Loan officers' decision strategies: an exploratory eye-tracking study

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Abstract

Loan officers' screening of potential borrowers and the assessment of their creditworthiness is crucial in the bank lending activity, and with the global financial crisis, during which poor loan quality increased the importance of studying loan officers' decision making has become even more clear. Existing research in judgment and decision-making demonstrates that to infer values on some criterion of interest, people sometimes rely on information-intensive strategies that attempt to integrate all available information and other times use information-frugal strategies that ignore some of the information, and that the latter may be more common among expert decision makers. In the present research we combine Bayesian latent-mixture modeling and analysis of eye-tracking data to explore the decision strategies and associated attention allocation mechanisms of 42 professional loan officers. In contrast to comparable studies in other decision domains, our modeling results suggest that the majority of loan officers used a compensatory strategy, with the information-intensive Weighted Additive strategy providing the best fit for the majority of subjects. The analysis of eye-tracking data provided corroboration to the modeling results and also revealed that visual search was mostly based on the position of the information rather than its importance. These results add new knowledge on experts' decision making, contribute to the field of neurofinance, and highlight promising avenues for future research and the design of decision support systems.

Keywords: decision making, attention, loan, neurofinance, information processing

JEL codes: C11, D87, G2, G21

1. Introduction

Loan officers play a key role in the screening of potential borrowers and in the assessment of their creditworthiness, as well as in monitoring them over the loan cycle after credit-granting decisions. The importance of their role in the banking and financial system has been underscored by the global financial crisis, during which bad loan quality rose. Loan officers' decision outcome is the result of several phases, during which information is scanned, processed, and integrated. Together, the processes of information gathering and integration define a decision strategy. Since people are equipped with a repertoire of different strategies for solving the problems they face, the question of which strategies loan officers rely on becomes pressing. Research in psychology shows that in some situations, individuals acquire and integrate all the relevant information by relying on so called information-intensive strategies. Other times people rely on heuristics or information-frugal strategies that ignore some of the available information.

Previous studies on loan officers' behaviour have focused on their use of accounting information in predicting business failure (Libby, 1975; Casey, 1980; Abdel-Khalik and El-Sheshai, 1980), the effect of task characteristics on information acquisition and choice (Casey, 1980; Biggs et al., 1985), and the role of different types of information in their decision making (Beaulieu, 1994; Catasús and Gröjer, 2003). Loan officers may rely on various information-processing strategies when performing credit assessment. But despite the importance of their role in the banking sector, there is scant research on the information processing strategies and the attention allocation mechanisms that underlie loan officers' decision making.

The main goal of the current study is to investigate the decision making strategies loan officers use when making lending decisions. This goal is pursued through two main analyses based on the data from an experiment that included 42 professional loan officers working at a major bank. During the experiment, loan officers were presented with a series of 30 decisions. In each decision, loan officers chose which of the two companies described by a series of financial and non-financial indicators *(cues)* is more credit-worthy.

In the first analysis we applied a modern Bayesian outcome-based classification approach to model loan officers' decision strategies, featuring three decision strategies. The first of these is the information-intensive and compensatory Weighted Additive strategy (Payne et al. 1993), according to which decision maker chooses the option with the highest weighted average value. The second strategy was the information-frugal and noncompensatory Take The Best strategy, according to which the decision maker chooses the alternative associated with the highest value on the most valid cue (Gigerenzer and Goldstein, 1999). Finally, we included the Equal Weights strategy (Einhorn and Hogarth, 1975) which can be formulated as a special case of the Weighted Additive strategy with all cue weights set to the same value (it is a compensatory strategy that takes into account all alternatives and cues).

The second analysis focused on the process of attention allocation over the financial and non-financial information describing the potential borrowing companies and was based on eye-tracking data. Exploiting an unobtrusive near-infrared light which captures the corneal reflection, eye-tracking is able to detect and measure oculomotor behaviour, providing rich indices of brain cognitive processes including attention. In fact, recording eye-movements with a resolution of milliseconds, eye-tracking permits to gather information about where the subject is looking at, i.e. which portion of the visual stimulus (that in our case consists in the cues of the prospectuses describing the competing companies), for how long, and the visual search pattern. The analysis of attention distribution over the information permits to validate the modeling findings about loan officers' use of decision strategies, and to extend them by exploring other features of information processing. In particular, eye-tracking data provided information about the cues' inspection process and the amount of attention dedicated to each cue. In addition, two dimensions of visual search were investigated. First, we investigated whether loan officers relied on *cue-based* processing, i.e. they compared the alternatives on a given cue before proceeding to the next cue, or on *alternative-based* processing, i.e. they investigated a single alternative on several cues before moving to the other alternative. Second, we investigated whether loan officers relied on *importance-based* or *position-based* search.

Results suggest that the majority of loan officers employed information-intensive strategies, with the majority classified as users of a compensatory strategy. In particular, 62% of loan officers were classified as Weighted Additive strategy users, 21% were classified as users of the compensatory Equal Weights strategy, and only 14% were classified as users of the noncompensatory Take The Best strategy (for one loan officers, the strategies Take The Best and Equal Weights had the exact same fit). The eye-tracking analysis corroborated the modeling results, revealed that the visual search of most loan officers was more consistent with either cue-based processing or a mixture of cue-based and alternative-based processing, and also showed that position-based search order predominated, i.e. the process of attention allocation was influenced by the position of the information more than its importance.

The remainder of the paper is organized as follows. Section 2 presents the literature on the information processing strategies and on loan officers' decision making. The method is described in Section 3, which is followed in Section 4 by the presentation of the behavioural and eye-tracking results. Section 5 provides the discussion and directions for future research.

2. Literature Review

2.1. Information processing strategies

When choosing between options, cognitive activities underling the choice imply the processing of different values (alternatives) associated to each attribute or piece of information (cues). Different information processing strategies can underlie the process through which subjects take a decision: *information-intensive* strategies or *information-frugal* strategies. The former are sometimes described as rational since they aim to make use of all available information thus approximating normative theories of choice (Luan et al., 2019). They are also compensatory, as cues lower in importance can in principle compensate for cues higher in importance. A prototypical strategy of this class is the Weighted Additive strategy (Payne et al., 1993) which determines the overall value of each alternative by multiplying every cue value with its respective weight and summing the resulting values; the alternative with the highest overall value is then selected. Conversely, information-frugal strategies, or heuristics, simplify decision making by ignoring some of the alternatives or some of the cues. A prototypical strategy of this class is the Take The Best strategy (Gigerenzer and Goldstein, 1999) which compares the alternatives by inspecting the cues sequentially in an order determined by their importance, starting with the most important cue. This strategy terminates search as soon as a discriminating cue is found and chooses the alternative with the better value on that cue. In this way, the Take The Best strategy substantially reduces the number of cues that need to be inspected compared to the Weighted Additive and other information-intensive strategies (Lee et al., 2017). Take The Best is a noncompensatory strategy, as cues lower in importance can never compensate for cues higher in importance. Empirical evidence suggests that together, the Weighted Additive strategy and the Take The Best strategy underlie and explain most of the choices in studies on multi-attribute decision-making (Rieskamp and Hoffrage, 1999, 2008; Bröder, 2000; Newell and Shanks, 2003).

The conditions under which people use information-intensive, compensatory strategies such as the Weighted Additive and information-frugal, noncompensatory ones such as the Take The Best have been a focus of intense interest in cognitive sciences and have especially focused on novice decision makers performing artificial tasks. But researchers have also begun to investigate how well these strategies capture the choices of experienced decision makers, such as magistrates making bail decisions, police officers and burglars assessing which property is more likely to be targeted for burglary, and airport customs officers judging which passengers are more likely to be smuggling drugs (Dhami and Ayton, 2001; Garcia-Retamero and Dhami, 2009; Pachur and Marinello, 2013).

With the present study, we aim at investigating the use of decision strategies among an important category of decision makers for the banking and financial system: professional loan officers. In the attempt to unveil what kind of decision strategies are likely to be the most prevalent among loan officers, we introduce two theoretical perspectives on strategy selection (Payne et al., 1993; Gigerenzer and Todd, 1999). The two perspectives share the foundational assumption that people possess a repertoire of decision strategies that they can draw upon; both also recognize that information-frugal strategies form a part of the repertoire in addition to information-intensive ones. Conversely, the two perspectives differ in their explanation of why people sometimes rely on information-frugal strategies. One perspective emphasizes that decision making involves an accuracy/effort trade off (Payne et al., 1993). Information-frugal strategies are thought to be less accurate than information-intensive ones while conferring the benefit of reduced effort (Shah and Oppenheimer, 2008). Their use can be rational if the accuracy gains of information-intensive strategies do not justify the increased costs in time, effort, and other resources (Gigerenzer and Gaissmaier, 2011). This assumption of an accuracy/effort trade-off is challenged by the research program on fast-and-frugal heuristics (Gigerenzer and Todd, 1999). These researchers point out that information-frugal strategies can in fact outperform information-intensive strategies even when it comes to accuracy and emphasize the study of the ecological rationality of different strategies – that is, the study of environmental conditions that determine how well a given strategy can accomplish the decision maker's goals. Simulation studies using real world data show that information-frugal strategies such as the Take The Best strategy can outperform information-intensive strategies such as the Weighted Additive strategy (Czerlinski et al., 1999; Şimşek, 2013; Lee et al., 2017; Luan et al., 2019).

The two perspectives outlined above inspire two contrasting hypotheses concerning the decision strategies used by experienced loan officers. The perspective emphasizing the accuracy/effort trade-off of decision strategies suggests that experienced decision makers may be more likely to use information-intensive strategies, such as the Weighted Additive strategy. Experience in a domain is likely to affect both dimensions of the trade-off between accuracy and effort. Concerning accuracy, experience could contribute to adaptive strategy selection through both training and selection effects. Concerning effort, it is well-known that experience decreases effort by making initially deliberate operations automatic through repeated application. Experienced decision makers might thus be able to carry out more information-intensive strategies with less effort than novice decision makers. Jointly, these observations seem to point in the direction of information-intensive strategies being the norm among loan officers. On the other hand, complex real world decision environments such as commercial lending are characterized by limited outcome data, cues of questionable validity, and changes. These are in fact the conditions under which information-frugal strategies seem to perform particularly well (Gigerenzer, 2008). The ecological rationality perspective would therefore suggest that experienced decision makers in these environments would be particularly likely to be using information-frugal strategies suited to these environmental conditions. Indeed, some recent studies support this view. Both Garcia-Retamero and Dhami (2009) and Pachur and Marinello (2013) report that the information-frugal Take The Best was the most prevalent strategy among experienced decision makers in their studies, focusing on burglary and airport customs patrol, respectively. In fact, experienced decision makers were more likely to be using the Take The Best strategy than novice decision makers.

2.2 Loan officers’ decision making

Loan officers’ decision making has always attracted researchers’ attention, especially from a normative financial perspective (see Rodgers and Johnson, 1998), as result of the fact than lending decisions on one hand are crucial for banks profitability and financial system stability, and on the other represent an ideal setting for studying decision making under risk or uncertainty. The literature on loan officers’ decision making has generally been focused on three main aspects: the process itself which leads to a decision outcome, the constituents of the decision process, and the quality of the decisions (Lipshitz and Shulimovitz, 2007).

With respect to the first strand of the literature, several researchers have tried to assess loan officers’ decision strategies which underlie the decision making process.

Biggs et al. (1985) examined whether, as for consumers making buying decisions, experienced bank loan officers’ decision strategies are contingent upon the characteristics of the task. Applying different process tracing methods, i.e. information boards and think-aloud verbal protocol analysis, they observe that when task size increased, loan officers tend to rely more on noncompensatory decision strategies, while their use of compensatory strategies increase when they were faced with similar profiles of candidate companies. These findings highlighted the importance to study decision strategies in the credit lending process given the associated implications for lending institutions in the design of information and decision support systems.

Using a realistic lending cases in an experimental setting with experienced loan officers, Danos et al. (1989) observed that loan officers tend to have a high level of confidence in the early stage of the process, when summarized accounting and background information are provided. Anyway, they found that loan officers did revise their decisions when new detailed information was provided later in the process, even when in contrast with their prior positions.

Rosman and Bedard (1999) contributed to the lending literature by analysing if different lenders’ strategies are associated to different decisions in the loan structure, suggesting that credit-granting decisions might be associated with the way loan officers analyse data. Using a computerized process tracing, they reported that the loan structure restrictiveness was negatively correlated with two decision process dimensions, i.e. the time dedicated to information evaluation and the information search pattern.

Other research programs focused on the influence of the expertise on loan officers' decision making, revealing that while experts tend to use mental checklist to drive their information acquisition and they also look for contradictory information, novices tend to process cues in the order they are presented, searching for confirmatory data (Anderson, 1988; Bouwman et al., 1987).

In the current study, we use a modern Bayesian outcome-based classification analysis to investigate the decision strategies used by loan officers. We contrast the information- intensive and compensatory Weighted Additive strategy with the information-frugal and noncompensatory Take The Best strategy. In addition, and following a number of previous studies, we also add the Equal Weights strategy (Einhorn and Hogarth, 1975) to our set of candidate strategies. This strategy can be formulated as a special case of the Weighted Additive strategy with all cue weights set to the same value. It is a compensatory strategy that takes into account all alternatives and cues and is therefore sometimes classified along with the Weighted Additive strategy as a "rational" strategy compared to Take The Best (Lee et al., 2019). On the other hand, the Equal Weights strategy does ignore some information (specifically the cue weights) and may therefore also be classified as an information-frugal strategy (Gigerenzer and Gaissmaier, 2011). Against the backdrop of the contrasting theoretical perspectives introduced above, we do not make a sharp prediction about loan officers' decision strategy use, instead formulating our main aim as a research question.

The great majority of previous studies about loan officers' decision strategies have been conducted through classical process methods which include the use of a closed information board, the mouse-tracking, and of think-aloud protocols. Anyway, information processing largely occurs below the awareness level, in an automatic and unconscious way, leading to consider the eye tracking as an ideal tool to open loan officers' black boxes. The eye-tracking provides rich data about subjects' cognitive activities allowing to explore new feature of economic behaviour in a relatively unobtrusive way (Orquin and Mueller Loose, 2013; Lahey and Oxley, 2016; Lynch and Andiola, 2018; Ceravolo et al. 2019a,b; Meißner and Oll, 2019). Among the different oculomotor behaviours, the fixation - a period of time during which the eye(s) remain relatively still on a specific piece of visual stimulus (Holmqvist et al., 2011) - is particularly useful for our purpose of investigating decision strategies. The duration of the fixation and the associated area on the visual stimulus are two interesting attributes which inform us about the amount of attention allocated to the specific source of information and the information the subject is attending to, respectively.

Exploiting the eye-tracking tool, we aim at objectively detect and measure the loan officers' process of attention allocation towards a visual stimulus depicting two competing companies requesting a loan and described by different cues. According to the Weighted Additive strategy and the Equal Weights strategy, (close to) all information should be inspected in each trial. In contrast, the information-frugal Take The Best strategy would inspect a much more limited amount of information.[1] Another important aspect of information processing revealed by eye-tracking is the type of visual search subjects engaged in. There are two main dimensions of visual search behaviour: cue-based vs alternative-based processing and importance-based vs position-based search. For what it

[1] For example, for the cue ordering supplied by the senior loan officer before the study, between one and three cues (9 - 6 pieces of information) would be inspected per trial.

concerns the difference between cue and alternative based processing, the former corresponds to comparing the alternatives on a given cue before proceeding to the next cue while the latter corresponds to investigating a single alternative on several cues before moving to the other alternative. The second dimension concerns the order in which cues were inspected: importance-based search examines cues in order of their importance while in contrast, position-based search is based on the spatial arrangement of cues on the screen.

3. Method

3.1. Participants

42 professional loan officers of a Dutch major bank voluntarily participated in this study. The sample size is in line with previous studies which investigated financial decision making using eye tracking (Ceravolo et al., 2019b; Husser and Wirth, 2014). After being welcomed and signing the informed consent statement, subjects read the instructions on paper and were given the opportunity to ask questions. There was no financial compensation for taking part in the study.

Out of the 42 participants in the sample, 35 (83.34 per cent) were males. The average age was 36 years (± 10) and the average professional experience, i.e. the number of years working specifically as a loan officer, was 9 years (± 9), ranging from less than a year to more than 40 years. All subjects had normal or corrected-to-normal vision. The study was approved by the Internal Review Board of the Erasmus Research Institute of Management.

3.2. Eye-tracking device and procedure

Eye movements were recorded using the SMI RED-250 (SensoMotoric Instruments GmBH, Berlin, Germany) system. The sampling rate was 250 Hz. Subjects were seated at a distance of 60 cm away from the monitor (22 inches; resolution: 1680 x 1050 pixels), and a chin rest was used to minimize head movement, ensuring rigorous data collection. Before each test, participants completed an eye-tracking calibration procedure and one practice trial. For each stimulus, 24 rectangular Areas of Interest (AOIs) were defined, as shown in Figure 1. Right before the main task, subjects read the text of the accountability manipulation (described in §3.3). Subjects then completed the first half of the main task. Each trial began with a blank screen (500 ms), followed by a fixation sign in the center of the screen (2000 ms), and later by the decision information. Subjects were instructed to press any key after they have made their decision, which they then indicated with a mouse-click. Following the first decisions, there was a short break. Afterwards, the calibration procedure was repeated, and subjects then completed the second half of the task. Finally, they completed the post-experimental questionnaire on paper (section 3.5). Each session included a single subject and lasted about 45 minutes.

< Insert Figure 1 about here >

3.3. Task

Every trial of the task featured two alternatives between two companies, each described by 12 cues, which have been selected in consultation with a senior loan officer working at the same bank as the subjects. The cues included six financial indicators that consisted in Cash to total assets, Current ratio, EBIT interest coverage, Funds from operations to total debt, EBITDA margin, and Total debt to

EBITDA; and other six indicators that consisted in Corporate governance, key-man and reporting, Management track record & strategy, Cost structure & operational efficiency, Growth, Geographical diversification, and Market leadership. Since financial indicators are continuous in nature, loan officers were informed that specific values on these cues were translated into five categories, namely very conservative, conservative, moderate, aggressive, and very aggressive. Of these five categories, only two were to appear in the task: conservative and aggressive, the first representing a positive cue value and the second a negative one. For the other six cues, subjects were told to assume that another loan officer has examined the company in question and reported a judgment of either well above average, above average, average, below average, or well below average. As with financial indicators, only two of these categories were to appear in the task: above average and below average, the first representing a positive cue value and the second a negative one. Subjects' task was to indicate which of the two companies in a given trial was the better candidate for loan approval. To construct the set of 30 trials used in the study, we followed a similar procedure as Pachur and Marinello (2013). First, we generated a set of all possible trials, before excluding (i) trials where one alternative dominated the other, (ii) trials in which the two alternatives were equally attractive according to the Equal Weights strategy, (iii) trials in which the two alternatives were equally attractive according to the Weighted Additive strategy (with cue weights supplied by above mentioned senior loan officer), (iv) trials in which the Equal Weights and Take the Best strategies made the same prediction, and (v) trials in which the Weighted Additive and Take the Best strategies made the same prediction. From the remaining trials, we randomly sampled 10 trials in which the most important cue (according to the senior loan officer) discriminated between the alternatives, 10 trials in which the second most important cue discriminated between the alternatives (whereas the most important one did not), and 10 trials in which the third most important cue discriminated between the alternatives (whereas the first two did not). All subjects completed this same set of trials. Trials were randomized across participants in order to ensure behaviour was not affected by the order stimuli were displayed, while the placement of cues and alternatives stayed constant between trials. We created four versions of the task which differed in the placement of the cues on the screen; each subject was exposed to one out of the four possible formats (between-subjects manipulation). Figure 1 shows the exact cue placement of version 1. The screenshots for the other three versions are available in the online project repository (see Availability of materials, data, and code).

Subjects were assigned randomly in one of the two accountability conditions. In the high accountability condition, subjects were instructed to make decisions as if they were part of their job and as if they would have to explain and defend them in front of the credit committee. They were also informed that the researcher will ask them to explain the reasoning behind their decisions. In the low accountability condition, subjects were instructed to follow their own, personal judgment and told that their decisions will not be evaluated by others.

3.4. Post-experimental questionnaire

The post-experimental questionnaire contained three parts. The first part asked the subjects to rank and rate the cues in order of their importance through a scale which went from 1 (completely unimportant) to 100 (extremely important). In some cases, subjects provided ranks and ratings that were not fully consistent. These subjects were asked to make the necessary changes to achieve consistency. In 2 cases, the researcher failed to spot the inconsistency, and in one case the subject refused to change his or her initial (and inconsistent) responses. The second part of the post-experimental questionnaire asked the subjects to rate (on a 1-7 Likert scale) how they perceived each cue. One question asked perceived objectivity, the other about perceived precision. The third part of the post-experimental questionnaire contained 5 demographic questions (gender, age, experience, title, and department).

3.5. Statistical analysis

In order to infer the decision strategies underlying the decisions of loan officers, a Bayesian latent-mixture modelling approach was used (Lee and Wagenmakers, 2014; Lee, 2016). Following Pachur and Marinello (2013) it has been assumed that the strategies potentially used by subjects were the Weighted Additive strategy, the Take The Best strategy, or the Equal Weights strategy. Whether a given strategy was used is not something that is directly observable, while it can rather be inferred on the basis of the fit between the predictions of the strategy and the observed decisions. For the Equal Weights strategy, predictions could be made a priori and were the same for all subjects. In contrast, the predictions of the Weighted Additive strategy depend on cue weights, which may differ among subjects. Cue weights have been retrieved from the cue importance rating task and been used to generate individualized predictions for the Weighted Additive strategy. Similarly, data from the ranking task were used to generate the predictions for the Take The Best strategy.

The three strategies included in the model specify which alternative should be chosen on any given trial. To increase the strategies' psychological plausibility, sharp predictions can be transformed to probabilities assuming that predictions are perturbed by random error (Broder and Schiffer, 2003). This approach was used for Equal Weights and Take The Best strategies. The assumption of random error seems relatively more problematic for the more complex Weighted Additive strategy, which requires the integration of all cue values and weights. Considering that the cue weights were provided retrospectively by our subjects, to the extent that these self-reported weights correlate imperfectly with "true" weights, apparent errors may arise. These errors will not be random; one flexible approach is to classify the trials according to the size of the difference in value between the two alternatives. Separate error parameters are then estimated for each such class, with the restriction that larger differences in value correspond to lower (or equal) probabilities of error (Hilbig and Moshagen, 2014; Lee, 2016; Heck et al., 2017). In the present study, this approach would have been too flexible as there were many classes of trials that featured only a single trial. For this reason, we developed a novel probabilistic version of the Weighted Additive strategy. The basic idea was to express the absolute value difference between the two alternatives as a proportion of the maximum possible absolute value difference (obtained by summing the weights) and map the resulting proportion to the probability of making an error.

The model is formalized in Figure 2. We use the graphical notation of Lee and Wagen-Makers (2014) in which nodes are used to represent variables and arrows are used to indicate dependencies between variables. The shape indicates whether the variable is discrete (squares) or continuous (circles), the color indicates whether the variable is observed (grey) or latent (white), and the border indicates whether the variable is deterministic (double-bordered) or stochastic (single-bordered). Finally, the two plates (one for subjects, one for trials) are used to indicate replication.

< Insert Figure 2 about here >

To make sense of the model, we started with the central node y_{ij}, which captures the decision made by subject *i* on trial *j*. It takes a value of 1 if company A was chosen and a value of 0 if company B was chosen. The probability that company A will be chosen depends, first, on ζ_i. This parameter indexes the strategy used by subject *i* and is given a uniform prior, meaning that, before the data are taken into account, the model considers the three strategies equally likely to be used. Second, the probability that company A will be chosen depends on the probability of "error", captured by the node ε_{ij}. The value of ε_{ij} in turn depends on the strategy used by the subject. For users of Equal Weights and Take The Best strategies, a single parameter is estimated. For users of the Weighted Additive strategy, however, the ε_{ij} varies by trial and depends on the value difference between the two alternatives ($Diff_{ij}$) as well as on the α_i parameter, which controls the shape of the relationship between $Diff_{ij}$ and ε_{ij}. Examples of how this relationship depends on the value of α are visualized as yellow dashed lines in Figure 2.

We implemented the model using the JAGS software (Plummer, 2003) and collected 20000 samples from each of three chains, after a burn-in period of 5000 samples and after thinning so that only each fifth sample was kept. We checked that the model converged by visually inspecting the chains and using the R statistic (Brooks and Gelman, 1998). In a following step, the model was fitted in order to classify subjects as users of the Weighted Additive, Equal Weight, or Take the Best strategy, on the basis of the fit between subjects' decisions and the prediction of these strategies.

Eye-tracking analyses were conducted on the fixations (minimum duration: 50 milliseconds) identified by the SMI-algorithm. The total number of observations is 1260, as result of 30 stimuli presented to 42 participants.

4. Results

4.1. Behavioural results and decision strategy classification

Cues rating and actual choice. The ratings assigned by the loan officers to the 12 cues used to present companies' profiles are displayed in Figure 3. In order to increase comparability between subjects, responses were standardized to a mean of zero and a standard deviation of one (computed separately for each subject) by subtracting to the raw response subject-specific mean and dividing the resulting score by the subject-specific standard deviation. Averages values correlate well with the ratings provided by a senior loan officer before the study (Pearson's r = + 0.78), even if a high variability among subjects is observed: no cue was consistently rated by every loan officer as either above or below average in importance. Conversely, when coming to actual choices made during the main task, across the 30 trials, a substantial agreement was observed since subjects on average picked the same decision alternative in 79% of the cases (range 60% - 98%).

< Insert Figure 3 about here >

Inferred decision strategies. With respect to inferred decisions strategies, the majority of subjects was classified as users of a compensatory strategy, with 62% classified as Weighted Additive strategy users and 21% as Equal Weights strategy users. Only 14% of subjects were classified as users of the noncompensatory Take The Best strategy, while for the remaining subject, the strategies Take The Best and Equal Weights had the exact same fit. Results are summarized in Figure 4. To take into account the uncertainty associated to the classification, two Bayes Factors (Kass and Raftert, 1995) for each subject were computed, comparing the fit of the inferred strategy with each of the remaining two strategies, and results are shown on the right side in Figure 4 (they were also used to order the subjects along the y-axis). For the vast majority of these subjects, there is clear evidence with respect to whether they used a compensatory strategy (Weighted Additive, Equal Weights) or a noncompensatory one (Take The Best). For about one half of the sample there is moderate or strong evidence for the inferred decision strategy, while for the other half, the Bayes Factor comparing the two best-fitting strategies is less than three. When considering the raw fit between subjects' decisions and the predictions of the inferred strategy, i.e. how often loan officers decided in accordance with the inferred strategy and how often they did not, the mean accordance rate is 84%, but there is significant variation among subjects.[2] This evidence is conveyed through cell saturation in Figure 4, where the accordance with the inferred strategy is represented by the highly saturated cells and the discordance by the low saturated ones.

< Insert Figure 4 about here >

4.2. Eye tracking results

Unique inspections. The mean number of fully inspected cues was 10.6 out of 12 (range: 7.3 – 11.9). These results are consistent with the modelling results reported above and suggesting that the majority of subjects used a compensatory strategy. Among the subjects classified as users of Take The Best strategy, the mean number of fully inspected cues was lower (9.3, range: 7.6 - 11.7).

Dwell time and fixation count. The computation of subject-level correlations between dwell time (or fixation count) and self-reported cue importance reveals a positive correlation for 87% of the subjects. The mean correlation is higher for Take The Best users (+ 0.55) than for Equal Weights users (+ 0.21), with Weighted Additive strategy users in between (+ 0.37) (Figure 5).

< Insert Figure 5 about here >

Information search. Another important aspect of information processing revealed by eye-tracking is the type of visual search subjects engaged in. We investigated two dimensions of search behaviour.

The first dimension concerns the distinction between cue-based and alternative-based processing. Concerning the relation between the decision strategies and this aspect of visual search, we make the following predictions. First, the Take The Best strategy users should engage in cue-based processing. Second, assuming that subjects choose the type of processing that is cognitively least costly, Weighted Additive strategy users should also engage in cue-based processing, as cues that do not discriminate between the two alternatives can be then easily disregarded. For the Equal Weights strategy, in contrast, alternative-based processing seems more likely because the Equal Weights strategy translates into a simple count of positively-valued cues.

The second dimension of visual search behaviour concerns the order in which cues were inspected. To analyse subjects' search orders, we classified each trial as position-based or importance-based. To do this, we considered only fixations targeting AOIs containing cue values; using the Levenshtein distance, we assessed if the actual sequence was closer to the sequence implied by position-based

[2] One subject that clearly stands out was classified as a user of the Weighted Additive strategy but more often than not made the opposite decision to the one prescribed by the strategy.

search or the sequence implied by the importance-based search.[3] Figure 6 displays the results. The mean proportion of within-cue transitions (same cue, different alternatives) is shown on the x-axis and ranges between 19% and 54%. The data are thus more consistent with cue-based processing for the majority of the subjects. Concerning cue search, we find that position-based order predominates. Forty-five percent of the subjects seemed to rely exclusively on position-based order and 93% relied on it more often than not. Only three subjects used importance-based search in the majority of trials. Finally, we do not observe striking differences between the users of different decision strategies. Even among Take The Best users, position-based search predominates, although the mean proportion of trials with position-based search is higher for users of Weighted Additive (89%) and Equal Weights (88%) strategies than for Take The Best users (77%).

< Insert Figure 6 about here >

No statistically significant differences in behavioural and eye-tracking results were found according to the accountability condition.

5. Discussion

The main aim of the current study was to investigate professional loan officers' decision strategies and their attention allocation towards financial and non-financial information in a probabilistic inference task. In each trial, loan officers had to inspect the profiles of two fictional companies and indicate which of the two companies seemed a better candidate for loan approval. Academics and practitioners have largely been interested in the identification of human decision strategies; surprisingly, despite being proved that the environment and the task are crucial in affecting strategies' selection, very few studies have explored experts' decisions and even fewer have focused on decision making in the banking and financial sector. While a strand of the literature might suggest that experts tend to integrate multiple pieces of diagnostic information in a compensatory way (Phelps and Shanteau, 1978; Glöckner and Betsch, 2008; Glöckner et al. 2012), another strand proposes that experts, because of their knowledge about intercorrelations between cues and their ability to distinguish relevant from irrelevant cues, tend to rely on simple, noncompensatory strategies. Focusing on experts' decision making in the financial domain, our study shows that most of the professional loan officers used a compensatory strategy. In particular, the Weighted Additive strategy was inferred for more than half of the sample,[4] revealing loan officers' tendency to rely on information-intensive processing rather than on heuristics. This result is important since it contrasts with some previous studies on experts' decision making, which revealed that most of the experts (experienced burglars and police officers, judges, airport customs officers) appeared to be following

[3] We considered only fixations targeting AOIs containing cue values. Next, we disregarded the information about the alternative which was attended to and removed repetitions. We recoded the resulting fixation sequences as strings. This enabled the use of the Levenshtein distance to check if the actual sequence was closer to the sequence implied by position-based search or the sequence implied by the importance-based search. To obtain unique strings for importance-based search, we used the cue ranking data instead of the cue rating data. The Levenshtein distance is the minimal number of character insertions, deletions, and substitutions needed to transform one string into another. If the Levenshtein distance for the position-based order was smaller than for the importance-based order, a trial was classified as position-based — and vice versa.

[4] It should be noted, however, that in a substantial minority of cases the Weighted Additive strategy and the Equal Weights strategy had a very similar fit.

the noncompensatory Take The Best heuristic (Dhami, 2003; Garcia-Retamero and Dhami, 2009; Pachur and Marinello, 2013). The contrasting evidence on decision strategies of the present results with previous findings in experts' decision making might be ascribable to the specificity of the loan approval process. Loan officers do not make hundreds of decisions a day and do not receive regular feedback on the quality of their decisions. In comparison with the other mentioned domains, that of commercial loan lending is characterized by the large amount and complexity of information, slower pace of decision making, lack of fast and unambiguous feedback, and the need to justify one's judgment to others. These factors seem likely to incentivize the usage of information-intensive, compensatory decision strategies (Andersson, 2004). Even if information-frugal strategies might simplify decision making at no cost to accuracy (Czerlinski et al., 1999; Şimşek, 2013; Lee et al., 2017; Luan et al., 2019), some of these same factors could prevent the discovery of this possibility. Our results on loan officers' decision strategies therefore underpin the importance of getting a better understanding of the cognitive processes underlying experts' decision making taking into account the specificity of the contexts in which decisions are taken. The comprehension of decision makers' cognitive processes permits to predict future decisional behaviour (Payne et al., 1978), having several implications in the design of decision support systems (Montgomery et al., 2004; Browne et al. 2007) and thus allowing to tailor the visual displays of information to actively support loan officers' decision-making processes.

Another finding of the present research is that, when rating the importance of financial and non-financial indicators, there is a high variability among subjects, i.e. loan officers tend to assign different weights to cues. Considering that the sample is made up of loan officers all belonging to the same financial institution, and that the Department to which they are affiliated does not explain this variability (as shown by an exploratory study on this data, not reported here), these results are interesting in revealing that there might be a low consensus among loan officers on the importance of the summary indicators. Also this behavioural finding is in contrast with a previous study on experts' decision making, which revealed a high consensus among experts on the importance of the cues. In fact, while in Pachur and Marinello (2013) 30 out of the 31 officers agreed in estimating a specific cue as the most important one, in our study, a similar consensus is not displayed.

In order to gain further insights into the similarities and differences among the users of different decision strategies and to unveil their attentional allocation process, we recorded and analyzed eye-tracking data. The analysis of loan officers' oculomotor behaviour reveals their attitude to engage in an exhaustive search, typically inspecting all or almost all of the information presented on the screen: the average number of fully inspected cues was slightly lower for users of the Take The Best strategy but still relatively high (10 out of the 12 cues, on average). Similarly, Andersson (2004) reported extensive information gathering in a study involving Swedish loan officers. Results are in line also with other research showing that although the Take The Best strategy sometimes provides a good account of people's choices, its information search predictions fare less well descriptively (Dummel et al., 2016). Concerning the type of visual search subjects engaged in, eye-tracking data suggested that most loan officers employed either cue-based processing or a mixture of cue-based and alternative-based processing. The prediction of the Take The Best strategy that subjects will tend to inspect cues in order of their importance held true for three subjects, and only one of them was classified as a Take The Best user. Where observed, the differences between users of different strategies were in line with expectations but relatively minor. For example, mean correlation between cue importance and the associated Dwell Time was highest among Take The Best users (as expected given its stopping rule) but positive across all three strategies. It is important to note, however, that the number of subjects classified as Take The Best users was low. Because we would expect the strongest differences to be between users of Take The Best and users of compensatory strategies, our observations need to be replicated in a study that would have a more even split between these strategies.

With respect to the other visual search dimension, eye-tracking data reveals that search order was most often determined by the arrangement of the cues on the screen, i.e. the position of the cue plays a stronger role in influencing visual search behaviour than cue importance. This finding is in line with other eye-tracking investigations in the field of financial decision making (Ceravolo et al., 2019b), and underpins the importance to consider the visual format through which information is conveyed, since previous studies outline that attention allocation might influence decision outcome and the perceived attractiveness of the options (Ceravolo et al., 2019a,b). When dealing with financial information, subjects are thought to be more rational than general consumers and therefore less sensitive to features of the visual stimuli that are not strictly relevant to solve the financial problem, i.e. the presentational format. According to standard financial theories, financial decision maker should not be affected by the visual representation of financial data; on the contrary, neurofinance is showing that investors and financial consumers might be affected by atmospheric and contextual elements also when dealing with financial data (Ceravolo et al., 2019a,b), through sometimes unconscious and automatic processes which are difficult to captures with standard approaches (Camerer et al., 2005). Therefore, if new knowledge is available about those processes and their impact on behaviours, also developers of decision support systems who operate in the banking and financial sectors might benefit from these findings.

The final aim of the study was to investigate the effects of a naturalistic accountability manipulation on predecisional and choice behaviour. As previously discussed, accountability looms large in loan officers' decision making and Andersson (2004) identified accountability as a possible explanation of extensive information gathering he observed among senior loan officers in his study. We assigned subjects to either a low accountability or a high accountability condition and compared the two groups on a variety of outcomes. The results, however, do not to support any clear conclusion. Our lack of clear results concerning accountability can be likely traced to the low sample size and the hypothetical nature of our manipulation. It is also possible that the effects of accountability are more internalized and therefore less responsive to situational manipulations (Russo et al., 2000), or that the effects vary significantly due to the different social constituencies of different loan officers (Brown, 1999).

Before considering promising avenues for future research, we note some limitations of the current study. First, the task we have used (decision between two alternatives) represents a simplification of the complex reality and of the task primarily faced by loan officers in their work (evaluation of a single alternative). Previous research shows that these two modes of decision making are not always exchangeable (Hsee, 1996). Second, the information conveyed by the cues in our task was simplified significantly to accommodate methodological and practical constraints. For example, cue values were categorized instead of being presented as exact values (in the case of financial cues) or in some even richer form (in the case of non-financial cues).

The current study highlights several promising avenues for future research. The version of the Weighted Additive strategy that we have developed needs to be investigated further. It would be instructive to compare the two versions of the strategy in a study in which cue weights were provided a priori and therefore known with greater precision than in the current study, where the weights were estimated by subjects themselves. Another important next step would be to also develop versions of the Equal Weights and Take The Best strategies that incorporate other theories of error (Heck et al., 2017). Finally, in our view a very promising direction for future research involves the integration of eye-tracking and decision data. In the current research, we have classified subjects as users of different decision strategies on the basis of decision data, and followed up by using eye-tracking data to highlight the similarities and differences between users of different strategies. A natural next step would be to formally include in the model visual behaviour as captured by eye-tracking, thus increasing the scope of the model (Rieskamp and Otto, 2006; Lee et al., 2019). Such a model could also include the possibility of strategy switches during the task (Lee, 2019). In a recent reanalysis of Walsh and Gluck (2016), Lee et al. (2019) found strong evidence for strategy switching in a large majority of subjects completing a probabilistic inference task. The development of these models will bring us closer to the challenging but important task of understanding the decision making of loan officers and other significant economic agents.

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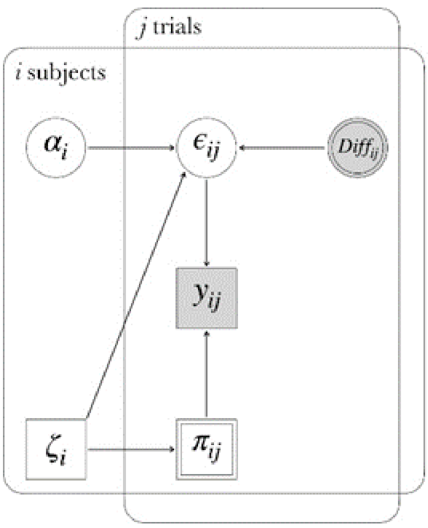
Figure 1. An example of the visual stimulus presented to loan officers

	Company A	Company B
Cash to total assets	conservative	conservative
Current ratio	aggressive	conservative
EBIT interest coverage	aggressive	conservative
Funds from operations to total debt	aggressive	conservative
EBITDA margin	conservative	conservative
Total debt to EBITDA	conservative	aggressive

	Company A	Company B
Corporate governance, key-man & reporting	below average	below average
Management track record & strategy	below average	below average
Cost structure & operational efficiency	above average	above average
Growth	below average	above average
Geographical diversification	above average	above average
Market leadership	below average	below average

Figure 2. A graphical model for inferring the subjects' decision strategies



$$\epsilon_{ij} = \frac{1}{2} - logit^{-1}\left(\frac{\alpha_i}{1-\alpha_i}\, logit(\frac{Diff_{ij}}{2})\right) \quad \text{if } \zeta_i = 1$$

$$\alpha_i \sim Uniform(0.001, 0.999)$$

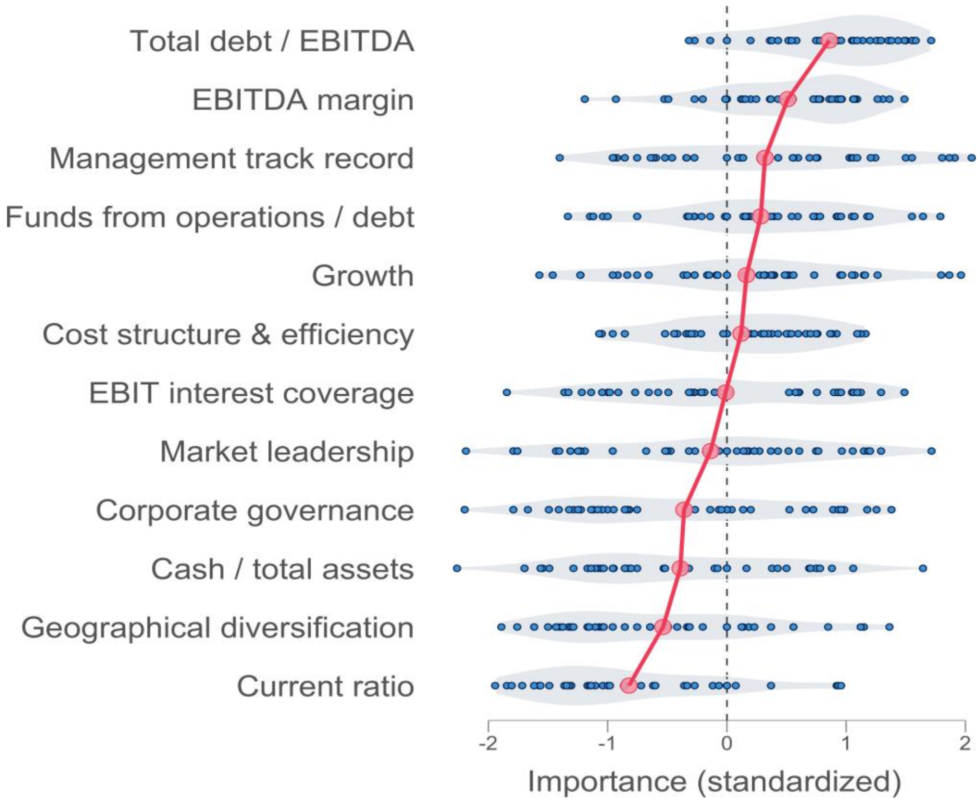
$$\epsilon_i \sim Uniform(0, 0.5) \qquad \text{if } \zeta_i \in \{2, 3\}$$

$$y_{ij} \sim \begin{cases} Bernoulli(1-\epsilon_{ij}) & \text{if } \pi_{ij} = A \\ Bernoulli(\epsilon_{ij}) & \text{if } \pi_{ij} = B \\ Bernoulli(0.5) & \text{otherwise} \end{cases}$$

$$\pi_{ij} = \begin{cases} WADD_{ij} & \text{if } \zeta_i = 1 \\ TTB_{ij} & \text{if } \zeta_i = 2 \\ EQW_j & \text{if } \zeta_i = 3 \end{cases}$$

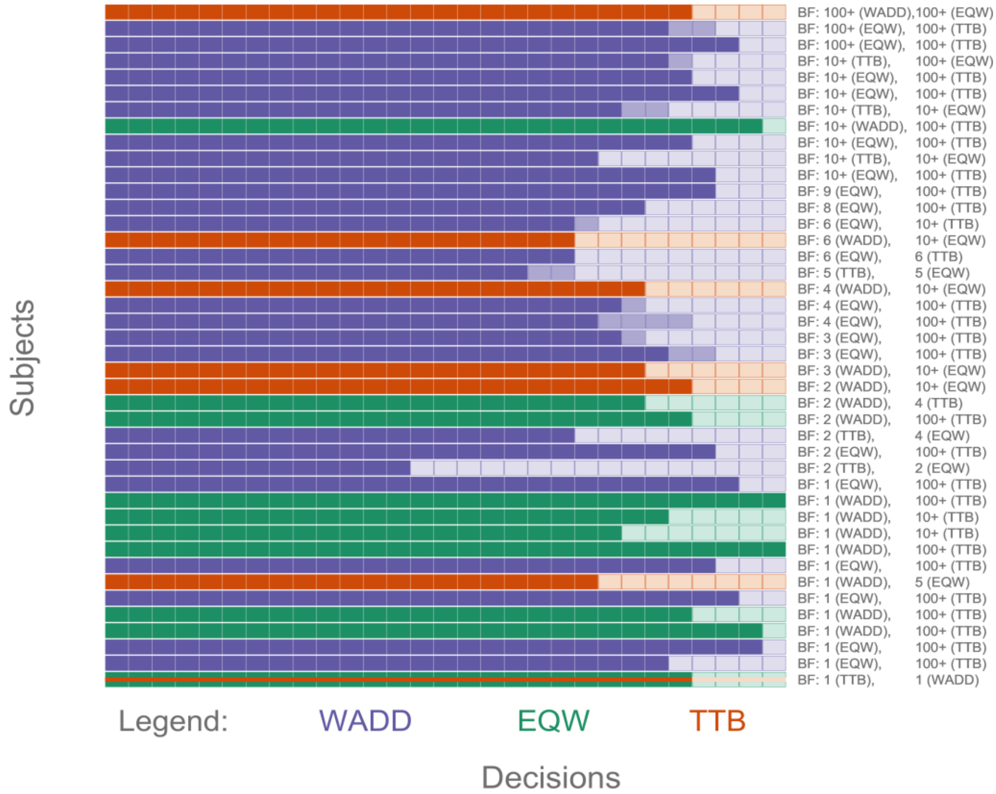
$$\zeta_i \sim Categorical(\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$$

Figure 3. Standardized importance ratings for the 12 cues used in the study



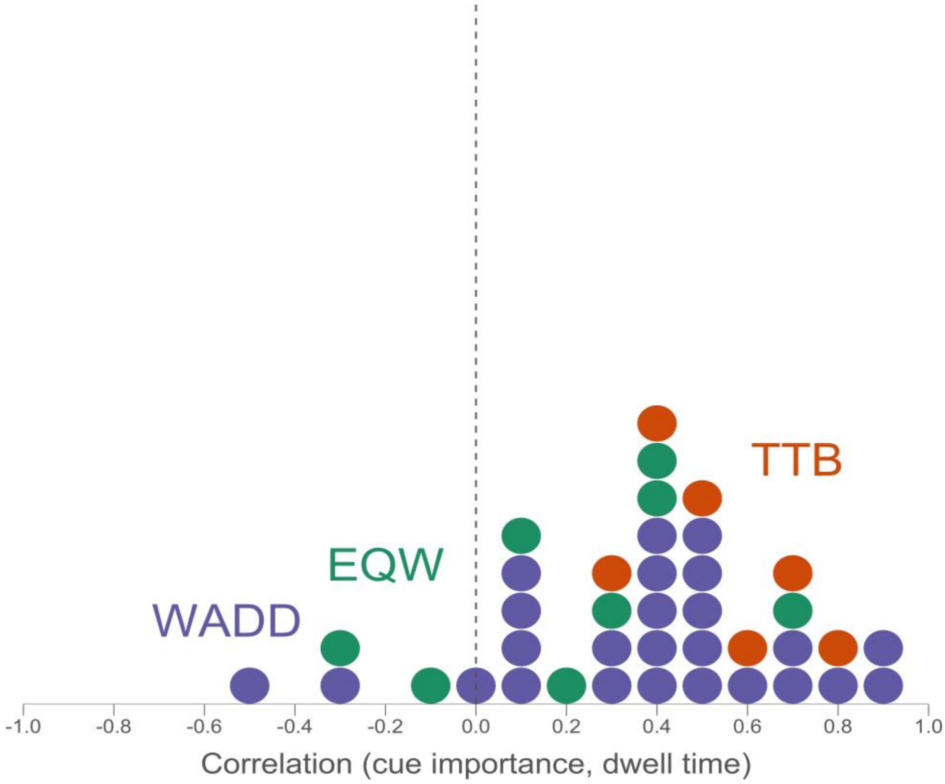
The raw responses were standardized by subtracting the subject-specific mean and dividing the resulting score by the subject-specific standard deviation. Blue circles represent individual ratings, shaded areas track the densities of the distributions of ratings, and the connected red circles show the averages.

Figure 4. Strategy classifications and associated accordance rates and Bayes Factors



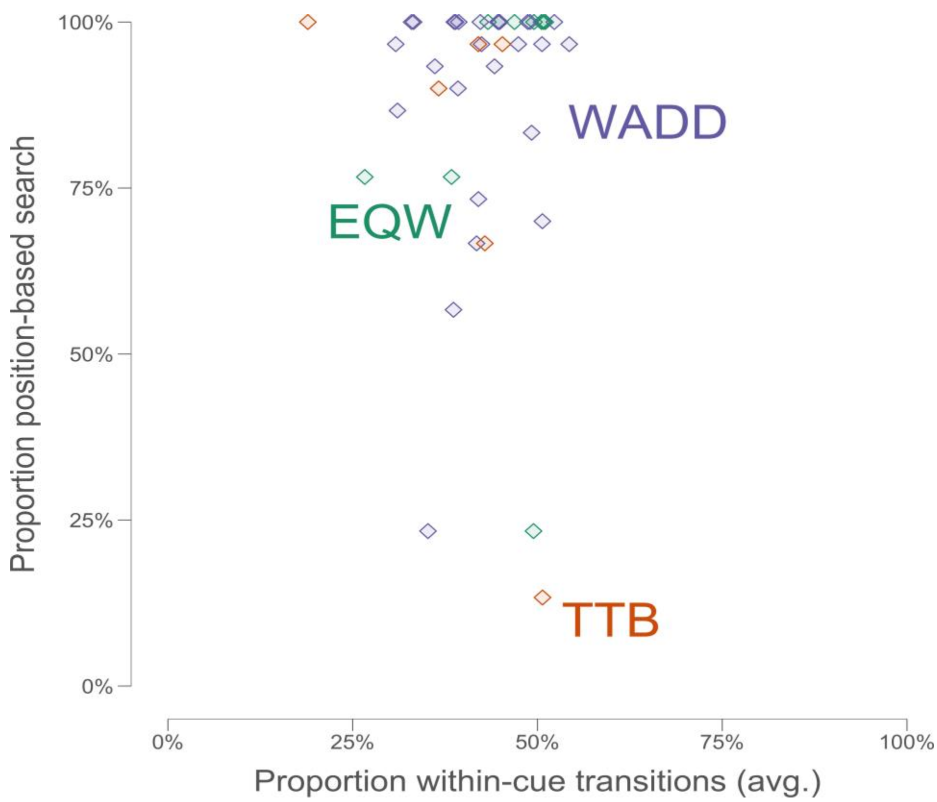
Each subject is represented by a single row, colored according to the strategy to which the subject was classified. The thirty columns represent thirty trials (order is not significant). High saturation of a cell signifies that the subject decided in accordance with their inferred strategy, low saturation signifies that they did not. In some trials, the two alternatives were deemed equally attractive by the Weighted Additive strategy; these trials are displayed in an intermediate saturation. The labels on the right communicate two (rounded) Bayes Factors. The first (second) Bayes Factor compares the inferred strategy with the strategy that has the second (third) best fit. For the subject represented by the bottom row, the Equal Weights and the Take The Best strategies had the exact same fit.

Figure 5. Correlation between cue importance and dwell time



Each circle represent one subject and its color conveys the decision strategy that the subject was classified as using (WADD = Weighted Additive strategy, EQW = Equal Weights strategy, TTB = Take The Best strategy). The x-axis represents Pearson's correlation between the importance assigned to a given cue and the dwell time for that cue.

Figure 6. Two dimensions of visual search behaviour revealed by eye-tracking



Each diamond represents one subject, and the color represents the inferred strategy (WADD = Weighted Additive strategy, EQW = Equal Weights strategy, TTB = Take The Best strategy). The x-axis shows the average proportion of within-cue transitions in a trial. The y-axis shows the proportion of trials in which the movement between cues was classified as position-based (as opposed to importance-based).