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THE COGNITIVE NEUROSCIENCE OF AUTOMATICITY: BEHAVIORAL AND BRAIN SIGNATURES

Sébastien Hélie

University of California, Santa Barbara

Denis Cousineau

Université de Montréal

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For correspondence,

Sébastien Hélie

Department of Psychology

University of California, Santa Barbara

Santa Barbara, CA 93106-9660

Phone: (805) 284-9474

Fax : (805) 893-4303

E-mail: helie@psych.ucsb.edu

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Automaticity is an important phenomenon that is ubiquitous in everyday life: most of our everyday activities appear effortless and automatic. Our ease in navigating the world is the result of thousands of interactions with similar objects in similar contexts, which routinize most everyday activities. This review paper focuses on psychology and neuroscience research related to the acquisition and the detection of automatic behavior. More precisely, we present a list of key behavioral signatures of automaticity, and a few process-based explanations of automaticity. This is followed by a presentation of recent neuroscientific models and data suggesting that automatic behavior is mostly realized in the brain cortex. This article concludes with a discussion of the interactions between the different levels of explanation of automaticity.

Keywords: automaticity, cognitive psychology, neuroscience, cognitive neuroscience.

Introduction

Automaticity is an important phenomenon that is ubiquitous in everyday life: most of our everyday activities appear effortless and automatic (Hélie, Waldschmidt, & Ashby, 2010). For instance, one can instantly recognize a car or sit in a chair. This ease in navigating the world is the result of thousands of interactions with similar objects in similar contexts, which routinize most everyday activities (Sun, 2004). This review paper focuses on psychology and neuroscience research related to the acquisition and the detection of automatic behavior. This is often done using behavioral features or *signatures*. The next section reviews some of the key behavioral signatures found in the literature. This is followed by a discussion of an alternative, process-based, definition of automaticity. Finally, results from neuroscience research on key brain areas involved in producing automatic behavior are reviewed.

Before proceeding further, it is important to distinguish between automaticity and expertise. Expertise typically connotes some extra unusual training or experience that is not shared by most people. For example, according to Palmeri, Wong, and Gauthier (2004) "…experts know more than novices. They can verbalize more properties, describe more relationships, make more inferences …" (p. 378). According to these definitions, a person who walks into a room and sits down in a chair without consciously identifying the object and/or planning the adequate series of motor movements is showing evidence of automaticity, but such behavior, by itself, provides no evidence of that person's expertise with any furniture categories. Many studies have compared the abilities of experts and novices (e.g., Johnson & Mervis, 1997; Medin, Lynch, Coley, & Atran, 1997), but because of the specialized training experts receive, these results tell us relatively little about normal, everyday automaticity.

Behavioral signatures

Many different criteria have been proposed in the literature to detect the presence of automatic behavior. A number of these are due to Schneider and Shiffrin (1977; Shiffrin & Schneider, 1977; for an updated list, see also Schneider & Chein, 2003). Here, we review some of the most common/influential criteria in the literature.

Automatic behavior is the result of extended training

This first feature of automaticity is the most intuitive and one of the least controversial for proponents of a feature-based definition of automaticity: one needs extensive practice to achieve a high level of performance (e.g., asymptotic behavior) and eventually automaticity. It was argued in Hélie et al. (2010b) that overtraining (i.e., extensive training after asymptotic behavior has been reached) constitutes a conservative lower bound in the definition of automatic behavior. For instance, Shiffrin and Schneider (1977) trained their participants for 25 sessions of visual/memory search, Hélie et al. (2010b) trained their participants for 20 sessions of perceptual categorization, Cousineau and Shiffrin (2004) trained their participants for 74 sessions of visual search, Muhammad, Wallis, and Miller (2006) trained their subjects for over a year in a "Same"-"Different" task, and Matsuzaka, Picard, and Strick (2007) trained their subjects for over two years in the discrete sequence production (DSP) task. In all of these cases, training was extended to make sure that performance was stable, and that extra training would not affect performance much. For instance, Hélie et al. (2010b) found no reliable effect of practice after four sessions of training in perceptual categorization using standard measures (e.g., mean reaction times, mean accuracy), but additional distance-to-bound analyses showed additional effects of practice until Session 14. Brain activation also kept evolving even after behavioral measures stopped changing (Hélie, Roeder, & Ashby, 2010). All these results suggest that overtraining may still have an effect, even though behavioral measures may appear to have reached asymptotes (Cousineau, Hélie, & Lefebvre, 2003).

Although extensive practice appears to be a necessary feature of automaticity, Schneider and Chein (2003) argue against its sufficiency. It was shown in Shiffrin and Schneider (1977) that the stimulus to response mapping also needs to be consistent throughout training. Overtraining in a varied mapping condition did not result in automatic behavior, even though performance became markedly faster and reached an asymptote. However, Cousineau and Larochelle (2004) showed that Stimulus → Response consistency was not an appropriate construct. Instead, they argued that consistency of the response had to be considered relative to both the context and the stimulus identity in order to account for category effects in automaticity. This raises the question as to whether automaticity is stimulus-driven or goal-driven, a still unresolved issue (either or both views has received support in the literature; see Moors & Houwer, 2006). In any case, these results are broadly consistent with the idea that automatic routines are developed because humans repetitively interact with similar objects in similar contexts.

Automatic behavior is fast

Automatic behaviors are usually performed faster than non-automatic behaviors (Moors & Houwer, 2006). For instance, identifying a square is an automatic process for most adults, and this process is faster than applying the formal rule (i.e., four sides of equal lengths, connected with four right angles). Likewise, Hélie et al. (2010a) found a 30% reduction of reaction times (RTs) in perceptual categorization after 20 sessions of practice. More impressively, monkeys trained for over two years in the DSP task (a version on the serial reaction time task where the subject does not have to wait for the stimulus to respond, thus allowing the possibility of negative RTs) made almost exclusively predictive responses, with a median RT of -200 ms (which means that the inter-response interval was only 200 ms; see Matsuzaka et al., 2007).

Schneider & Chein (2003) further argue that automatic processes are not only faster but also processed in parallel. In Schneider and Shiffrin's (1977) visual search paradigm, the search rate for non-automatic search was about 50 ms/item, and the RT variance increased with every additional item (a strong indication of serial processing: Townsend & Ashby, 1983). In contrast, automatic search was performed with a search rate of about 2 ms/item, suggesting that automatic search was performed mostly in parallel. It should be noted that faster automatic processing is a feature of automaticity that is also predicted by most proponents of a process-based explanation of automaticity (e.g., Logan, 1988, 1992), who generally do not acknowledge the diagnostic value of features of automaticity (see next section).

However, one difficulty with using the feature "fast" as an indication of automaticity is that it is arbitrary. For instance, the search rate is often used in visual search paradigms to assess the presence of automaticity (as described above). The distribution of search rates in a given experiment is often bimodal, with a (slow) mode in the vicinity of 40 ms/item and a (fast) mode in the vicinity of 0 ms/item. Common wisdom states that search rates below 10 ms/item are indicative of an automatic behavior (Kramer, Strayer, & Buckley, 1990). However, Wolfe (1998) challenged this view by showing that search rates across a few hundred different experiments showed absolutely no sign of bimodality in their distribution. The distribution of search rates for these experiments was unimodal and smoothly spanned the whole range from 0 ms/item to 100 ms/item. The smoothness of the distribution and the absence of bimodality suggest that the 10ms/item boundary between "fast" and "slow" processes is arbitrary and therefore inadequate.

Automatic behavior is efficient

Automatic behaviors are thought to be efficient, that is, they require little effort and therefore are not much affected by concurrent tasks (Moors & Houwer, 2006). For instance, most drivers can hold a coherent conversation while driving. Also, automatic visual search can be performed with a working memory load without much decrement of performance (Schneider & Fisk, 1982). In addition, automatic rule-based perceptual categorization can be performed concurrently with a working memory task with a decrement in categorization accuracy of less than 1% (Hélie et al., 2010b). The same dual task has been shown to strongly interfere with non-automatic rule-based categorization (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). As a last example, reciting a series of digits does not affect performance in a priming task (an example of automatic process; Hermans, Crombez, & Eelen, 2000).

One issue with the efficiency criterion is that the notion of effort is difficult to define. It can be defined operationally by the absence of impact of a dual task (as done in the examples above). However, the problem with this definition is that it is theoretically loaded: It assumes that (a) there is a limited pool of central processing capacity available, (b) the dual task draws on this pool and, (c) a behavior, once automatized, does not need as much processing capacity. Each one of these assumptions has been challenged (for a review, see Moors & Houwer, 2006). In addition, measuring efficiency using accuracy alone can be problematic, as there are various speed-accuracy trade-off behaviors (e.g., fast guessing, Eriksen, 1988; slowing down processing to increase accuracy, Meyer, Irwin, Osman, & Kounios, 1988; skipping a few locations in visual search task, Cousineau & Shiffrin, 2004; etc.) that can be used strategically by the participants. Hence, using this criterion alone to detect the presence of automaticity can be controversial.

Automatic behavior is inflexible

Once initiated, the processes responsible for automatic behaviors run to completion and therefore are difficult to control (Schneider & Chein, 2003). This is also sometimes referred to as behavioral ballisticity (Bargh, 1992) or behavioral inflexibility (Shiffrin & Schneider, 1977). One way to measure process inflexibility is to change the response locations associated with the stimuli. This can be easily accomplished by switching the locations of the response buttons. This manipulation in a perceptual categorization task after extensive practice resulted in a decreased accuracy and increased RT (Hélie et al., 2010b). Yet, model-based analyses showed that participants were still using the optimal categorization strategy; they were struggling at suppressing the response associated with the stimuli. Surprisingly, there was almost no recovery from this switch even after 600 trials of practice. Process inflexibility (as described above) should not be confused with the notion of initiation inflexibility: if the appropriate stimulus is perceived, it is processed automatically. A classical example of this phenomenon is the Stroop effect: When one sees a word, it is automatically read and inhibiting or interrupting the behavior in order to identify the ink color is nearly impossible. Initiation inflexibility may be indicative of a behavior that is more automatized than process inflexibility.

The above results suggest that process inflexibility and initiation inflexibility could be improved as criteria for establishing automaticity if they were augmented with resistance to recovery to become *enduring* inflexibility. For instance, Shiffrin and Schneider (1977) reported a resistance to recovery in a visual search task. After 2,100 trials of practice, a change of target mapping in the automatic condition produced interference that lasted for roughly 2,500 trials. Likewise, Hélie et al. (2010b) trained their participants for more than 10,000 trials in perceptual categorization before a button switch and most participants did not show any sign of recovery after 600 button-switch trials. In contrast, Maddox et al. (2010) trained their participants for 300 trials of perceptual categorization before the button switch and found significant recovery after 300 button-switch trials. Together, these results suggest that the duration of interference due to a button (or stimulus mapping) switch increases with the duration of pre-switch training. Hence, the duration of the interference or the rate of recovery can be good indicators of the extent of behavioral automaticity.

Discussion

This section tried to compile a list of the most common and least controversial behavioral signatures of automaticity. However, care must be used with such a list of behavioral signatures for at least two reasons. First, it is unclear (and highly controversial) that automaticity can be established by using behavioral signatures alone. For one thing, this list may not be exhaustive. For instance, automaticity is also frequently associated with other (unobservable) features such as "unconsciousness" or "unintentional" (for a review, see Moors & Houwer, 2006). Also, completely different sets of criteria have been proposed by proponents of process-based explanations of automaticity (as described in the following section). Likewise, the most widely used automaticity criterion in the animal learning literature[1] is that the behavior is largely independent of any ensuing reward (Dickinson, 1985). This criterion differs substantially from both the behavioral signatures listed above and the process-based explanations of the next section. Finally, even in the unlikely event that an exhaustive list of criteria could be established, it is unclear whether all these criteria would need to be simultaneously present or how many need to be observed for a behavior to be labeled "automatic".

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[1] In the animal learning literature, automatic behaviors are often called *habits*.

A second problem with using behavioral signatures to detect the presence of automaticity is that many of the popular behavioral criteria of automaticity were proposed before multiple memory systems were modeled and observed (e.g., Ahby & O'Brien, 2005). For example, this is true for all of the criteria suggested by Shiffrin and Schneider (1977). Little work has been devoted to a careful empirical investigation of whether these criteria should apply equally regardless of the memory systems that are implicated [but see Helie et al. (2010b) for an exploration of efficiency and inflexibility in automatic perceptual categorization involving different memory systems]. In fact, there is reason to believe that the memory systems do matter. For example, several studies reported that a dual task that required working memory and executive attention (a measure of efficiency) interfered with initial rule-based category learning but not with information-integration category learning (Waldron & Ashby, 2001; Zeithamova & Maddox, 2006). Also, Ashby, Ell, and Waldron (2003) reported that switching the position of the response buttons (a measure of behavioral inflexibility) interfered with initial information-integration performance but not with initial rule-based performance. Therefore, blindly applying the Shiffrin and Schneider (1977) efficiency and inflexibility criteria would lead one to the erroneous conclusion that information-integration categorization is automatic after the first training session. Such a conclusion would be incompatible with the first criteria above (i.e., extended training), because accuracy in information-integration tasks requires several thousand trials to asymptote. For this reason, more work is required before the behavioral signatures of automaticity can be reconciled with multiple memory systems theories.

Process-based explanations of automaticity

While the feature-based definition of automaticity has fueled psychology research for many years, others have criticized this approach for its lack of process-based explanation (e.g., Logan, 1988). For instance, one may observe that automatic behavior is efficient, but this alone does not explain why or how the behavior becomes efficient. This shortcoming can be addressed by specifying cognitive processes that lead to efficiency. Two general approaches have been suggested: *strategy shift* and *algorithm strengthening*.

Strategy shift

In strategy shift approaches, automatic behavior is the result of cognitive processes that are qualitatively different from those responsible for non-automatic behaviors. For instance, Logan's (1988) instance-based theory of automaticity proposes that a task-related algorithm and a single-step memory retrieval process race to produce a response. With extensive practice, the number of memory traces grows, thus increasing the likelihood that single-step memory retrieval process will win the race. According to this theory, automatic behavior is the result of single-step memory retrieval. Hence, identifying the presence of automaticity becomes a problem of detecting the signature (features) of single-step memory retrieval in task performance. These features depend on assumptions about how memory retrieval is achieved. For instance, Logan (1988) assumed, among other things, that instances were automatically encoded and that memory retrieval was the result of a race among independent memory traces. As such, automaticity could be detected by the presence of a power law speed up of mean reaction times and their standard deviations (with equal rates, Newell & Rosenbloom, 1981; Rickard, 1997). In addition, the reaction time distributions should be Weibull with a shape parameter constrained by the rate of the power law speed up (Cousineau, Goodman, & Shiffrin, 2003; Logan, 1992). Lastly, there should be item specific facilitation for repeated stimuli (Logan, 1988).

As another example of strategy shift, Hélie and Ashby (2009) recently proposed a model of automaticity in rule maintenance and application. In this model, non-automatic rule application relies on rule maintenance in working memory, which is eventually replaced by automatic associative processing (i.e., a direct Stimulus → Response association). The Hélie and Ashby model predicts the absence of button-switch interference for non-automatic rule-based categorization (because rule application is controlled by working memory), and the presence of a button-switch interference after the development of automaticity (because of the Stimulus → Response associative processing). Also, the model predicts the presence of dual-task interference for non-automatic rule application and its disappearance after the development of automaticity. In the Hélie and Ashby model, working memory is required only for non-automatic rule application. These predictions were confirmed experimentally in Hélie et al. (2010b).

Algorithm strengthening

In the algorithm strengthening view, automatic behavior is the result of cognitive processes similar to those involved in non-automatic behavior. The main difference between automatic and non-automatic behavior is that the algorithm responsible for the behavior is better tuned after extensive training. For instance, Haider and Frensch (1996) suggested that participant performances were improved after the development of automaticity because the participants were parsing the stimuli to process only the task-relevant information. As a result, faster and improved performance did not result from a change in how the task was processed but from a change in the amount of information that was processed. An example of this strategy can be illustrated by looking for spelling errors in proper nouns in a manuscript. In such a case, the search can be limited to words that are capitalized (instead of looking at all the words). This ability to better parse the stimulus information is algorithmic in nature, which suggest that automaticity is task specific; not stimulus specific. This theory was initially proposed to explain participant performances in a string verification task (Haider & Frensch, 1996, 1999), and

Cousineau and Larochelle (2004) found supporting evidence in a visual search task. In the latter, the visual attributes most diagnostic were learned and processed first after extensive training. When the diagnostic set of attributes is short (as is likely the case in a consistent-mapping situation), RTs are fast; when the diagnostic set of attributes is long or when no such minimal set exists, RTs are slow. This framework could account for all the aspect of performance in many different mapping conditions with many different sets of stimuli.

Another example of algorithm strengthening is chunking (Anderson, 1992; Rosenbloom & Newell, 1986). In chunking, the algorithm (usually a memory trace or a rule) is made more efficient by representing a larger amount of information that is meaningful for the task at hand. For instance, one can remember a phone number by chunking the digits into meaningful units to increase memory capacity (e.g., a phone number can correspond to one's wedding anniversary). Also, if a series of rules are repeatedly chained together, a chunk can be created so that a single rule can produce the final behavior following the adequate initial condition (Anderson, 1992). For instance, if the desire to play a game of tennis leads to searching for an opponent (Rule 1), and searching for an opponent leads to contacting Jim (Rule 2), one may replace the application of these two rules by the application of a new (chunked) rule that specify that one should contact Jim whenever s/he desire to play a game of tennis. Because fewer steps are involved in applying one rule (compared to a series of rules), error is less likely and the resulting behavior can generally be achieved faster and more accurately.

Discussion

The process-based view of automaticity constitutes theoretical progress over a strict behavioral signature definition of automaticity because an explanation is now provided, and this explanation justifies the choice of features to look for (addressing the first problem discussed in the feature-based view above). In addition, a process-based view makes explicit the processing resources so that interference with a dual task can be predicted explicitly (addressing the second problem of the feature-based view discussed above). Yet, while a process-based view of automaticity provides a more substantive explanation of automaticity than a view based solely on behavioral features, it still suffers from some difficulties.

A first problem comes from the fact that in diagnosing automaticity, a shift is made from searching for features of automaticity to features of the processes underlying automaticity. For instance, Logan's (1988) theory shifts the problem of identifying automatic behavior to finding behavioral signatures of single-step memory retrieval. The Hélie and Ashby (2009) model shifts the problem to searching for the features of direct Stimulus → Response association. One possible consequence of this problem is that each theory will develop its own set of processing features, which may result into dozens of specialized definitions of automaticity. Fractionalizing the concept of automaticity is likely to reduce its usefulnees.

A second problem with process-based explanations of automaticity is that different theories can account for similar behavioral phenomena using distinct explanations. This is called model mimicking (Townsend, 1990). For instance, one of the main findings in Hélie et al. (2010b) is that performances in rule-based and information-integration categorization are similar after the development of automaticity (for a review of dissociations in non-automatic categorization, see Ashby & Maddox, 2005). This is consistent with a theory assuming separate rule-based and information-integration learning systems but a common "automatic" processing mode (as suggested by, e.g., Ashby, Ennis, & Spiering, 2007; Hélie & Ashby, 2009). However, the convergence of performance can also be explained by Logan's (1988, 1992) instance theory of automaticity. According to Logan, algorithms that can achieve the task compete (race) with a single-step memory retrieval process to provide a response on every trial. Each category structure might be processed by a different algorithm, which would explain the performance differences early in training (when the response is algorithm-driven). However, the responses become memory-driven after the development of automaticity, and memory retrieval would be similar regardless of category structure (because the stimuli were the same).

These two problems are in fact mirror images of one another. In the first problem, one concept, automaticity, is broken down in multiple specialized concepts of automaticity. In the second problem, a single data set, the observable, can be explained by numerous and distinct theories of automaticity. This profusion of alternative concepts/theories points to the indeterminacy underlying the search for understanding automaticity. This may reflect only the current state of the research and more refined behavioral measures or more refined conceptual definitions may lie ahead of us. This general problem was identified early on by Newell (1992), who stated that “cognitive theory is radically underdetermined by data” (p. 426). One possible solution to this problem is to take neuroscience data into consideration.

The neuroscience of automaticity

Neuroscience research on automaticity started with the idea that automatic processes are akin to reflexes (Sherrington, 1906). As such, the dominant theory in the 20th century was that novel behaviors require attention and control, and thus rely on cortex, whereas automatic behavior does not require either of these components, and thus does not rely on cortex. While progress in understanding the neuroscience of non-automatic processes has been rather quick, progress in understanding the neuroscience of automatic processes has been slower (Ashby, Turner, & Horvitz, 2010). This might be explained in part by the high cost of time and money required to study automaticity from a behavioral point of view. These costs are multiplied when such studies are embedded within neurological methodologies.

The role of the basal ganglia in automatic behavior

One of the first revisions to the above-described theory of automaticity involved the basal ganglia (BG), a subcortical brain area, in the learning of novel (non-automatic) behavior (Packard & Knowlton, 2002). First, let us discuss the anatomy of the BG. The BG can be subdivided into several smaller areas. Keys among them are the striatum, which receives inputs from most cortical areas, and the globus pallidus, which is the main output region of the BG. The globus pallidus projects to different thalamus nuclei, which can send activation back to most cortical areas. Based on afferent connections, the striatum can be further divided into the associative striatum (mostly the caudate) and the sensorimotor striatum (mostly the putamen). This coarse anatomical description is sufficient to understand the present discussion.

Automaticity research over the past decade suggests that the associative striatum is involved in the learning of novel behaviors (e.g., Hélie et al., 2010a; Miyachi, Hikosaka, & Lu, 2002). In the Hélie et al. study, BOLD signal in the head of the caudate was correlated with accuracy in rule-based categorization in the first training session. In the Miyachi et al. study, single-cell recordings in the associative striatum showed activation during initial learning of a sequence learning task. However, these very same cells stopped firing after extensive practice. A similar result was found in Hélie et al., where the correlation between head of caudate BOLD signal and accuracy quickly became negative after four sessions of practice. Interestingly, Miyachi et al. found that cells in the sensorimotor striatum became highly active after extensive practice. These cells were not active in the learning of novel behaviors. These results suggest that the development of automaticity constitutes a transfer of control from the associative striatum to the sensorimotor striatum. Inactivation studies further support this interpretation (Miyachi et al., 1997).

The role of the cortex in automatic behavior

The role of the sensorimotor striatum in the production of automatic behavior has been challenged by recent findings (for a review, see Turner, McCairn, Simmons, & Bar-Gad, 2005). For instance, inactivation of the globus pallidus (which essentially prevents the BG from influencing the cortex) has a limited effect on the production of overlearned sequences (Desmurget & Turner, 2010). Also, Hélie et al. (2010a) found that the BOLD responses in all BG areas were not correlated with accuracies after extensive practice in a rule-based categorization task. Further, BOLD responses of all thalamic nuclei were either non-correlated or negatively correlated with accuracies after extensive practice (thus removing the main communication pathway between cortical and subcortical brain areas). Together, these results suggest that automatic behavior is mostly cortical. So, what is the role of the basal ganglia in the development of automaticity? One possibility is that the basal ganglia might be used to train corticocortical connections between associative sensory areas and premotor/motor areas responsible for automatic behavior. This is because the striatum processes dopamine with a high enough temporal resolution to match the conditions necessary for reinforcement learning (Calabresi, Picconi, Tozzi, & Fillippo, 2007), whereas cortical dopamine has very low temporal resolution (Seamans & Yang, 2004). Hence, the cortex is not suited for trial-and-error learning, but could learn stimulus-response associations with Hebbian learning if trained in a mostly *errorless* manner by the BG. Ashby et al. (2007) recently proposed a computational model of automaticity in information-integration categorization that embodies this general idea. The SPEED model provided a good fit to several data sets, and an extension suggest that a similar pattern may hold for rule-based categorization (Hélie & Ashby, 2009). These models are further supported by the results of Muhammad et al. (2006), who found rule-selective cells in the dorsal premotor cortex that fired earlier and more strongly than rule-selective cells in the prefrontal cortex and the head of the caudate after more than a year of training in a “Same”-“Different” task. These results suggest that the premotor cortex was responsible for the automatic behavior, and that prefrontal and striatal cells were a byproduct of earlier stages of learning. Hélie et al. (2010a) found similar results in a rule-based categorization task. After 20 sessions of training, only cortical brain area BOLD signals were positively correlated with accuracy (especially in the premotor cortex).

Discussion

Studying the development of automaticity is difficult because it is characterized by changes in widely distributed neural networks, rather than in some single brain region. The more classical views of automaticity suggested that automaticity could be detected by an overall increase or decrease of brain activity, but a recent review suggest that things are not that simple. Kelly and Garavan (2005) reviewed many studies of practice-related changes in brain activation and found evidence for increases, decreases, but also for redistribution (i.e., activation in some brain areas increases while activation in others decreases). Together with the previously described results, this evidence suggest that non-automatic behavior is both cortical and subcortical, but that automatic behavior is the result of direct cortical connections that have been trained by the BG. However, these findings may be dependent on the task being practiced, and a more fine-grained analysis is likely to yield a more complex picture.

Conclusion

Much progress has been achieved in automaticity research over the past century. This research is especially important since most of our everyday decisions and actions are automatic. Yet, a quick search of psychology article databases suggest that the ratio of published articles addressing initial learning compared with published articles addressing automaticity is about 82 to 1 (Hélie et al., 2010b). Fortunately, more research is now being conducted and process-based and neuroscience theories are now available to supplement lists of behavioral signatures. These three approaches covered in this review article map well with Marr's (1982) levels of explanations. The behavioral criteria can be seen as determining what needs to be understood (the computational level), the process-based explanations provide insight into how automaticity can be achieved (the algorithmic level), and the neuroscience research provides an explanation of how automaticity can be implemented in a brain (the implementation level). Marr argues that all three of these levels are necessary to provide a complete explanation of a phenomenon and we likewise argued that each level by itself is underdetermined. However, we do not believe that each level should be studied independently. As lower levels are made more explicit, they should determine the content of higher level constructs. For example, specifying a theory at the algorithmic level helps determine what behavioral signatures to look for. This influence must however be bidirectional. For example, not observing the presence of predicted signatures must in turn force revisions at the algorithmic level. For this reason, automaticity researchers should consider all three types of data/evidence simultaneously. This review is an attempt at providing a unique platform to present the behavioral and brain signatures of automaticity together in hope of galvanizing the development of more complete theories and models.

Acknowledgments

Requests for reprints should be addressed to Sébastien Hélie, Department of Psychology, University of California, Santa Barbara, CA 93106-9660, or using e-mail: helie@psych.ucsb.edu.

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