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THE NATURE OF AFFECT IN THE STRUCTURAL MERE EXPOSURE EFFECT

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This paper investigates the characteristics of the affective component in the structural mere exposure effect (SMEE). Two approaches are considered – fluency attribution approach (FA) and affect as predictive efficiency approach (APE) – within a predictive coding framework. Using the artificial grammar learning and affective priming paradigms, we demonstrate that a violation of implicitly learned regularities elicits an automatic negative affective response. This result suggests that SMEE can be observed without any overtly evaluative judgment. Participants' decisions on the grammaticality of stimuli did not change this pattern. We conclude that SMEE is based on the affective response to prediction errors made by the cognitive system and may include the fluency attribution process in the later stages of processing.

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Keywords: Implicit learning; structural mere exposure; affect; predictive coding; conflict; fluency.

JEL Classification: Z

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Introduction

Implicit learning is the ability to learn complex structures from the environment with limited access to the resulting representations for awareness and verbalization. Such learning manifests itself not only in behavioral adjustments but also in changes in the affective evaluation of new objects similar to those seen before. The nature of this affective reaction remains unclear. In this article, we present two experiments examining the nature of this phenomenon.

Artificial grammar learning (AGL) is a basic paradigm for studying implicit learning (Reber, 1967). Participants are presented with the sequence of stimuli (usually letter strings) which are constructed from basic elements using the same algorithm – an artificial grammar. In the second phase of the experiment, participants have to classify new stimuli as consistent with the same artificial grammar or not. The basic result is that participants can classify new stimuli at an above-chance level without being able to report the structure they had learned.

The affective manifestation of implicit learning was initially reported by Gordon and Holyoak (1983), who asked participants to evaluate the pleasantness of new stimuli on a 1–7 scale instead of classifying them as grammatical or not. Gordon & Holyoak reported that on average participants rated grammatical items as more pleasant than ungrammatical ones. Interestingly, in this study participants were not informed that any grammar even existed. This preference for grammatical items was called the structural mere exposure effect (SMEE) and was successfully replicated in a number of studies (Folia & Petersson, 2014; Johansson, 2009; Manza & Bornstein, 1995; Newell & Bright, 2001).

In this study, we test two possible approaches to SMEE. The first one is the fluency attribution approach (FA) (Bornstein & D'Agostino, 1994; Unkelbach & Greifeneder, 2013). According to this approach, grammatical stimuli are processed quicker than ungrammatical ones, giving the experience of ease of processing, which can be attributed to pleasantness if asked about it (Manza & Bornstein, 1995; Ivanchei, 2014; Price & Norman, 2008; Whittlesea & Price, 2001).

The second approach is the predictive processing view, which suggests that the brain constantly generates predictions for future events and evaluates its own prediction efficiency (Friston, 2010; Clark, 2013). As prediction error minimization is the main criterion for predictive processing, familiar unambiguous and non-conflict stimuli are perceived as well predicted. Some authors on predictive processing suggest that the efficiency of predictions can be experienced affectively (Van de Cruys, 2017; Chetverikov & Kristjansson, 2016). We refer to this approach as the affect as predictive efficiency approach (APE).

To the best of our knowledge, APE and FA have not been compared directly although there are some studies showing how these approaches may generate the opposite predictions. In Braem and Trapp (2017), participants learned predictive relationships within a sequence of stimuli. They found that predictable stimuli are processed faster than predictive ones. However, predictive stimuli are evaluated as more pleasant. Thus, they reported a clear dissociation between fluency and affect (which was caused by the predictive efficiency).

Theoretically, APE and FA differ in several respects. First one is the nature of the subjective feeling caused by fluency and efficient predictions. FA suggests that the experience of fluency has no valence and can be attributed to very different effects – from familiarity to truth, depending on the question the participant was asked (Oppenheimer, 2008; Alter & Oppenheimer, 2009). APE suggests that a prediction error experience has an affective nature (van der Creus, 2017; Chetverikov & Kristjansson, 2016; see also Botvinick (2007) for a related claim). Thus, affect is an essential component of this phenomenon and not just an attribution of some other kind of arousal within the task context.

The second important distinction lies in the timing of these effects. Empirical results show that fluency can be attributed to affect even three seconds after the stimulus onset (Winkielman & Cacioppo, 2001), whereas the affect from predictive efficiency was shown to fade or even reverse 800 ms after the stimulus onset (Fritz & Dreisbach, 2015). These two points may be summarized in the theoretical notion of the automaticity of affect in the prediction processing framework in contrast to the deliberate attribution stage in the fluency approach.

The third distinction is related to error processing. APE suggests that errors may be considered the result of inefficient predictive activity, and thus may be marked with a negative affect (Chetverikov, 2014; Chetverikov & Kristjánsson, 2016). Errors may also invoke conflict within the cognitive system as a new piece of conflicting information in the system, lowering the probability of efficient predictions (Chetverikov & Kristjánsson, 2016). Errors may also aversively mark situations of low processing efficiency (Botvinick, 2007). FA does not make any predictions regarding errors (unless they are associated with faster response times).

We relied on these three distinctions between the two approaches to find out which of them better accounts for SMEE.

Most SMEE studies have been run with preference judgments employing an arbitrary liking scale, which allows participants to make slow, deliberate decisions on the pleasantness of the stimuli. In the present study, we tested the hypothesis that the affective response to a violation of the implicitly learned grammar is automatic and thus very fast. Additionally, we tested whether it occurs without any overt stimuli liking decision. To test this idea, we employed the affective priming paradigm (Fazio, 2001). This paradigm estimates the affective valence of a stimulus (prime) by comparing the categorization speed of subsequent stimuli (targets) of a positive vs. negative valence. Positively valenced primes enhance the speed of subsequent positive targets and negatively valenced primes speed up negative targets. Using this paradigm, researchers could demonstrate the aversive nature of conflicts and inefficient predictions in information processing (Dreisbach & Fischer, 2012; Fritz & Dreisbach, 2013; Fritz & Dreisbach, 2015; Schouppe et al., 2015). In Dreisbach and Fischer (2012), positive targets were categorized on average faster than negative ones, however, this difference was much higher following congruent Stroop-stimuli rather than incongruent ones. Schouppe et al. (2015) demonstrated similar results with an Eriksen flanker task. We assume that a violation of the grammar in the test phase of an AGL-experiment may be considered a prediction violation and thus a kind of conflict. However, in this case, participants are not consciously aware of this conflict. There is some evidence of aversive responses to subliminal conflicts (Frings & Wentura, 2008). However, in AGL, stimuli are supraliminal, but still leaving conflict unconscious due to the complexity of their structure. We wanted to test if it is possible to detect an aversive response to this kind of conflict in AGL.

Based on the differences between FA and APE listed above, we formulate separate hypotheses for the affective priming paradigm as a measure of SMEE in implicit learning.

1) APE predicts that ungrammatical stimuli will prime a more negative affect than grammatical ones, as the former will be poorly predictable which will automatically activate a negative affect. FA does not predict this, as long as the affective priming paradigm leaves no room for the controlled attribution of the fluency experience to the positive affect.

2) APE predicts that SMEE will be stronger on trials with short prime-target SOA as the affect is a sign that predictive efficiency is automatic and thus very fast. Even if fluency attribution can cause affective priming, fluency attribution should be unaffected by the prime-target SOA variation.

3) APE predicts that erroneous responses will prime negative responses because errors lead to conflict within the cognitive system and lower predictive efficiency. Fluency attribution processes should be insensitive to these phenomena.

We tested first two hypotheses in Experiment 1, where participants observed grammatical and non-grammatical stimuli (serving as primes) presented for varying durations and evaluated affective targets right after these stimuli. This was done after they learned the structure of the artificial grammar through the presentation of a distinct set of grammatical items in the learning phase. The third hypothesis was tested in Experiment 2, where participants not only observed the primes but also classified them as grammatical or not before the evaluation of the targets.

Experiment 1

Participants

Thirty volunteers (1734 years old, mean age = 21.7; 26 women) participated in the experiment. Some were students of the Psychology Department at St. Petersburg State University, others were recruited through advertising outside the department. All participants gave informed consent prior to the study. The experiment was approved by the ethics committee at St. Petersburg State University.

Materials

For the AGL task, we used a set of strings generated by Dienes & Altmann (1997) with Reber's original (1967) grammar. However, instead of letter strings, we used different geometric shapes embedded in each other following Pothos & Bailey (2000). The inner shape corresponded to the first letter of a string and outer shape corresponded to the last letter of a string. Fig. 1 shows examples of stimuli construction.

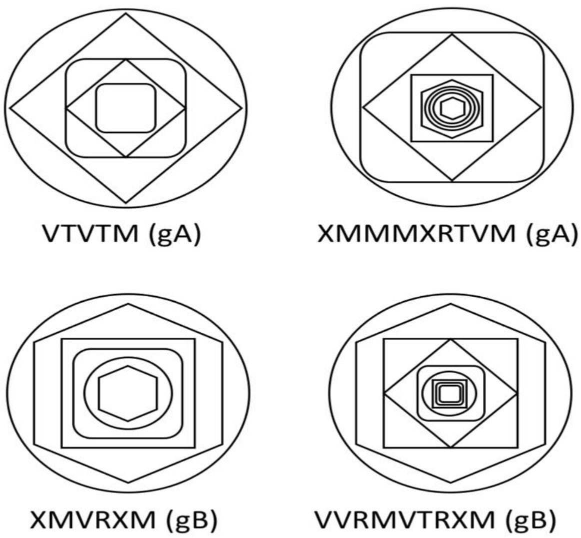

Fig. 1. The examples of stimuli for two experiments (gA – consistent with grammar A, gB – consistent with grammar B) with the corresponding letters from Dienes & Altmann (1997). In the present experiments, we used white contours on a black background (see Fig. 2).

72 stimuli were generated. We used a two-grammar design (following Dienes & Altmann, 1997) to make the same test stimuli grammatical for one subgroup of participants and ungrammatical for the other. During the learning phase, two subgroups of participants memorized stimuli constructed according to the two different grammars (grammar A for subgroup A and grammar B for subgroup B). Eighteen stimuli were presented to each group. In the test phase, all the participants were presented with the same set of 36 new stimuli. Eighteen items were consistent with the grammar A and the other 18 items were consistent with the grammar B. Thus, the first 18 stimuli were grammatical for the subgroup A and ungrammatical for the subgroup B and vice versa. With such a design, all implicit learning and the affective priming effects observable in the experiment cannot be attributed to the *a priori* structure of the stimuli. All the stimuli were 7 cm in width and height (the diameter of the outer circle, was 7 cm). All the stimuli were presented in white on a black background on a 14-inch computer screen.

In the affective judgment task, 18 high-valence (positive) and 18 low-valence (negative) pictures equated for arousal were selected from the International Affective Picture System, IAPS (Lang et al., 2008). The positive pictures had a mean valence of 6.71 (SD = 0.41) and a mean arousal of 5.16 (SD = 0.36); the negative pictures had a mean valence of 2.83 (SD = 0.39) and a mean arousal of 5.15 (SD = 0.51). The pictures were 20.4 x 15.3 cm and were also presented on a black background.

Procedure

In the first phase of the experiment (the learning phase), participants were instructed to memorize the presented stimuli (Fig. 2). Participants were shown 18 “grammatical” shape combinations, presented twice in a random order. Each shape combination appeared on the screen for 5000 ms.

In the second phase (the test phase), participants were told that they would be presented with new shapes combinations as well as emotionally valent images. They were told that their main task was to evaluate the valence of the affective images as fast as possible. Each trial started with a presentation of grammatical or ungrammatical shape combinations (prime stimulus) for 500, 1000, 1500 or 2000 ms (the duration was randomly selected for every trial), followed by the affective picture (target stimulus), which remained on the screen until a response was given. The response-trial interval was 2000 ms.

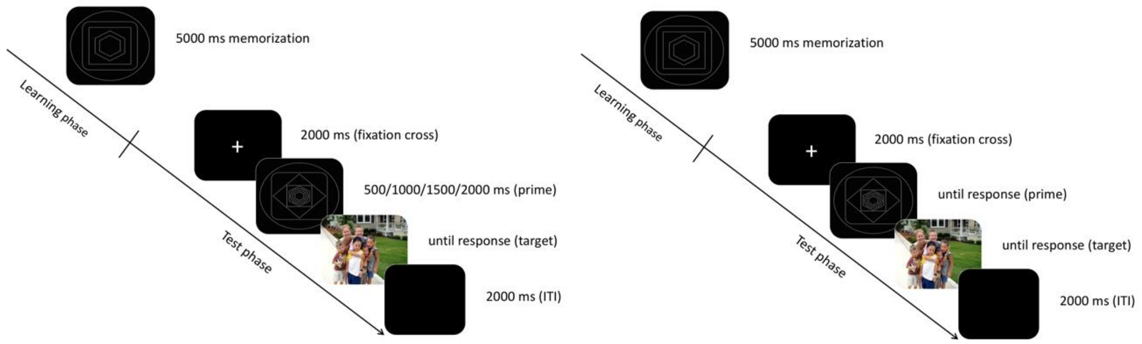

Fig. 2. The procedure of Experiment 1 (left panel) and Experiment 2 (right panel).

Overall there were 36 primes (18 grammatical and 18 ungrammatical) and 36 targets (18 positively and 18 negatively affective pictures). These stimuli were presented twice, such that each prime was paired with both a positive and negative target and each target was paired with both a grammatical and an ungrammatical prime. The resulting number of test trials was 72.

Response keys for affective judgment task were the “S” key labeled with a green sticker and marked “+” for positive pictures and the “X” key labeled with a red sticker and marked “-” for negative pictures. Participants performed the affective judgment task with their left hand (middle finger for “S” and index finger for “X”).

Results

Data analysis details

We deleted from the analysis all the affective categorization trials which were faster than 200 ms and 5% of the slowest responses for every participant. The first trials were also discarded. Only correct categorization decisions were analyzed. RTs were log-transformed due to non-normality. Unless otherwise specified, for all main parts of the analysis we used medians aggregated by affective targets as data points.

Prime grammaticality effect

Response times. First, we assessed the effect of prime grammaticality on the RT of the affective target categorization. We ran a 2 × 2 repeated-measures ANOVA with prime grammaticality as the within-subject factor and target valence as the between-subject factor. The full model revealed no significant effect on the α level of 0.05. Interaction between target valence and prime grammaticality was marginally significant, $F(1, 34) = 4.05$, $p = .052$, $\eta_g^2 = 0.03$.

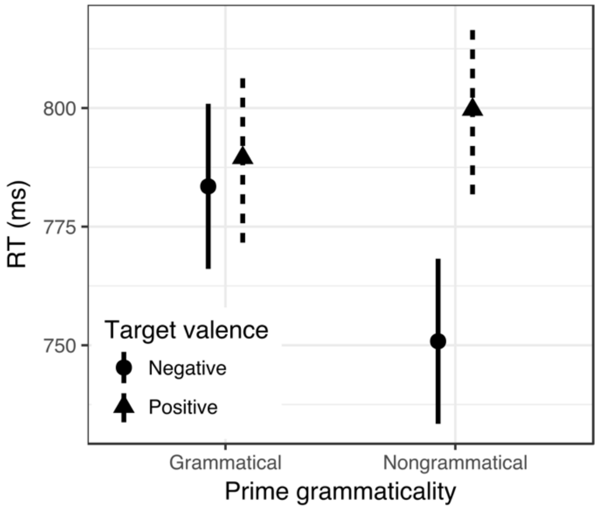

Fig. 3. Target categorization RT by prime grammaticality and target valence. Bars represent 95% confidence intervals.

A separate, paired t-test for grammatical primes did not show a significant difference between log-RTs of the positive and negative targets, $t(17) = 0.32$, $p = .749$, Cohen's $d = 0.15$. A separate, paired t-test for ungrammatical primes was significant, $t(17) = 3.10$, $p = .006$, Cohen's $d = 1.50$ (Bonferroni correction for multiple comparison does not affect these conclusions).

Second we added the duration of the prime presentation to the full model which is a within-subject factor variable with two levels: short presentations (500 and 1000 ms) and long presentations (1500, 2000 ms). We analyzed only two levels of this variable because, due to the random variation of the presentation times, there were not enough trials for averaging in each of initial four levels (500, 1000, 1500, and 2000 ms). In this 3-way ANOVA, we observed two significant effects – the effect of target valence, $F(1, 34) = 5.12$, $p = .030$, $\eta_g^2 = 0.05$, and target valence × prime grammaticality interaction, $F(1, 34) = 6.41$, $p = .016$, $\eta_g^2 = 0.03$. The target valence × prime grammaticality × prime duration interaction was only marginally significant, $F(1, 34) = 3.21$, $p = .082$, $\eta_g^2 = 0.02$. We ran two separate models for fast and slow prime presentations. Significant target valence and the prime grammaticality interaction was observed only for short presentations, $F(1, 34) = 7.21$, $p = .011$, $\eta_g^2 = 0.07$, and not for long presentations, $F(1, 34) = 0.03$, $p = .863$, $\eta_g^2 = 0.00$. Interestingly, for long prime presentations, categorization response times for ungrammatical primes became faster than for grammatical primes, $F(1, 34) = 4.52$, $p = .041$, $\eta_g^2 = 0.04$.

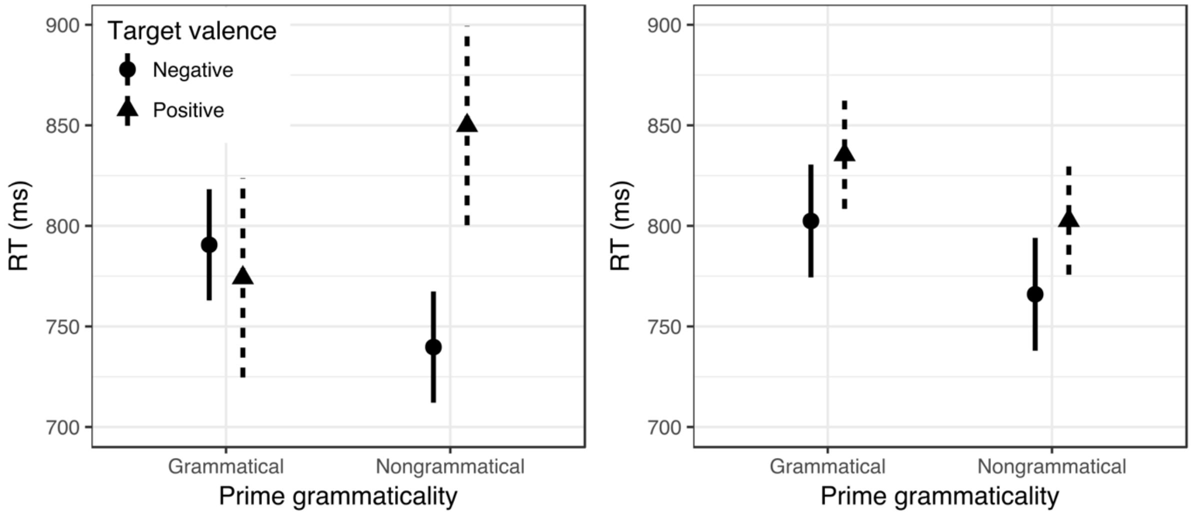

Fig. 4. Target categorization RT by grammaticality and target valence for short (left panel) and long (right panel) prime presentations.

Discussion

In the first experiment, we investigated the automaticity of the affective response in AGL. Using the affective priming technique, we observed stronger negative priming by ungrammatical stimuli rather than by grammatical ones as demonstrated by the faster categorization of the negative rather than positive targets following the ungrammatical prime presentation. Following grammatical primes, no difference was found in the RTs of positive and negative target categorization.

This effect was moderated by prime exposure time. Short exposure times (< 1500 ms) resulted in significantly stronger negative priming following ungrammatical stimuli compared to grammatical ones, while long exposures (1500–2000 ms) did not provide any significant effects.

We can conclude that, perceived in the same context, new unfamiliar stimuli are experienced as aversive stimuli in comparison to novel stimuli structurally similar to those seen before. However, this effect is quite short-term.

In the second experiment, we investigated how participants' decisions on prime stimuli change this automatic affective response. Studies deriving predictions from the predictive activity of the cognitive system show that participants' decisions on primes can change the affective response to conflict substantially. Chetverikov and colleagues found a decreased valence of stimuli associated with participant errors (Chetverikov, 2014; Chetverikov & Filippova, 2014; Chetverikov et al., 2015; Chetverikov et al., 2017). In these studies stimuli that were erroneously classified (e.g. omissions in the recognition task – Chetverikov, 2014) were subsequently evaluated as more negative, or transferred negative valence to the associated stimuli (Chetverikov et al., 2017). Ivanchei et al. (2018) found the same effect for errors using the affective priming paradigm in the Eriksen flanker task. Within a wider predictive processing framework (reward prediction, see Silvetti et al., 2011) Shouppe et al. (2015) showed that in poorly predictable situations (incongruent flanker stimuli), correct responses elicit a positive affect, therefore demonstrating one more effect of participants' decisions on the automatic affective processing of stimuli. Based on these decision-related affective effects in the literature, we decided to test whether the classification of the prime stimuli as grammatical or not would change the observed negative priming. FA predicts the independence of the affective valence of primes from decisions made on them, whereas APE would predict changes according to the accuracy of prime classification.

Experiment 2

Participants

Thirty volunteers (18–44 years old, mean age = 23.5; 24 women) took part in the experiment. Some were students of Psychology Department at St. Petersburg State University, others were recruited through advertising outside the department. All participants gave informed consent prior to the study. The experiment was approved by the ethics committee at St. Petersburg State University.

Materials and procedure

The stimulus material and procedure in Experiment 2 were identical to those in Experiment 1, except for a few details. After the learning phase, participants were informed that the shape combinations they had seen were constructed according to some set of rules and that they would then be presented with new shapes, which they should decide were consistent with these rules (grammatical stimuli) or not (ungrammatical stimuli). After each decision, they should perform the affective judgment task. Shape combinations were on the screen until a response was given (for 4000 ms maximum; after that stimulus disappeared and a target picture was presented).

In this experiment, the prime presentation finished with participants' classification responses (or after 4 seconds), so prime duration was not experimentally varied.

Response keys for the artificial grammar task were "K" key labeled with a green sticker for grammatical stimuli and "L" key labeled with a red sticker for ungrammatical stimuli. Participants performed the artificial grammar task with their right hand (index finger for “K” and middle finger for “L”).

Results

Artificial grammar learning

The mean accuracy of prime classification was 63.3% (SD = 12.1) correct responses. This was significantly higher than 50% chance-level, $t(29) = 6.02$, $p < .001$, Cohen’s $d = 2.23$.

For the affective evaluation analysis, data analysis details were the same as in the first experiment – except for the trials in which participants did not classify prime in the allotted 4 seconds. These trials (3.6 %) were not analyzed.

Prime grammaticality effect

Response times. As in Experiment 1, we first assessed the effect of prime grammaticality on the RT of affective target categorization. We ran a 2 × 2 repeated-measures ANOVA with prime grammaticality as the within-subject factor and target valence as the between-subject factor. The main effects were not significant, Fs < 1. However, interaction was significant, $F(1, 34) = 9.15$, $p = .005$, $\eta_g^2 = 0.11$, indicating affective priming. Fig. 4 shows that after grammatical primes, positive targets were classified faster than negative ones, and vice versa after ungrammatical primes.

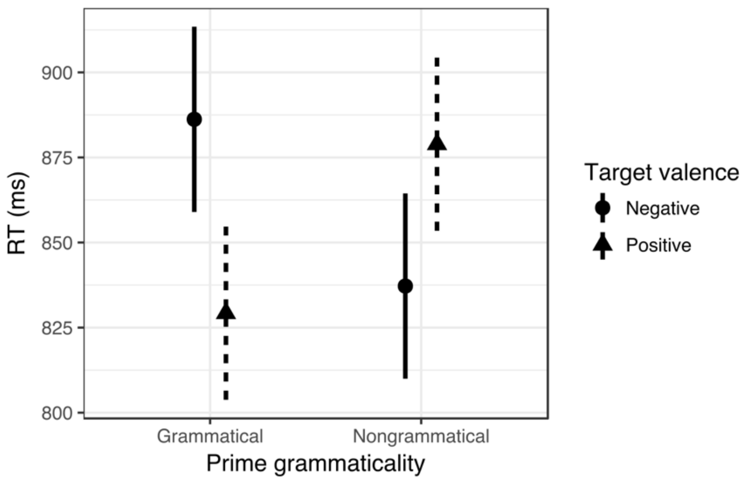

Fig. 5. Target categorization RT by prime grammaticality and target valence. Bars represent 95% confidence intervals.

A separate, paired t-test for grammatical primes revealed a significant difference between RTs for positive and negative targets, $t(17) = -2.94$, $p = .009$, Cohen’s $d = -1.42$. A separate, paired t-test for ungrammatical primes failed to reach significance, $t(17) = 1.61$, $p = .125$, , Cohen's $d = 0.78$ (Bonferroni correction for multiple comparison does not affect these conclusions).

Prime classification accuracy effect

Response times. We analyzed the effects of the accuracy of prime classification as grammatical or not on subsequent target categorization. We ran a 2 × 2 repeated-measures ANOVA with prime classification accuracy as the within-subject factor and target valence as the between-subject factor and target categorization RT as the dependent variable. No effects were significant, all $Fs < 1$.

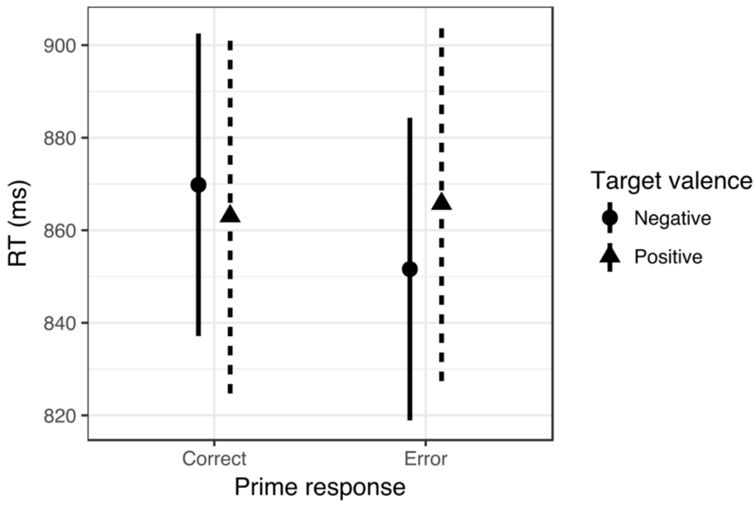

Fig. 6. Target categorization RT by prime accuracy and target valence. Bars represent 95% confidence intervals.

Prime grammaticality and accuracy interaction

We conducted a separate analysis of the grammaticality effects for trials with correctly and incorrectly classified primes. No three-way interaction was found for prime grammaticality × target valence × prime accuracy model.

Discussion

In contrast to Experiment 1, in Experiment 2, participants classified primes as grammatical or not before categorizing affective targets instead of merely observing primes. The change in design did not affect the main result of the first experiment, namely the interaction between prime grammaticality and target valence affecting the RT of target classification. However, whereas in the first experiment where we found negative priming by ungrammaticality, here we observe positive priming by grammaticality.

Despite the fact that we replicated the main effect of grammaticality, prime classification accuracy did not affect the main result – contrary to the predictions of APE. One possible explanation is the implicitness of the conflict in our study, while in the Eriksen flanker task, participants are usually consciously aware of the conflicts in the stimuli and of the accuracy of their decisions.

General discussion

In the two experiments, we investigated the automatic affective processing of new stimuli related to a previously learned implicit structure. Instead of typical deliberate liking decisions, we applied the affective priming paradigm to detect fast automatic affective responses to a violation of the implicitly learned grammar. This paradigm does not require the participants to evaluate grammatical / ungrammatical stimuli, using instead separate targets for evaluation. This allowed us to derive dissociated predictions from two approaches to SMEE. The results allow us to conclude that affective responses evoked by grammar violation are not just byproducts of processing but are related to some core process of predicting the outer world by the human cognitive system.

We observed affective priming in both experiments. In the first experiment, a negative response to ungrammatical stimuli was observed. In the second experiment, a positive response to grammatical stimuli was the primary source of the observed affective priming. This finding supports the hypothesis that affect in implicit learning reflects the predictive activity of the cognitive system, devaluating poorly predictable stimuli and valuing predictable ones.

The second experiment was conducted not only to replicate the results of the first, but also to investigate the possible effects of decisions made on the primes on the observed effects. However, we did not find any effects of participant errors contrary to the predictions of APE by some authors (Chetverikov & Kristjansson, 2016). In our study, the priming effect of grammatical and ungrammatical stimuli did not differ following correct and erroneous grammatical classifications of the primes. The absence of a negative valence of erroneous responses may be related to the unawareness of errors – in the AGL task, participants usually do not know that they have made an error. Whereas error-related devaluation was usually demonstrated on conscious errors (Chetverikov & Filippova, 2014; Chetverikov et al., 2015; Chetverikov et al, 2017; Ivanchei et al., 2018; Schouppe et al., 2015; however, see Chetverikov, 2014 for an exception). Alternatively, our failure to detect error-related devaluation may be related to the small amount of conflict in erroneous trials.

In AGL, the percentage of correctly classified stimuli is usually not much higher than 60 or 70%. In our study, it was 63.3%. Erroneous responses might not have been caused by or did not cause a strong conflict with the rest of acquired information because not enough of the grammar was learned by most of the participants. This hypothesis may be tested in a separate study which would look into the condition of better learning which at the same time remains implicit.

In sum, we found evidence for the predictive processing account of affective valence in implicit learning. FA cannot explain such fast affective reactions without the overt evaluation decisions of the stimuli. Importantly, in Experiment 1, we observed the effect only with short presentations of the primes. This is indicative of the affect caused by the prediction error but not for the fluency attribution. We did not find additional support for APE with predictions regarding the effect of participants' decision accuracy.

To this end, with the present results, we cannot rule out FA. However, we found at least an additional (if not the main) source of affective valence in AGL. This constitutes the novelty of our study. Future research may clarify the relationships between the experienced fluency and the positive affect due to the predictive activity of the cognitive system. These two approaches may not be mutually exclusive and fluency may play a role in the later stages of processing.

There is another approach to SMEE, which we did not consider due to its ambiguity: hedonic fluency theory. This theory suggests that fluency has positive valence itself (Reber et al., 2004). This theory has empirical support (Winkielman & Cacioppo, 2001) and some contradictory findings (Gerger, Forster, & Leder, 2017). For our research problem, it was important whether there is an additional, attributional, processing stage in SMEE. According to hedonic fluency theory, there is no need for such a stage. Therefore, despite the reference to fluency, within our research problem, this approach may be considered as related to APE, and thus supported by our data.

Our study contributes not only to the implicit learning literature but also to conflict processing studies, which usually use conflicts determined by previous experience. Among the most popular paradigms are the Stroop task and the Eriksen flanker task, which employ pre-determined sources of conflict. In the present study, we investigated conflict created during learning throughout the experiment. This approach allows us to study the emergence of an affective response in the dynamic and the basic underlying mechanisms of the predicting activity of the cognitive system. This may be done using concurrent measures of cognitive surprise from the beginning of the learning process (e.g. using pupil dilation measures, see Braem et al., 2015). The second advantage of our paradigm is that it creates implicit conflict in contrast to most studies in conflict processing domain. In AGL, participants are usually not aware of the learned grammar rules (however, part of their knowledge may be conscious, see Dienes & Scott, 2005; Ivanchei & Moroshkina, 2018). Unconscious conflict/error monitoring has been debated for a long time (Gehring et al., 1993; Desender, Van Lierde, & Van den Bussche, 2013; Charles, Van Opstal, Marti, & Dehaene, 2013), and some data have been presented on the aversive response to subliminal conflict (Frings & Wentura, 2008). Behavioral changes on the basis of conflict processing (conflict adaptation) were shown to occur only when participants experience the conflict subjectively (Desender, Van Opstal, & Van den Bussche, 2014). Our study gives additional support to the idea of automatic conscious affective responses to unconscious conflicts and therefore widens our knowledge of the mechanisms underlying conflict adaptation.

We think that this process is crucial for implicit learning where participants somehow may use their unconscious knowledge to guide behavior. Many studies show that in AGL, being unable to report any corresponding knowledge of the grammar, participants usually have some metacognitive sensitivity when applying this knowledge, i.e. they successfully discriminate between their correct and erroneous trials after classifying stimuli as grammatical or not (Dienes & Berry, 1997; Wierzchoń, Asanowicz, Paulewicz, & Cleeremans, 2012). People can also strategically apply different parts of their implicit knowledge according to the explicit demands of the task (Norman, Scott, Price, & Dienes, 2016). We suppose that this awareness about implicit knowledge application and metacognitive sensitivity may be rooted in affective processes which were investigated in this study. Facing new grammatical and ungrammatical stimuli, participants may use affect to make decisions or to their evaluate confidence in these decisions. Together with the experience of fluency, it may be regarded as a fringe feeling that helps us use all the available information, even if it is unconscious (Mangan, 2003). However, our data do not address this idea, which should be tested in a separate study.

Our study has some limitations. First, we did not measure the awareness of the grammar knowledge in either experiment. Pilot studies and informal post-experimental interviews revealed that the materials we used (geometric shapes) are more difficult for explicit learning than letter strings which we used in previous studies. In the first experiment, we did not inform participants about any regularities in the stimuli at all. Thus, we can be confident that learning was implicit and the observed effects can be attributed to unconscious conflict. However, it is still possible that proper measures of awareness (see e.g. Timmermans & Cleeremans, 2015) reveal that participants who had more explicit knowledge, or in trials where explicit knowledge application was possible, demonstrated larger priming by grammar violation. The second limitation is related to the timing variable. We did not have enough data points due to the random generation of prime durations in the first experiment, thus our conclusions on this variable are tentative. The investigation of temporal dynamics of the automatic affective response in AGL may be the aim of a separate study with controlled variation of prime duration and with a between-subject design (as done by Fritz and Dreisbach (2015) for Stroop stimuli).

Conclusion

In two experiments, we demonstrated that AGL produces affective responses to new stimuli depending on the structural similarity to learnt items. This affect is very fast and was observed without overt evaluative judgment. Therefore, it reflects the efficiency of the predictive activity of the cognitive system rather than the fluency attribution process. This study contributes to our understanding of the affective consequences of cognitive processes and suggests new directions for further investigation in different research domains.

Compliance with Ethical Standards

This study was funded by the Russian Science Foundation (grant number 17-78-10230).

Conflict of Interest: Ivan Ivanchei declares that he has no conflict of interest. Alexey Asvarisch declares that he has no conflict of interest.

Ethical approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent: Informed consent was obtained from all individual participants included in the study.

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