What is Adaptive about Adaptive Decision Making?

A Parallel Constraint Satisfaction Account.

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Abstract

There is broad consensus that human cognition is adaptive. However, the vital question of how exactly this adaptivity is achieved has remained largely open. Herein, we contrast two frameworks which account for adaptive decision making, namely broad and general single-mechanism accounts versus multiple-strategy accounts. We propose and fully specify a single-mechanism model for decision making based on parallel constraint satisfaction processes (PCS-DM) and contrast it theoretically and empirically against a multiple-strategy account. To achieve sufficiently sensitive tests, we rely on a multiple-measure methodology including choice, reaction time, and confidence data as well as eye-tracking. Results show that manipulating the environmental structure produces clear adaptive shifts in choice patterns – as both frameworks would predict. However, results on the process level (reaction time, confidence), in information acquisition (eye-tracking), and from cross-predicting choice consistently corroborate single-mechanisms accounts in general, and the proposed parallel constraint satisfaction model for decision making in particular.

Keywords: Adaptive Cognition, Parallel Constraint Satisfaction, Adaptive Decision Making, Probabilistic Inferences, Decision Strategies

1. Introduction

One of the most well-established notions about human behavior and thought is that both are somehow adapted to the environment (Brunswik, 1956) and “[t]he view of Homo sapiens as an adaptive decision maker has continued to receive support” (Weber & Johnson, 2009, p. 76). Indeed, the question of which behavior may be considered rational has long been argued to depend on the environment and the goals of the organism or agent (Chater, Oaksford, Nakisa, & Redington, 2003; H. A. Simon, 1956) and it has been investigated how empirically verifiable principles of human cognition “can be viewed as arising from the rational adaptation of the cognitive system to the problems and constraints that it faces” (Chater & Oaksford, 2000, p. 107). One of the most basic of these problems we face is the necessity to make accurate inferences in a fundamentally uncertain world providing only probabilistic information or cues (Brunswik, 1952; Gigerenzer, Hoffrage, & Kleinbölting, 1991) that may vary in validity across different environments. The major challenge for research is thus to understand how decision makers adapt to this variation.

In what follows, we pose the question what exactly is adaptive about adaptive decision making. More specifically: How do decision makers react to different environmental structures appropriately when relying on probabilistic cues to draw inferences? At the level of theoretical frameworks, these questions have been tackled by two distinct approaches: (a) by proposing broad models of cognition which specify a general mechanism that can apply to many tasks, domains, and environments (e.g., Busemeyer, Pothos, Franco, & Trueblood, 2011; Busemeyer & Townsend, 1993; Dougherty, Gettys, & Odgen, 1999; K. Fiedler, 2000; Lee & Cummins, 2004; Newell, 2005) or (b) by assuming a repertoire of more or less specialized cognitive tools, many of which are optimally suited for a narrow set of situations only (e.g., Beach & Mitchell, 1978; Gigerenzer, Todd, & The ABC Research Group, 1999; Payne, Bettman, & Johnson, 1993; Scheibehenne, Rieskamp, & Wagenmakers, 2013).

Concerning the adaptation to varying environments when drawing probabilistic inferences, these two frameworks differ as follows: In the former "single-mechanism" view, decision makers differ in the weighting of the cues fed into the *same* system and thus generally make decisions based on a single mechanism of information integration. In the latter "multiple-strategy" view, by contrast, decision makers select qualitatively *different strategies* for different environments and thus rely on distinct mechanisms.

Herein, we put forward a general single-mechanism model for probabilistic inferences that is based on a connectionist parallel constraint satisfaction approach to cognition (see McClelland et al., 2010; Read, Vanman, & Miller, 1997; Rumelhart, Hinton, & McClelland, 1986, for overviews). Corresponding models have been successfully applied to account for phenomena in a broad range of domains including perception (McClelland & Rumelhart, 1981), analogies (Holyoak & Thagard, 1989), impression formation (Kunda & Thagard, 1996), preference construction (D. Simon, Krawczyk, & Holyoak, 2004), legal reasoning (Holyoak & Simon, 1999; D. Simon, Snow, & Read, 2004), and person construal (Freeman & Ambady, 2011). More specifically, we generalize and extend previous accounts (Betsch & Glöckner, 2010; Glöckner & Betsch, 2008a; Holyoak & Simon, 1999) and put forward a fully specified parallel constraint satisfaction model for adaptive decision making that can accommodate individual differences in information integration. We then contrast this model theoretically to the multiple-strategy approach and finally tease the two apart empirically in a set of experiments by investigating their capabilities to predict choices, decision time, and confidence on the level of individuals as well as general patterns of information search.

2. Single-mechanism Models of Decision Making and the Parallel Constraint Satisfaction Model

Broad models of cognition typically aim to explain adaptivity by specifying plausible cognitive mechanisms that approximate rational solutions (e.g., Hintzman, 1984; Kruschke, 1992). The idea is that "[f]ormal rational principles spell out the optimal solution" and "well-adapted agent[s] will approximate this solution to some degree" (Chater & Oaksford, 2000, p. 112). One class of broad single-mechanism theories of cognition that approximate rationality through mechanisms taking into account (and weighting) all evidence, are random-walk or diffusion models (e.g., Busemeyer & Townsend, 1993; Diederich, 2003; Krajbich & Rangel, 2011; Lee & Cummins, 2004; Ratcliff & McKoon, 2008; Usher & McClelland, 2001). In simple terms, their basic idea is that information is sampled continually and evidence accumulated over time until a certain threshold is researched and it is exactly this threshold which constitutes the adaptive component of these models. As a vivid metaphor, Newell (2005) coined the term of an "adjustable spanner" to reflect the idea of a single tool (or cognitive mechanism) which achieves flexibility through adaptively setting an evidence-threshold.

One common feature of these models is the assumption of unidirectional reasoning from information to decisions, implying that information in itself is accumulated but that its' evaluation is not changed in the decision process. In connectionist implementations of these evidence accumulations models (e.g., Busemeyer, Jessup, Johnson, & Townsend, 2006; Busemeyer & Johnson, 2004; Usher & McClelland, 2001, 2004) this is usually reflected in unidirectional spread of activation. However, the assumption of unidirectional reasoning has been challenged in several domains, especially in light of *coherence effects*, that is, systematic shifts in how information is evaluated *within* the decision process (i.e., before a decision is made) to support the emerging favored decision (e.g., Bond, Carlson, Meloy, Russo, &

Tanner, 2007; Brownstein, 2003; Brownstein, Read, & Simon, 2004; Carlson & Russo, 2001; DeKay, Patino-Echeverri, & Fischbeck, 2009; Glöckner, Betsch, & Schindler, 2010; Holyoak & Simon, 1999; Russo, Medvec, & Meloy, 1996; D. Simon, Snow, et al., 2004). As such, bidirectional reasoning has found substantial support.

Correspondingly, bidirectional reasoning is a core property of connectionist parallel constraint satisfaction networks (McClelland & Rumelhart, 1981; Thagard, 1989, 2000). Their general idea follows in the Gestalt tradition of psychology by assuming a cognitive system which minimizes informational conflict to form a coherent mental representation of the problem at hand simultaneously taking into account bottom-up (e.g., observed cues) and top-down (e.g., conceptual knowledge) influences (see also Clark, 2013). One such theory is the parallel constraint satisfaction (PCS) model by Glöckner and Betsch (2008a). Therein, it is assumed that processes of decision making can be modeled by spreading activation mechanism in relatively simple symbolic networks. The PCS model describes fast, automatic processes that lead to consistent mental representations of the task and intuitive choices that emerge without awareness of the process itself (Glöckner & Witteman, 2010). According to PCS, the initial process automatically attempts to make sense of the available information. External information is combined with information from memory and spreading activation mechanisms are applied to form the most coherent mental representation given logical constraints within this set of information. If the resulting mental representation is highly coherent clearly indicating that one option is better than the other(s), a decision is instantly made without further deliberation. If coherence is below a certain threshold, deliberate processes are additionally activated.

In a probabilistic inference task, networks in the model consist of two layers of nodes representing options (second layer) and cues (first layer) that provide information concerning the options on the relevant criterion (see also Figure 1, below). Bidirectional links between nodes capture mutual coherence or conflict between the represented concepts. First layer cue nodes receive activation from a general activation (or driver) node. The degree of activation depends on the relative weight of cues. Cues, in turn, support or inhibit second layer option nodes (that is, an option can have a positive or negative cue value). As a consequence of the bidirectional character of links, cue nodes themselves can be supported or inhibited when certain options are more or less strongly activated. Furthermore, mutual inhibition is assumed between second layer option nodes (i.e., favoring one option implies disfavoring the other(s)). Spreading activation mechanisms maximize coherence under parallel consideration of all constraints given by the structure of the network (cf. Hopfield, 1982).

However, the PCS model has attracted criticism, especially for being insufficiently specified (Marewski, 2010) and thus, potentially, too flexible (see also Glöckner & Betsch, 2011). The weakness of the original PCS model by Glöckner and Betsch was that - although the process of information integration was mathematically well described - the specification of the network structure on which these processes act remained too flexible. That is, as with most of the previous PCS models introduced above, the development of the informational basis remained outside of the scope of the model (Shultz & Lepper, 1996). However, considering the increasing importance of model comparisons this state of affairs is indeed unsatisfactory and a serious limitation, given that overly flexible models may explain anything and thus nothing at all (Roberts & Pashler, 2000). Specifically, it remained open how validities of cues are transformed into network parameters. This gap needs to be closed for the PCS model to be fully-specified.

Recent work attempted to address the problem by calculating averaged predictions over a range of parameters (Glöckner & Hodges, 2011) or trying to develop transformation functions for specific tasks (Glöckner & Betsch, 2012; Glöckner et al., 2010; Glöckner & Bröder, 2011). We will elaborate on this work and develop a fully specified PCS model for decision making (PCS-DM) in two implementations: (i) a zero-free parameter implementation and (ii) a one-free parameter implementation which can accommodate individual differences and differences between tasks. Thereby, a) a complete set of transformation functions is defined, describing how the decision task is translated into a network structure, b) an algorithm is defined that simulates spreading activation in the network and generates output given the network structure, and c) the translation of network output to multiple behavioral parameters is defined.

2.1 Transformation into Network Structure: Mental Representations

We consider probabilistic inference tasks in which a decision between two options X and Y is made (for example, which of two cities is more populous) based on a set of binary cues (e.g., which city is a capital or has an international airport). Options X and Y are defined by the presence or absence of cues k as cue vectors $X \equiv (x_1 \ldots x_k)$ and $Y \equiv (y_1 \ldots y_k)$ with $x_i = 0$ indicating absence and $x_i = 1$ indicating presence of the cue and cues differing in their validity $V \equiv (v_1 \ldots v_k)$. The validity of cue i is defined as the conditional probability of an option with a positive cue value having a higher criterion value in a given reference class than an option with a negative cue value; or formally (Gigerenzer et al., 1991; Lee & Cummins, 2004):

$$v_i \equiv p(X > Y \mid x_i = 1, y_i = 0). \qquad (1)$$

In PCS networks, all options and cues are represented by nodes that vary in activation a with a^o_j denoting activation of option j and a^c_i denoting activation of cue i. A driver node V is defined which has a constant activation of 1 and conceptually represents the general concept of validity of observed cues. Connections between nodes are all bidirectional and have weights w in the range of $w \in [-1; 1]$. A weight of zero indicates no connection and positive (negative) weights indicate mutual support (inhibition) between the nodes. All nodes can potentially be connected with each other by weights, thus resulting in a symmetric connection weight matrix M with n rows and columns ($n = I + J + 1$; with I and J indicating the total number of cues and options, respectively) with weights in the off-diagonal cells and zeros in the diagonal (see also Rumelhart et al., 1986). Each decision task is transformed into such a unique connection weight matrix (Figure 1, top) as follows:

$$w_{v(i)} = (v_i - 0.5)^P \tag{2}$$

$$w_{c(i)o1} = 0.01 \text{ if } x_i = 1 \text{ and } -0.01 \text{ otherwise} \tag{3}$$

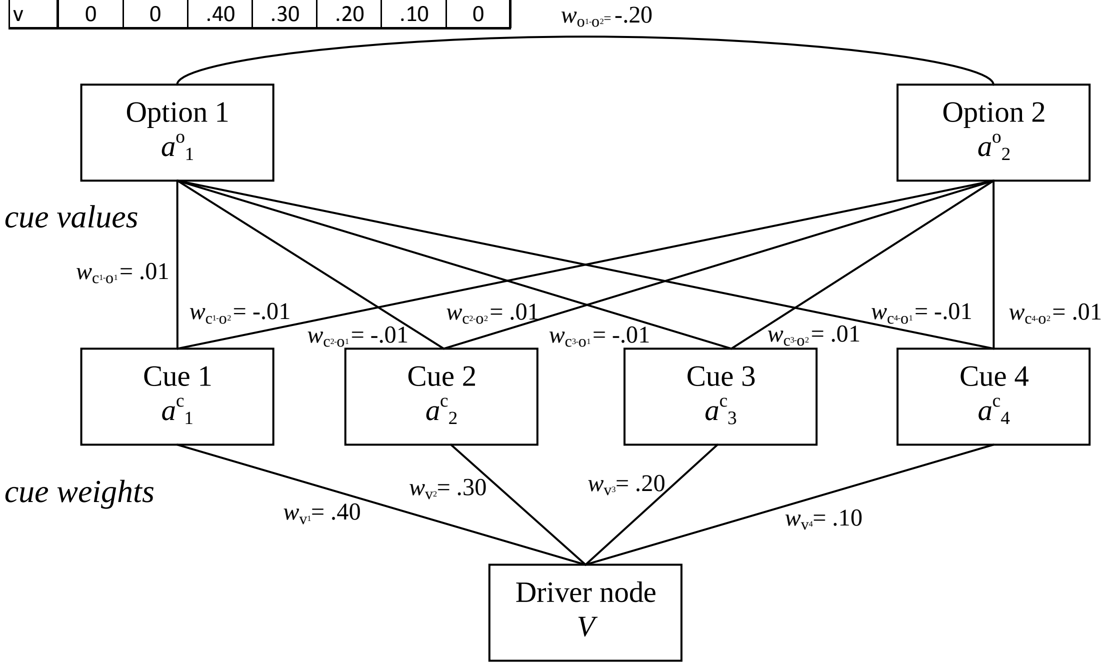
$$w_{c(i)o2} = 0.01 \text{ if } y_i = 1 \text{ and } -0.01 \text{ otherwise} \tag{4}$$

$$w_{o1o2} = -0.20 \tag{5}$$

where $w_{v(i)}$ are the connections between nodes V and c_i representing cue validities; and $w_{c(i)o(j)}$ is the *cue value* of cue i concerning option j and w_{o1o2} is the degree of mutual exclusion of options 1 (=X) and 2 (=Y).

Figure 1. Matrix representation and network representation of a decision task in PCS-DM. The matrix is symmetric and only connections under the diagonal are shown.

	o1	o2	c1	c2	c3	c4	v
o1	0						
o2	-.20	0					
c1	.01	-.01	0				
c2	-.01	.01	0	0			
c3	-.01	.01	0	0	0		
c4	-.01	.01	0	0	0	0	
v	0	0	.40	.30	.20	.10	0



Transformations in equation (3) to (5) are commonplace (e.g., Glöckner et al., 2010; Glöckner & Bröder, 2011; Holyoak & Simon, 1999; Thagard, 1989) and sensitivity analyses have shown that the selection of specific values has little influence on predictions as long as inhibitory connections are relatively strong compared to excitatory connections (e.g., Thagard, 1989). PCS-DM predictions, however, strongly depend on Equation 2. In this equation for calculating connection weights, validities are corrected for chance level (.50) to avoid that irrelevant cues have a weight. More importantly, the parameter P allows PCS-DM to capture individual differences in the subjective sensitivity to differences in cue validities. Low sensitivity is captured by low P, with $P = 0$ as hypothetical minimum, representing a special case in which all information is weighted equally. By contrast, high sensitivity for cue validities is captured by large values of P with high values as special cases in which less valid cues cannot overrule more valid ones. In the current PCS-DM implementation, we restricted P to intermediate sensitivity values in the interval [1,2] to reduce the model's capability to mimic simple strategies on the level of choices and to render parameter search computationally tractable.

P captures sensitivity at the level of individuals, that is, it determines how an individual transforms explicitly provided or learned information about a cue's predictive power (i.e., cue validity) into a weight. Stated differently, P describes a core property of a psychological transformation process that precedes decision making.[i]

To determine a point of comparison and to identify a single reference value to which P can be set, and thereby render the PCS-DM model void of any free parameters, we used a Monte-Carlo simulation. In doing so, we implemented the general notion of approximating the rational solution as is inherent in the idea of adaptive cognition (Chater & Oaksford, 2000). Specifically, the aim was to find the value of P that maximizes the overlap between PCS choice predictions and the rational Naïve Bayesian solution (Lee & Cummins, 2004)[ii]. We found that in randomly generated tasks and sets of validities in a four-cue environment this is the case for P = 1.9 (for similar results in a more comprehensive simulation see also Jekel, Glöckner, Fiedler, & Bröder, 2012). In this case, the observed overlap between the Naïve Bayesian solution and PCS predictions was p = .96 (N = 5.000). We consequently used P = 1.9 to implement PCS-DM without any free parameters, thus predicting behavior with an unfitted PCS-DM for all individuals and all environments.

The connection weight matrix M can also be graphically depicted as a network of nodes with two layers (i.e., cues and options) as shown in the lower part of Figure 1. This network structure representation of M models the *mental representation* of the given decision task by one specific individual.

2.2 Spreading Activation Mechanism

In line with the general idea of a single-mechanism operating on whatever information is fed into the system, PCS-DM integrates all available pieces of information. The connection matrix M is the input and a spreading activation mechanism deterministically leads to a vector of output variables (i.e., predictions). The PCS process is simulated as a repeated simultaneous updating process of activation a in the network according to the sigmoid activation function proposed by McClelland and Rumelhart (1981):

$$a_i(t+1) = a_i(t)(1 - decay) + \begin{cases} if \quad input_i < 0 \quad input_i(a_i(t) - floor) \\ if \quad input_i \geq 0 \quad input_i(ceiling - a_i(t)) \end{cases} \tag{6}$$

with

$$input_i(t) = \sum_{j=1 \to n} w_{ij} a_j(t) \,. \tag{7}$$

where $a_i(t)$ represents the activation of the node i at iteration t. The parameters *floor* and *ceiling* stand for the minimum and maximum possible activation and they are herein always set to constant values of -1 and +1 (e.g., Read et al., 1997; Thagard & Verbeurgt, 1998). $Input_i(t)$ is the activation that node i receives at iteration t, which is computed by summing up all products of activations and connection weights w_{ij} for node i. *Decay* is a constant decay factor *decay* = .1 (e.g., Freeman & Ambady, 2011). In simple networks, the activation of nodes converges towards stable levels within less than 500 iterations.[iii] Stability is considered to be reached once changes in activation are below a certain stability threshold for more than 10 iterations. Specifically, it is determined whether changes in the overall energy in the network are below 10^{-6}. Energy is calculated by:

$$Energy(t) = -\sum_{i}\sum_{j} w_{ij} a_i a_j \tag{8}$$

The iterative algorithm minimizes energy and maximizes coherence under parallel consideration of all constraints.[iv]

The properties of the spreading activation mechanism and the network underlying PCS-DM have been extensively explored in previous simulation studies (e.g., Glöckner & Hodges, 2011; Jekel et al., 2012) and the operation of the network as well as the resulting predictions for behavior are manifold and well-documented (e.g., S. Fiedler & Glöckner, 2012; Freeman & Ambady, 2011; Holyoak & Simon, 1999; Thagard, 1989).

As sketched in the introduction, the PCS-DM model is an instance of a single-mechanism account of probabilistic inferences and it can thus be contrasted theoretically against the multiple-strategy framework. In PCS-DM, adaptivity is routed in the network structure which can operate on whatever probabilistic cues are currently available and whatever objective or subjective weights are attached to them. It thus mirrors the view that "[a]daptive cognition is the ability to utilize and combine elementary cues in countless ways, depending on the requirements of the current situation." (K. Fiedler, 2010, p. 27). This very notion drives the distinction between single-mechanism models such as PCS-DM and the alternative multiple-strategy approach. In the latter, many specific and in themselves mostly inflexible strategies are proposed. Typically, these consider cues in certain pre-specified order and often only one cue at a time (e.g., Gigerenzer, 2004). The flexibility needed for cognition to be adaptive is achieved through the sheer number of strategies available. In what follows, we briefly sketch the multiple-strategy view and discuss the empirical evidence available so far.

3. The Multiple-strategy Approach

Since the seminal work of Payne and colleagues roughly two decades ago (Payne, Bettman, & Johnson, 1988; Payne et al., 1993), the idea of adaptive strategy selection has become widely accepted. Specifically, it purports that decision makers will select among a set of strategies, reflecting an effort-accuracy trade-off (Payne, Bettman, & Luce, 1996): Some strategies are easier to apply (e.g., a lexicographic rule) but also yield less accuracy than more complex and thus demanding strategies (e.g., a weighted-additive rule). All these rules are applied in a serial fashion such that more complex rules necessarily demand more resources and time. Depending on the given constraints (e.g., capacity limitations or situational time pressure) and the importance of the decision, individuals are assumed to apply the best-suited strategy (e.g., Payne et al., 1996; Rieskamp & Hoffrage, 2008). Many empirical investigations have confirmed the idea of qualitatively different strategies in information acquisition (e.g., Payne et al., 1988; Payne et al., 1996).

Although retaining the original assumption of a selection among multiple strategies, the “adaptive toolbox” view suggested by Gigerenzer and co-workers (Gigerenzer et al., 1999) presumes that simple heuristic strategies need not necessarily yield less accuracy than more complex mechanisms (Gigerenzer & Goldstein, 1996; see also Payne et al., 1988). Indeed, though depending crucially on the structure of the environment, this assumption sometimes holds (Hogarth & Karelaia, 2007). More importantly, the adaptive toolbox view specifically purports that different strategies “exist” at the processing level, that is, different rules describe the actual information *integration* mechanism (Gigerenzer, Hoffrage, & Goldstein, 2008), not merely information search. In recent years, several simple and yet often surprisingly accurate heuristics have been proposed as part of the adaptive toolbox – most prominent of all, the take-the-best heuristic (TTB; Gigerenzer & Goldstein, 1996). This strategy searches through cues in order of validity and chooses the option to which the first discriminating cue points. We consider Gigerenzer's adaptive toolbox which extends Payne et al.'s notion of adaptive decision making as the quintessential multiple-strategy model, since it explicitly pertains to the information integration level. Most vitally, like its predecessor, it assumes that certain situations or environments will lead to more or less application of qualitatively different decision strategies, such as simple heuristics (Hilbig, Erdfelder, & Pohl, 2012; Rieskamp & Hoffrage, 2008).

Much in line with this approach, a noteworthy number of studies have identified conditions which lead to choices more or less in line with simple, non-compensatory strategies like TTB (Bröder & Gaissmaier, 2007; Bröder & Schiffer, 2003b, 2006b; Newell, Weston, & Shanks, 2003; Pohl, 2006; Rieskamp & Hoffrage, 2008; Rieskamp & Otto, 2006). In particular, higher cue dispersions (i.e., large differences between cue validities) result in more choices consistent with TTB as compared to low cue dispersion (i.e., cues have similar validities) (Bröder, 2003; Newell & Shanks, 2003). This finding has been interpreted as evidence for adaptive shifts between strategies (e.g., Gigerenzer & Gaissmaier, 2010), because TTB is a superior strategy in an environment with high cue dispersion: If one cue is much more predictive than all others, TTB will allow for many correct inferences (while necessitating less processing time, Gigerenzer & Goldstein, 1996) and it would thus seem adaptive to shift towards this strategy. As such a shift is mirrored in the choice patterns that have been observed repeatedly (Bröder, 2003; Rieskamp & Otto, 2006), there appears to be much evidence for the idea that shifting between distinct strategies constitutes the adaptive aspect of decision making.

However, the previously sketched findings are less conclusive than they appear at first glance. As others have noted (e.g. Bröder & Newell, 2008; Lee & Cummins, 2004), the finding of different choice patterns in different environments does not conflict with broad single-mechanism models that assume a single process operating on whatever information is fed into the system. Specifically, if – in a non-compensatory environment – cues with high validity dispersion are integrated in a weighted-additive manner, choices will necessarily resemble a non-compensatory rule. It is thus entirely open whether more choices in line with non-compensatory rules in a corresponding environment are actually produced by a switch in strategies or simply adaptation of cue weights in the same underlying mechanism. In addition, single-mechanism accounts by no means assume that it must always be the case that information search is exhaustive. Clearly, under time pressure or high information costs, a decision maker may only acquire, say, one cue (Newell & Shanks, 2003). In this case, again, the choice predicted by a single-mechanism model must necessarily overlap with the prediction of the non-compensatory TTB strategy. It is therefore vital to distinguish between information *integration* processes versus information *acquisition* (cf. Betsch, 2009). In essence, the findings of Payne and co-workers (e.g. Payne et al., 1996) certainly corroborate different strategies of information acquisition. However, none of the findings reported so far can conclusively imply that decision makers switch strategies on the level of information integration processes.

One methodological remedy - to trace information integration rather than acquisition processes - is to make information easily accessible and openly available at no cost (Glöckner & Betsch, 2008b). In this case, findings are least likely a product of different information search patterns. However, even under such conditions, choice data will often be inconclusive, since single-mechanism and multiple-strategy accounts can perfectly mimic each other in terms of choice predictions (Hilbig & Pohl, 2009). However, only if the predictions of competing approaches are unconfounded, can any insight be gained from choice data (Bröder & Schiffer, 2003a; Hilbig, 2010; Moshagen & Hilbig, 2011). To overcome these limitations inherent in considering choice data alone, the following empirical investigations take into account multiple dependent measures in a simultaneous maximum likelihood estimation including choices, response time, and confidence ratings (Glöckner, 2009; Jekel, Nicklisch, & Glöckner, 2010), further flanked by information search data and tests of cross-prediction. Thereby, we test the ability of PCS-DM – as compared to a multi-strategy approach – to account for adaptive decision making.

Indeed, recent work pitting single-mechanism models against multiple-strategy models hints that the former may indeed be superior: Söllner et al. (2014) used a newly developed information intrusion paradigm. After inducing use of TTB by participants, it was investigated whether spontaneously revealing strategy-irrelevant information (i.e., information of cues that should not be considered according to TTB) nonetheless influenced behavior. The results were clear cut: even though all traditional indicators implied that people use a TTB strategy, the strategy-irrelevant information intruded into the decision process and had systematic influences on choices and information search as predicted by single-mechanism models. Similarly, in another test of single-mechanism models against multiple-strategy models, Glöckner and Betsch (2012) found that cues with low validity that did not influence discrete choice behavior can both speed up and slow down choices. This finding cannot be easily reconciled with existing multiple-strategy models but is handled seamlessly by single-mechanism accounts. Based on these recent investigations, we predict that the single-mechanism PCS-DM will be the superior model.

4. Hypotheses and Methodological Preliminaries

As implied above, we aimed to test whether information integration is actually best described by strategy shifts or a single mechanism which merely attaches different weights to cues, depending on the environment. According to the multiple-strategy account, different environmental cue dispersions should affect the probability of using different strategies

(Bröder & Newell, 2008; Bröder & Schiffer, 2006a). For example, if there is one highly valid cue accompanied by three notably less valid ones (high cue dispersion), decision makers should shift towards non-compensatory strategies such as TTB (Bröder, 2003; Rieskamp & Otto, 2006). By contrast, in an environment with low cue dispersion (i.e., four cues with rather similar validities), more compensatory rules should be applied. In effect, switches in choice behavior would have to be accompanied by respective qualitative changes in process measures (such as decision time and confidence rating patterns) as they are assumed to reflect strategy shifts.

Importantly, the single-mechanism approach – and the PCS-DM model proposed herein as an implementation of the latter – would also expect changes in choice patterns comparing high versus low cue dispersion environments. However, it does not presume that different strategies are used; instead, changes in choice patterns are attributed to adapting cue weights in the same underlying mechanism. Therefore, although choices should shift to *resemble* non-compensatory rules more when the cue dispersion is high, they would not be *produced* by such rules. Thus, process data (decision times and confidence ratings) should be accounted for best by the same (PCS-DM) model for all kinds of cue dispersions and thus across experimental manipulations of environmental structures.

As hinted above, we considered reaction time and confidence data in addition to choices. To provide a more direct comparison of models, we resort to a multiple-measure maximum-likelihood (MM-ML) strategy classification method that was developed to determine the strategy a participant most likely used based on simultaneous consideration of choices, response latencies, and confidence ratings (Glöckner, 2009). The method estimates the (maximum) likelihood for observing the behavior of each person, given the application of each model under consideration. Participants are classified as users of the strategy with the highest likelihood (corrected for the number of free parameters according to the Bayesian information criterion, BIC; Schwarz, 1978).[v] More details on MM-ML are provided in Appendix A.

4.1 Competing Models and Predictions for Choices, Reaction Times, and Confidence

To represent the single-mechanism approach, we considered the PCS-DM model specified above which assumes automatic weighted compensatory information integration and has been shown to explain behavior in different kinds of decision tasks well (Glöckner & Bröder, 2011; Glöckner & Herbold, 2011; Glöckner & Hodges, 2011; Hochman, Ayal, & Glöckner, 2010). However, as mentioned above, it has been argued that general implementations of connectionist models such as PCS-DM run the risk of low predictive power due to high flexibility and many free parameters (Roberts & Pashler, 2000). The problem can be solved by correcting for model flexibility (Pitt & Myung, 2002; Pitt, Myung, & Zhang, 2002). In a first step, we follow this approach and use standard statistical correction methods. In a second step, we apply a cross-prediction (or cross-validation) approach which avoids the problem less formally (Stone, 1974).

To represent the multiple-strategy account, we implemented three strategies along the lines of previous investigations: typically, compensatory and non-compensatory strategies are considered to demonstrate a strategy-shift caused by differences in environmental cue-dispersions (e.g., Bröder, 2003; Bröder & Schiffer, 2006a; Rieskamp & Otto, 2006). We followed this approach: Decision makers may resort to a compensatory equal weights strategy (EQW) which assumes counting the number of positive cues for each option while ignoring cue weights (e.g., Payne et al., 1988) or a compensatory weighted additive strategy (WADD) which assumes weighting cues by (chance corrected) validity, adding them up, and choosing the option with the higher sum.[vi] Secondly, we incorporated the non-compensatory TTB strategy (Gigerenzer & Goldstein, 1996), predicting choices determined by the first most valid discriminating cue. We test the hypothesis that individuals select strategies adaptively to the structure of the environment in that the proportion of alleged TTB users increases from compensatory to non-compensatory environments and vice versa for alleged users of WADD and EQW. More generally, decision makers classified as users of TTB, or EQW and to a certain degree also alleged users of WADD (but see discussion below) will all be considered support for the multiple-strategy account.

Predictions for choices, decision times, and confidence are derived from the different strategies using standard procedures (e.g., Bröder & Gaissmaier, 2007; Glöckner, 2009; Glöckner & Betsch, 2008b; Glöckner & Bröder, 2011; Glöckner & Hodges, 2011). The PCS-DM model produces a vector of output variables that predict multiple aspects of behavior. Choices are made for the option with the highest activation. For simplicity we stick to this simplified implementation in the main test although a probabilistic implementation of PCS-DM is described and tested in Appendix B (see also Glöckner, Heinen, Johnson, & Raab, 2012), leading to the same conclusions. Decision time is assumed to be a monotonically increasing function of the number of iterations needed to reach a stable solution in PCS-DM. Confidence is a monotonically increasing function of the absolute difference in activation between the two options.

For the serial, step-wise process models TTB, EQW and WADD, decision time predictions result from the number of elementary information processes necessary to apply them (Payne et al., 1988), which are transformed to contrast weights. For EQW and WADD, which make equal time predictions across all types of cue patterns, contrast weights are zero. Confidence for TTB is derived from the validity of the first differentiating cue and thus the one which allegedly determined the choice alone (Gigerenzer et al., 1991). For EQW and WADD, confidence mirrors the absolute difference between the unweighted sums or weighted sums, of positive cue values for the options.

Model predictions for the choices patterns (Table 1) used (in the test phase of) the following experiments are summarized in Table 2. Since the predictions are the basis for the analyses reported below, we explain them in more detail. For cue patterns 1 to 5 the most valid cue differentiates between options (favoring option A). According to TTB, no further cues are considered and option A is chosen. In cue pattern 6, however, two further cues have to be considered until the third cue differentiates (again favoring option A). Hence, TTB predicts choice for option A across all cue patterns, but shorter decision times for patterns 1 to 5 as compared to cue pattern 6. These decision time predictions are interval scaled and transformed into contrasts that add up to 0 and have a range of 1 for mere convenience: Cue patterns 1 to 5 receive weights of -0.167 and cue pattern 6 receives a weight of 0.833 for response times. Confidence predictions of TTB are higher for the first 5 cue patterns than for the last, since the validity of the first discriminating cue is higher for the former; the contrast weights are thus 0.167 and -0.833, respectively. Note, that although confidence predictions would usually differ between environments (even for the same cue pattern), this is not the case here because normalization is done per conditions (since analyses are run per condition).

Predictions for WADD follow from calculating weighted sums of validities and cue values and comparing them between options. Consequently, predictions also differ between environments. Cue validities are corrected for chance level in this calculation by subtracting .50. For cue pattern 4 in the compensatory environment in Experiment 1, for example, the weighted sum for option A = .15 - .10 - .10 -.05 = -.10 and for option B = -.15 + .10 + .10 + .05 = .10 so that option B should be chosen. For cue pattern 2 this relation reverses and option A should be chosen (i.e., .15 + .10 - .10 - .05 = .10 vs. -.15 - .10 + .10 + .05 = -.10). The absolute differences in weighted sums is used for confidence predictions (again normalized to contrast weights). For cue patterns 2 to 5 in the first environment this difference is the same (.20), whereas it is lower for cue pattern 6 (.10) and higher for the first cue pattern (.60), after normalization this results in the contrast weights presented in Table 2. According to WADD, the number of calculation steps and hence decision time should be independent of cue patterns, so time contrasts are all the same. For EQW, predictions are derived using the same mechanisms as for WADD except that all validities are replaced by 1.

In all experiments, we set out to test whether different environmental conditions would indeed produce strategy shifts as predicted by a multiple-strategies account of decision making as shown previously (Bröder, 2003). Thus, we manipulated the cue dispersion inherent in environments to reflect either a non-compensatory or a compensatory structure. To check whether the manipulation of the environment induced a behavioral adaptation and to measure the strength of this adaptation we analyzed effects on choice behavior for cue pattern 3, for which both single-mechanism models and multi-strategy models would predict a change in choices, either due to different cue weights (single-mechanism) or a strategy switch from TTB to EQW or WADD (multi-strategy). In the following, we will also refer to it as the critical cue pattern.

Table 1

Item types used in all experiments

	CUE PATTERNS											
	1		2		3		4		5		6	
Cues	A	B	A	B	A	B	A	B	A	B	A	B
Cue 1	+	-	+	-	+	-	+	-	+	-	-	-
Cue 2	+	-	+	-	-	+	-	-	-	+	-	-
Cue 3	+	-	-	+	-	+	-	-	+	-	+	-
Cue 4	-	+	-	+	-	+	-	+	-	+	-	+

Note: A and B represent the choice options in each type of decision task and cues are sorted in order of decreasing validity.

Table 2

Predictions of Strategies

	CUE PATTERNs																	
	1			2			3			4			5			6		
	cho	time	conf	cho	time	conf	cho	Time	conf	cho	time	conf	cho	time	conf	cho	time	conf
Experiment 1: Compensatory Environment (v_1 = .65; v_2 = .60; v_3 = .60; v_4 = .55)																		
TTB	A	-.167	.167	A	-.167	.167	A	-.167	.167	A	-.167	.167	A	-.167	.167	A	.833	-.833
EQW	A	0	.667	A/B	0	-.333	B	0	.667	A/B	0	-.333	A/B	0	-.333	A/B	0	-.333
WADD	A	0	.700	A	0	-.100	B	0	-.100	A	0	-.100	A	0	-.100	A	0	-.300
PCS (P=1.9)	A	-.391	.573	A	-.115	.140	B	.609	-.199	A	-.184	-.227	A	-.115	.140	A	.195	-.427
Experiment 1: Non-Compensatory Environment (v_1 = .95; v_2 = .70; v_3 = .60; v_4 = .55)																		
TTB	A	-.167	.167	A	-.167	.167	A	-.167	.167	A	-.167	.167	A	-.167	.167	A	.833	-.833
EQW	A	0	.667	A/B	0	-.333	B	0	.667	A/B	0	-.333	A/B	0	-.333	A/B	0	-.333
WADD	A	0	.551	A	0	.244	A	0	-.372	A	0	.090	A	0	-.064	A	0	-.449
PCS (P=1.9)	A	-.352	.488	A	-.259	.321	A	.148	-.257	A	-.148	.014	A	-.037	-.054	A	.648	-.512
Experiment 2, 3 & 4: Compensatory Environment (v_1 = .875; v_2 = .797; v_3 = .734; v_4 = .656)																		
TTB	A	-.167	.167	A	-.167	.167	A	-.167	.167	A	-.167	.167	A	-.167	.167	A	.833	-.833
EQW	A	0	.667	A/B	0	-.333	B	0	.667	A/B	0	-.333	A/B	0	-.333	A/B	0	-.333
WADD	A	0	.670	A	0	-.026	B	0	.019	A	0	-.120	A	0	-.214	A	0	-.330
PCS (P=1.9)	A	-.598	.642	A	-.121	.026	B	.106	.025	A	.083	-.153	A	.129	-.181	A	.402	-.358
Experiment 2, 3 & 4: Non-Compensatory Environment (v_1 = 1; v_2 = .75; v_3 = .625; v_4 = .5625)																		
TTB	A	-.167	.167	A	-.167	.167	A	-.167	.167	A	-.167	.167	A	-.167	.167	A	.833	-.833
EQW	A	0	.667	A/B	0	-.333	B	0	.667	A/B	0	-.333	A/B	0	-.333	A/B	0	-.333
WADD	A	0	.583	A	0	.250	A	0	-.417	A	0	.083	A	0	-.083	A	0	-.417
PCS (P=1.9)	A	-.429	.553	A	-.323	.331	A	.422	-.375	A	-.195	.030	A	-.046	-.091	A	.571	-.447

Note: Strategy predictions for *cho*ices, decision *time*, and *conf*idence. A and B stand for the predicted option. "A/B" indicates random choices between A and B. Predictions for decision times and confidences are expressed in contrast weights that add up to zero and have a range of 1. Contrast values represent relative weights comparing different cue patterns for one strategy. v indicates the validity of cues in each environment.

5. Experiment 1: Cue values given

In the first experiment, we used the product selection paradigm from previous studies (Glöckner & Betsch, 2008b; Hilbig & Moshagen, in press). Therein, participants are provided with information from four experts (cues) with different predictive validity (cue validity) and select the better of two products (options) in tasks with varying prediction patterns (cue patterns, see Table 1). Experts provide dichotomous quality ratings (good vs. bad) for each product. Following the procedure used in previous studies, information was presented in an *open matrix* such that all information was openly visible at no cost to ensure that the information search was not artificially constrained (Glöckner & Betsch, 2008b; Söllner, Bröder, & Hilbig, 2013). The order of cues and options was randomized to avoid effects of pattern learning or recognition and no feedback on choices was provided.

5.1 Method

5.1.1 Participants and design

Participants were 86 individuals from the MPI Decision Lab subject pool.[vii] They were mainly students of the University of Bonn (mean age: 21.8 years; 66 female). The experiment lasted approximately 15 minutes and was part of a 1 hour experimental battery. Participation was compensated for by approximately 12 Euro (approx. USD 16.80) in total. We used a two-factorial 2 (ENVIRONMENT: compensatory vs. non-compensatory) x 6 (CUE PATTERN) design with CUE PATTERNs as repeated factor (see Table 1). Each cue pattern was presented ten times resulting in a total of 60 choices to be made. Participants were randomly assigned to one of the two environment conditions with high vs. low differences in cue validities between cues. The cue validities v_i were .95, .70, .60, and .55 in the non-compensatory conditions and .65, .60, .60, and .55 in the compensatory condition. Considering that cue validities are scaled between .5 (chance) and 1 (perfect prediction), we used a large range of the scale for the non-compensatory environment (.95 - .55 = .40) and only a narrow part of it for the compensatory environment (.65 - .55 = .10). To ensure a strong model-comparison, we selected the values such that the difference between environments was even more extreme than in the previous studies by Rieskamp and Otto (2006; non-comp: .90 - .60 = .30; comp: .77 - .54 = .23).

5.1.2 Materials and procedure

The experiment was entirely computer-based. Participants were instructed to repeatedly select the better of two options. They were informed about the experts' (i.e. cues') predictive validities. To additionally facilitate participants' understanding of the cue validity concept, they were informed that a validity of .50 represents chance level and a validity of 1 represents a cue making perfect predictions. Moreover, participants were asked to make good decisions and to be as fast as possible in deciding (Fazio, 1990). All eight pieces of information were simultaneously presented in an information matrix (see format used in Table 1). The presentation order of cues and options in the matrix was randomized. Cue values were represented by the symbols "+" (good) and "-" (bad). Participants selected one of the options by mouse click. Choices and decision times were recorded. After each choice, a confidence rating scale appeared and participants rated the confidence in their judgment on a scale from *very uncertain* (-100) to *very certain* (100) using a horizontal scroll bar. At the end of each trial, a blank screen was presented, prompting participants to click on a continue button which was centered on the screen to proceed to the next trial. Throughout the experiment, no feedback was provided.

A warm-up decision trial was used to familiarize participants with the material and the procedure. It was followed by 60 target trials, which were presented in randomized order. A 1-minute break was embedded after half of the trials to minimize the effects of decreasing concentration.

5.2 Results

Manipulation checks. Participants followed the instructions and made relatively fast decisions (*MD*=3.2 sec, *SD*=2.6 sec). Decision times did not differ between conditions, Wilcoxon z = 1.58, p = .12. As we intended, the environment manipulation produced a clear effect on choices, particularly for the critical Cue Pattern 3. Specifically, in this pattern, participants showed more choices for option A in the non-compensatory as compared to the compensatory condition, $t(84) = 4.64$, $p < .001$, Cohen's d = 1.0. This mirrors the typical finding of choices being more aligned with a non-compensatory (TTB) strategy in a non-compensatory environment. However, as outlined above, this might either indicate increased reliance on a non-compensatory strategy or result from different weights being attached to cues. We tested these two explanations against each other by investigating choices, decision times, and confidence separately as well as jointly using MM-ML.

As mentioned above, we considered TTB, EQW, and WADD as strategies from the adaptive toolbox. For the single-mechanism approach we implemented a first version of PCS-DM, PCS_{fix}, without any free parameter with P = 1.9 derived from the simulation above. Additionally, we implemented a second fitted version of PCS-DM, PCS_{fitted}, which estimates one individual P parameter per participant, representing participants' sensitivity to differences in cue validities. Using a basic model fitting procedure, we searched for the estimate of P in [1…2] in steps of .1 that maximized the MM-ML log-likelihood for each individual. For both conditions, the optimal P values (reported in Table 7) were significantly lower than 1.9 (both t > 7.5, $p < .001$), which indicates that participants were insufficiently sensitive to differences in cue validities, although cue validities were explicitly provided.

Table 3

Choice Adherence Rates

		Weighted Compensatory Strategies			Heuristics	
	N	PCS_{fitted}	PCS_{fix}	WADD	EQW	TTB
			Experiment 1			
Non-Comp	43	.97 (.006)[a]	.92 (.012)[b]	.92 (.012)[b]	.71 (.032)[c]	.92 (.012)[b]
Comp	43	.97 (.009)[a]	.97 (.009)[a]	.97 (.009)[a]	.91 (.027)[b]	.86 (.009)[b]
			Experiment 2			
Non-Comp	28	.96 (.017)[a]	.92 (.021)[b]	.92 (.021)[b]	.65 (.037)[c]	.92 (.021)[b]
Comp	29	.99 (.004)[a]	.99 (.004)[a]	.99 (.004)[a]	.98 (.012)[a]	.84 (.004)[b]
			Experiment 3			
Block 1						
Non-Comp	32	.93 (.024)[a]	.89 (.031)[b]	.89 (.031)[b]	.69 (.034)[c]	.89 (.031)[b]
Comp	31	.93 (.024)[a]	.93 (.024)[a]	.93 (.024)[a]	.97 (.016)[a]	.78 (.022)[b]
Block 2						
Non-Comp	31	.94 (.021)[a]	.83 (.023)[b]	.83 (.023)[b]	.86 (.038)[b]	.83 (.023)[b]
Comp	32	.93 (.025)[a]	.93 (.025)[a]	.93 (.025)[a]	.95 (.018)[a]	.79 (.024)[c]
			Experiment 4			
Non-Comp	18	.93 (.027)[a]	.86 (.039)[b]	.86 (.039)[b]	.76 (.050)[b]	.86 (.039)[b]
Comp	16	.95 (.041)[a]	.95 (.041)[a]	.95 (.041)[a]	.97 (.025)[a]	.80 (.042)[b]
			Overall			
Non-Comp	152	0.95	0.89	0.89	0.73	0.89
Comp	151	0.96	0.96	0.96	0.95	0.82

*Note: SE*s are provided in parentheses. For EQW choice adherence is calculated excluding patterns for which random choice was predicted. Overall is the by *N* weighted average of adherence rates. Adherence rates with different superscript a, b, or c differ significantly at $p < .05$ (comparisons are always calculated within experiment and condition).

Adherence rate. According to the multiple-strategy account, one should expect that the adherence rates (i.e., proportion of choices in line with strategy predictions) for strategies differ between environments. According to the single-mechanism view, the adherence rate for the PCS-DM model implementations should be high for both environments. Adherence rates are provided in Table 3[viii] which shows that the PCS models leveled with or outperformed

TTB, WADD and EQW in both environments. Overall, the error in choice predictions ε ($\varepsilon = 1 -$ *adherence rate*), was lowest for PCS_{fitted} ($\varepsilon = 0.029$). When giving both approaches the best shot in comparing the fitted PCS-DM implementation against the adaptive usage of the best heuristic for each environment (i.e. use TTB in the non-compensatory and WADD in the compensatory environment) the fitted PCS-DM implementation outperformed the toolbox implementation significantly ($\varepsilon = .029$ vs. $\varepsilon = .056$; $t(85) = 4.31$, $p < .001$). Note, however, that this comparison has to be interpreted cautiously since the model flexibility of PCS_{fitted} and the toolbox implementation are not directly comparable (but see overall analysis below). Furthermore, note that PCS_{fitted} outperforms WADD in the non-compensatory environment. This shows that PCS-DM is more than simply a strategy that approximates WADD. By taking into account individual differences in sensitivity to cues in the parameter P, PCS-DM allows to describe and predict choice behavior better than WADD models even if cue weighting is suboptimal from a rational point of view.

Decision time. We analyzed time on the individual level by correlating observed response times with predictions (cf. Table 2) separately for each individual collapsed by cue pattern. The selection of different decision strategies in different environments should be accompanied by an increased correlation between predicted and observed decision time for the selected strategy. According to the single-mechanism view, in contrast, correlations should always be highest for the PCS-DM model. To reduce the influence of outliers and to account for learning effects, time was ln-transformed and order effects were partialled out. The resulting corrected time scores were used in all analyses (except for cross-prediction; see below).

Correlations were averaged and tested using Fisher z-transformation and comparing transformed scores using *t*-tests. Averaged individual level correlations for strategies were in the range between $r = .04$ and $r = .68$ (Table 4). PCS_{fitted} predicted time best in both environments, followed by PCS_{fix}. In both environments, the two PCS-DM implementations predicted time significantly better than TTB, EQW and WADD (the latter two strategies predicting zero correlations).

Table 4

Individual-level correlations between predicted and observed decision time

	N	Weighted Compensatory Strategies			Heuristics	
		PCS_{fitted}	PCS_{fix}	WADD	EQW	TTB
		Experiment 1				
Non-Comp	43	.68[a]	.55[b]	(0)[d]	(0)[d]	.39[c]
Comp	43	.59[a]	.36[b]	(0)[c]	(0)[c]	.04[c]
		Experiment 2				
Non-Comp	28	.83[a]	.71[b]	(0)[d]	(0)[d]	.19[c]
Comp	29	.63[a]	.56[b]	(0)[d]	(0)[d]	.24[c]
		Experiment 3				
Block 1						
Non-Comp	32	.64[a]	.56[b]	(0)[d]	(0)[d]	.31[c]
Comp	31	.51[a]	.41[b]	(0)[c]	(0)[c]	.02[c]
Block 2						
Non-Comp	31	.65[a]	.52[b]	(0)[d]	(0)[d]	.17[c]
Comp	32	.57[a]	.37[b]	(0)[c]	(0)[c]	.10[c]
		Experiment 4				
Non-Comp	18	.84[a]	.71[b]	(0)[d]	(0)[d]	.24[c]
Comp	16	.57[a]	.52[a]	(0)[b]	(0)[b]	.15[b]
		Overall				
Non-Comp	152	.71	.59	0	0	.27
Comp	151	.57	.43	0	0	.10

Note: Correlations were calculated per individual for the six cue patterns and then averaged using Fisher-z-transformation. EQW and WADD predict zero correlations. Overall is the *N*-weighted average of coefficients. Correlation with different superscripts a, b, c, or d differ significantly at $p < .05$ (comparisons are always calculated within condition and experiment and based on comparisons of Fisher-Z-transformed scores).

Confidence. According to the multiple-strategy framework, strategy selection should also result in an increased correlation between observed and predicted confidence for the respective strategy whereas, according to the single-mechanism approach, the PCS-DM model should best account for confidence in both environments. We again calculated individual-level correlations between predicted and observed confidence and aggregated across environments using Fisher-Z-transformations (Table 5). In the non-compensatory environment, correlations for the PCS-DM implementations and WADD were significantly higher than for TTB and EQW. In the compensatory environment PCS_{fitted} predicted confidence significantly better than WADD and PCS_{fix}. Correlations for TTB and EQW were far lower than for the other models.

Table 5

Individual-level correlations between predicted and observed confidence

		Weighted Compensatory Strategies			Heuristics	
	N	PCS_{fitted}	PCS_{fix}	WADD	EQW	TTB
		Experiment 1				
Non-Comp	43	.89[a]	.87[a]	.87[a]	.18[c]	.73[b]
Comp	43	.81[a]	.70[c]	.75[b]	.36[d]	.37[d]
		Experiment 2				
Non-Comp	28	.87[a]	.86[b]	.88[a]	.03[d]	.49[c]
Comp	29	.76[a]	.72[b]	.70[c]	.35[e]	.53[d]
		Experiment 3				
Block 1						
Non-Comp	32	.80[a]	.75[b]	.77[a]	-.11[d]	.23[c]
Comp	31	.75[a]	.67[b]	.66[b]	.50[c]	.50[c]
Block 2						
Non-Comp	31	.83[a]	.79[a]	.81[a]	.13[c]	.49[b]
Comp	32	.49[a]	.44[a]	.45[a]	.14[b]	.28[b]
		Experiment 4				
Non-Comp	18	.87[a]	.81[b]	.84[a]	.40[c*]	.44[c]
Comp	16	.84[a]	.80[b]	.79[b]	.34[d]	.55[c]
		Overall				
Non-Comp	152	.85	.82	.84	.11	.50
Comp	151	.72	.65	.66	.34	.43

Note: Correlations were calculated per person for the six cue patterns and then averaged using Fisher-z-transformation. Overall is the *N*-weighted average of coefficients. Correlation with different superscripts a, b, c, d or e differ significantly at $p < .05$ (comparisons are always calculated within condition and experiment and based on comparisons of fisher-Z-transformed scores). * due to a large standard error this value does also not differ significantly from PCS and WADD.

Strategy Classification. Finally, data were analyzed using the MM-ML (see Appendix A). Strategy predictions concerning choices, decision time, and confidence were simultaneously compared with the overall data vector of each individual. For each participant, the BIC for each strategy was obtained, thus determining the fit while penalizing models with more free parameters (Myung, 2000; Schwarz, 1978; Wasserman, 2000). This punishes PCS_{fitted} for having one free model parameter, while the other strategies have zero free parameters concerning their application. It has been shown that taking into account global fit of each strategy reduces the risk of misclassification due to individuals using mixed or not-considered strategies (Moshagen & Hilbig, 2011). To account for this problem we do not classify participants as users of a strategy that show a significant misfit in choice predictions compared to the saturated model with a separate error parameter for each cue pattern using a likelihood ratio-test setting $\alpha = .01$.[ix]

Table 6

MM-ML Strategy Classification

	N	not classif.	Weighted Compensatory Strategies			Heuristics	
			PCS $_{fitted}$	PCS$_{fix}$	WADD	EQW	TTB
Experiment 1							
Non-Comp	43	0	.60	.09	.16	0	.14
Comp	43	0	.30	.30	.26	0	.14
Experiment 2							
Non-Comp	28	2	.65	.08	.15	0	.12
Comp	29	0	.45	.34	.17	0	.03
Experiment 3							
Block 1							
Non-Comp	32	2	.80	.07	.06	.03	.03
Comp	31	0	.35	.16	.32	.16	0
Block 2							
Non-Comp	31	5	.85	.07	0	.07	0
Comp	32	2	.30	.17	.43	.03	.07
Experiment 4							
Non-Comp	18	0	.72	0	.17	.11	0
Comp	16	1	.47	.27	.20	0	.07
Overall							
Non-Comp	152	9	.71	.07	.11	.03	.07
Comp	151	3	.36	.25	.28	.04	.07

Note: Overall refers to the weighted average of strategy use. Individuals for which the best strategy showed significant choice-misfit compared to a saturated model were not classified. Percentages of strategy use are with respect to classified individuals only. Percentages that do not add up to 1 are due to rounding.

Overall, classified strategies explained individuals' data considerably better than the second best strategies (median *BF* = 42.3), indicating some reliability in strategy classification. Clearly, the two implementations of PCS-DM accounted best for a majority of participants in both environments (Table 6). There was no strategy shift between the two conditions from non-compensatory to compensatory strategies (i.e., TTB vs. other), χ^2(1, N=86) = 0, p = 1. The power of this test was 1 - β = .99 to detect a strong effect of w = .5 (Faul, Erdfelder, Lang, & Buchner, 2007) which should be assumed given the large effect on choices reported in the manipulation check. There was no tendency towards increased TTB usage in the non-compensatory environment condition. Interestingly, the free parameter P in PCS_{fitted} seems to improve the fit of PCS-DM more clearly in the non-compensatory than in the compensatory environment. Finally, it should be noted that there was a considerable proportion of WADD users. In line with previous findings (Glöckner & Betsch, 2008b), however, participants made decisions very rapidly (median less than 4 seconds) making it rather unlikely that they used a serial stepwise calculation of weighted sums.

Table 7

Parameters for the fitted version of PCS-DM

	fitted *P*	
	M	*SE*
Experiment 1		
Non-Comp	1.51	0.05
Comp	1.55	0.05
Experiment 2		
Non-Comp	1.62	0.05
Comp	1.86	0.04
Experiment 3		
Block 1		
Non-Comp	1.57	0.04
Comp	1.67	0.07
Block 2		
Non-Comp	1.48	0.05
Comp	1.65	0.07
Experiment 4		
Non-Comp	1.45	0.07
Comp	1.92	0.06

Note: Fitted *P* refers to the individually fitted parameters for the strategy PCS_{fitted}.

5.3 Discussion

Overall, the data indicate that in non-compensatory environments decision makers seem to use more extreme weighting of cues in a single compensatory mechanism as implemented in PCS-DM. However, we also observed a tendency that individuals are not sufficiently sensitive to differences in cue validities as indicated by sensitivity parameters *P* below optimal value of 1.9. The results yield no support for the interpretation that decision makers adaptively select between qualitatively different strategies in the sense of different underlying processes. Rather, one single mechanism accounted better for choices, decision time, and confidence even in two very different environments. This finding is in line with previous results (Bröder, 2000, 2003; Glöckner & Betsch, 2008b; Glöckner & Moritz, 2009; Hilbig & Pohl, 2009) indicating that the majority of participants typically use weighted compensatory strategies but extends them by supporting PCS-DM as a candidate process model for most of these participants.

However, it might be questioned whether the findings from Experiment 1 generalize to other settings or are caused by specific properties of the task. One of the cornerstone assumptions of the multiple-strategy approach is that adaptive strategy selection is based on previous learning (Rieskamp, 2008) which was not possible in the current paradigm. Furthermore, some prior investigations did not provide decision makers with explicit information about cue validities (e.g., Bröder, 2003) and used different tasks. To test the generality of our findings, we conducted a second experiment taking these issues into account.

6. Experiment 2: Strategy Learning

In the experiment, we used the stock-market paradigm developed by Bröder (2003) – and explicitly cited as producing evidence for adaptive strategy shifts (e.g., Gigerenzer &

Gaissmaier, 2010) – in which participants can use information from four dichotomous cues to select between two stocks. Decision makers are not provided with information about cue validities but must learn these and the success of different strategies in an initial learning phase. We again manipulated environments between participants and used the same payoff-scheme for compensatory and non-compensatory environments as Bröder (2003; Exp. 1).

6.1 Method

6.1.1 Participants and design

Fifty-seven participants recruited from the MPI Decision Lab subject pool took part in the experiment (mean age: 24.7 years; 31 female). The experiment lasted approximately 30 minutes and was part of a 45 min experimental battery. Participations' compensation was partially performance dependent and amounted on average to 11.74 Euro (approx. USD 16.15) including a flat fee of 4 Euro. We again used a two-factorial 2 (ENVIRONMENT: compensatory vs. non-compensatory) x 6 (CUE PATTERN) design with CUE PATTERNs as repeated factor. The experiment consisted of a learning phase and a test phase with 60 decisions each. Participants were randomly assigned to one of the two environment conditions. We used the payoff-functions by Bröder (2003, Exp. 1)[x] to construct these environments which translate into cue validities v_i of 1, .75, .625, and .5625 for the non-compensatory conditions and .875, .797, .737, and .656 for the compensatory condition. Hence, the range of cue validities was high for the non-compensatory condition (.4375) and much lower for the compensatory condition (.219).

6.1.2 Materials and procedure

Participants repeatedly select the better of two stocks based on four advisors (cues). They were again asked to make good decisions and to be as fast as possible in deciding. In line with Bröder (2003), participants were not informed about the cues' predictive validities but only about the order of validities (i.e., validity decreases from advisor 1 to 4). The test phase replicated Experiment 1 using the same cue patterns (Table 1) and dependent measures. However, in line with Bröder (2003) but in contrast to Experiment 1 the presentation order of the cues was fixed. The initial learning phase used a similar procedure. Participants were presented with a random sample of 60 cue patterns from the total 120 possible cue patterns and received feedback concerning the payoff of the chosen option and the non-chosen option after each trial. Payoffs were given in the artificial unit "penunzen" which were exchanged at a rate of 250 : 1 into Euro. The manipulation of environments was achieved by implementing the compensatory and the non-compensatory payoff function and providing the respective feedback about payoffs in the learning phase. There was no measurement of confidence in the learning phase. Again a warm-up decision trial was used to familiarize participants with the material and the procedure and the items in the learning and test phase were presented in randomized order.

6.2 Results

Inspection of choices in the test phase revealed that our manipulation of the environment in the learning phase was again successful. For the critical Cue Pattern 3, participants showed more choices of option A in the non-compensatory as compared to the compensatory condition, $t(55) = 8.20$, $p < .001$, Cohen's $d = 2.2$. The effect size was even considerably larger than in Experiment 1 with explicitly provided cue validities. Decisions in the test phase were again very fast which renders the application of a deliberate weighted compensatory calculations quite unlikely ($MD = 1.42$ sec, $SD = 1.43$ sec). Furthermore, the individual parameters for PCS_{fitted} did not differ significantly from the value assumed by

PCS_{fix} (i.e., $P = 1.9$) in the compensatory condition, $t(28) = -1.01$, $p = .32$, but was significantly lower in the non-compensatory condition, $t(27) = -5.9$, $p < .001$ (see Table 7).

The findings concerning adherence rates (Table 3), time (Table 4), confidence (Table 4), and decision strategy (Table 5) closely replicate results from Experiment 1. Overall, PCS_{fitted} again showed the highest adherence rates and the lowest error in choice predictions ($\varepsilon = 0.023$). Again comparing PCS_{fitted} with a toolbox assuming that decision makers choose the optimal strategy in each environment revealed that PCS_{fitted} leads to lower errors in choice predictions, ($t(56) = 2.85$, $p = .006$). Also, both versions of PCS-DM predicted participants' decision time very well, and significantly better than TTB, EQW and WADD in both environments (Table 4; all $t > 7.7$, all $p < .001$). Concerning confidence, both versions of PCS-DM and WADD show strong correlations in both environments, which are significantly higher than correlations for TTB and EQW (all $t > 4.3$, all $p < .001$).

Correspondingly, according to MM-ML, the PCS-DM implementations again accounted best for the large majority of participants in both environments and there was no strategy shift between the two conditions from non-compensatory (TTB) to compensatory (all other) strategies, $\chi^2(1, N=55) = 1.33$, $p = 0.25$. The power of this test was excellent ($1 - \beta = .96$). There was, nevertheless, a minuscule tendency towards increased TTB usage in the non-compensatory environment condition.

6.3 Discussion

To account for the crucial aspect of potential strategy learning, we used a paradigm including a learning phase that very closely resembled prior studies. Our results concerning choices are basically consistent with previous findings (Bröder, 2003; Rieskamp & Otto, 2006) in that choices (particularly in the critical cue pattern) were more in line with the non-compensatory TTB strategy in the non-compensatory environment condition and more in line with the compensatory EQW strategy in the compensatory environment. At first sight, this appears to confirm a strategy shift. However, analyses of decision times and confidence as well as a comprehensive MM-ML method (Glöckner, 2009) show no strategy shift on the underlying process level. Changes in choices between conditions were accompanied by changes in decision time and confidence as predicted by the multi-strategy account. Given these results, it is more plausible to assume that decision makers adapt weights (in a single compensatory process) as captured in PCS-DM rather than selecting qualitatively different strategies at the level of information integration processes. Interestingly, in the learning paradigm used in Experiment 2, individuals learned to adapt their sensitivity to cue weights almost perfectly to the optimal weighting in the compensatory environment. Nonetheless, we still find too low sensitivity in the non-compensatory environment.

Hence, for environments with a fixed structure (stable cue validities), our findings hint that adaptivity is achieved through adapting weights as suggested by PCS-DM. However, environments are often also characterized by instability and it remains unclear whether PCS-DM can also capture individual adaption following a change in cue validities. Previous research indicates that individuals partially tend to stick to their initially learned behavior (Bröder & Schiffer, 2006a; Rieskamp, 2006), which has been interpreted as support for multiple-strategy models in that people stick to previously learned strategies (Rieskamp, 2006). Interestingly, this stickiness is particularly strong if there is a shift from compensatory to non-compensatory environments, indicating that individuals have a hard time learning to ignore less valid evidence (Bröder & Schiffer, 2006a). According to PCS-DM, such stickiness would be reflected in suboptimal adaption (and thus insufficient differences) in the P parameter. Specifically, one can expect to find lower P parameters after switching from compensatory to non-compensatory environments, indicating insufficiently adapted sensitivity to differences in cue validities (since lower sensitivity to cue validities leads to more compensatory choices).

In a third experiment, we therefore investigated whether our findings in favor of PCS-DM generalize to an unstable, changing–environments situation. Specifically, we test whether the same individuals adapt to different environmental structures by switching strategies or by adapting weights. Aside from providing a possibility to replicate findings from Experiment 2, the within-subjects comparison allows for a more powerful test of the null-hypothesis concerning strategy change, and it should provide insights concerning how PCS-DM can handle potential inertia effects and slow adaptation by changes in the sensitivity parameter *P*. We additionally intended to rule out the potential alternative explanation for Experiment 2 that individuals made decisions by pattern recognition in that the presentation order of cues was randomized.

7. Experiment 3: Strategy Learning in Changing Environments

We again used the stock-market paradigm with open information presentation. In the experiment, participants essentially ran through the procedure of Experiment 2 twice with changing environments between the two runs.

7.1 Method

7.1.1 Participants and design

Sixty-three individuals from the MPI Decision Lab subject pool took part in the experiment (mean age: 25.7 years; 42 female). The experiment lasted approximately 60 minutes. Participations' compensation was performance dependent and amounted on average to 11.85 Euro (approx. USD 16.35). We used a three-factorial 2 (ENVIRONMENT: compensatory vs. non-compensatory) x 6 (CUE PATTERN) x 2 (ORDER: Non-compensatory first vs. second) design with CUE PATTERNs and ENVIRONMENT as repeated factors. The experiment consisted of two blocks of learning phase and test phase with 60 decisions each. Participants were randomly assigned to one of the two possible order conditions. We used the same compensatory and non-compensatory payoff functions as in the previous experiment.

7.1.2 Materials and procedure

Materials and procedure were essentially the same as in Experiment 2 with only a few extensions. Following Bröder and Schiffer (2006a; Exp. 1) we used a hint that the environment might change between the first and the second block of the experiment. This hint was presented directly before the second block started and stated: "The companies [belonging to the stocks] in the second part are different from the companies in the first part. They are active on different market segments. The predictive power of the experts can be very different for different marked segments. The validity order of the experts, however, remains stable." Furthermore, the presentation order of cues on the screen was randomized to rule out pattern recognition and the exchange rate was changed to 320 : 1 in order to account for the higher outcomes due to doubling the number of trials.[xi]

7.2 Results and Discussion

In the first block, for the critical Cue Pattern 3 participants showed more choices for option A in the non-compensatory (p_A = .60) as compared to the compensatory (p_A = .04), condition, $t(61) = 7.60$, $p < .001$, Cohen's $d = 1.9$. In the second block, this difference was considerably smaller replicating the inertia effect of previous studies (non-compensatory: p_A = .26; compensatory: p_A = .08, $t(61) = 2.40$, $p = .02$, Cohen's $d = 0.6$). The difference between blocks was almost exclusively driven by the fact that decision makers starting with a compensatory environment showed less shifts towards non-compensatory choices in the second block compared to those who started with the non-compensatory environment as indicated by a significant order x environment interaction in a repeated measurement ANOVA ($F(1,122) = 13.39$, $p < .001$). This result replicates the respective asymmetry observed by Bröder and Schiffer (2006a; Exp. 1).

Decisions in the test phase of both blocks were again made very fast and time decreased from block 1 (*MD* = 2.78 sec, *SD* = 2.34 sec) to block 2 (*MD* = 2.17 sec, *SD* = 1.69 sec). Overall, decisions were made slower than in Experiment 2 which was most likely due to the random order of cues used in this study. Again, participants seemed to be insufficiently sensitive to differences in cue validities as the *P* parameter for PCS_{fitted} was significantly below 1.9, the parameter assumed for PCS_{fix} in both blocks (all $t > 3.4$, $p < .01$; see Table 7).

The results of the first block replicate the findings from Experiment 2 on all dependent variables. In both environment conditions and both blocks, individual level correlations between strategy predictions and observed data for time (Table 4) were significantly higher for both versions of PCS-DM than for any of the alternative strategies (i.e., WADD, TTB and EQW). Concerning confidence predictions, the two PCS-DM versions and WADD outperformed TTB and EQW in all block by condition combinations (Table 5). Results concerning decision time and confidence were very similar between the two blocks except that confidence correlations were somewhat lower for PCS-DM implementations in the second block potentially indicating the inertia effect mentioned above. Compensatory PCS-DM and WADD were dominantly used in both blocks (Table 6).

To test changes in strategies between block 1 and block 2 we conducted a Stuart–Maxwell marginal homogeneity test on a k x k table of strategies used in the first and the second block of the experiment. The test turned out to be far from significant, $\chi^2(4; N = 55) = 2.19$, $p = .70$ despite reasonable power ($1 - \beta = .86$; assuming a large effect and $\alpha = .05$). There was hence no evidence for strategy shifts from a within-subjects perspective. In line with Experiment 2, the between subjects comparisons testing for shifts from compensatory to non-compensatory strategies (i.e., TTB vs. other strategies) did not indicate changes in strategy selection between conditions neither for the first (χ^2(1; *N* = 61) = 1.05, *p* = .31) nor the second block (χ^2(1; *N* = 56) = 1.8, *p* = .18).

As indicated by the ANOVA of adherence rates reported above and in line with previous findings, learning to ignore information after switching from a compensatory to a non-compensatory environment is a challenge for participants. PCS_{fitted} captures this asymmetric inertia effect very well by individual differences in sensitivity *P*. Specifically, there is a significant interaction between order (of blocks) and block (repeated measurement ANOVA: *F*(1,122) = 5.38, *p* =.02). This interaction is mainly driven by the significant drop of *P* for participants who first decided in a compensatory and then in a non-compensatory environment, *t*(60) = 2.39, *p* = .01. These findings show that PCS-DM can account both for adaptation in changing environments but also for partially insufficient adaptation (as has been previously reported).

The results extend those found in Experiments 1 and 2 to instable changing-environment situations. Again taking into account decision time and confidence, the interpretation of previous results in favor of strategy shifts based on choices only (e.g., Rieskamp & Otto, 2006) have to be reconsidered. However, a closer look at the results of Bröder and Schiffer (2006a, p. 911) already provides some indication that individuals do not change strategies. In terms of classic process tracing measures (e.g., Payne et al., 1988), there was no difference in information search behavior between the first and the second part depending on whether or not the environment changed. Nevertheless, these results were produced using a Mouselab paradigm which has been shown to influence choice behavior and sometime to hinder automatic processes as postulated by PCS (Glöckner & Betsch, 2008b). For a more conclusive test of our hypothesis that individuals adapt weights within one mechanism rather than adaptively selecting between different strategies, we conducted another experiment using eye-tracking.

8. Experiment 4: Eye-tracking

8.1 Method

Experiment 4 replicates Experiment 2 (with environment manipulated between subjects and a fixed presentation order of cues), but extends it by recording eye-fixations (for a recent review of eye-tracking studies in decision making see Orquin & Mueller Loose, 2013). According to the multiple-strategy approach, there should be clear differences in information search patterns between environments in that decision makers focus mainly on the most important cue in the non-compensatory environment and about equally on all cues in the compensatory environment. Also, information search should be mainly within cues in non-compensatory environments, whereas it should be searched within alternatives in compensatory environments (cf. Payne et al., 1988). According to the single-mechanism account, all cues should be focused on in both environments and this information should only be assigned different weights afterwards (during information integration), thereby leading to distinct choice patterns.

Thirty-four participants from the MPI Decision Lab subject pool took part in the experiment (mean age: 24.7 years; 16 female). The experiment lasted approximately 30 minutes. Participations' compensation was again performance dependent and amounted on average to 11.53 Euro (approx. USD 15.91) including a flat fee of 4 Euro.

Eye movements were recorded using two Eyegaze binocular systems (LC Technologies). We used them in a monocular mode with a sampling rate of 60 Hz using the right eye only. The system is based on the pupil-center/corneal reflection method to determine eye gaze and has an accuracy of about 0.45°. This method captures voluntary, saccadic eye movements that fixate a target object on the fovea. An infrared-sensitive video camera, positioned below the computer monitor, observes the subject's eye and specialized image software generates x, y coordinates for the gaze point on the monitor screen. Fixations were identified using a fixation deviation tolerance of +/- 20 pixels (horizontally and vertically) and a minimum fixation time of 50 msec.

8.2 Results and Discussion

Our environment manipulation again had a strong effect in that participants showed more choices for A in the critical Cue Pattern 3 in the non-compensatory (p_A = .47) as compared to the compensatory (p_A = .06) condition, $t(32) = 3.54$, $p < .001$, Cohen's $d = 1.25$. Behavioral data replicated the findings from Experiment 2 in that the two implementations of PCS-DM again accounted best for the dependent measures separately as well as in the overall MM-ML analysis (Tables 3 to 5). More importantly, we considered participants information search in terms of fixations and information search transitions. We defined equally-sized areas of interest around the two matrix fields containing information (i.e., plus or minus) separately for each cue and calculated standard information search measures that are classically assumed to reflect adaptive strategy selection (Payne et al., 1988), namely: a) the proportion of fixation time on the most important attribute (PTMI), and b) an index reflecting relative amount of cue-based (-) and alternative-based (+) processing[xii]. There were no differences in these fixation-based processing measures between conditions (Table 8) indicating that adaptation to environments was not due to application of qualitatively different strategies (e.g., more focus on the most valid cue due to increased reliance on TTB in non-compensatory environments). Note that the power for detecting an effect in the latter analyses was excellent (power = .97; for a one-sided test assuming $d = 1.25$, cf. choice analysis above) indicating that it is rather unlikely that there was a shift in information search between environments and thus providing no support for selection of different strategies in the two environments.

Table 8

Information search in Experiment 4

	Condition			
	Non-comp	Comp	$t(32)$	p
PTMI	.50	.49	0.23	.82
PAYNE-Index	.20	.10	0.74	.46

Note: PTMI = the proportion of fixation time on the most valid cue in relation to fixations to all other cues; PAYNE index = an index reflecting relative amount of cue-based (-) and alternative-based (+) information search (i.e., fixation transitions within cues vs. within alternatives).

Of course, as a potential limitation to this eye-tracking study it has to be acknowledged that conclusions rest on the correspondence assumption that there is a substantial correlation between overt fixations and the information currently considered. We cannot completely rule out that individuals, for example, mentally fixate on the most valid cue without necessarily looking at it. Still, although such divergences might occasionally occur, much research indicates that attention is usually directed to the information that is processed (e.g., Just & Carpenter, 1976; Orquin & Mueller Loose, 2013; Renkewitz & Jahn, 2012). Furthermore, note that our findings could also not be easily accounted for by additionally assuming that people are involved in initial screening, since fixations from such screening phase and a subsequent decision phase should be additive so that on average still the expected effects should be observed (but perhaps to a smaller degree due to increased noise).

9. Cross-Prediction Analysis Experiments 2 - 4

The analyses of Experiment 1 to 4 show that using one free parameter *P* in PCS-DM could increase the fit to the data for many but not all participants, even when correcting for the increased flexibility using BIC. Nevertheless, going beyond comparing strategy fit using BIC, we aimed to check the robustness of the results in using the fitted version of PCS-DM and competing adaptive strategy selection models for cross-predicting choice and decision time in trials that were not used for parameter estimation. A secondary aim of the cross-prediction exercise was to test the following potential weaknesses of previously reported analyses: a) the results concerning the superior performance of PCS-DM could be due to the specific cue patterns used in the strategy classification phase which might be particularly well predicted by PCS-DM. Following up on this b) it is possible that the selection of cue patterns might have influenced individuals' strategy classification by inducing some strategies to be more often applied than others. Finally, c) it might be criticized that the analysis of decision time based on log-transformed data used in MM-ML is not appropriate for testing interval scaled predictions of models that are not transformed according to a logarithmic function.

To address these concerns, we compared the performance of PCS_{fitted}, WADD, EQW, and TTB separately and in combination in an adaptive toolbox implementation in predicting choices and decision time in the last 1/3 of choices of the learning phase in Experiments 2, 3, and 4. In Experiment 3, we predict choices for blocks 1 and 2 using the respective parameters. Note that the learning phase contained a random sample of 60 different cue patterns which were shown in an individually randomized order. Therefore, the analysis contained all 60 cue patterns each one decided upon by about one third of the participants. We used the last 20 trials of the learning phase assuming sufficient PCS-DM parameter learning or strategy selection learning after 2/3rd of the learning phase. Confidence was not measured in the learning phase and therefore predictions could not be tested.

Note that parameters P for PCS_{fitted} were estimated from behavior in the test phase only, to predict behavior in the last part of the learning phase constituting an out-of-sample or cross prediction. Similarly, based on the assumption that participants learn from feedback to select the most appropriate strategy, we implemented a cross prediction of the adaptive toolbox in that for each participant we determined the strategy he or she (most likely) used based on choice adherence rates in the test phase (calculated as reported above) to predict choices in the last 20 trials of the learning phase. If there was a tie, the simpler and more frugal strategy was selected for cross-prediction (i.e., TTB > EQW > WADD). For the analysis of decision times, we did not use logarithmic transformations and we did not partial out learning effects to avoid changing the metric of the data (which of course comes at the cost of increased error variance). We dropped the highest 5% of the decision times to decrease the influence of outliers. Further analyses show that results are robust to changes of this restriction. To avoid the possibility that strategies can profit from making many random-choice predictions, we punished random choice predictions by counting them as half an error in the calculation which equates the expected error from true random choices. Due to the randomization, all participants worked on a different subset of cue patterns which were not necessarily all sufficiently diagnostic to allow a reliable strategy classification on an individual level. We therefore analyze the fit of individual behavior and strategy predictions only in the aggregate.

PCS_{fitted} showed the highest average choice adherence rates in all three experiments (Figure 2), which was significantly higher than the adherence rate of the toolbox and the individual heuristics EQW and TTB (all $t > 2.23$, all $p < .05$). Noteworthy, a WADD strategy alone showed better performance in cross-prediction than the toolbox as a whole (but see below). The high adherence rate for PCS_{fitted} of about 95% is particularly noteworthy keeping in mind that individuals had to learn cue-validities from feedback quite quickly and that cue-patterns were not repeated. In Experiment 3, we find that errors reduce from block 1 to block 2 for PCS_{fitted}, the toolbox model, and WADD (all $t > 2.5$, all $p < .05$). This provides evidence that the above mentioned inertia effect that influences behavior in block 2 is not driven by increased randomness in choices.

Figure 2. Cross-prediction of choice behavior. *p* indicates the proportion of choices that adhere to individual strategy predictions (adherence rates) in the last third of the learning phase. Error bars indicate 95% CI. For PCS_{fitted} and the Toolbox model cross-predictions are based on fitting in the test-phase. Adherence rates are calculated per participant and then averaged. The toolbox model assumes an adaptive strategy selection between TTB, EQW and WADD.

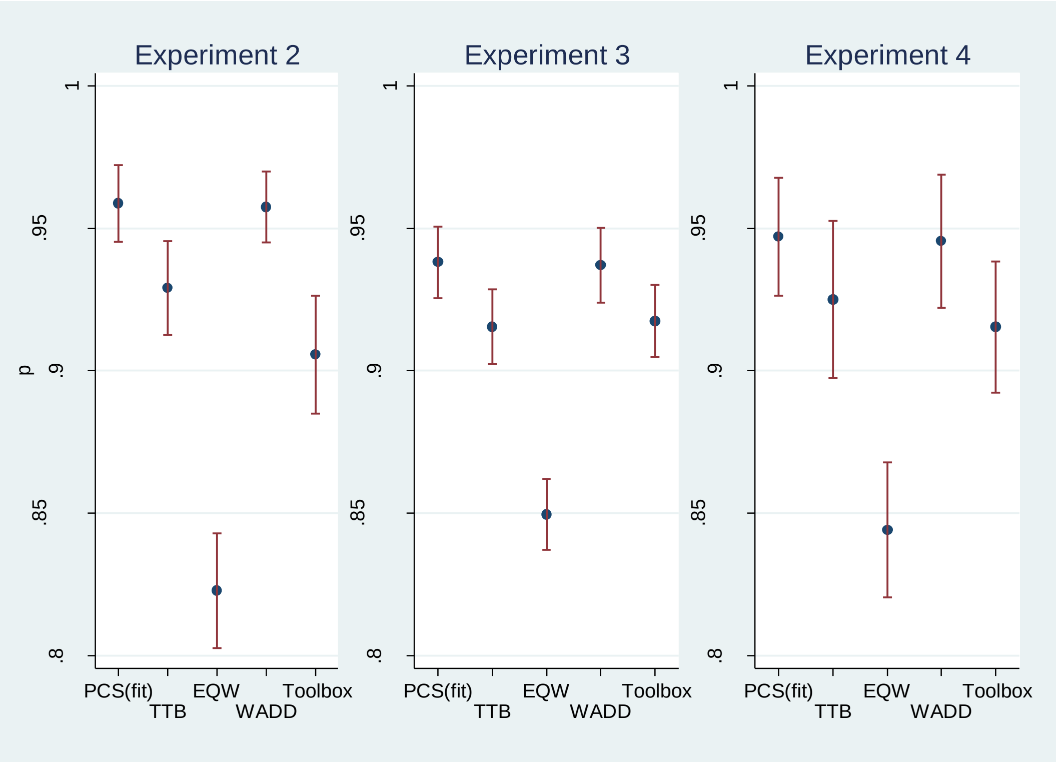
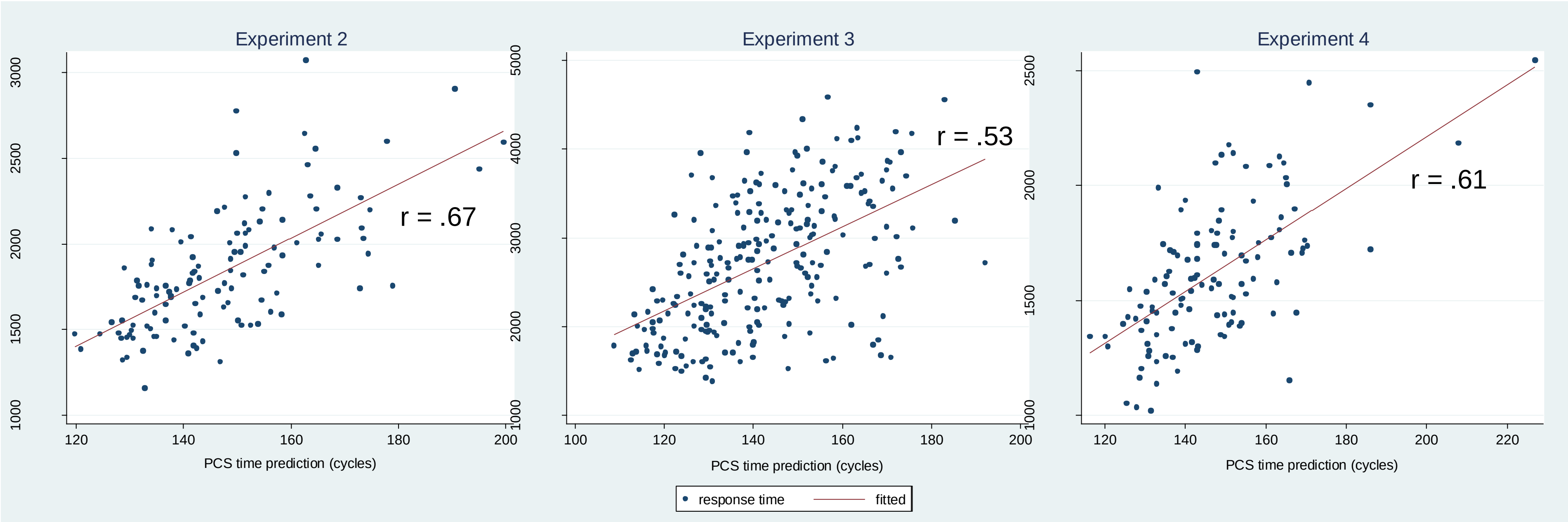


Figure 3 plots the observed decision times per cue-pattern (i.e., 60), environment (i.e., compensatory vs. non-compensatory) and block (only in Exp. 3) against the predictions of $PCS_{fitted.}$ PCS_{fitted} significantly predicted decision times in all three experiments (all $r > .52$; $p < .001$), whereas TTB did not predict decision time in any of the experiments (all $r < .08$, all $p > .23$; predictions not shown). Note that EQW and WADD predict no differences in decision times, hence the systematic differences in line with PCS_{fitted} speak against applications of these strategies.

Figure 3. Cross-prediction of decision time for PCS_{fitted}. Response times and time predictions are shown for each of 60 cue patterns and the two environments (compensatory vs. non-compensatory) collapsed across participants. For Experiment 3, response times are furthermore split by phase (first vs. second). Coefficients indicate Pearson correlations. Response times in the upper 5-percentile were excluded.



As a final critical test, we investigated for Experiments 2 to 4 whether behavior could be better explained by a single-mechanism PCS-DM or a strategy selection learning (SSL) model (Rieskamp & Otto, 2006), a formally specified strategy selection approach for the adaptive toolbox. Given that, unlike single strategies, SSL is formulated as a probabilistic choice model, the comparison necessitated to extend the PCS-DM model introduced above by including a probabilistic choice rule. This choice rule transforms differences in activation of option nodes in choice probabilities using a logit function, thus necessitating one additional parameter (for details see Appendix B). Both models were fitted per participant to the learning trials and the resulting parameters were fixed to predict the subsequent test-trials for the same participant. The results remained essentially the same as for the analyses described above: in cross-prediction, the single-mechanism PCS-DM theory accounted better for behavior of the majority of participants (71%), whereas the behavior of a minority (29%) was better explained by a multiple-strategy SSL theory.

10. General Discussion

For some time now, there is relatively strong consensus that cognition in general (Anderson, 1991; Chater & Oaksford, 2000) and processes of judgment and decision making in particular (Weber & Johnson, 2009) reflect the ability to adapt to different environments, tasks, and goals (Brunswik, 1955; H. A. Simon, 1956). However, what exactly is adaptive about adaptive decision making? On the level of theoretical frameworks there are two distinct answers to this question: One class of approaches emphasizes broad and general models of cognition, typically specifying a process or mechanism which approximates rational solutions (e.g., Busemeyer & Townsend, 1993; K. Fiedler, 2000). Herein, we have specified one such single-mechanism model for probabilistic inferences, the PCS theory for decision making (PCS-DM). In this approach, the only aspect changing adaptively is the environmental information concerning cue validities and the sensitivity to differences concerning these cue validities (as captured by the sensitivity parameter *P*), whereas the information integration mechanism per se remains the same (Glöckner & Betsch, 2010; Newell, 2005). In essence, weighted additive information integration is assumed (Busemeyer & Townsend, 1993; Newell, Collins, & Lee, 2007), though this does not rule out the possibility that, under some circumstances, only part of the information is considered – as it may be costly or too difficult to obtain/retrieve (Bröder & Newell, 2008).

By contrast, the second approach to explaining adaptive decision making typically assumes a repertoire of more narrow strategies or tools (Gigerenzer & Gaissmaier, 2010; Gigerenzer & Selten, 2001; Gigerenzer et al., 1999), from which the decision maker selects one which is best suited for the current environment and constraints (cf. Payne et al., 1993). Thus, adaptivity lies in choosing between different strategies of information integration (Gigerenzer et al., 1999). Typically it is assumed that strategies' potential success in different environments is learned (Rieskamp & Otto, 2006).

Unfortunately, both approaches (single-mechanism versus multiple-strategies) make similar behavioral predictions in many situations and are thus difficult to tease apart (Newell & Bröder, 2008). That is, observable shifts in choice patterns across different environments (as reported by Bröder, 2003; Bröder & Schiffer, 2006a; Rieskamp & Hoffrage, 2008; Rieskamp & Otto, 2006) can either be due to the application of qualitatively different strategies or result from attaching different weights to cues in the same underlying mechanism. To overcome this limitation, we relied on process measures (reaction times and confidence ratings) in a multiple-measures approach (Glöckner, 2009) as well as cross-prediction. In one experiment we additionally used eye-tracking to record information acquisition. Finally, we included a complex model comparison against a fully specified strategy selection model for the toolbox (Rieskamp & Otto, 2006). Thereby, it could be tested whether changes in choice patterns – due to different environmental structures –are most likely produced by different underlying processes or, rather, the same mechanism operating on other cue weights. In four experiments, we compared the predictions of the single-mechanism PCS-DM model with those from a toolbox consisting of a weighted additive strategy (WADD, e.g., Payne et al., 1988), an equal weights strategy (EQW, e.g. Payne et al., 1988), and the lexicographic take-the-best heuristic (TTB, Gigerenzer & Goldstein, 1996).

In all experiments, we manipulated the structure of the environment in terms of cue validities, so as to produce one with a compensatory and one with a non-compensatory structure. We implemented this manipulation between subjects (Experiments 1, 2 and 4) or within-subjects (Experiment 3) and with explicit cue validities (Experiments 1) or cue learning (Experiments 2, 3, and 4). Across the different implementations of the environment-manipulation, the multiple-strategy account predicts shifts towards TTB from the compensatory to the non-compensatory environment on all dependent measures, and corresponding effects on choice patterns have been reported repeatedly (Bröder, 2003; Rieskamp & Otto, 2006). The single-mechanism account, by contrast, predicts that behavior in either environment is best accounted for by PCS-DM and that changes in choice patterns are accompanied by very different gradual changes in process measures such as decision times or confidence patterns.

Across experiments and analyses, the results were relatively clear cut: Whereas we fully replicated large changes in choice patterns, there was no evidence for switches in the underlying information integration mechanism. Rather, the single-mechanism PCS-DM model accounted for data best across all conditions, corroborating the assumption that adaptivity lies in adapting cue weights rather than selecting different strategies. It should be noted that the PCS-DM model used was fully specified and did not comprise any free parameters in one of the implementations. This PCS-DM without fitted parameters can approximate the rational naïve Bayesian solution well and actually accounted surprisingly well for choices, decision times, and confidence ratings in probabilistic inference tasks. Nonetheless, letting the sensitivity parameter P – which captures subjective differences in scaling of and sensitivity towards cue validities – vary freely provided significant additional fit and further insights. As indicated by *P* values predominantly below the optimum value of 1.9, most decision makers showed a lower sensitivity to cue weights than would be necessary to approximate the Naïve Bayesian solution. Stated differently, although decision making most likely proceeded in a weighted compensatory manner (by constructing coherence), differences between cues were only insufficiently taken into account in decision makers' mental representations of the task. This reduced sensitivity was stronger in non-compensatory environments than in compensatory ones, and learning seemed to lead to better adjustment. Furthermore, we found insufficient adjusting of cue weights once the environmental structure changed. This explains previous findings on maladaptive routines (Bröder & Schiffer, 2006a) within the PCS-DM framework.

Noteworthy, the cross-prediction analysis further revealed that a singly WADD strategy predicts choices better than an adaptive toolbox consisting of multiple strategies. This positive result for WADD depends crucially on the fact that we implemented the strategy with chance correction for cue validities; otherwise WADD leads to choice predictions so unreasonable that one cannot expect any individual to actually adhere to them (see also Footnote 4). Previous studies interpreted as showing strategy switches (e.g., Rieskamp, 2006; Rieskamp & Otto, 2006) usually relied on WADD without such chance correction and it is thus a question for future research to determine how strongly previous findings result from this methodological choice.

In the fourth experiment, we set out for an in-depth process test and investigated whether changes in choice patterns conditional upon changing environments are accompanied by different patterns of information search. This was clearly not the case – providing further evidence for the view that differences in choices were not due to switching between distinct strategies. Stated simply, decision makers did not focus exclusively on the single best cue in the non-compensatory environment and they did not search more strongly within cues – as must be expected if the changes in behavior were due to a shift towards increased use of TTB. Rather, information search did not differ between environments.

10.1 PCS-DM and alternative models

PCS-DM is based on a connectionist mechanism that provides a cognitive and evolutionarily plausible implementation for automatic processes of coherence structuring in decision making. This mechanism is assumed to have developed from basic processes of perception (McClelland & Rumelhart, 1981) and reflects basic properties of the brain (Clark, 2013). The core advantage of PCS-DM over previous models is that it specifies a general network structure and a flexible transformation function, thus allowing for precise predictions of choice, decision time, and confidence. At the same time, it achieves adaptivity through one free parameter that captures intra- and inter-individual differences in the sensitivity to (the distribution of) cue validities. Specifically, individuals may differ in how they translate information about the world into their mental representation of the decision task. This simple, one-parameter model can be fitted to choice sets consisting of 60 trials only and nonetheless predicts (a) other choices with less than 5% error, (b) confidence (at the level of individuals) with an average correlation of r = .78, and (c) response time with r = .64. Hence, in light of its limited flexibility, PCS-DM provides a parsimonious account for the data.

By comparison, the alternative Two-Stage Dynamic Signal Detection model (Pleskac & Busemeyer, 2010) that can also predict choices, decision time, and confidence is based on an evidence accumulation account requiring 12 parameters. A direct comparison to this model is not possible here since the latter model necessitates several thousand trials for parameter estimation. We leave this comparison to future research. PCS-DM provides a simple alternative in which decision time and confidence can be predicted after fitting the model to a small set of choices only or even without fitting at all (i.e. using the naïve rational version). In addition, PCS-DM also explains further established findings such as coherence effects that have been demonstrated for the probabilistic tasks investigated here and cannot be explained by evidence accumulation models.

In the current article, we did not include a direct tests against a Bayesian hierarchical model of multiple strategies (Scheibehenne et al., 2013), which estimates probabilities for a mixture of strategy users at the group level. The reason for this is that we aim to make point predictions for choices, response time, and confidence at the level of individuals and tasks, which would require substantial and non-trivial extension of the currently available account.

10.2 Statistical concerns and limitations

Methods for quantitative model comparisons necessarily rely on assumptions, which have to be critically inspected and openly acknowledged. One major concern is whether models' flexibility is sufficiently taken into account in model comparison. The MM-ML method applied here relies on the standard correction based on the Bayesian Information Criterion (see also Appendix A), which, however, has the potential shortcoming that it does not take into account that flexibility might differ even for models with the same number of parameters (Hilbig & Moshagen, in press; Popper, 1934/2005). Furthermore, it might be argued that the independence between errors in confidence, decision time, and choice presumed by MM-ML is questionable (cf. Pleskac & Busemeyer, 2010, Appendix B). However, given that we come to the same conclusion when relying on a cross-prediction approach these concerns, although generally important, do not critically influence the conclusions of the current work.

Furthermore, one may question whether the superiority of PCS-DM over the multi-strategy approach in the strategy classification is only due to the fact that the former is superior in explaining decision time and confidence, whereas the approaches perform similarly in terms of accounting for choices. Although it is true that PCS-DM accounts very well for response time and confidence, the results from the cross prediction show that it is also superior to the multi strategy approach when considering choice predictions in isolation. Stated differently, our general conclusions do not depend on how decision time and confidence predictions are derived for various strategies.

Finally, it should be acknowledged that we investigated a PCS mechanism for probabilistic inference tasks only. Likewise, the specific multi-strategy approach we included, the adaptive toolbox, has mainly been investigated in and specified for this domain. Also, the transformation functions of PCS-DM are specifically tailored for this kind of situations. It thus remains a quest for future research to investigate whether fully specified PCS mechanisms for other domains such as risky choice or multi-attribute decision making perform similarly well. We cannot rule out that multi-strategy accounts perform better in other domains (or that superior multi-strategy models for probabilistic inference tasks are developed in the future). Recent eye-tracking studies, however, indicate that PCS is a promising account for describing the processes underlying risky choices (S. Fiedler & Glöckner, 2012; Glöckner & Herbold, 2011; see also Glöckner & Pachur, 2012) and expert decisions in sports as well (Glöckner et al., 2012). Also, for probabilistic inferences involving recognition information, PCS has been shown to be superior to heuristics (Glöckner & Bröder, 2011, 2014) and PCS mechanisms provide one of the most established accounts for legal decision making (Glöckner & Engel, 2013; D. Simon, 2004; Thagard, 2006). The fact that coherence effects - that are predicted by PCS mechanisms but cannot be explained by any heuristic specified so far (Glöckner et al., 2010) - have been observed for many domains of decision making speaks for the generality of the PCS mechanism.

10.3 PCS-DM within a broader framework for information acquisition

Importantly, the current results do not imply that choices resembling non-compensatory strategies such as TTB do not occur. On the contrary, as has been repeatedly shown (Bröder & Gaissmaier, 2007; Bröder & Schiffer, 2003b, 2006b; Hilbig, Erdfelder, &

Pohl, 2010; Rieskamp & Hoffrage, 2008), choices will conform to such strategies quite often under certain circumstances. A shift toward more TTB-like choices – for example with increasing cue dispersion – is indeed predicted by the multiple-strategy and the single-mechanisms frameworks alike. Similarly, other conditions or individual differences (Hilbig, 2008) will determine the degree to which choices resemble non-compensatory strategies. However, the current results do show that – on the level of underlying processes – such changes in choice patterns need not be attributed to decision makers switching between strategies. Rather, we obtained support for the single-mechanism view that different (subjective) weights are attached to the information under different conditions.

Likewise, the current findings by no means imply that information search is not driven by different strategies. Our conclusion does not conflict with the noteworthy body of previous findings providing ample evidence for different information search patterns (Payne et al., 1988; Payne et al., 1996). Clearly, whenever decision makers are faced with serial and stepwise information search (Hausmann & Läge, 2008), when information is costly (Newell & Shanks, 2003), or when it must be effortful retrieved from memory (Bröder & Schiffer, 2003b) we consider it likely that high cue dispersion, time pressure, or other factors will lead to information search as predicted by TTB. When this (only partially acquired) information is then fed into the (single) information integration system, choices in line with TTB must prevail even if the underlying mechanism is one of weighted-compensatory information integration, as confirmed herein – in line with other single-mechanism accounts of decision making (Busemeyer & Johnson, 2004; Busemeyer & Townsend, 1993; Lee & Cummins, 2004; Newell & Lee, 2007). Future research should thus aim for a more integrative and comprehensive understanding of the interplay between information acquisition (which may well conform to a multiple-strategy account) and information integration (which, as the current findings imply, is best described by a single-mechanism view). Importantly, it has to be ensured that potential extensions of PCS-DM to information search remain sufficiently specified to make precise predictions that are testable, thus retaining a high empirical content of the model (Glöckner & Betsch, 2011).

In sum, the current work lends support for explaining adaptive cognition through broad general-principle models and questions the notion that decision makers necessarily achieve adaptivity by selecting from some repertoire of distinct strategies on the information integration level. At the same time, our results are fully consistent with the view that '*apparently* people select different strategies depending on various aspects of the inference situation' (Rieskamp & Hoffrage, 2008, p. 259, emphasis added). At the surface, this observation holds. However, a closer look at the process level reveals little evidence for strategy shifts. Instead - in probabilistic inferences from given information - adaptive decision making is best explained through a single, global process integrating information in a compensatory manner and thus approximating rational solutions – as would be expected of a model that mirrors adaptive cognition (Chater & Oaksford, 2000).

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Appendix A: Multiple-Measure Maximum Likelihood (MM-ML) Estimation Method

Let n_j be the number tasks of type j that are presented and let n_{jk} be the number of correct predictions of strategy k. The likelihood of observing a certain number of correct predictions n_{jk} given a constant error rate follows a binomial distribution. Hence, the likelihood of observing a set of choices given a strategy k and a constant error rate ε_k can be calculated by:

$$L_{k(C)} = p(n_{jk} | k, \varepsilon_k) = \prod_{j=1}^{J} \binom{n_j}{n_{jk}} (1-\varepsilon_k)^{n_{jk}} \varepsilon_k^{(n_j - n_{jk})} . \tag{A1}$$

The single free parameter ε_k can be estimated by:

$$\hat{\varepsilon}_k = \left[\sum_{j=1}^{J} (n_j - n_{jk}) \right] \div \left[\sum_{j=1}^{J} n_j \right] \tag{A2}$$

Under the assumption that log-transformed response latencies are normally distributed, the likelihood value of observing a log-transformed decision time x given $N[\mu, \sigma]$ can be calculated by the density function of the normal distribution:

$$p(x|\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} , \tag{A3}$$

and for a set of i independent observations $\vec{x}$ drawn from the same distribution by:

$$L_{k(T)} = p(\vec{x}|\mu,\sigma) = \prod_{i=1}^{I} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_i-\mu)^2}{2\sigma^2}} . \tag{A4}$$

Let us denote time predictions of strategies t_i and assume that they are scaled as contrast weights which add up to 0 and have a range of 1. Let us further assume that decision times for the item i are drawn from different normal distributions with means

$$\mu_i = \mu + t_i R , \tag{A5}$$

in which R represents a (non-negative and to be estimated) scaling parameter. Under the assumption of independence, the likelihood for observing a set of choices and decision times drawn from different normal distributions (with equal σ) can then be calculated by inserting equation A5 in equation A4 and multiplying with equation A1:

$$L_k = p(n_{jk}, \vec{x} | k, \varepsilon_k, \mu, \sigma, R) = \prod_{j=1}^{J} \binom{n_j}{n_{jk}} (1-\varepsilon_k)^{n_{jk}} \varepsilon_k^{(n_j - n_{jk})} \prod_{i=1}^{I} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_i - (\mu + t_i R))^2}{2\sigma^2}} . \quad \text{(A6)}$$

The likelihood for observing a set of confidence values that are randomly drawn from different normal distributions around different means can be estimated by replacing the respective contrast weights in the likelihood term for decision time in equation A6 (right part). From adding subscript $_T$ and $_C$ for parameters referring to decision time and confidence, respectively, results the estimation for the total MM-ML likelihood:

$$L_{total} = p(n_{jk}, \vec{x}_T, \vec{x}_C | k, \varepsilon_k, \mu_T, \sigma_T, R_T, \mu_C, \sigma_C, R_C) =$$
$$\prod_{j=1}^{J} \binom{n_j}{n_{jk}} (1-\varepsilon_k)^{n_{jk}} \varepsilon_k^{(n_j - n_{jk})} \prod_{i=1}^{I} \frac{1}{\sqrt{2\pi\sigma_T^2}} e^{-\frac{(x_{Ti} - (\mu_T + t_{Ti} R_T))^2}{2\sigma_T^2}} \prod_{i=1}^{I} \frac{1}{\sqrt{2\pi\sigma_C^2}} e^{-\frac{(x_{Ci} - (\mu_C + t_{Ci} R_C))^2}{2\sigma_C^2}} . \quad \text{(A7)}$$

Likelihood values L_k are corrected for the different numbers of free parameters N_p using the Bayesian Information Criterion (BIC) which also takes into account the number of observations N_{obs} (Schwarz, 1978):

$$BIC = -2\ln(L) + \ln(N_{obs}) N_p . \quad \text{(A8)}$$

Appendix B: A model comparison between a probabilistic Parallel Constraint Satisfaction Theory ($_p$PCS) and Strategy Selection Learning Theory (SSL)

In this appendix, we report results from an additional test of the parallel constraint satisfaction theory for decision making (PCS-DM) introduced in this paper against the Strategy Selection Learning theory (SSL; Rieskamp & Otto, 2006), a formalized theory that aims to specify how people select strategies based on reinforcement learning. SSL provides probabilistic choice-predictions, thus, to be able to compare both approaches, we develop an extended probabilistic model implementation $_p$PCS by adding a probabilistic choices rule including one additional parameter beyond the sensitivity parameter *P*. After formally specifying both models, we present results from a model comparison using data from all experiments that comprised a learning phase (i.e., Experiments 2 to 4) for which learning approaches such as SSL are applicable.

Model Specifications

Specification of $_p$PCS

According to the PCS model for decision making, participants translate cue validities into subjective weights in a mental representation corresponding to their individual sensitivity captured in the parameter *P*. The most coherent solution given this mental representation is generated by the spreading activation mechanism described in the main text resulting in activations a_p and a_{np} that lie in the interval [-1; 1] for the preferred and the non-preferred option (in the two-option case). According to the probabilistic model $_p$PCS, the probability for choosing the preferred option given the parameters for cue-pattern *t* follows from a standard logistic choice function (cf. Glöckner, Heinen, Johnson, & Raab, 2012, p. 331)

$$p\left[x = preferred \mid P, \lambda, t\right] = \frac{e^{\lambda a_{p(t)}}}{e^{\lambda a_{p(t)}} + e^{\lambda a_{np(t)}}} \tag{B1}$$

with λ indicating the steepness of the choice function. The probability of choosing the preferred over the non-preferred options increases with the advantage in activation of the preferred over the non-preferred option as well as with λ. The model predicts random choices if either the activation of both options is equal or if λ equals zero (or both). Considering a set of decision trials $t = \{1 \ldots T\}$, the log-likelihood function of the observed choices is

$$\ln(L_{PCS}) = \sum_{t=1}^{T} \ln(p\left[x = preferred \mid P, \lambda, t\right]) \,. \tag{B2}$$

The maximum log-likelihood of the choices of a participant can be calculated by finding the parameters P and λ that maximize $ln(L_{\text{PCS}})$ for all cue-patterns T. For our simulations, we search the optimal P in the interval [1, 2] and λ in the interval [0, 5].

Specification of SSL

According to the Strategy Selection Learning theory (Rieskamp & Otto, 2006), people learn to choose a strategy s_k from a set of K strategies based on the feedback they receive in the previous trials of a probabilistic decision task. In line with previous work (e.g., Rieskamp & Otto, 2006), we consider two strategies, a compensatory and a non-compensatory one. Specifically, we assume s_k = {TTB, WADD}, that is, participants can either apply Take-the best (TTB) or a weighted additive model with corrected cue validities (WADD). SSL allows participants to differ in their initial preference for applying one strategy over the other which is captured by the parameter β_{TTB} ranging from 0 to 1 (and $\beta_{\text{WADD}} = 1 - \beta_{\text{TTB}}$, indicating the complementary probability for WADD). According to SSL, participants can also differ in the extent to which they are influenced by new experiences during the experiment and/or how strongly they stick to their initial preferences for strategies. This is accounted for by the parameter w, with $1 \leq w \leq 100$. A high w results in a slow learning rate. According to SSL, feedback leads participants to develop expectancies that a strategy s_k (cf. Rieskamp, 2006, Equation 2, p. 1356) results in a correct choice.[xiii] For the first decision trial $t = 1$ expectancies for strategy k are defined by:

$$q_{t=1}(s_k) = \omega\beta_{s_k} \tag{B3}$$

These expectancies for the success of a strategy are transformed into probabilities for applying a strategy according to (cf. Rieskamp, 2006, Equation 1, p. 1356):

$$p_t(s_k) = \frac{q_t(s_k)}{q_t(s_k) + q_t(s_{\neg k})} \tag{B4}$$

That is, the probability of applying strategy s_k for cue-pattern t is the expectancy of strategy s_k normalized by the sum of expectancies of both strategies in order to receive probabilities that range from 0 to 1. The expectancy of strategy s_k is updated in the next and all following $t > 1$ decision trials according to (cf. Rieskamp, 2006, Equation 3, p. 1356):

$$q_{t>1}(s_k) = q_{t-1}(s_k) + I_{t-1}(s_k) \times r_{t-1}(s_k)\,. \tag{B5}$$

That is, the expectancy of strategy s_k being successful in the current trial $t > 1$ is the sum of the expectancy of the strategy for the previous decision trial t - 1 and the payoff received for the previous decision trial r_{t-1} multiplied by an indicator I_{t-1} (all with respect to strategy s_k). The indicator I_{t-1} is 1 if the choice made was in line with the prediction of the strategy in the previous task t - 1. If the participant did not choose the option predicted by the strategy, the indicator is coded as $I_{t-1} = 0$ and, thus, the expectancy for strategy s_k does not change. If both strategies make the same prediction and the participant decided in line with the strategies, I_{t-1} equals the probability predicted for the selection of the strategy, that is, $I_{t-1} = p_t(s_k)$. The expectancy of a strategy can only have positive values. In case the expectancy of a strategy is below 0, the expectancy is set to a value of .0001 (Rieskamp, 2006, p. 1356). Allowing for an error ε in the application of strategies, the probability for a decision for option *A* given strategy s_k and error ε, with $0 < \varepsilon < .5$, is (cf. Rieskamp, 2006, Equation 4, p. 1357):

$$p_t(A \mid s_k, \varepsilon) = (1-\varepsilon) \times p_t(A \mid s_k) + \varepsilon \times p_t(B \mid s_k)\,. \tag{B6}$$

Finally, the probability of a choice for option *A* independent of the strategy s_k is the product of the probability for the application of strategy s_k and the probability of a choice for option *A* given strategy s_k and ε summed over all *K* strategies (cf. Rieskamp, 2006, Equation 5, p. 1357):

$$p_t(A) = \sum_{k=1}^{K} p_t(s_k) \times p_t(A \mid s_k, \varepsilon)\,. \tag{B7}$$

To receive the sum of the log-likelihoods for the choices observed for a participant, two matrices, $\mathbf{P}_{T,2}$ and $\mathbf{I}_{2,T}$, are multiplied. In the first column of matrix $\mathbf{P}_{T,2}$, logarithmic probabilities for a choice for option *A* are included; in the second column, all logarithmic probabilities for a choice for option *B* are included. Matrix $\mathbf{I}_{2,T}$ indicates the choices of a participant: if a participant chooses option *A* in trial *t*, $c_t = 1$; if she chooses option *B*, $c_t = 0$. Matrix $\mathbf{R}_{T,T}$ results from a matrix multiplication of matrix $\mathbf{P}_{T,2}$ and matrix $\mathbf{I}_{2,T}$:

$$R_{T,T} = P_{T,2} \times I_{2,T} = \begin{bmatrix} \ln(p_1(A)) & \ln(1-p_1(A)) \\ \ln(p_2(A)) & \ln(1-p_2(A)) \\ \vdots & \vdots \\ \ln(p_T(A)) & \ln(1-p_T(A)) \end{bmatrix} \times \begin{bmatrix} c_1 & c_2 & \cdots & c_T \\ 1-c_1 & 1-c_2 & \cdots & 1-c_T \end{bmatrix} \tag{B8}$$

The maximum of the log-likelihood function $\ln(L_{\mathrm{SSL}})$ of the choices of a participant can be calculated by finding the individual parameters of ω in the interval [1,100] (Rieskamp, 2006, *p*.1362), β_i in the interval [.001,.999], and ε in the interval [.001,.499] that maximize the sum of the log-likelihoods in the diagonal of the matrix $\boldsymbol{R}_{T,T}$:

$$\ln(L_{SSL}) = \sum_{t=1}^{T} R_{t,t} \tag{B9}$$

Calculation of posterior probabilities

To account for model flexibility, the Bayesian Information Criterion (BIC, Schwarz, 1978) is calculated for model m_j = {PCS, SSL}(Pleskac & Busemeyer, 2010) from the log-likelihoods $\ln(L_{mj})$ as defined in the above equations by:

$$BIC_{m_j} = -2\ln(L_{m_j}) + \ln(T) \times p_{m_j} \tag{B10}$$

with T indicating the number of decision trials and p_{mj} indicating the number of free parameters. $_{\text{P}}$PCS includes two free parameters (i.e. sensitivity to cue-validities P and determinism parameter in the choice function λ), whereas SSL includes three free parameters (i.e., initial preference β_{TTB}, learning rate w, and application error ε).

Finally, the posterior probability for PCS, Pr(PCS|D), that is, the probability of PCS as the data generating mechanism under consideration of the observed choices D and under the assumption of equal prior probabilities for PCS and SSL, can be calculated based on the BIC$_{mj}$ values according to (cf. Wagenmakers, 2007, Equation 11, p. 797):

$$\Pr(PCS \mid D) = \frac{e^{-0.5BIC_{PCS}}}{e^{-0.5BIC_{PCS}} + e^{-0.5BIC_{SSL}}} \tag{B11}$$

and

$$\Pr(SSL \mid D) = 1 - \Pr(PCS \mid D). \tag{B12}$$

Comparative model test: model-fitting and cross-prediction

Procedure

Experiments 2 and 4 started with 60 training trials including feedback for which SSL and $_{p}$PCS were fitted using a maximum-likelihood approach. In Experiment 3, models were fitted for the first 180 decision tasks, that is, the first 60 tasks with feedback from a compensatory or non-compensatory environment (dependent on the condition for the participant), followed by 60 tasks without feedback, and finally followed by 60 tasks with feedback from the non-compensatory or compensatory environment. Estimations were done in R (R Core Team, 2013) based on a grid-search that provided the starting values for a constrained quasi-Newton method (Byrd, Lu, Nocedal, & Zhu, 1995).[xiv] Optimal parameters were fixed and used to cross-predict choices in the remaining 60 decision tasks in all three experiments. Note that for cross-prediction there are no model-parameters fitted and therefore the formula for the Bayesian Information Criterion reduces to: $BIC_{mj} = -2 \times ln(L_m)$. Each participant was classified as a user of $_{p}$PCS or SSL according to the posterior probability of each model separately for both the model-fitting and cross-prediction phase. One complication in evaluating models in the model fitting phase resulted from TTB and WADD making the same predictions for the cue-patterns used in the non-compensatory condition (Table 2) and therefore for SSL w and β_{TTB} can take any value and therefore cannot be reliably estimated from the data in the non-compensatory condition of Experiments 2 and 4. That is, when both strategies lead to the same predicted choices, any initial preference for a single strategy (i.e. β_{TTB}) and any shift in preferences for a strategy during the experiment (i.e. w) lead to the same predicted choices. In this case, SSL is identical to the application of TTB resp. WADD with a strategy-application error ε (Bröder & Schiffer, 2003a). In our analysis we did not punish SSL for the superfluous parameters and used only one free parameter for calculating BICs in these conditions. The proportion of classified SSL users from model fitting in Experiments 2 and 4 reduces considerably when using three parameters for the punishment term. In the discussion of the results we focus on the cross-prediction results, which avoid this problem.

Results

Individually fitted parameters for $_{p}$PCS (Table B1) show that participants are not sufficiently sensitive to differences in cue validities. Individually fitted parameters for SSL show that participants initially prefer WADD with a β_{TTB} = .38 (i.e., β_{WADD} = .62) being significantly smaller than .5, $t(108) = -3.96$, $p < .001$. The mean estimated strategy-application error was small. Estimated parameter values for SSL are comparable to values previously reported in the literature (cf. Rieskamp & Otto, 2006, Table 3, p. 224).

Table B1

Means and standard errors for the fitted parameters for $_{p}$PCS and for SSL

	$_{p}$PCS				SSL					
	P		λ		w		β_{TTB}		ε	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
non-compensatory environment										
Exp. 2	1.39	0.05	3.56	0.23	–	–	–	–	.05	.01
Exp. 3	1.47	0.06	2.64	0.14	33.98	7.7	.32	.06	.09	.02
Exp. 4	1.26	0.07	3.23	0.26	–	–	–	–	.08	.02
Overall	1.39	0.04	3.11	0.12	33.98	7.7	.32	.06	.08	.01
compensatory environment										
Exp. 2	1.57	0.06	3.21	0.15	49.50	8.59	.44	.05	.01	<.01
Exp. 3	1.25	0.05	3.03	0.16	39.52	7.86	.30	.06	.06	.01
Exp. 4	1.62	0.08	2.98	0.15	35.55	11.19	.55	.07	.02	.01
Overall	1.45	0.04	3.09	0.09	42.58	5.14	.41	.03	.03	.01

Notes: The parameters of $_{p}$PCS are P = sensitivity for differences in cue-validities and λ = sensitivity for differences in activation of option nodes. The parameters for SSL are w = learning parameter, β_{TTB} = initial preference for TTB, and ε = strategy application error. Cells with hyphens indicate conditions in which TTB and WADD lead to the same predicted choices for all tasks and thus ε is the only free parameter in SSL (see text).

The mean of the posterior probabilities for the identified $_{p}$PCS users (*Pr* = .92, *SE* = .01) substantially and significantly higher ($p < .01$) than for identified SSL users (*Pr* = .86, *SE* = .02) (Table B2). Thus, when a participant is classified as a user of SSL, evidence for SSL is on average less strong. Most importantly, when using the estimated parameters for both models in cross-prediction of individual choices, $_{p}$PCS accounted better for the majority of participants (71%) whereas behaviour for considerably fewer participants (29%) was best predicted by SSL.

Table B2

Strategy classification for $_{p}$PCS versus SSL and posterior probabilities for participants classified as user of the respective strategy

	Classification (%)		Pr($_{p}$PCS|D)		Pr(SSL|D)	
	$_{p}$PCS	SSL	Mean	SE	Mean	SE
Model-fitting						
Exp. 2	40	60	.86	.02	.85	.02
Exp. 3	79	21	.95	.01	.82	.04
Exp. 4	53	47	.89	.02	.91	.01
Overall	59	41	.92	.01	.86	.02
Cross-prediction						
Exp. 2	66	34	.76	.03	.79	.04
Exp. 3	75	25	.95	.02	.87	.05
Exp. 4	74	26	.85	.04	.83	.07
Overall	71	29	.86	.02	.83	.03

Footnotes

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[i] Note that this conception captured in PCS-DM is psychologically very different from the idea that there is a mixture-distribution of individuals using different strategies as is presumed by recent multi-strategy approaches (e.g., Scheibehenne et al., 2013). It is also different from the idea that each individual selects from a mixture-distribution of strategies that can be described with certain mixture parameters (Davis-Stober & Brown, 2011).

[ii] We calculated the posterior probability according to Bayes' theorem assuming independence of cue predictions and equal priors.

[iii] Note that although convergence in finite time is not guaranteed for this class of networks, we did not find a single case of non-convergence in millions of simulations with randomly generated patterns of decision tasks for the simple network structure proposed herein (e.g., Jekel et al., 2012).

[iv] We provide a web-based graphical user interface for PCS-DM at http://coherence-based-reasoning-and-rationality.de/software.html .The interface allows simulations of PCS-DM with up to 8 binary cues and freely chosen validity weights, sensitivity *P*, and default model parameters.

[v] The MM-ML has been shown to be an unbiased method for identifying individual decision strategies and is an extension of the choice based strategy classification method proposed by Bröder and Schiffer (2003a). To sketch the advantages, MM-ML is a) more efficient than the previously used method, b) unbiased, and c) allows for reliably differentiating between strategies that make the same choice predictions, given that effects on decision times and confidence are large ($d > 1$).

[vi] Since we use binary choices the chance level is .50 so that cues with a validity of .50 have no informative value and should be ignored. Implementing WADD without such a chance

correction would lead to the prediction that two entirely uninformative cues (say, both with a validity of .50) can overrule highly valid cues (say, one cue with a validity of .99). This would lead to entirely unreasonable choice predictions for non-compensatory environments, besides being psychologically completely implausible (see Glöckner & Betsch, 2008b). We return to this issue in the discussion.

[vii] Participants signed up online using the subject-pool management software ORSEE (Greiner, 2004).

[viii] Note that EQW predicts random choices in four out of six cue patterns. Adherence rates were calculated without penalizing for this fact, considering the cue patterns with clear predictions only.

[ix] To test the robustness of our results, we reran the analysis including all participants (i.e., without exclusion due to global misfit), which lead to the same conclusions.

[x] The non-compensatory payoff function was: $P = 40 * c1 + 20 * c2 + 10 * c3 + 5 * c4 + \text{Random}$; the compensatory payoff function was: $P = 27 * c1 + 24 * c2 + 21 * c3 + 18 * c4 + \text{Random}$. Random is drawn from a uniform distribution in the interval [-10; 10]. Cue validities were calculated considering an environment with equal probability of all 120 paired comparisons between all of the $2^4 = 16$ different cue constellations per option (without considering the random component).

[xi] We also added a short post-experimental questionnaire for which results are not reported since they did not bring further insights.

[xii] The index is calculated as follows: Payne index = ((within-alternative-transitions) – (between-alternative-transitions)) / ((within-alternative-transitions) + (between-alternative-transitions))).

[xiii] Note that Equation 2 in Rieskamp (2006, p. 1356), includes an additional parameter $r_{correct}$, that is, the payoff for a correct decision in $t = 1$, which is used as a “scaling constant that

allows comparisons of SSL across tasks with different payoffs". Since payoff in the current experiments is determined by cue weights and a random component, there is no fixed payoff for a correct decision and $r_{correct}$ was omitted (i.e. $r_{correct} = 1$).

[xiv] For 30% of participants, the quasi-Newton method did not reach a solution due to the boundaries set for β_i (i.e., [.001,.999]) and ε (i.e., [.001,.499]). For these participants, we systematically increased/decreased the boundaries by adding/subtracting .001 to the minimum/maximum boundary until the method found a solution: The method found a solution for ~ 96% of all participants in the range β_i = [.006,.995] and ε = [.006,.495]. We also used the optimal solution from the grid-search in case (3% of participants) the maximum-likelihood value for a set of parameters was higher.