appears when the information presentation format is in some way organised compared to when it is disorganised. On the other hand, the information presentation format can make the direction of information search more alternative- or attribute-wise. However, it is not straightforward to interpret the direction of information search when the matrix format is used. Therefore, combined, these two measures provide more information about information search processes in different information presentation formats, and particularly in the matrix format. Table 6 shows an overview of means, standard deviations and 95% confidence intervals for the SSI and SI across conditions.

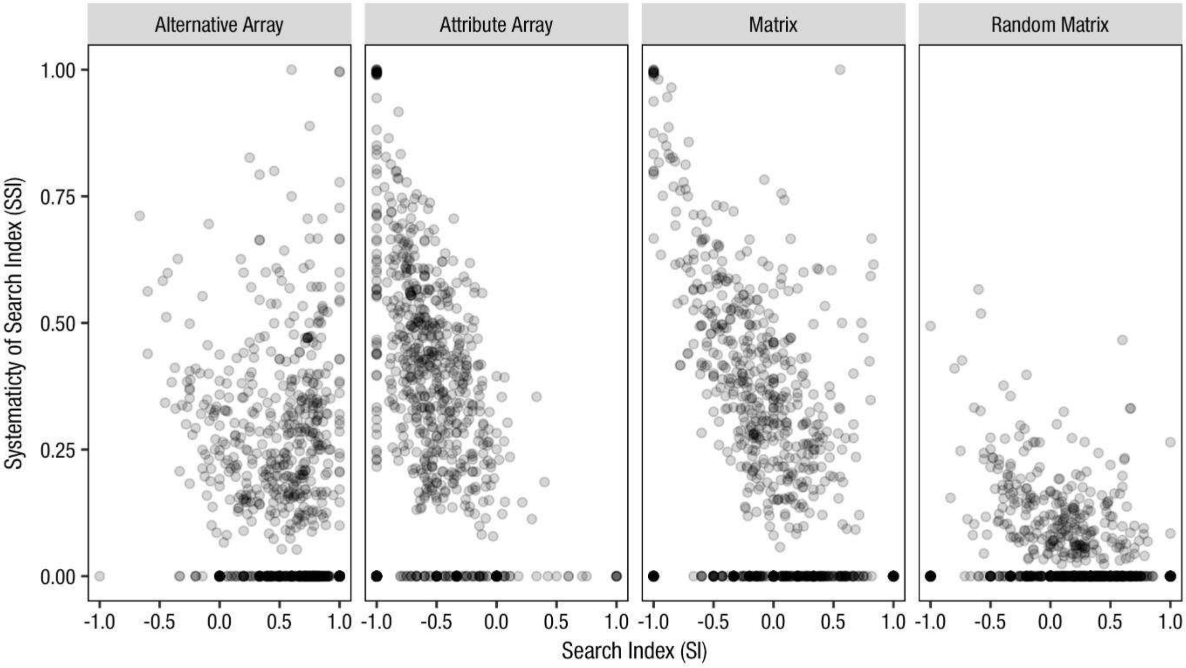

Figure 2. Systematicity of Search and Search Index across conditions on a trial level.

Table 6

An overview of means, standard deviations and 95% confidence intervals for the Systematicity of Search Index (SSI) and Search Index (SI) across conditions

	SSI			SI		
Condition	M	SD	95%CI	M	SD	95%CI
Alternative array	.18	.20	[.16, .19]	.55	.36	[.52, .57]
Attribute array	.33	.25	[.31, .35]	-.54	.35	[-.57, -.52]
Matrix	.26	.26	[.24, .27]	-.07	.45	[-.10, -.04]
Random matrix	.05	.08	[.04, .05]	.15	.44	[.12, .18]

Importance of data pre-processing for the SSI. As noted in the first and the second step of the SSI calculation (see Calculating the Systematicity of Search Index section), we did certain data pre-processing before identifying alternative- and attribute-wise patterns. In the first step we removed subsequent fixations from the string, i.e. two or more fixations in a row to the same attribute within an alternative. In the second step, we used the ‘relaxed frequency and order’ rule to identify alternative-wise patterns, i.e. in each substring we ordered the elements alphabetically and deleted every repeating instance of an element. To see how the SSI performs when we do not do any data pre-processing, we repeated the analyses without applying any data pre-processing first. We also calculated the SI for such data set. Table 7 shows an overview of means, standard deviations and 95% confidence intervals for the SSI and SI across conditions.

Table 7

An overview of means, standard deviations and 95% confidence intervals for the Systematicity of Search Index (SSI) and Search Index (SI) across conditions when no data pre-processing is used

	SSI			SI		
Condition	M	SD	95%CI	M	SD	95%CI
Alternative array	.01	.03	[.00, .01]	.75	.20	[.74, .76]
Attribute array	.04	.08	[.03, .04]	.20	.28	[.20, .22]
Matrix	.02	.06	[.02, .03]	.37	.30	[.35, .39]
Random matrix	.00	.02	[.00, .01]	.65	.24	[.63, .66]

From the previous table, we can see that both indices are affected by the lack of data pre-processing. The SSI does not capture almost any systematicity, whereas the SI is biased in the alternative-wise direction. This suggests that data pre-processing is a prerequisite to obtain meaningful SSI and SI values.

Performance of the SSI when search is random. To calculate the probability of observing any SSI value different from zero when search is random, we generated a random data set with 5000 trials of length 50 which corresponds to the average length of a trial in our data set. To generate fixations to alternatives and attributes, we used a combination of four alternatives and four attributes sampled randomly from a uniform distribution with each combination of alternatives and attributes having an equal probability of being fixated on (.0625). We then calculated the SSI as previously explained. Figure 3 shows the frequencies of observing the SSI values.

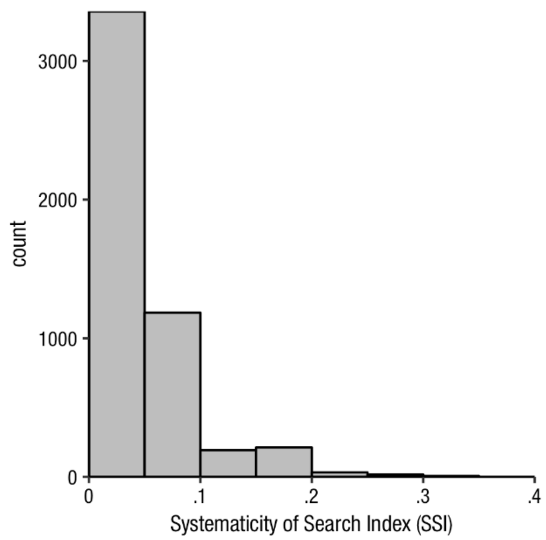

Figure 3. Frequencies of SSI values when search is random.

Figure 3 shows that the SSI values of zero were obtained most frequently. Furthermore, we have not observed values greater than .313. For instance, the SSI value of .313 occurred only twice (p = 2/5000 = .0004). Finally, the observed SSI value when search is random was on average .04.

The influence of threshold for pattern classification on the SSI. One challenge to the SSI is under-classifying patterns due to the relatively strict rule of minimum four transitions. This is particularly noticeable in the bottom of Figure 2 where one can see that a substantial amount of cases across all conditions are classified as having the SSI = 0 (42.82%). The proportion of zeros per condition was 43.18%, 24.38%, 37.92% and 65.83% for the alternative, attribute, matrix and random matrix condition respectively. It is clear that the largest proportion of such cases is found in the random matrix condition (65.83%) which is 38.42% of all cases where the SSI = 0. This is the condition where we expected unsystematic search and thus the SSI not to identify any systematicity. However, the findings are somewhat unsettling for other conditions where we expected relatively systematic search. This is particularly noticeable in the alternative condition where the proportion of the SSI = 0 is 43.18% (25.20% of all cases where the SSI = 0). This happens because of the relatively strict criterion of minimum four transitions. We therefore reduced the threshold for classifying substrings as patterns to the length of two for both alternative- and attribute-wise patterns and repeated the analyses. Table 8 shows an overview of means, standard deviations and 95% confidence intervals for the SSI across conditions.

Table 8

An overview of means, standard deviations and 95% confidence intervals for the Systematicity of Search Index (SSI) across conditions when threshold is reduced to the length of two

	SSI		
Condition	M	SD	95%CI
Alternative array	.62	.16	[.61, .64]
Attribute array	.68	.16	[.66, .69]
Matrix	.72	.16	[.71, .73]
Random matrix	.37	.16	[.36, .38]

In Table 8 we can see the SSI values when the threshold for classifying patterns is minimum of two transitions. The table shows that the SSI is much higher in all conditions, i.e. conditions with organised as well as disorganised information presentation format (compare Table 6). Only .02% of cases were classified as having the SSI = 0. The proportion of zeros per condition was .02% for the alternative, attribute and matrix and .04% for the random matrix condition. We also repeated the analysis regarding the performance of the SSI when search is random. Figure 4 shows the frequencies of the SSI values.

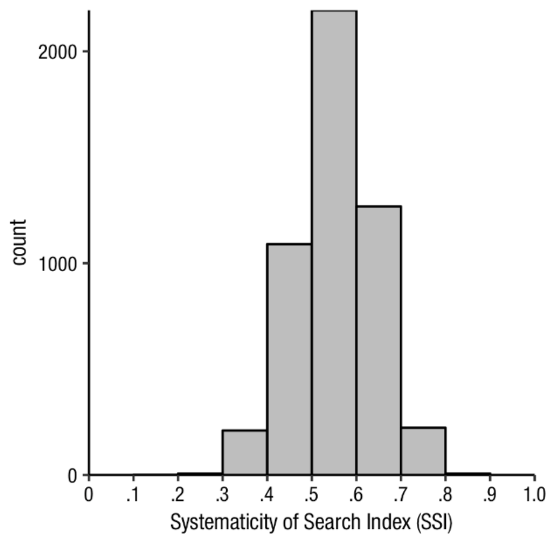

Figure 4. Frequencies of SSI values when search is random and threshold reduced to the length of two.

Figure 4 shows that the SSI values between .50 and .60 were the most frequent. The observed SSI value when search is random was on average .55.

Discussion

We proposed a new measure, the Systematicity of Search Index (SSI), as an additional measure for exploring information search behaviour. We developed a measure for exploring how systematic decision makers are when searching for information by determining the proportion of non-random search, i.e. search that is alternative- or attribute-wise corrected for chance. We tested the validity of this measure in a discrete choice experiment with four within-subjects conditions (alternative array, attribute array, matrix and random matrix) using eye tracking. In each condition, we used different visual presentations to create either organised or disorganised information presentation format. We expected that the SSI would be higher in environments where information is visually organised compared to environments where it is disorganised. We also expected that the SSI could serve as a useful complementary measure to the SI, especially in situations where decision makers make approximately the same amount of alternative- and attribute-wise transitions (SI $\approx$ 0).

Our findings support both of our expectations regarding the performance of the SSI. The findings show that there is a difference between the SSI in conditions with organised (alternative array, attribute array and matrix) versus disorganised (random matrix) information presentation format with the largest difference being between the random matrix compared to the attribute array condition, $d = -1.52$. We also observed a large difference between the random matrix and the matrix condition as well as the random matrix and the alternative array condition, $d = -1.11$ and $d = -.86$ respectively. Furthermore, the SSI was on average higher in the alternative array, the attribute array, and the matrix condition compared to the random matrix condition (see Table 6) which confirms the validity of the measure.

When comparing the SI in the conditions with organised and disorganised information presentation format, we observed the largest difference between the random matrix and the attribute array condition, $d = 1.75$. We also observed a large difference between the random matrix compared to the alternative array condition, $d = -.98$, and a medium difference between the random matrix compared to the matrix condition, $d = .50$. As expected, participants on average produced more alternative-wise transitions in the alternative array condition and more attribute-wise transitions in the attribute array condition. In the matrix condition, participants on average made approximately an equal amount of alternative- and attribute-wise transitions, while in the random matrix condition they on average made slightly more alternative- than attribute-wise transitions (see Table 6).

The findings also show that the SSI appears to be useful in situations where the SI is close to zero. This is noticeable in the matrix condition where the SI suggests that participants are, on average, being equally alternative- and attribute-wise (SI = -.07), whereas the SSI suggests that although this may be the case, it did not happen by chance (SSI = .26). In addition, the SI in the random matrix condition suggests that participants on average produced slightly more alternative-wise transitions (SI = .15), whereas the SSI suggests that this most likely happened by chance (SSI = .05). In addition, we believe that the SSI may be useful in other situations as well and not just SI ≈ 0. This is clear from the findings reported in Table 6 which suggest that the SI may be strongly influenced by the visual presentation of information. In such situations, the SSI can show whether the relatively high SI occurs due to characteristics of the stimulus or actual systematic behaviour.

Since we identified data pre-processing as the first step in the procedure for calculating the SSI, we tested its importance for the SSI. We found that the SSI is strongly affected by the lack of data pre-processing (see Table 6 and Table 7). This finding is not surprising because when there is no data pre-processing it is very unlikely to observe two identical subsequent alternative-wise substrings. Therefore, alternative-wise patterns are very scarce. Attribute-wise patterns are also scarce because there are few patterns where participants are fixating on the same attribute across different alternatives without making any refixations. Data pre-processing also affected the SI which in all conditions produced values indicating completely alternative-wise search. This happens because without any pre-processing there are many refixations within each alternative. This suggests that data pre-processing is a prerequisite to obtain meaningful SSI and SI values.

To inspect how the SSI performs when search is random, we calculated the probability of observing any SSI value different from zero when the string is truly random (see Fig 3). To obtain this, we generated a random data set of a similar structure to our original data set. The findings show that the most frequent SSI value is zero and that the values greater than .3 are rarely observed. Furthermore, the observed SSI value when the string is truly random is on average .04 which we consider a rather negligible bias. Therefore, the SSI appears to be a reliable measure of the systematicity of information search when search is truly random.

Finally, we explored the SSI when the minimum pattern length is two. When the minimum length is four, many of the substrings remained unclassified (≈ 43% of the SSI = 0). On the other hand, when the minimum length is two, the SSI = 0 in only .02% of cases. Additionally, the average SSI per condition became much higher (compare Table 6 and Table 8). Also, when we analysed random data, we obtained high SSI values (see Figure 4). Clearly, both approaches have some advantages and disadvantages. When the minimum length is four, all shorter substrings are classified as the SSI = 0. This does not necessarily mean that the search is unsystematic, but that the criterion is not met. When the minimum length is two, we obtain high SSI values for random data (.55 on average). Also, setting the minimum length to two is computationally more expensive. However, when analysing non-random data, we can still distinguish the search in organised from disorganised information presentation layout. We leave it to the reader to decide on which approach to take.

Limitations and future directions. One possible limitation of the proposed measure could be that here the SSI is used to explore information search by testing it for the strict compensatory and non-compensatory strategies only. Therefore, we neglected the entire repertoire of strategies that a decision-maker could use dependent on the decision-maker's characteristics, decision task and the decision environment (Payne, Bettman, & Johnson, 1993). However, we deem this was an appropriate approach to start out with when developing a new measure for exploring information search which could also serve as a complementary measure to the SI. Another limitation is that in comparison to the SI measure, the SSI could be perceived as a slightly more complex measure which may deter decision researchers from using it. We also discussed issues when calculating the SSI with different minimum pattern lengths.

Finally, one may argue that different, possibly more reliable, ways of assessing the systematicity of search exist. One such example would be sample entropy (Richman & Moorman, 2000) which determines the disorderedness of the time series. For instance, using sample entropy one could assume that a string containing only one type of patterns (e.g. 'pppp', N_{pppp} = 4) is more systematic than a string containing two types of patterns (e.g. 'sfsf', N_{sfsf} = 2 and 'pbpb', N_{pbpb} = 2). However, seen from the point of a psychological process, it is not clear that the latter is more disordered, i.e. less systematic – both could, for instance, be part of a heuristic or decision strategy. Put differently, since the aim of the SSI is assisting in a psychological interpretation of search data, with the SSI we do not wish to suggest that attribute-wise patterns are more systematic than alternative-wise patterns. Instead, both types of patterns contribute to the systematicity. Therefore, sample entropy would not assist us with obtaining systematicity in such a way.

To tackle some of the previously mentioned limitations, our future plan is to test the SSI by adjusting it so that it captures the systematicity of various search strategies, preferably in different decision environments with different decision tasks. For instance, the SSI could capture type V to type VII transitions proposed by Ball (1997). In this way, the SSI would gain more power to discriminate between specific decision strategies such as weighted additive, equal weight or majority of confirming dimensions. In addition, to simplify the use of the SSI, we developed an R package which should make the use of the SSI almost as simple as the use of the SI. The package can be accessed at the following link: https://github.com/sonjaPerkovic/SSI.git. When it comes to setting the threshold for the minimum pattern length, we discussed the pros and cons of two accounts (minimum length four vs. minimum length two). Since each approach has disadvantages, future studies should address solutions.

Finally, the SSI could be adapted and applied in any domain which includes a choice between different alternatives consisting of different attributes such as, e.g. risky choice, preferential choice, strategic choice and intertemporal choice. For instance, in decisions from experience (Hertwig, Barron, Weber, & Erev, 2004; Hills & Hertwig, 2010; Noguchi & Hills, 2016; Wulff, Mergenthaler Canseco, & Hertwig, in press), as part of a risky choice domain, randomness has, to the best of our knowledge, not been assessed. Therefore, a metric such as the SSI, which shows how different from random a search process is, would be useful.

Conclusion

Our findings contribute to the existing knowledge on information search by providing a new measure for exploring the pattern of search. The SSI has the merit of calculating the systematicity of information search by taking into consideration the probability of a search sequence being due to chance. Furthermore, the SSI is a measure based on multiple-step transitions and, therefore, addresses some of the limitations of single-step transition measures summarized by Ball (1997). It can, therefore, shed light on processes not captured by the SI. Generally speaking, the SSI is useful as an additional measure for exploring information search; however, it is also useful as a complementary measure to the SI. That said, the SSI is useful for classifying the entire range of the SI in terms of systematicity, but even more so in situations when the SI is close to zero. More specifically, when the SI is close to zero, all we know is that information search consists of approximately equal amounts of alternative- and attribute-wise transitions. Therefore, extra information on whether information search did or did not occur by chance in this situation, which is provided by the SSI, is beneficial. It is important to note that the two measures are related, since they both rely on alternative- and attribute-wise transitions/patterns, but are different in terms of what they measure, i.e. the SSI measures systematicity and the SI measures direction of information search. Our experiment confirms the validity of the new measure by showing that decision-makers' systematicity of information search depends to a great extent on the visual format of an environment. Hence, the SSI can be used for calculating the systematicity of information search in process-tracing studies and, therefore, serve as a complementary measure to existing measures for exploring the pattern of information search.

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