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Implicit Statistical Learning in Real World Environments Behind Ecologically Rational Decision Making

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Abstract

Ecological rationality results from matching decision strategies to appropriate environmental structures, but how does the matching happen? We propose that people learn the statistical structure of the environment through observation and use the learned structure to guide ecologically rational behavior. We study this learning hypothesis in the context of organic foods by asking why people believe organic foods are more healthful despite evidence to the contrary. In Study 1, we show that products from healthful food categories are more likely to be organic. In Study 2, we show that perceptions of the healthfulness and amount of organic products across food categories are accurate. In Study 3, we show that people perceive organic products as more healthful when the statistical structure justifies this inference. Our findings suggest that people believe organic foods are more healthful and use this cue to guide behavior because organic foods are, on average, 30% more healthful.

Keywords: decision making; implicit statistical learning; ecological rationality; eye tracking; field study

While it is certainly true that people sometimes behave irrationally, there are also plenty of examples of rational behavior in specific contexts. For instance, we may behave extremely shortsighted in the grip of our urges (Ariely & Loewenstein, 2006) while in other situations the same gut feeling may save the day (Klein, 1998). This situational intelligence has been studied under different names such as ecological rationality (Gigerenzer, Todd, & the ABC Research Group, 1999; Todd, Gigerenzer, & the ABC Research Group, 2012) and naturalistic decision making (Klein, 2008). To understand ecological rationality, it is essential to know when and why structures in the mind match structures in the environment (Todd & Gigerenzer, 2007). In Brunswik's terms, matching results from relying on cues with a high ecological validity (Brunswik & Kamiya, 1953). However, the most ecologically valid cue is not always available so we may have to rely on other, less valid, cues. In a Nordic consumer context, for instance, the Keyhole label is a 100% valid cue for a healthful product (Orquin, 2014), but the Keyhole is only available on 39% of healthful products. In contrast, the organic label is available on 100% of organic products (Orquin, 2014). When cue availability varies, it is an advantage to know many cues because it reduces the number of times we must choose at random (Berretty, Todd, & Martignon, 1999). Imagine searching for a quality watch. You know only that Swiss watches are of high quality, but during the search you observe that Swiss watches are more expensive than other watches. When later presented with a watch of unknown origin, you may still infer its quality from its price since the two are correlated. While the learned cue is valid in the learning context, it may mislead you if applied in other contexts e.g., inferring wine quality from prices since the two are not correlated (Goldstein et al., 2008). Acquiring and exploiting ecologically valid cues should, therefore, be an important part of shaping ecologically rational behavior in uncertain environments, but how does this happen? One answer might be implicit statistical learning.

Implicit statistical learning shows that adults and infants can learn the statistical properties of the environment merely through observation (Conway & Christiansen, 2006; Perruchet & Pacton, 2006). Such unsupervised learning allows us to infer distributional properties, correlations, and transition probabilities in the environment (Thiessen, Kronstein, & Hufnagle, 2013) and the learning happens fast (Saffran, Newport, Aslin, Tunick, & Barrueco, 1997), across sensory modalities (Conway & Christiansen, 2005), and in different domains (Brady & Oliva, 2008; Kushnir, Xu, & Wellman, 2010; Xu & Garcia, 2008). While implicit statistical learning is mainly concerned with language and visual learning, we believe it offers an opportunity to understand ecological rationality in decision making.

Here, we study this mechanism in the context of organic foods. It is well known that people believe organic foods to be more healthful than their conventional counterparts (Hughner, McDonagh, Prothero, Shultz, & Stanton, 2007) even though there is no conclusive scientific evidence behind this belief (Barański et al., 2014; Dangour et al., 2009; Smith-Spangler et al., 2012). Despite a lack of scientific evidence, we propose that the *organic = healthful* belief could be ecologically rational if the environment is structured such that organic foods are, in some way, more healthful than non-organic foods. While currently there is no evidence for such a claim, we surmise that organic foods are more prevalent in unprocessed, as opposed to processed, food categories, that is to say, that unprocessed foods (e.g., vegetables, fruit, milk, meat, eggs, etc.) are more likely to be organic than processed foods (e.g., frozen pizzas, candy, chips, ready meals, etc.). If this is true, then the *organic = healthful* belief would be ecologically rational; a person primarily purchasing organic foods would have a higher likelihood of buying from healthful (unprocessed) food categories.

We, therefore, expect that there is a correlation between organic and more healthful (unprocessed) food products in the natural environment. Next, we expect that people will learn about this statistical structure, which is reflected in perceptions of organic products as more prevalent in healthful food categories. Finally, we expect that it is possible to experimentally reproduce implicit statistical learning by manipulating the correlation between organic and health cues. Specifically, a positive correlation between organic and health cues will increase attention to, and use of, organic cues when estimating food healthfulness.

We test these assumptions in three studies. Study 1 is a field study from six Danish supermarkets in which we test the first assumption by obtaining the correlation between organic food prevalence and the healthfulness of food categories. We obtain the healthfulness of food categories through a panel of food and nutrition experts. In Study 2, we test the second assumption in an online study where participants provide estimates of the healthfulness and prevalence of organic foods for the food categories identified in Study 1. In Study 3, we test the third assumption in an eye-tracking experiment by manipulating the correlation between organic and health cues in a health judgment task.

Study 1

In Study 1, we investigate the assumption that there is a correlation between the likelihood of a product being organic, and the likelihood of that product being healthful. We obtain the true percentages of organic products across food categories in six supermarkets, as well as estimates of food healthfulness from a panel of food and nutrition experts. We expect to find a positive correlation between organic food prevalence and food healthfulness.

Methods

Design and procedure. To obtain estimates of organic product prevalence, we manually counted the number of conventional and organic products. The counting took place in six supermarkets in Aarhus, Denmark; of these, three would be considered small, one medium, and two large. The counting was performed by both authors. The coding scheme was developed over three rounds by adding new categories as new products were encountered. The inclusion criterion was whether a food product could be consumed independently of other products or ingredients. More specifically, it was decided that raw ingredient subcomponents (e.g., flour, salt, sugar etc.) would not be taken into consideration. As a result, 54 food categories emerged and were used as a base for developing a coding scheme. The initial coding scheme consisted of 17 super-ordinate categories and 54 sub-ordinate categories. The coding scheme was revised two more times, in the second and the fourth store respectively. The final coding scheme consisted of 17 super-ordinate and 59 sub-ordinate categories. Organic products within those 59 food categories were detected by inspecting the presence of a Danish organic label or the EU organic label. To ensure that the counting performed by the authors was unbiased, an independent coder blind to the study hypotheses was used in one supermarket. The intercoder reliability was very high, $r = .96$.

To obtain objective estimates of the healthfulness of the 59 food categories, 15 nutrition and food scientists were asked to complete a short survey, indicating the healthfulness of each category on a 7-point Likert scale ranging from ‘extremely unhealthful’ to ‘extremely healthful’. Ten participants completed the survey. One expert provided the same score for all 59 food categories and was excluded from further analysis, resulting in a final sample of nine experts.

Results

The field data show that organic food products are more prevalent in food categories that require less processing. For instance, food categories such as whole-grain pasta, brown rice, milk, eggs etc. have a higher prevalence of organic food products compared to categories such as ready meals, candy, chips and canned meat. An overview of the total number of food products, percentage of organic products, and corresponding expert estimates can be found in Table 1 (columns two to four).

Table 1. Average number of products, percentage of organic products, and expert and consumer estimates of healthfulness.

Category	Totals	% organic	Experts	Consumers
Whole wheat pasta	17.33	84.39	5.38	5.06
Non-dairy milk	9.17	78.94	4.5	4.61
Brown rice	3.83	64.58	5	5.27
Milk	15.33	53.47	5.5	5.09
Unprocessed breakfast cereals	28.17	50.89	5.88	5.21
Eggs	9	36.82	6.38	5.22
Oil	30.33	31.46	4.88	4.16
Plain yoghurt & plain yoghurt products	19.5	30.67	6.13	4.99
Syrups	32.17	29.67	1.88	2.94
Crispbread & rice cakes	37	27.15	4.75	4.35
Dried fruits, nuts & seeds	100.33	25.97	5.25	4.84
Vegetables	136.33	25.45	6.63	6.16
Butter	14.67	24.46	2.75	3.34
White rice	15.83	22.92	3.5	3.57
Fruit	39.50	20.61	6.13	5.80
Honey	8.5	20.4	3.38	4.36
Juices	57.83	19.39	3.63	4.02
Processed meat	25.17	18.79	2.38	2.87
Marmalade	51.17	16.37	2.88	3.15
Chocolate spreads	14	16.26	2	2.74
Savoury biscuits	11.17	15.48	2.5	3.09

Table 1 Continued

Category	Totals	% organic	Experts	Consumers
Fruit yoghurt	42	14.86	3	4.07
Frozen meat	13.33	14.35	4.5	4.49
Fresh meat	62.17	13.08	5	4.96
Dark bread	25.33	12.37	6.25	5.52
Canned vegetables	91.5	12.23	4.88	4.5
Cream	12.33	11.42	2.63	3.04
Frozen fruit	6.5	11.21	5.38	4.82
Frozen bread	19.67	10.78	4.13	3.67
Cheese	153.67	10.56	4.5	4.57
Frozen vegetables	33.33	9.9	6.25	5.27
Canned fruit	15.83	9.89	3.5	3.96
Sauces (tomato + pesto)	42.83	9.58	4.63	4.05
Cold cuts	123	9.29	3.5	4.02
White pasta	36	8.21	2.75	3.2
Ice cream	39.5	7.49	2.25	2.68
Dressings (salad dressings, mayo,	76.5	6.38	3.38	2.86
Cake & sweet biscuits	80.67	5.49	2.13	2.24
Muesli & protein bars	16	5.28	4	4.09
Frozen ready meals	64.67	5.11	2.5	3.22
Processed breakfast cereals	25.33	4.71	1.75	2.66
White bread	42	4.19	2.88	2.77
White wine	44.83	4.18	4	3.36
Sodas	109.5	3.51	1.5	2.06
Alcoholic beers and shakers/breezers	131.33	3.32	3	2.45
Mayo based salads	36.83	3.03	3	3.09
Chips	56.33	2.67	1.5	1.92
Red wine	121.17	2.59	4.38	3.69
Candy	382.83	2.19	1.38	1.92
Soups	12.83	1.31	4	3.97
Frozen fish	15.17	1.04	6	5.21
Ready meals (dry)	17.33	0.83	2.88	3.16
Processed fish (fridge)	49.17	0.76	5.25	4.99
Sauce as a ready meal	38	0.29	2.13	2.95
Takeaway meal	4.67	0	3	3.18
Canned fish	35.5	0	5.63	4.63
Canned meat	5.83	0	3.25	3.56
Fresh fish	5.17	0	6.63	5.99
Ready meals (fridge)	11.17	0	2.75	3.27

We find a medium-sized, positive correlation between the true percentage of organic food products and healthfulness estimates by experts, $r = .35$, $CI_{95} = [.1, .56]$ (see Fig. 1a).

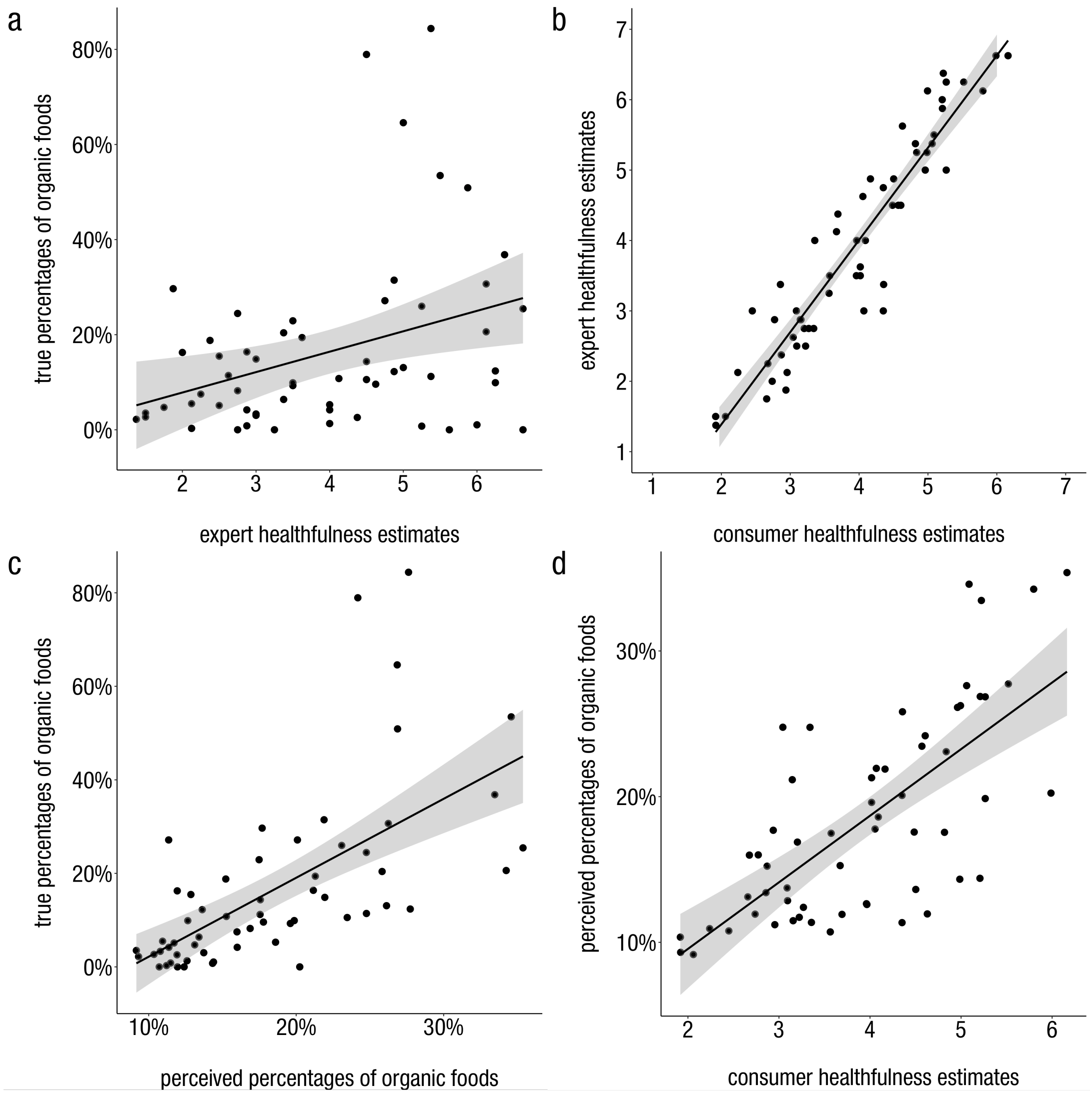

Fig. 1. Scatter plot of (a) the true percentages of organic foods and expert healthfulness estimates, (b) healthfulness estimates by experts and consumers, (c) the true and perceived percentages of organic foods and (d) the perceived percentages of organic foods and healthfulness estimates by consumers. The trend lines in all plots represent the best-fitting, linear regression line and its 95% confidence interval.

Next, we calculated the expected healthfulness of conventional and organic foods. We find that organic foods, $M = 4.47$, $SD = 1.48$, are, on average, 30% more healthful than conventional foods, $M = 3.44$, $SD = 1.59$, $d = .65$.

Discussion

Study 1 confirms our assumption that more healthful product categories have a higher prevalence of organic foods. It seems that this happens for two reasons. First, it may be more difficult to produce processed organic foods since multiple ingredients must be organic, meaning that highly processed foods with many ingredients are rarely organic. These highly processed categories such as ready meals, candy, and chips tend to be unhealthful foods. Second, it appears that producers target health-conscious, organic consumers, which leads to an overrepresentation of organic foods in more healthful subcategories e.g, whole-grain pasta is more likely to be organic than normal pasta.

Study 2

In Study 1, we found a correlation in the environment between the likelihood of a product being organic and the likelihood of that product being healthful. Per our assumptions, people learn this statistical structure and this should be reflected in their ability to accurately estimate the percentage of organic products across food categories. In Study 2, we conduct an online study to test this assumption. Given that people learn about the statistical nature of the environment, we expect to find a strong correlation between their perceptions and the true state of the environment.

Methods

Participants. Seven hundred and seventy-three participants representative of the Danish population were recruited through a consumer panel provider. Six hundred and thirty-seven participants completed the study. The participant age range was from 17 to 81 (M = 42.95, SD = 16.09) with an approximately even distribution of male and female participants (315 women). The sample captured a broad spectrum of the population with regards to age, gender, education and shopping behavior as well as psychographic dimensions. For a full description of the sample, see Figure S1-S3 in the supplementary materials. Each participant received approximately €1 for completing the study. The sample size was decided by maximizing within budget constraints. A post-hoc power analysis was conducted using the 'pwr' package in R (Champely, 2017) and revealed that the power to detect a small-sized effect (d = .2; see Cohen, 1988) with the sample size of 637 and the alpha level .05 is .99.

Materials and procedure. Participants were recruited online, and all gave informed consent before commencing the study. Participants were asked to estimate the percentage of organic foods for the 59 food categories identified in Study 1. Subsequently, participants were asked to estimate the healthfulness of each food category on a 7-point Likert scale ranging from 'extremely unhealthful' to 'extremely healthful'. Besides the main variables, we also collected demographic and psychographic information about the sample as well as information about organic purchasing behavior. Organic purchasing behavior was measured with two items. The first item measured the frequency of purchasing organic foods with a 7-point unipolar scale ranging from 'never' to 'always' (Magnusson, Arvola, Hursti, Åberg, & Sjödén, 2001). The second item measured the percentage of organic foods purchased with a visual analogue scale ranging from 0 to 100. Organic purchasing attitudes were measured by asking participants to indicate how 'good', 'important' and 'wise' they think it is to purchase organic food products. Seven-point bipolar scales were used ranging from 'very bad' to 'very good', 'very unimportant' to 'very important', and 'very foolish' to 'very wise' (Magnusson et al., 2001). Beliefs about organic foods were measured by asking participants to rate on a 7-point Likert scale whether they think organic products are 'healthier', 'tastier', 'have less calories', 'better quality', 'fresher', and 'safer' than conventional products.

Results

Combining the data from Study 1 and Study 2, we find a strong, positive correlation between the true and perceived percentages of organic food products across food categories, $r = .65$, $CI_{95} = [.45, .77]$, suggesting that participants have accurately learned the prevalence of organic foods across categories. The results also show a strong, positive correlation between expert and consumer healthfulness estimates, $r = .95$, $CI_{95} = [.91, .97]$, suggesting that participants make very accurate healthfulness estimates. Finally, we find a strong, positive correlation between consumer perceptions of organic food prevalence and food healthfulness, $r = .72$, $CI_{95} = [.55, .81]$. An overview of the consumer estimates can be found in Table 1 (column five). Figure 1b, 1c and 1d show scatterplots of the observed data.

Discussion

Study 2 supports our assumption that people learn the statistical structure of their environment. People accurately estimate the prevalence of organic foods across food categories and make very accurate estimates of food healthfulness compared to food and nutrition experts. Interestingly, there is a stronger correlation between consumer perceptions of organic prevalence and healthfulness estimates, r = .72, than between the true prevalence and expert estimates, r = .35. This could be due to the *organic = healthful* belief influencing either the perception of organic prevalence or the healthfulness of food categories.

Study 3

While Study 1 and 2 have provided evidence in support of the implicit statistical learning hypothesis, the studies are correlational in nature. In Study 3, we therefore conduct a lab-based, eye tracking study, manipulating the correlation between organic and health cues. We ask participants to select the most healthful of eight alternatives. As an objective health cue, we use the Nordic Keyhole label which indicates healthful alternatives within a product category (Ministry of Food, 2013). Because the Keyhole is present only on some healthful products (Orquin, 2014), it is useful to rely on other cues as well when judging a product's healthfulness. It is, therefore, our expectation that participants are more likely to attend to organic products when organic cues are positively correlated with health cues compared to situations with zero or negative correlation.

Methods

Participants. Seventy-Eight Danish participants were recruited through a consumer panel provider. Seven participants were excluded after the experiment due to insufficient data quality resulting in a total sample of 71 participants. The participants ranged in age from 18 to 74 years (M = 45.73, SD = 15.12) with more male than female participants (19 women). Only participants with normal, or corrected-to-normal, and full color vision were included in the study. Each participant received a gift card of approximately €34 for completing the study. All participants gave informed consent. The sample size was decided by maximizing within budget constraints, which gave at least 20 participants per cell thereby exceeding the threshold suggested by Simmons, Nelson, & Simonsohn (2011).

Stimuli and apparatus. The experimental stimuli consisted of 50 choice sets of processed food products, each with eight alternatives positioned in a 4x2 array with a separation of 5.1° horizontal and 10.3° of vertical visual angle. Each alternative contained several features, i.e., product picture, name, brand, price, weight, and two manipulated features – a Keyhole label and an organic label. The degree of overlap between the Keyhole and organic labels varied across three conditions (25%, 50% and 75% overlap). More specifically, the number of the Keyhole and organic labels was constant across conditions (four Keyhole and four organic labels). Therefore, 25% overlap between labels implies that only one product bears both labels, r = -.5, 50% of overlap implies that two products bear both labels, r = 0, and 75% overlap implies that three products bear both labels, r = .5. An example of the stimuli is shown in Figure 2. The labels were randomly distributed across alternatives in each choice set, and the presentation order of the choice sets was randomized across participants.

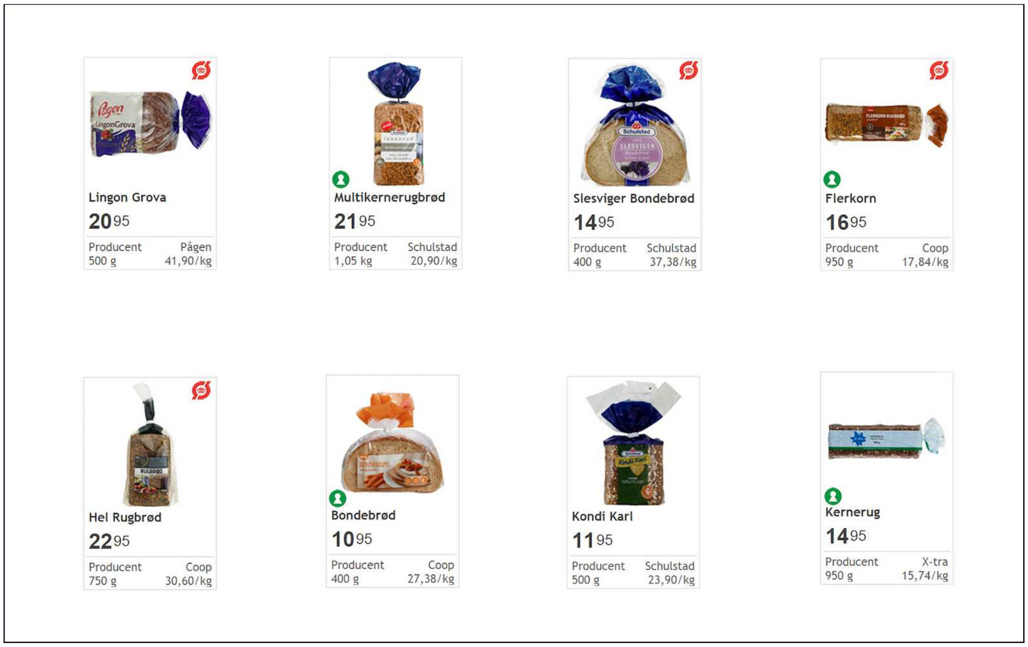

Fig. 2. Example of a choice set with 25% overlap (-.5 condition) between the Keyhole and organic labels

Eye movements were recorded using a Tobii T60 XL eye tracker with a temporal resolution of 60 Hz and a screen resolution of 1920 × 1200 pixels. Average viewing distance was 60 cm from the screen and a chin rest was used to stabilize head position. Areas of interest (AOIs) were determined by defining the pixel positions of the manipulated labels in each choice set (16 possible positions). Fixations were identified using a velocity based algorithm (I-VT algorithm) with default settings. Specifically, the maximum length of the gap between fixations was set to 75 ms. Noise reduction function was not applied, and we used averaged data from both eyes. The velocity threshold was set to 30°/s. Fixations with a duration less than 60 ms were discarded. The margins of the AOIs were set to approximately .15° larger than the actual labels to consider the inaccuracy in recording of fixation locations. There have been several attempts to define the most suitable AOI margins (Orquin, Ashby, & Clarke, 2016). More specifically, we tested margins of 0°, .15° and .5° of visual angle for a random sample of three participants and six trials per condition with a total number of 432 hand-coded AOIs. We used the hand-coded, fixation count as criterion and compared this with the fixation count for each AOI margin size by counting the number of false negatives and false positives. We found that different AOI sizes influenced the results with respect to the number of false negatives and false positives registered. The AOI size of .15° of visual angle had the most acceptable rates of false negatives and false positives.

Procedure. The study was conducted in a light-controlled, laboratory environment. Upon arrival, participants were greeted and seated in front of the eye-tracker. We adjusted the height of the chin rest and proceeded with calibration using the Tobii Studio 9-point calibration procedure. After calibration, each participant was randomly assigned to one of the three conditions. The experiment started with instructions to select the most healthful alternative among eight food products and to indicate the choice with a mouse click. A fixation cross lasting 1000 ms appeared before each choice set. Participants used as much time as needed to make their choices.

Results

Eye movement analysis. To test whether decision makers attend more to the organic label when there is a high degree of overlap between the organic and Keyhole label, we analyzed the eye tracking data by means of a generalized linear mixed model. The model was fitted using the ‘lme4’ package in R (Bates, Mächler, Bolker, & Walker, 2015). We used fixation selection (AOI-fixated or not) as a dependent variable, and condition and label type as independent variables. The best-fitting model had a binomial response distribution, a logit link function and two random intercepts grouped by participant and choice set. The analysis revealed no significant main effect of condition, $\chi^2(2, 70) = .63$, $p = .73$, a significant main effect of label type, $\chi^2(1, 70) = 24.58$, $p < .001$, and a significant interaction effect between the condition and label type, $\chi^2(2, 70) = 24.13$, $p < .001$. A post-hoc power analysis was conducted using the 'simr' package in R (Green & MacLeod, 2016) and revealed that observed power for the interaction effect in 500 simulated studies is .99, CI_{95} = [.98, .99].

To interpret the direction of the interaction effect, we plotted the fixation likelihood across condition and label type (see Fig. 3). The Figure 3 shows that participants attend to the organic label more frequently at the expense of the Keyhole label as the degree of overlap between the two labels increases.

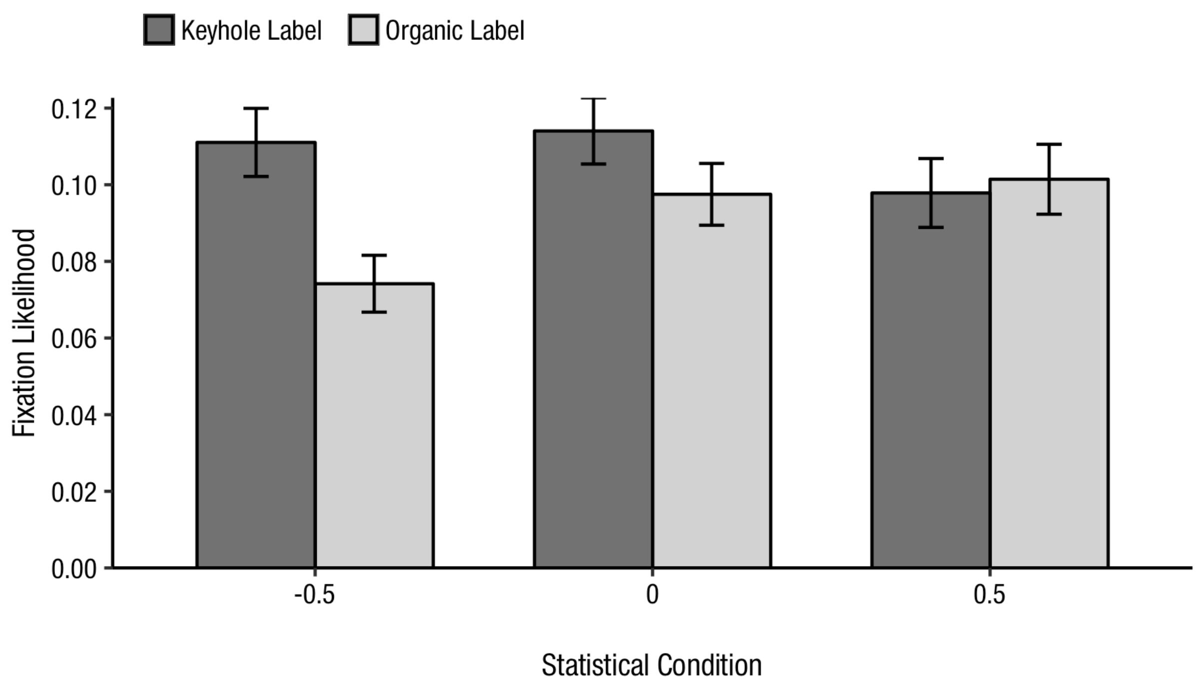

Fig. 3. Fixation likelihood for the Keyhole and organic labels across conditions. Error bars represent 95% confidence intervals.

Follow up analysis. One potential problem with the fixation likelihood analysis is that fixations to the organic label in the .5 condition could be an artefact. Specifically, the pattern in Figure 3 could result if participants searched for the Keyhole label and then fixated the remaining information on Keyhole labeled products. If this was the case, we would expect the Keyhole to drive fixations to the product, i.e. participants should be faster to fixate the Keyhole label than the organic label. To exclude this possibility, we inspected the cases where participants fixated both labels. As can be seen in Table 2 below, participants who fixated both labels on a product were equally likely to fixate the Keyhole label and the organic label first. We take this to imply that the Keyhole label did not drive fixations and hence that the results of the fixation likelihood analysis are not artefactual.

Table 2. Number of cases where the Keyhole or the organic label was fixated first given that both labels were fixated on a product

Condition	Keyhole first	Organic first
-.5	18	15
0	29	31
.5	42	44

Choice analysis. To examine the effect of the condition on participants' choice of organic products, we fitted individuals by means of multinomial logit models using the 'mlogit' package in R (Croissant, 2013). Each individual was fitted with a null model, including only intercepts for the eight product alternatives, and a full model including a term for product type, i.e., whether the alternative had a Keyhole label, organic label, both labels, or none of the labels. We calculated the AIC difference as $AIC_{full} - AIC_{null}$. Out of 71 participants, 42 were identified as label users ($AIC_{diff} > 0$) and 29 were identified as non-label users ($AIC_{diff} \leq 0$). We then calculated the standardized mean difference between the choice likelihood in the .5 and -.5 conditions for the products with an organic label and products with both labels correcting for chance level:

$$SMD = \frac{(M_{.5} - M_{-.5}) - (M_{.5\,chance} - M_{-.5\,chance})}{SD_{pooled}}$$

For label users we find a medium increase in the likelihood of choosing products with an organic label in the .5 condition, SMD = .42, and a large increase in the likelihood of choosing products with both labels, SMD = .83, relative to the -.5 condition. For non-label users we find that choices are close to chance level for products with an organic label, SMD = -.08, and products with both labels, SMD = .06. Figure 4 shows the choice likelihood across conditions for products carrying organic, Keyhole, both, or neither of the labels.

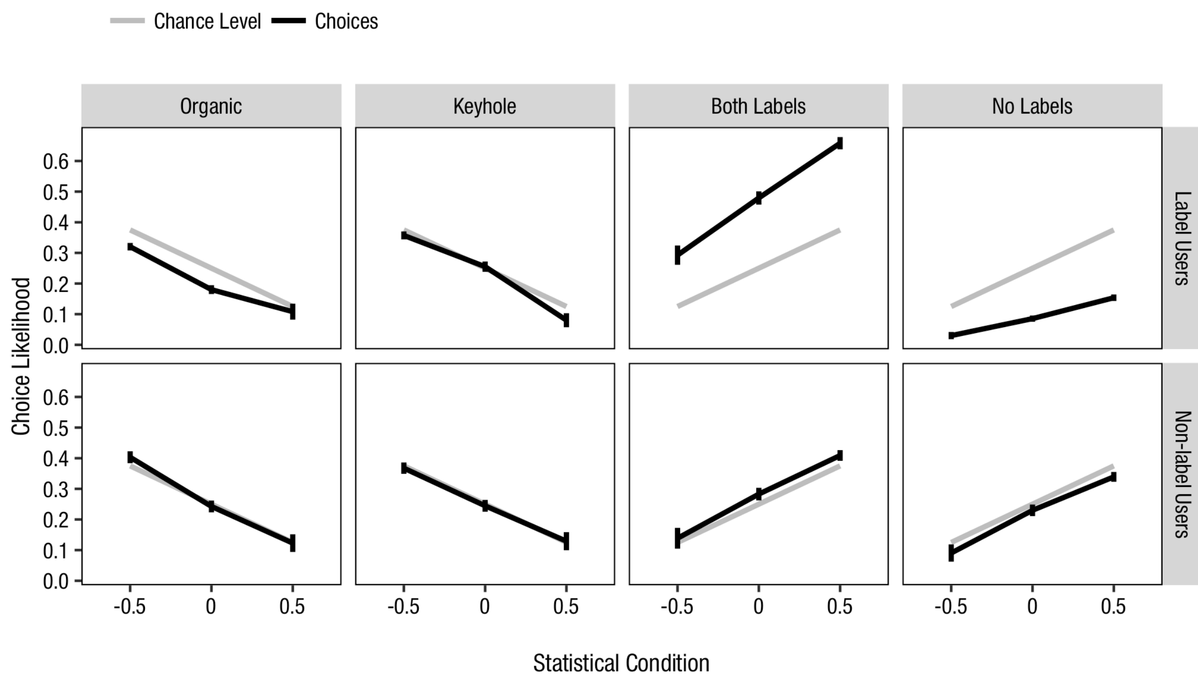

Fig. 4. Likelihood of choosing products according to label type and condition for label users and non-label users. The black line represents observed choice likelihood, the grey line represents chance level choice, and error bars represent 95% confidence intervals.

Discussion

In Study 3, we experimentally investigate whether people are capable of learning the statistical structure of a natural environment. We find that participants respond to the statistical structure, both in their eye movements and their choices. When there is a positive correlation between organic and health cues, participants are more likely to fixate on organic labels. This gaze bias suggests that participants in this condition consider the organic label as relevant to the health judgment task (Orquin & Mueller Loose, 2013). We also find that the majority of participants incorporate labels in their judgments, and these participants are more likely to choose products with organic labels when there is a positive correlation. Figure 4 shows that participants choose products with both labels (black line) more often than what is expected by chance (grey line) in all three conditions. This means that participants generally prefer products with both labels to products with either label or no label. The preference for having both labels increases under a positive correlation. Overall, the findings support our assumption that people are, without explicit instructions, capable of learning the statistical structure of the environment and apply the learned cue in their decision making.

General discussion

We expected that people learn statistical structures in their environment and use this information to shape ecologically rational decision making. We study this hypothesis in the context of organic foods. In Study 1, we find that a correlation exists in the environment between organic food prevalence and food healthfulness. In Study 2, we find that people are familiar with this statistical structure, which is reflected in a highly accurate perceptions of organic prevalence across food categories. In Study 3, we find that a positive correlation between organic and health cues leads people to attend more to organic cues when judging food healthfulness compared to a negative or zero correlation. This is observed as a higher likelihood of fixating on organic cues and a higher likelihood of choosing products with organic labels in the positive correlation condition. We take this to imply that people are capable of learning the statistical structure of the environment and to apply the learned cue correctly when making decisions. Our findings contribute to a better understanding of ecological rationality by showing how implicit statistical learning can lead to accurate beliefs about correlational structures in the environment. These beliefs translate into decision behavior that matches the environment and produces ecologically rational behavior.

Author contributions

Both authors developed the study concept. Both authors contributed to the study design. Testing and data collection were performed by both authors. S. Perkovic performed the data analysis and interpretation under the supervision of J. L. Orquin. S. Perkovic drafted the manuscript, and J. L. Orquin provided critical revisions. Both authors approved the final version of the manuscript for submission.

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