Role of implicit learning abilities in metaphor understanding

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Abstract

Although the use of metaphors is a central component of language, the processes that sustain their comprehension have yet to be specified. Work in the fields of both metaphors and implicit learning suggests that implicit learning abilities facilitate the comprehension of metaphors. However, to date, no study has directly explored the relationships between the understanding of metaphors and so-called implicit learning tasks. We used a meaning decision task comparing literal, metaphorical and meaningless expressions to assess metaphor understanding and a probabilistic serial reaction time task for assessing implicit learning. Our results show that implicit learning positively predicts the time gap between responses to literal and metaphorical expressions and negatively predicts the difference between metaphorical and meaningless expressions. Thus, when confronted with novel metaphors, participants with higher implicit learning abilities are better able to identify that the expressions have some meaning. These results are interpreted in the context of metaphor understanding and psycholinguistic theories.

Highlights

- The role of implicit learning in the comprehension of metaphors is examined.
- Implicit learning facilitates the understanding of literal expressions.
- Rejection of meaningless expressions is enhanced by implicit learning abilities.
- The impact of implicit learning on metaphor understanding is indirect.
- Implicit learning helps to disentangle meaningful from meaningless items.

Keywords: implicit learning, metaphors, figurative language, language processing, statistical learning

1. Introduction

1.1. Metaphors

Non-literal language is a kind of language from which, beyond the literal meaning, different interpretations can be extracted (Colston & Gibbs, 2002). In addition to irony and proverbs, metaphors constitute a huge proportion of non-literal language in our daily conversations (Lakoff & Johnson, 1980). Despite their importance, the processes that are involved in the understanding of metaphors are by no means understood.

Metaphors are expressions in which a semantic mapping between two conceptual domains is created. For instance, the sentence “Time is a thief” does not mean that time steals things (the literal meaning) but that time passes quickly and we risk missing opportunities (the figurative meaning). The use of metaphors is so widespread in human language that it is considered to be a fundamental conceptualization strategy (Lai, 2008). Indeed, according to Lai, the act of exploring the set of correspondences from a source to a target domain allows one to better understand the target thanks to the source’s conceptual structure.

Different types of metaphors are described in the literature. These types can be classified according to either their frequency (i.e., conventional vs. novel metaphors) or their structure (e.g., nominal vs. verbal metaphors). Concerning frequency, conventional metaphors (e.g., “Life is a journey”) are used daily, familiar and easy to understand (Giora, 1997; Lakoff & Johnson, 1980). Their meaning is nearly lexicalized and, most often, speakers do not even notice that they are using figurative language (Zufferey & Moeschler, 2015). Unlike conventional metaphors, novel metaphors are unusual in language production and their understanding depends on different cognitive processes than those involved in conventional metaphor processing (Ahrens et al., 2007). Whereas conventional metaphors are nearly lexicalized, the meaning of novel metaphors requires a listener to establish links between two concepts, namely the topic and the vehicle (Zufferey & Moeschler, 2015). An example of a novel metaphor appears in the sentence “His legs are rubber,” in which “rubber” is the vehicle and “legs” the topic.

Regarding structure, metaphors are frequently studied in their nominal forms (“X is a Y”; e.g., “Life is a journey”) in which both X and Y belong to the grammatical category of nouns. In this kind of metaphor, the two concepts are linked by applying the terminology of the vehicle to the terminology of the topic (Kiddon & Brun, 2011). For instance, in the sentence “Experience is a candle […],” a partial similarity of the vehicle “candle” is ascribed to the topic “experience” (Tourangeau & Sternberg, 1982). Hence, in this kind of metaphor, although the two concepts are not semantically close, a similarity is sought between them. In verbal metaphors, the focus is on the link between the verb and the vehicle (e.g., “the storm rumbles”), the topic (e.g., “the peasant tames the land”), or both (e.g., “clouds are courting the stars”) (Le Ny & Franquart-Declercq, 2002; Obert et al., 2014). In other words, metaphors represent a deviation in the meaning of the words composing them (Le Ny & Franquart-Declercq, 2002).

Nevertheless, few studies have explored the mechanisms involved in the production and comprehension of metaphors, although several suggestions have been made. For instance, on the topic of metaphor creation, Beaty and Silvia (2012) highlighted the role of executive functions. As for their understanding, an analogical mapping of different similarity levels, such as the attributes of the concept (in nominal metaphors) or their relations (in verbal metaphors), is required (Glucksberg, McGlone, & Manfredi, 1997; Holyoak & Koh, 1987; Le Ny & Franquart-Declercq, 2002). Thus, the understanding of nominal metaphors requires that the vehicle and the topic share identifiable common properties (Glucksberg et al., 1997). For instance, in the metaphor “this lawyer is a shark,” one should attribute appropriate features from the vehicle "shark" to the topic "lawyer" (e.g., is dangerous) and suppress inappropriate ones (e.g., has 300 teeth, is a marine animal) (Fernández, 2007). According to some authors, verbal metaphors are processed in the same way as nominal ones (Glucksberg, 2003), whereas others consider that they have special status (Le Ny & Franquart-Declercq, 2002; Utsumi & Sakamoto, 2011). For example, Le Ny and Franquart-Declercq (2002) suggest that understanding verbal metaphors depends on the central meaning of the verb, as well as all the topics and vehicles that it is possible to associate with this verb. Although there seems to be no consensus on how metaphors are understood, it nevertheless appears that their understanding may depend on implicit mechanisms.

1.2. Implicit learning

1.2.1. Implicit learning and language

Reber (1967) was the first to suggest that language could be acquired by implicit learning mechanisms. More recently, Saffran, Aslin, and Newport (1996), who first used the term "statistical learning" (also called implicit learning; Perruchet & Pacton, 2006), showed that 8-month infants were able to segment words based only on the statistical properties of language. Since these initial publications, many studies have explored the role of implicit learning in several aspects of language. Implicit learning appears to contribute both to low-level processes and to higher-level ones (Romberg & Saffran, 2010). At a lower level, human beings can apply transitional probabilities when learning speech sounds (e.g., Frost & Monaghan, 2016). At a higher level, they can learn the syntactic structure of a language (Thompson & Newport, 2007) and use verb-related distributional information to construct and understand meaningful sentences (Thothathiri & Rattinger, 2016).

Yu and Smith (2007) showed that the mapping between a word and its referent was remarkably efficient in various learning conditions. Indeed, it appears that adults are highly sensitive to probabilistic relationships between a word and its meaning (Vouloumanos, 2008). Implicit learning mechanisms are also involved in second language acquisition (Pajak, Fine, Kleinschmidt, & Jaeger, 2016). Moreover, the role of implicit learning in language has been explored at the individual level: long-term storage of syntactic structures during childhood (Kidd, 2012) and language comprehension in adults are enhanced in individuals with greater implicit learning abilities (Misyak & Christiansen, 2012).

According to Frost and Monaghan (2016), the same class of mechanisms (i.e., statistical learning) can account for word learning and structural generalization. We suggest that these mechanisms could extend the understanding of figurative language, and specifically metaphors, more broadly. Indeed, Lidz and Gagliardi (2015) argue that the capacity to produce and understand language intrinsically depends on implicit learning mechanisms that sustain the acquisition of relevant information to make inferences about the features of the grammar (i.e., a given class of words must be followed by another specific class of words – e.g., determiners precede nouns in English). This explanation provides a framework that accounts for the capacity to produce and understand novel sentences (i.e., situations that fall outside of a person's experience). It also explains how one can distinguish possible from impossible sentences of a language.

This view seems coherent with the dual-path model, a connectionist model that represents how humans acquire and process language (Chang, Dell, & Bock, 2006). The architecture of this model has two pathways: a meaning system and a sequencing system. The model is rather similar to Ullman's (2001) Declarative/Procedural model since the meaning system can be compared with declarative memory and the sequencing system with procedural memory. In the dual-path model, the sequencing system implicitly learns the syntactic structure of language. Interestingly, when the model learns syntactic structure, it also acquires semantic information. For instance, the model learns what kinds of things can be drunk or eaten. Thanks to the way that the sequencing system acquires semantic information about a word in position *N*, the model can predict what words are allowed in position *N+1*. For instance, the sequencing system might learn that some kinds of verbs (e.g., *kill, hurt, assassinate*) are most often followed by animate beings (e.g., humans or animals), are less often followed by abstract concepts (e.g., *hope, friendship*), and are never followed by inanimate objects (e.g., *rock, sheet*). This mechanism could explain how metaphors are understood thanks to implicit learning mechanisms.

1.2.2. Implicit learning and metaphors

An initial piece of evidence was provided by Glucksberg, Gildea, and Bookin (1982), who suggested that the understanding of metaphors is so automatic that it cannot be inhibited. This view is shared by Le Ny and Franquart-Declercq (2002), who claimed that verbal metaphor understanding relies on a form of implicit knowledge of possible verb-noun combinations. In their view, during verb processing, a verb activates various traits of its central meaning. If traits of a patient of the action are semantically congruent with the verb's traits, it will facilitate its acceptance. This could occur via the preactivation of some specific traits of the patient. A metaphor can be understood if the patient used in the metaphor belongs – even if it is unusual – to the set of possible patients of the verb. Interestingly, the set of possible patients that each individual possesses for any specific verb is hypothesized to be organized according to an implicit gradient. Similarly, Utsumi (2007) emphasized that the comprehension of metaphors can be explained by semantic richness. Given that Rabovsky, Sommer, and Rahman's (2012) study showed that semantic richness depends on implicit learning, there appears to be a link between implicit learning and the comprehension of metaphors.

Several studies in the field of implicit learning also support this possibility. First, Kaufman et al. (2010) showed that individual differences in implicit learning, defined as the automatic and unconscious learning of complex regularities from our environment, could explain individual differences in analogical verbal reasoning. In the classical form of an analogical verbal reasoning task, one has to find the link between two *a priori* unrelated concepts. Usually, the task takes the following form: “A is to B what C is to D.” For instance, “Paris:France::Brussels:Belgium” illustrates this kind of structure. In the sentence “Paris is to France what Brussels is to …,” one has to first spot the link between “Paris” and “France” (“is the capital of”), then apply it to “Brussels” and deduce the answer “Belgium.” In this kind of task, one has to establish links between disconnected (or unrelated) information, look at familiar things from a different angle and interpret unfamiliar things to the light of similar things (Zhao et al., 2011). Interestingly, the description of the analogical verbal reasoning task highlights the fact that it requires similar processes to those involved in understanding new metaphors (i.e., those that are not lexicalized but require the identification of shared properties to understand them). Moreover, according to Zhao et al. (2011), metaphors can be seen as part of analogical verbal reasoning because their understanding is sustained by similar reasoning. Indeed, in the nominal metaphor “this lawyer is a shark,” one has to extract the appropriate features of the topic “shark” and apply them to the agent “lawyer” in order to understand the figurative meaning of the sentence. Thus, given that implicit learning abilities are involved in analogical verbal reasoning and that understanding metaphors can be seen as a kind of analogical verbal reasoning, it seems likely that implicit learning abilities are involved in the understanding of metaphors.

This hypothesis was tested by Li, Guo, Zhu, Yang, and Dienes (2013). In their study, participants had to perform a task with two phases: a training phase and a testing phase. During the training phase, they were taught to use four symbols that they did not know in sentences. Two of these symbols were associated with a near distance and the other two were associated with a far distance. Participants were not told that each pair of symbols was also associated with a height-related meaning (i.e., high and low). During the training phase, each symbol was used only in descriptions of spatial height (e.g., the sky should be associated with the symbol that represents “high” and the ground with “low”). After the training phase, participants were asked to complete sentences with the symbols used in that phase. Among the target items, there were items that represented social power (e.g., “captain” – “sailor”) instead of spatial height. The authors showed that participants were able to generalize the use of the symbols to the metaphorical sense of height. According to these authors, the mapping between the literal and metaphorical meanings of the symbol was sustained by implicit learning mechanisms.

Although Li et al.’s (2013) study was the first to explore the role of implicit learning in metaphors, it was not able to determine whether implicit learning processes are involved in the creation or comprehension of metaphors since participants had to choose the correct symbol (which can be seen as creation) in a stipulated context (which can be seen as comprehension). According to our review, it seems more likely that implicit learning processes sustain the comprehension rather than creation of metaphors (although we cannot exclude the latter possibility). This issue can be addressed by adapting the judgment task used by Lai, Curran, and Menn (2009). In their study, participants had to indicate on a Likert scale whether an expression did or did not make some sense (i.e., perfect sense, some sense, little sense, no sense). By using this task with a binary approach (does the sentence make sense? yes/no), reaction times should be less influenced by hesitation in choosing between the possible choices (e.g., for me, does the sentence make sense at level 2 or level 3?). Moreover, the use of a binary approach allows one to avoid the possibility that participants understood the different levels of the Likert scale differently (i.e., a sentence could make some sense for one individual but little sense for another, although both understood the sentence similarly).

1.2.3. The measurement of consciousness

Another limitation of Li et al.'s (2013) study is the measures used to ensure the implicit nature of the learning. They used three measures: the "zero correlation criterion," the "guessing criterion" and "trial-by-trial structural knowledge attributions." The zero correlation criterion states that knowledge is unconscious if there is no correlation between the subject's confidence in his/her answer and the answer's precision (Dienes & Berry, 1997). According to the guessing criterion, knowledge is unconscious if an individual succeeds at a task above the chance level despite thinking that he/she was guessing at the answers (Cheesman & Merikle, 1984). Finally, trial-by-trial structural knowledge attributions allow participants to assess their own structural knowledge when they are asked to judge the answers provided (Dienes & Scott, 2005). All these measures are considered to be subjective measures and have been criticized by Shanks, Lamberts, and Goldstone (2005), among others. Subjective measures are not deemed to be reliable given that they do not meet the criterion of exhaustivity (i.e., the test must be sensitive to all of conscious knowledge). These criticisms are reinforced by the fact that, for all these measures, some participants in Li et al.'s study developed some explicit awareness during the task. Moreover, Li et al. (2013) used the Bayes factor in order to determine whether explicit processes were involved in the task. Bayes factors are alternatives to null hypothesis tests. In the more simplistic situation, they are obtained by the ratio of two likelihoods (i.e., the logarithm of a probability). The first likelihood is the probability that the dataset brings evidence for a given *a priori* chosen difference (i.e. the presence of explicit knowledge) and the second probability is the probability that the dataset is coherent with the absence of difference (i.e., absence of explicit knowledge). If the ratio is superior to 3, it can be interpreted as supporting the presence of a difference; if it is inferior to 0.33, it can be interpreted as supporting the absence of the difference; if it is between 0.33 and 3, it is uninformative. In Li et al.'s (2013) study, the Bayes factor was uninformative on the possible involvement of explicit processes. Thus, a cautious position would not rule out the possibility that the results can, at least partly, be attributed to the intervention of explicit mechanisms. In addressing this issue, we can rely on Jiménez (2003), who has suggested that implicit learning mechanisms can be reliably assessed by a probabilistic serial reaction time task (SRT task) (see also Kaufman et al., 2010).

Indeed, the SRT task, developed by Nissen and Bullemer (1987), is one of the most widely used tasks for exploring implicit learning. In this task, participants are asked to respond as accurately and as quickly as possible to stimuli that appear on a screen by pressing the key that corresponds to their location on the screen. Unbeknownst to the participants, stimuli do not appear randomly but follow a sequence. Usually, there are four locations and learning is evidenced after several training blocks by shorter reaction times for the learning sequence in comparison to the reaction times for another sequence (the transfer block). In the probabilistic version of the SRT task (Schvaneveldt & Gomez, 1998), irregularities are introduced in the sequence according to a probabilistic mechanism (see section 2.2.1 for details). In such a task, implicit learning is attested to by faster responses for probable than for improbable items. This task is claimed to be less sensitive to explicit influences than the deterministic version of the task (e.g., Stefaniak, Willems, Adam, & Meulemans, 2008). In fact, the irregularities introduced in the task make it almost impossible for participants to detect the sequence pattern. This is true even when participants are explicitly told about the structure of the task (Stefaniak et al., 2008). Thus, given that the probabilistic SRT task is less controversial, it can be used to reduce the issues raised by Li et al.'s (2013) study.

2. Aims and hypotheses

Although Li et al.'s (2013) study provided some initial evidence concerning the relationships between implicit learning mechanisms and metaphors, two issues remain to be addressed. The aim of our study is to address these issues by investigating the impact of implicit learning abilities on the understanding of metaphors. If implicit learning abilities are involved in analogical verbal reasoning (Kaufman et al., 2010), and if understanding metaphors is sustained by analogical verbal reasoning (Zhao et al., 2011), then we can predict that participants with better implicit learning abilities should be better able to understand metaphors.

More specifically, we used a meaning decision task in which participants had to decide whether they were able to make sense to verb + patient expressions. There were three categories of expressions: literal ("catapulter des pierres" ["catapult rocks"]), novel metaphorical ("catapulter des paroles" ["catapult speech"]) and meaningless (i.e., sentences for which it would be very hard to find a meaning, such as "adopter un nuage" ["adopt a cloud"]). If there is a spreading activation gradient based on the congruence between the verb and the patient (Benau, Morris, & Couperus, 2011), and if richer concepts are activated faster (Kounios et al., 2009), individuals who have larger semantic networks should be quicker at finding a meaning for literal expressions since they should have more features associated with each concept (i.e., greater semantic richness) and more patients considered as congruent with each verb (which increases the probability that the patient of the expression will belong to the set of patients preactivated by the automatic spreading activation).

Concerning the processing of metaphors, given that we used novel metaphors, the metaphorical expressions could not benefit from automatic spreading activation. Consequently, because participants with richer semantic networks would likely explore more indirect connections, the temporal interval between literal and metaphorical expressions should be longer for those individuals. Since Rabovsky et al. (2012) showed that semantic richness depends on implicit learning, participants with larger semantic networks should have greater implicit learning abilities. Thus, the interval between the literal and the metaphorical expressions should be longer for those participants. Once spreading activation processes fail to find a preexisting meaning in the semantic networks, participants have to find possible links between the verb and the patient in order to create a meaning for a metaphorical expression. In this case, individuals must identify appropriate features of both the verb and the patient that can be used to make sense of the expression. Because the identification of similarity in a verbal reasoning task depends on implicit learning abilities, we hypothesized that participants with better implicit learning abilities would be better in identifying metaphorical meaning than participants with lower implicit learning abilities, and should be faster at finding meanings for metaphorical expressions. Finally, when an individual fails to find any meaning because the patient is impossible (i.e., meaningless expressions), the participant should decide that it is not possible to make sense of the expression. Thus, as participants with better implicit learning abilities should find meanings for metaphorical expressions quite easily but should not be able to find any meanings for meaningless expressions, the interval between metaphorical expressions and meaningless expressions should be longer for participants with better implicit learning abilities than for those with lower implicit learning abilities.

2. Method

2.1. Participants

Eighty-six participants took part in this study (47 women; mean age: 23 years old; minimum age: 18; maximum age: 35). Exclusion criteria were the presence of learning disabilities, any history of psychiatric or speech problems, and consumption of alcohol or cannabis (or other drugs) in the last 48 hours. Inclusion criteria were to be French native speakers, aged between 18 and 35 years old. All participants signed an informed consent form. The study was carried out in accordance with the guidelines of the Helsinki Declaration.

2.2. Materials and procedure

All the participants had to perform the SRT task, a meaning judgment task and the Mill Hill vocabulary test (Deltour, 1993), in this order.

2.2.1. Serial reaction time task

The SRT task used in the current study was constructed similarly to Kaufman et al.'s (2010) task. Participants sat in front of a computer screen on which four white arrows were presented on one horizontal line against a black background. Each location was associated with a key on the keyboard (i.e., from left to right, the "c," "v," "b" and "n" keys on an AZERTY keyboard). The stimuli were white dots which could appear below any of the four locations. Participants were asked to press the key corresponding to the location of each stimulus as quickly and as accurately as possible. The participants did not know that the stimuli were not randomly generated but followed a probabilistic sequence, which was produced with 85% regular and 15% irregular items. The learning sequence was a second-order conditional (SOC) sequence. For half of the participants, the learning sequence was “1-2-1-4-3-2-4-1-3-4-2-3” and the irregularities were generated from a second SOC sequence, “3-1-4-2-1-3-2-3-4-1-2-4.” For instance, if a break was generated for the fourth location of the learning sequence (i.e., “4”), the irregularity was produced as follows: given that the “4” appearing in the fourth position of the learning sequence is preceded by the “2-1” association, the location of the irregularity is “3” since the “2-1” association is followed by “3” in the other sequence (for a more detailed description, see Kaufman et al., 2010). The sequences were counterbalanced for the other half of the participants. The stimulus onset asynchrony was 250 ms. The task was composed of 8 blocks of 120 items for a total of 960 stimuli. Each block was separated from the next one by a pause.

2.2.2. Meaning decision task

Forty-seven literal (e.g., “catapult rocks”) and 47 meaningless (e.g., “adopt a cloud”) verb + patient expressions were constructed. To match the 47 literal expressions, we tried to create metaphorical expressions (e.g., “catapult speech”) with the same verb, but we succeeded for just 41 of them, resulting in a total of 135 expressions (47 literal + 47 meaningless + 41 metaphorical). The patients in the literal and metaphorical expressions were paired according to their frequency and length. Meaningless expressions were built from different verbs associated with different patients than in the literal and metaphorical expressions. Several of these 135 expressions appeared to be equivocal (e.g., meaningless expressions for which a meaning could be found or metaphorical expressions that were not novel) and were removed from the material. After this first screening, 38 literal, 38 metaphorical (paired with the literal), and 19 meaningless expressions remained. Among these items, the literal expressions can be considered as easy, familiar and having a high imagery level; the meaningless expressions can be considered as being difficult, unfamiliar and having a having low imagery level; and the metaphorical expressions fell between the literal and meaningless expressions on these three measures. We ensured that these criteria were met by asking 180 participants to judge the difficulty (on a 7-point Likert scale in which 1 = “very difficult to find a meaning” and 7 = “very easy to find a meaning”), familiarity (on a 7-point Likert scale in which 1 = “not familiar at all” and 7 = “very familiar”), and imagery scales (on a 7-point Likert scale in which 1 = “very difficult to represent” and 7 = “very easy to represent”). Each participant made only one judgment (i.e., familiarity or difficulty or imagery) and only for (1) literal and meaningless expressions or (2) metaphorical expressions, but not both, given that the verbs were the same in the literal and metaphorical expressions. The normative data for these three measures are presented in Table 1.

INSERT TABLE 1 ABOUT HERE

Participants saw a black fixation cross on a white background for 250 ms. After the fixation cross, a verb + patient expression appeared in lowercase on the screen in black characters on a white background. The expression remained on the screen until the participant responded. Participants were asked to determine whether they could find some spontaneous meaning for the expression that appeared on the screen.

2.2.3. Mill Hill vocabulary test (Deltour, 1993)

In this test, participants had to decide which of possibilities is the synonym of a given word. The test is composed of 34 items organized according to an increasing difficulty. One point is attributed for each correct response. This test allows researchers to determine participants’ vocabulary level in order to control for individual differences in the analyses.

3. Results

Statistical analyses were performed using R software (R core team, 2017), as well as the "nlme" (Pinheiro, Bates, DebRoy, Sarkar, & R core team, 2017), "psych" (Revelle, 2017), and "WRS2" (Mair, Schoenbrodt, & Wilcox, 2017) packages.

Data were aggregated by using the median correct responses for each participant computed separately for blocks and item and expression types in the SRT task and meaning decision task, respectively. In the meaning decision task, the response "has some meaning" was considered as correct for the literal and metaphorical expressions, while the response "has no meaning" was considered as correct for the meaningless expressions. Globally, the task was understood and performed seriously given that the mean errors were 1.76 for the literal condition, 3.49 for the metaphorical condition and 3.68 for the meaningless condition. One participant was removed from the analysis because the visual inspection of leverage measures (Cook's Distance and hat matrix) indicated that it affected both the main analyses.

3.1. Implicit learning effect

To determine whether learning occurred during the SRT task, we used a linear mixed model on reaction times (RTs) with Block (8 levels) and Type of item (2 levels: probable vs. improbable) as within-participant variables (i.e., crossed variables). This analysis revealed a significant effect of Block, $F(7,588) = 8.67$, $p < .001$, and a significant effect of Type of item, $F(1,672) = 130.83$, $p < .001$, showing that probable items were processed faster than improbable ones. Finally, the interaction was also significant, $F(7,672) = 6.43$, $p < .001$.

The polynomial contrast indicated that the decrease in RTs followed a linear relationship, $t(588) = –6.42$, $p < .001$, $r^2 = 0.07$, and that the gap between probable and improbable items also tended to increase linearly, $t(672) = –4.21$, $p < .001$, $r^2 = 0.03$ (Figure 1).

INSERT FIGURE 1 ABOUT HERE

The fact that probable items were processed faster than improbable ones suggests that implicit learning occurred. Thus, it was relevant to compute a learning index for each participant. Kaufman et al. (2010) highlighted the importance of using a reliable measure of implicit learning (for a more general view, see also Siegelman & Frost, 2015). Following their recommendation, the learning index was obtained by counting the number of probable items that were processed significantly faster than the improbable items. The significance level was determined by the fifth percentile of improbable items.

To ensure that our measure was reliable, split-half reliability on Blocks 3 to 8, as in Kaufman et al.'s (2010) study, was calculated using the "psych" package (Revelle, 2017). This analysis revealed that the minimum split-half reliability was .47, the mean split-half reliability was .48 and the maximum split-half reliability was .63. Our measure appears at least as reliable as Kaufman et al.'s (i.e., .44), and possibly better. We also used standardized Cronbach's alpha, and its value was quite similar to the value for split-half reliability (i.e., .53).

3.2. Types of expressions in metaphor processing task.

To test the hypothesis that the meaning decision task should be sensitive to the difference in processing between literal and metaphorical expressions, we computed a linear mixed model on RTs with the Type of expression (3 levels: literal, metaphorical, meaningless) as a within-participant variable (i.e., crossed variable), which was complemented by an ANOVA on trimmed means due to the asymmetry of the residual distribution. This analysis revealed a significant effect of Type of expression, both for the linear mixed effects estimation, $F(2,168) = 39.35$, $p < .001$, and for the trimmed mean ANOVA, $F(1.5, 75.17) = 33.00$, $p < .001$.

Orthogonal planned comparisons revealed that the expressions correctly classified as meaningful (i.e., literal and metaphorical) were processed faster than the meaningless ones, $t(168) = 7.77$, $p < .001$, $r^2 = .26$. Moreover, literal expressions were processed faster than metaphorical ones, $t(168) = 4.28$, $p < .001$, $r^2 = 0.10$ (Figure 2).

INSERT FIGURE 2 ABOUT HERE

The fact that metaphorical expressions were processed slower than literal expressions and faster than meaningless expressions makes it relevant to compute indices to assess participants' ease in understanding metaphors. In accordance with Le Ny and Franquart-Declercq's (2002) work, these two indices were formulated within the framework of general models of language comprehension and based on the incremental nature of language comprehension. According to this view, semantic representations of verbs contain knowledge of the participants involved in the situation described by the verb (Ferretti, McRae, & Hatherell, 2001; McRae, Ferretti, & Amyote, 1997). For instance, people know that a typical patient of the verb *assassinate* is a human being. This knowledge is used to pre-activate the salient semantic features of the verb's typical agents and patients. The meaning of each incoming word is supposed to be incorporated, as soon as it is encountered, into the representation of the statement that is under construction. As a result, this representation is gradually adapted and progressively refined, taking into account the meaning of each word and its context. In this regard, a non-conventional metaphor expresses an innovative meaning: metaphor comprehension should involve the activation of the non-salient features of words that are appropriate in the context of the metaphor. Finally, when none of the features of the words in question are appropriate, no meaning can be found. Thus, some verb patients are easily accepted, given that it is likely that their features are pre-activated (i.e., a process of meaning retrieval for literal expressions); unusual patients may be accepted if non-salient features can be activated (i.e., a process of sense creation for metaphorical expressions); and some patients are considered as impossible because even their non-salient features are inappropriate, as is the case for our meaningless expressions. In other words, each of the three conditions represents a different level of acceptability on the continuum of patient acceptability described by Le Ny and Franquart-Declercq (2002).

Since adults are sensitive to very small probabilistic differences (e.g., in the context of mapping new word–object pairs; Vouloumanos, 2008), metaphorical expressions should be considered as much less probable than literal ones but should be much more probable than meaningless ones. Differences in RTs should be larger for participants who are more sensitive to probabilistic regularities, that is, participants with better implicit learning abilities. This hypothesis can be tested by calculating two indices on the correctly classified expressions. The first index (Index 1) was calculated as follows: $\frac{RT_{metaphorical} - RT_{literal}}{mean\ RT}$. The second index (Index 2) was computed as $\frac{RT_{meaningless} - RT_{metaphorical}}{mean\ RT}$. For both these indices, the difference between conditions was divided by the mean RTs of the three conditions (considered as the baseline) in order to control for differences in individuals' processing speed.

3.3. Implicit learning abilities in the understanding of metaphors

To determine the impact of implicit learning abilities in finding meanings for metaphorical expressions, we executed two multiple regression analyses. In the first analysis, the dependent variable was Index 1 and independent variables were the implicit learning index and the Mill Hill vocabulary score (to control for vocabulary knowledge, which could help in finding meaning). Multinormality was violated, so we used robust statistics (i.e., bias-corrected and accelerated (BCA) bootstrapping). This analysis revealed that the slope of the implicit learning abilities index was positive and significantly different from 0. This model explains 11% of the variance, $F(2,82) = 4.99$, $p = .009$. The impact of each variable is presented in Table 2.

INSERT TABLE 2 ABOUT HERE

This analysis suggests that the RT interval between the literal and metaphorical conditions increases for individuals with higher implicit learning abilities.

We performed the same analysis with Index 2, revealing that the slope of the implicit learning abilities index was negative and significantly different from 0. This model explains 6 % of the variance, $F(2,82) = 2.66$, $p = .076$. The impact of each variable is presented in Table 3.

INSERT TABLE 3 ABOUT HERE

This analysis shows that the RT interval between the metaphorical and meaningless conditions decreases for individuals with higher implicit learning abilities.

3.4. Supplementary analysis

Given that, contrary to our hypothesis, the regression coefficient for implicit learning abilities is negative, we performed exploratory analyses to determine whether this index was influenced most by the processing time for metaphorical or for meaningless expressions. More specifically, if one postulates that processing time for meaningless expressions does not vary and that processing time for metaphorical expressions does vary, the correlation between Index 2 and the metaphorical condition would be 1. This correlation could be interpreted as showing that individuals with lower values for Index 2 find it difficult to make sense of metaphorical expressions, while individuals with higher values can quite easily find some meaning for metaphorical expressions. Conversely, if one postulates that processing time for meaningless expressions varies and that processing time for metaphorical expressions does not, the correlation between Index 2 and the meaningless condition would be 1. In that case, individuals with higher values for Index 2 have more difficulties rejecting meaningless expressions than individuals with lower values. Obviously, both postulates are unlikely and the reality is likely to be between these extremes. Nevertheless, it is possible to determine whether one aspect (i.e., ease of finding a meaning for metaphors or difficulties rejecting meaningless expressions) is predominant by comparing the two correlations. To determine which condition was more associated with Index 2 (i.e., time cost of meaning creation or ease of rejecting meaningless expressions), we performed two correlation analyses: one between Index 2 and RTs for the metaphorical condition and one between Index 2 and RTs for the meaningless condition. When normality was respected, the Bravais-Pearson coefficient is reported, while Spearman's rho is used when normality was violated. The first analysis explored the correlation between the time required in the metaphorical condition and Index 2. It revealed that metaphor processing was negatively correlated with Index 2, rho = –.347, $p = .001$. The second analysis explored the correlation between the time required in the meaningless condition and Index 2; this analysis revealed a significant positive correlation, $r = 0.60$, $p < .001$.

As expected, both conditions were correlated with Index 2. In order to determine which view is more likely (i.e., time cost of meaning creation or ease of rejecting meaningless expressions), we compared the values of both correlations with the absolute value. It appears that Index 2 is more associated with the meaningless condition than with the metaphorical condition, $z = 2.12$, $p = .03$, suggesting that larger values of Index 2 can most likely be attributed difficulties rejecting meaningless expressions.

These three supplementary analyses remain significant even after a Holm correction of probability.

4. Discussion

Although metaphors are a fundamental part of language and are widely used to conceptualize complex ideas (Lai, 2008), little is known about the fundamental processes that influence metaphor comprehension. Several studies have suggested that implicit learning abilities may be involved in the understanding of novel metaphors (Kaufman et al., 2010; Li et al., 2013; Zhao et al., 2011). Thus, we hypothesized that, beyond the role of implicit learning abilities on syntax (Thompson & Newport, 2007), word acquisition (e.g., Vouloumanos, 2008), second language learning (Pajak et al., 2016) and even comprehension of literal language (Misyak & Christiansen, 2012), they could play a more specific role in metaphor understanding. Although this question was addressed in Li et al.'s (2013) study, we noted several limitations of that study; in particular, the measure of implicit learning could be questioned and it was not clear whether implicit learning mechanisms were involved in the creation or in the understanding of metaphors. To get around these limitations, we followed and attempted to improve on Kaufman et al.'s (2010) suggestion that a reliable measure should be used to assess implicit learning abilities, and used a meaning decision task to explore metaphors.

Concerning the measure of implicit learning abilities, although Kaufman et al.'s (2010) measure was reliable, it could be claimed to lack sensitivity. Our measure – the number of probable items that were processed significantly faster than the improbable ones (i.e., RTs inferior to the fastest 5% of the improbable items) – appears as reliable as Kaufman et al.'s, but we believe it to be more sensitive. Nevertheless, our study does not allow us to assess the test-retest reliability, which can be weak for the SRT task (Siegelman & Frost, 2015). This question should be addressed in future studies.

In the meaning decision task, we showed a gradient of increasing processing time from literal expressions to metaphors and finally to meaningless expressions. This result is in accordance with Le Ny and Franquart-Declercq's (2002) view of the semantic congruence hypothesis. In their view, the processing of a verb automatically activates congruent patients, which facilitates decisions regarding the meaning of the verb + patient expression. Since patients in literal expressions present the highest probability of activation, their processing should be facilitated in comparison to the novel metaphor expressions, which explains why metaphorical expressions are processed slower than literal ones. Similarly, given that the patients in the meaningless expressions are improbable, they are not activated by the verb and more time is required for their processing.

The presence of this gradient made it relevant to explore the processes involved in the comprehension of metaphors. Our results showed that individuals with better implicit learning abilities presented larger time intervals between the RTs for literal and metaphorical expressions. This result is consistent with our hypothesis that individuals with better implicit learning would create more and stronger associations in their semantic networks. Indeed, implicit learning abilities are involved in semantic richness (Rabovsky et al., 2012), which would allow literal expressions to be processed very quickly by automatic spreading activation processes. Conversely, when participants have to find a meaning for a metaphorical expression, this kind of meaning retrieval is not possible given that we used novel metaphors. Thus, participants with richer semantic networks may have had to explore and reject more possible meanings than individuals with less rich semantic networks; as a result, the former required more processing time. This explanation can also be applied to the meaningless condition since the patients in these expressions did not match any of the possible patients activated by the verb. Our interpretation is coherent with the suggestion that language abilities can be predicted by inter-individual differences in implicit learning, and more specifically with Rabovsky et al.'s (2012) view that implicit learning and semantic richness are associated. Our interpretation, whereby inter-individual differences in implicit learning are involved in language proficiency, could be quite easily tested by determining whether individuals with larger semantic priming effects also have enhanced implicit learning abilities. Moreover, if a link between semantic priming and the comprehension of metaphors is observed, it would give more support to the semantic congruity hypothesis.

We suggested that Index 2 (i.e., the difference between the metaphorical and meaningless conditions) could reflect the probabilistic continuum of acceptability between an unusual but acceptable and an extremely unlikely patient. For the unusual acceptable patient, a sense can be created by activating non-salient features of the words, while this is almost impossible for the extremely unlikely patient. Given that individuals are highly sensitive to probabilistic constraints of language, participants with greater implicit learning abilities should find it easier to identify that metaphorical patients are more probable than meaningless ones (leading to larger values for Index 2). Contrary to our hypothesis, though, the slope between Index 2 and implicit learning abilities was negative, which means that the RT differential between the metaphorical and meaningless expressions was shorter for individuals with higher implicit learning abilities. This result can be interpreted in light of Benau et al.'s (2011) finding that semantic incongruities are processed fast (see also Kutas & Hillyard, 1980). Similarly, Glucksberg et al. (1982) observed that, when participants were asked to reject incorrect literal sentences, they were slower to reject sentences for which a metaphorical sense could be found (e.g., "some jobs are jails") than sentences for which it was not possible to find a metaphorical meaning (e.g., "some roads are jails").The correlations indicate that the size of Index 2 depends more on the time needed to decide that an expression in the meaningless condition does not have any sense than on the time to decide that an expression in the metaphorical condition could have a meaning. Thus, people with higher implicit learning abilities tend to process semantic incongruity more efficiently, and the role of implicit learning abilities may be directly related not to the comprehension of metaphors but rather to the intuition that it is or is not possible to find a meaning for an expression. Thus, it looks as if participants with higher implicit learning abilities are more sensitive to the certitude that the patient is an impossible one, which means that the level of certitude is equally high for a probability of 1 than for a probability of 0 that an event can occur and reach a minimum when probability is 0.5. This view is coherent with Benau et al.'s (2011) finding that semantic incongruities are processed fast (see also Kutas & Hillyard, 1980). In other words, participants with higher implicit learning abilities may be more efficient at distinguishing between expressions with no meaning and expressions with a meaning, even if the meaning is not easily processed (as in novel metaphorical expressions). Our interpretation is close to Bolte and Goschke's (2005) view that semantically coherent sentences are processed automatically and depend on the intervention of implicit and associative processes.

The results of our study also seem coherent with the neuroanatomical and pathophysiological literature. Implicit learning is partly sustained by the basal ganglia (Meier et al., 2013; Wilkinson, Khan, & Jahanshahi, 2009), which may also be involved in metaphor processing (Uchiyama et al., 2012). Indeed, Copland (2003) showed that people suffering from a basal ganglia lesion were impaired at processing ambiguous sentences. Given that metaphors can be seen as ambiguous sentences because they can possess two different meanings (i.e., the literal and the metaphorical one), their processing should also be sustained by the basal ganglia. Moreover, according to Chenery, Angwin, and Copland (2008), the basal ganglia may facilitate and/or suppress different meanings relative to a context in which there are lexical ambiguities, which recalls the suppression mechanism posited to be involved in the comprehension of nominal metaphors (Fernández, 2007). Finally, Sato, Schafer, and Bergen (2015) pointed out that understanding metaphors may rely partly on the activation of cerebral area dedicated to sensorimotor control (i.e., the basal ganglia). Nevertheless, to date, no study has tried to establish a possible connection between the cerebral areas involved in metaphor processing and implicit learning, and further studies should be conducted to explore this possibility. For instance, the investigation of populations with lesions in the basal ganglia, such as patients with Parkinson's disease or Huntington's chorea (Wilkinson et al., 2009; Willingham & Koroshetz, 1993), could provide further evidence about the relationships between implicit learning abilities and metaphor comprehension. This study provides additional evidence that implicit learning abilities affects even the highest level processes of language. Our results also have some implications for populations suffering from language impairments, such as children with specific language impairment (SLI). Indeed, it has been shown that these children present lower implicit procedural learning abilities (e.g., Ullman & Pierpont, 2005; Lum, Gelgic & Conti-Ramsden, 2010; Gabriel et al., 2013). Thus, considering the results of the present study, one could hypothesize that children with SLI might have some difficulties understanding metaphors. This question remains to be addressed.

One key limitation on the current study is the fact that it does not allow us to determine whether the meanings attributed to the metaphors are qualitatively better for participants with higher implicit learning abilities than for those with weaker abilities. Further studies should explore this issue.

5. Conclusions

This study aimed to explore the involvement of implicit processes in metaphor processing. Our results corroborate Li et al.'s (2013) findings with a more robust and reliable measure of implicit learning: implicit learning abilities are involved in the understanding of metaphors. Our results are also coherent with Kaufman et al.'s (2010) study. Our study opens up new research perspectives, especially in the exploration of the link between semantic priming processes and metaphor processing, and of spreading activation mechanisms, and could have implications for the identification of difficulties in SLI patients.

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Figure captions

Figure 1: Mean RTs (milliseconds) depending on the type of sequence (improbable vs. probable) and the type of block (1 to 8).

Figure 2: Mean RTs (milliseconds) depending on the type of expression (literal vs. metaphorical vs. meaningless).

Figure 1.

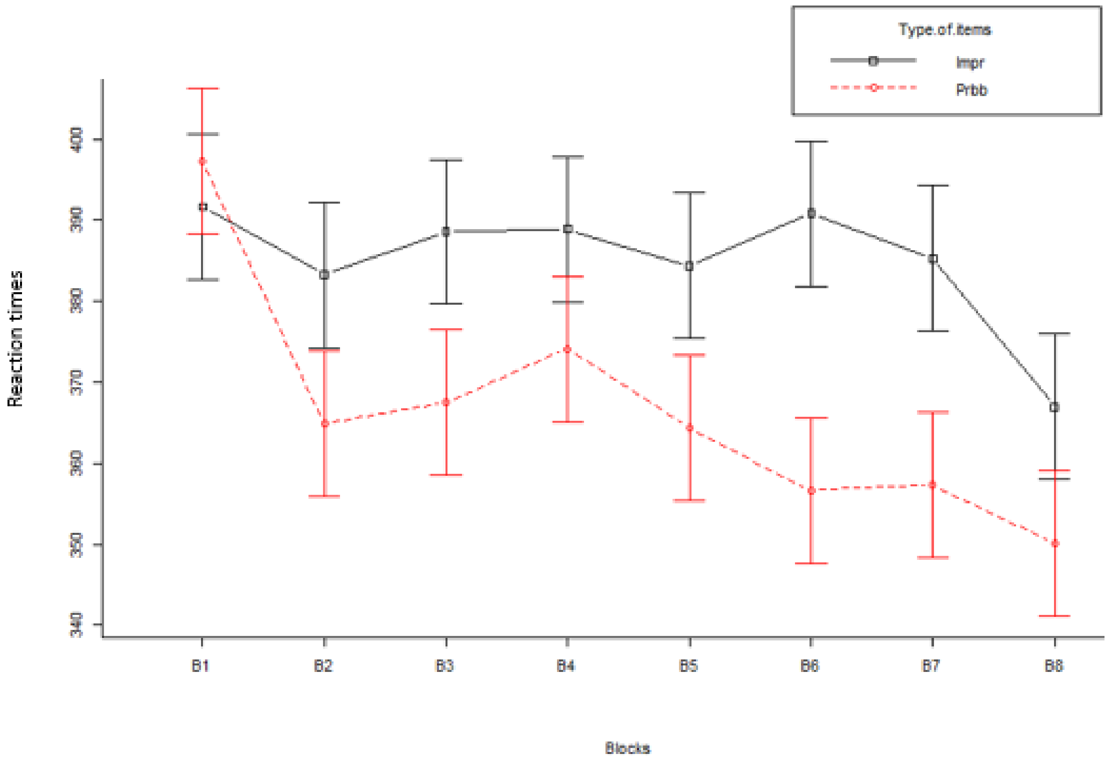
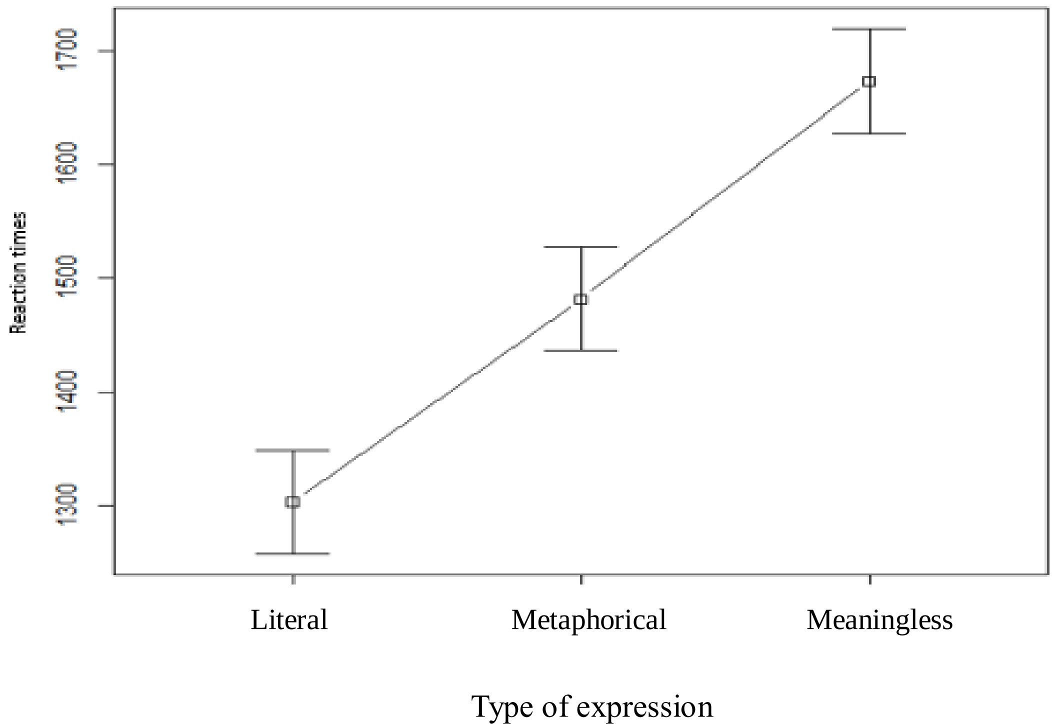

Type.of.items
Impr
Prbb
Reaction times
340
350
360
370
380
390
400
B1
B2
B3
B4
B5
B6
B7
B8
Blocks

Figure 2.



Reaction times
1700
1600
1500
1400
1300
Literal
Metaphorical
Meaningless
Type of expression

Table 1. Mean (and SD) for the different types of expressions.

	Literal	Metaphorical	Meaningless
Familiarity	4.78 (0.69)	3.44 (0.6)	1.69 (0.39)
Difficulty	2.03 (0.65)	2.7 (0.71)	4.6 (0.58)
Imagery	3.6 (1.15)	2.94 (0.68)	1.16 (0.19)

Table 2. Regression coefficient (and confidence interval estimated by bias-corrected and accelerated bootstrapping) for the effect of implicit learning abilities and Mill Hill vocabulary score on Index 1 (semantic richness).

Variable	b (BCA bootstrap CI)	β	t	p	ΔR^2
Implicit learning	0.002 (0.001, 0.003)	0.314	3.006	.004	0.094
Mill Hill	0.005 (–0.003, 0.012)	0.122	1.172	.245	0.015

Table 3. Regression coefficient (and confidence interval estimated by bias-corrected and accelerated bootstrapping) for the effect of implicit learning abilities and Mill Hill vocabulary score on Index 2 (sense creation).

Variable	b (95% bootstrap CI)	β	t	p	ΔR²
Implicit learning	–0.003 (–0.007, –0.0001)	–0.23	–2.15	.035	0.056
Mill Hill	0.005 (–0.010, 0.022)	0.072	0.672	.503	0.005