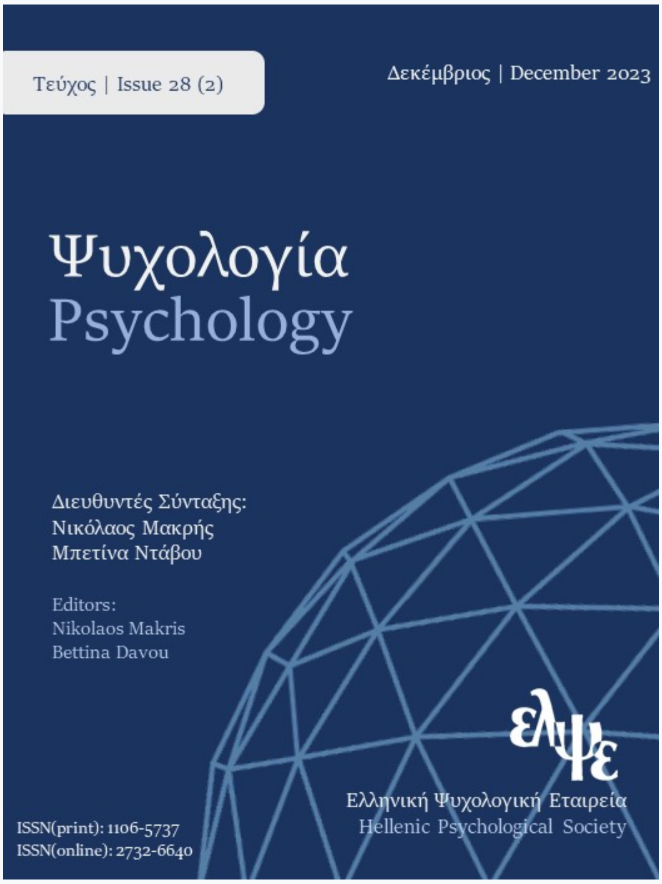
Psychology: the Journal of the Hellenic Psychological Society

Vol 28, No 2 (2023)

Special Section: Nous: A powerful machine



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doi: [10.12681/psy_hps.36225](https://doi.org/10.12681/psy_hps.36225)

To cite this article:

Ziori, E. (2023). The power of the cognitive unconscious: The case of implicit learning. *Psychology: The Journal of the Hellenic Psychological Society*, *28*(2), 1–22. https://doi.org/10.12681/psy_hps.36225

ΨΥΧΟΛΟΓΙΑ | PSYCHOLOGY, 28(2), 1-22

Ελληνική Ψυχολογική Εταιρεία
Hellenic Psychological Society

ΒΙΒΛΙΟΓΡΑΦΙΚΗ ΑΝΑΣΚΟΠΗΣΗ | REVIEW PAPER

The power of the cognitive unconscious: The case of implicit learning

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KEYWORDS

Unconscious knowledge,
Implicit learning,
Unconscious processes,
Consciousness

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ABSTRACT

The present paper highlights the power of unconscious processes within the framework of implicit learning, a research area that has attracted extensive attention in the past decades. More specifically, it discusses theoretical issues concerning this multifaceted type of learning that occurs without conscious awareness and presents various applications in different learning settings and research domains, and in varied populations. Another main focus of this review is on recent advances in our understanding of the factors that affect implicit learning, including motives, attention, affective states, and general knowledge. The paper ends with conclusions and general principles drawn from research on a phenomenon with extended applications both in the lab and in everyday life and underlines the necessity for further research that will refine our methods of distinguishing conscious and unconscious processes and provide answers to unresolved issues and contradictory findings.

Introduction and a brief historical overview

The cognitive unconscious has prompted a recent explosion of scientific interest and an increasing bulk of research in the fields of cognitive psychology and cognitive science. The rather delayed engagement of psychologists with unconscious mental processes can be attributed, to a great extent, to the dominance of behaviorism for a great part of the 20th century. This influential school of thought focused on observable outward reactions to stimuli, leaving no room for the inner experience of the mind.

The delayed interest in unconscious mental processes may also be attributed to the unavoidable impact that Continental rationalism and British empiricism, two philosophical schools of thought of the 17th and 18th centuries, had on the more recent science of western psychology. Descartes, the influential representative of rationalism, considered self-evident "…that there can be nothing in the mind, in so far as it is a thinking thing, of which it is not aware…" (Descartes, 1984, p. 171). Similarly, Locke, one of the most prominent philosophers of the British Empiricism, theorizes that we are always conscious of what we think and rejects the possibility of unconscious mental processes "…for it is altogether as intelligible to say that a body is extended without parts as that any thing thinks without being conscious of it…" (Locke, 1805, p. 89). Besides the many differences between the philosophical traditions that Descartes and Locke espoused, with continental rationalism favouring innate ideas and British empiricism the power of experience in knowledge acquisition, what is clear from the arguments above is that both these influential philosophers postulated that all mental processes are accessible to consciousness. And even though, within the above philosophical currents, one might find notions that were consistent with unconscious aspects of thought, like those of Leibnitz, Spinoza, and Hume, it seems that they were not so resounding as to degrade the powerful impact that the Cartesians' and Lockeans' criticism against the notion of unconscious thought had on the budding science of psychology and the work of early cognitivists and still has on the views of some psychologists today.

A school of thought that appeared at the beginning of the 20th century and highlighted the power of unconscious mental states was psychoanalysis. However, the dynamic unconscious, as originally conceived by Freud, differed from the cognitive unconscious, which it inspired. The mental entities entailed in the psychoanalytic unconscious concern the whole personality (e.g., desires, fears, beliefs, memories) rather than its cognitive and perceptual aspects. Another difference between the Freudians' and cognitive scientists' stance towards unconsciousness is that the former attributed the inability of mental states to enter consciousness to the mechanism of repression, whereas the latter attributed the above inability to the architecture of the brain (e.g., Baars, 1988; Edelman & Tononi, 2000) or to knowledge representations (e.g., Carruthers, 2000; Rosenthal, 2005).

In the last four decades, there has been an unprecedented interest in the investigation of cognitive processes that occur outside consciousness. A main reason for this powerful turn to the study of unconscious cognitive processes is their eminent place in the abundant and complex aspects of everyday life and cognition, such as in decision making, language skills, emotions, perception, motor learning, beliefs, attitudes, and biases, which makes them hard to ignore or fail to impress even the sceptics.

The cognitive unconscious has elicited considerable research on different areas, such as subliminal perception, namely perception that occurs below the threshold of consciousness (e.g., Cheesman & Merikle, 1984, 1986), blindsight (e.g., Weiskrantz, 1986, 1996), implicit memory (e.g., Graf et al., 1985; Schacter et al., 1989), and implicit learning (e.g., Janacsek et al., 2012; Opitz et al., 2020; Reber, 1967). Implicit memory is strongly related to implicit learning but differs from it mainly in the time point of the occurrence of unconsciousness, with a lack of conscious awareness appearing during the acquisition of structural knowledge in implicit learning and during retrieval of a previous event in implicit memory. Blindsight is another impressive phenomenon of unconscious processing, widely known among both psychologists and philosophers. Blindsight patients have a blind part in a visual field and, as a result, claim that they do not see objects presented in that field. However, what is impressive is the fact that blindsight patients are able to respond correctly in forced-choice discriminations, even though they claim that they base their responses on pure guessing; thus, they have no knowledge of their knowledge or, in Perner and Dienes's (2003) terms, they have "unconscious awareness". All the above examples provide substantial proof of the existence of unconscious cognition.

The present review focuses on implicit learning, a renowned example of unconscious processing in the field of cognitive psychology, which refers to learning that occurs without conscious awareness or access to the acquired knowledge. The investigation of this aspect of cognition started in the 1960's with the work of the pioneer in the field, Arthur Reber (see e.g., 1967, 1969); but the soil was still infertile, as Behaviorism was still exerting a strong impact on learning that was devoid of any cognitive component.

The cognitive revolution that was launched in the 1950s by groundbreaking researchers, including Miller, Bruner, Chomsky, and Neisser distanced itself from the behaviorist approach and moved towards the study of higher human cognition, like language, which required the use of sophisticated experimental paradigms. Chomsky's (1959) notorious debate against Skinner's view (1957) that language can be explained like any other acquired behavior through reinforcement and conditioning set the way towards such an experimental investigation of language. Miller (1956) was also among the leading names in the cognitive revolution, known for his collaboration with Chomsky and his experiments and mathematical methods for the investigation of mental processes, and mainly those of language and working memory. In fact, Reber's acquaintance with Miller's work on grammar learning was crucial for the onset of his famous experiments on the learning of "artificial grammars" that ensued and initiated a stream of publications on implicit learning. However, it wasn't until the 1990s that the research area of implicit learning met its utmost recognition among cognitive psychologists and cognitive scientists in general, after the burst of research on implicit memory, with seminal papers of researchers like Schacter and his co-workers (e.g., Graf & Schacter, 1985; Schacter, 1982, 1987), Roediger (1990), and Squire (1992a, 1992b). Fodor (1983, p.86) went even further to state that "practically all psychologically interesting cognitive states are unconscious...".

Implicit learning processes have since attracted the ongoing interest of researchers and resulted in an increasing number of publications, but not without debates between the proponents of implicit learning and those who might even doubt its existence. A main issue of this debate concerns the provision of evidence of the unconsciousness of implicit processes. To this end, many researchers have actively engaged in the challenging endeavor of trying to develop sophisticated measures and experimental tasks that are appropriate to distinguish between conscious (explicit) and unconscious (implicit) learning.

The aim of the present paper is to put forward recent advances of research on different domains of implicit learning that will hopefully promote new inter- and intra-disciplinary conversations, ideas, and research work on a phenomenon that, as will be shown below, dominates our lives. In the sections that follow, I briefly present a general definition of implicit learning that is adopted in the present paper, as well as the main measures and experimental techniques that have been designed and used to study this complex yet fascinating phenomenon, and then I selectively review existing evidence of some of the most pervasive unconscious (implicit) influences in various settings and different populations. Finally, I focus on some top-down factors, like prior knowledge, goals, and motives, that recent research, as opposed to older implicit learning studies which relied almost exclusively on the processing of highly artificial stimuli like strings of letters or shapes, has shown that may well go hand in hand with implicit learning in a meaningful world.

Definition of implicit learning and measurement issues

Implicit learning is generally defined as a process of acquiring knowledge of complex structures that occurs without effort or intention and in such a way that people have no conscious awareness of what they have learned or even that they have learned at all (Reber, 1993). The core aspects of this type of learning concern both the process of knowledge acquisition, which occurs in a passive, non-analytic fashion, without the application of explicit strategies, and the knowledge acquired under such non-analytic conditions, namely, the knowledge that, as is generally known and defined in the present work, occurs outside conscious awareness, that is, independently of consciousness. Thus, the process of implicit learning gives emphasis on the methods or conditions that promote incidental, non-analytic knowledge acquisition, whereas implicit knowledge concerns the resulting lack of conscious awareness, as assessed by different measures and methodological tools.

A phenomenon that has been related to implicit learning is *insight learning*, where insight, specifically within the Gestalt approach, is thought of as a mental restructuring during problem solving. Researchers, however, have opposing views as to the consciousness involved in insightful problem solving, with some arguing that this restructuring is a conscious and attention demanding process (e.g., Gick & Lockhart, 1995), others equating it with an automatic process that does not require metacognition (e.g., Siegler, 2000), and an increasing number of researchers showing that insight learning involves many stages with both conscious and unconscious components (e.g., Hélie & Sun, 2010; Weisberg, 2015).

Another phenomenon which by some authors is considered equivalent (or even synonymous) to implicit learning is *latent learning*, a term originally used in the context of non-human behavior (see e.g., Tolman & Honzik, 1930), but later often encountered in human learning as well. Latent learning refers to the acquisition of knowledge that occurs without reinforcement and without being immediately apparent to others. With the right incentive, however, this hidden knowledge may manifest itself and become available to verbal report and thus to consciousness. On the other hand, implicit learning, which, in contrast to latent learning, may result in readily observable behavioral changes, gives emphasis in the learner's lack of conscious awareness of the acquired knowledge, which they cannot report if they are asked to do so.

Implicit learning stimulated a long-lasting debate and animated discussions among researchers who struggled for years following the original studies of Reber on Artificial Grammar Learning (AGL) to measure and prove the unconsciousness of implicit learning. A main reason for researchers' failure to reach a consensus was their difficulty in agreeing on a commonly accepted defining criterion of consciousness and in establishing ways of distinguishing between learning that occurred with and without conscious awareness. The strong proponents of unconscious (implicit) processing are enchanted by their intuitive or unconscious knowledge, which finds applications in abundant paradigms of both laboratory and everyday settings. Language acquisition is one of the most compelling and most cited paradigms of implicit learning, in that children all over the world acquire their mother language without any instruction or intention to learn and without conscious awareness of their knowledge, that is, without being able to describe the basis or the complex structure of their knowledge. However, there are some researchers who question the unconsciousness of knowledge acquired in implicit learning tasks (e.g., Dulany et al., 1984; Perruchet & Pacteau, 1990; Shanks & St John, 1994). For example, Dulany et al. (1984) suggested that participant's performance in a well-known implicit learning task, namely in AGL, may be attributed to conscious (explicit) memory of the study stimuli rather than to unconscious (implicit) knowledge of their underlying structure.

A major part of the above disagreement originates from the fact that consciousness is a multifaceted phenomenon and has therefore been described in many ways and from the prism of different models. The different measures on the existence or lack of conscious awareness of knowledge acquired in implicit learning tasks are supported by different theories of consciousness. One example is the Higher Order Thought (HOT) theory (Carruthers, 2000; Rosenthal, 1986, 2005), according to which a mental state is conscious when we have a higher order thought for this state, that is, when we have meta-representations, and we thus know that we know. This theory is consistent with subjective measures of consciousness that are often applied in implicit learning tasks. Among the most widely known measures that have been used in the implicit learning literature, especially in the early studies, are people's verbal reports on the relevant knowledge they might have relied on during a training and/or testing phase of an experimental task. Participants' inability to report such knowledge was taken as evidence of a lack of conscious awareness. However, verbal reports have received the greatest share of criticism and have been characterized as an inadequate measure of conscious awareness (see e.g., Dulany et al., 1984; Newell & Shanks, 2014). Other more recent subjective measures applied in different implicit learning paradigms (e.g., Dienes et al., 1995; Ziori & Dienes, 2006, 2008) are people's confidence ratings on the correctness of their responses or the approach proposed by Dienes and Scott (2005; Scott & Dienes, 2008) and used in many implicit learning studies (e.g., Fu et al., 2009; Norman & Price, 2012; Ziori et al., 2014; Ziori & Dienes, 2015), whereby participants are asked to specify the explicit strategies (e.g., rules, memory) or the implicit strategies (e.g., guessing, intuition) on which they based their decisions/classifications.

Other researchers (e.g., Dulany et al., 1984) have argued that people have conscious knowledge of a stimulus if they are able to distinguish it from other stimuli with the use of objective measures (e.g., forced-choice tests). This line of argument is in contradiction to the case of blindsight patients who are able to make correct forced-choice judgments, without however relying on conscious mental states. Another approach used by researchers (e.g., Destrebecqz & Cleeremans, 2001; Jiménez et al., 2006; Norman et al., 2016) in their pursuit to estimate the contribution of conscious and unconscious knowledge in implicit learning tasks is the use of variants of the process dissociation procedure that was first applied in the implicit memory research (Jacoby, 1991). This method asks participants to either make use of information seen in a previous phase or to avoid using such information. On this account, unconscious knowledge is thought to act automatically and affect performance independently of the experimenter's instructions or even in complete contradiction to them, whereas conscious processes correspond to the application of intentional, strategic control over knowledge, which forms a frequently used criterion for defining consciousness. In particular, the above approach of measuring conscious awareness is supported by theories that focus on the architecture of the cognitive system, like Baars's (1988) Global Workspace model, according to which conscious knowledge is flexible and accessible to various cognitive processes, such as directed attention and executive control.

As evidenced from the brief review of some of the most widely used measures in the area of implicit learning, different measures tap into different aspects of consciousness and thus no single measure may fully clarify and capture the multiple facets of consciousness (see Ziori, 2011 for a more analytical presentation of implicit learning measures).

Experimental tasks of implicit learning

Among the most influential and widely used experimental paradigms in the area of implicit learning are the Artificial Grammar Learning (AGL) task (e.g., Prince et al., 2018; Reber, 1967; Danner et al., 2017; Dienes et al., 1995) and the Serial Reaction Time (SRT) task (e.g., Destrebecqz & Cleeremans, 2001; Gaillard et al., 2009; Hsiao & Reber, 1998; Janacsek et al., 2020; Nissen & Bullemer, 1987).

In AGL tasks, participants are first exposed to a set of strings of letters (or any other symbols) that have been generated by artificial finite-state grammars. After the exposure phase, participants are informed for the first time that the study stimuli followed a set of complex rules, without receiving any further information about the nature of these rules and are then asked to see novel strings of symbols and decide which of these strings obey and which violate the grammar rules. A common finding is that participants' performance exceeds a chance level, which suggests learning the structure of the grammar. Many different measures of conscious awareness have provided evidence of unconscious knowledge of artificial grammars, with participants, for example, demonstrating a lack of metaknowledge, or being unable to justify or control their acquired knowledge. The AGL paradigm can not only disambiguate the contribution of implicit and explicit knowledge, but it also informs us on the structural types (e.g., rules vs. similarity) of this knowledge (For a review of the knowledge types acquired in AGL, see Pothos, 2007, and Ziori & Pothos, 2015).

In the SRT paradigm, participants observe and are asked to provide fast responses to successive stimuli that appear in one of several locations on a computer screen in a repeating, predetermined by the experimenter sequence. The main finding is that people can learn the sequence implicitly, as evidenced by their decreased response times (RTs) for stimuli following the repeating sequence relative to their RTs for stimuli that follow an unpracticed sequence, even though they may be unaware of the structure of the practiced sequence.

Other well-known experimental paradigms of implicit learning include probabilistic learning (e.g., Knowlton et al., 1994), prototype category learning (e.g., Posner & Keele, 1968), and the control of complex systems (Berry, 1993; Berry & Broadbent, 1984). A representative example of probabilistic learning is the weather prediction task, where participants have to combine information from different clues that together designate the probability of positive or negative weather outcomes. Feedback is provided after each prediction, which gives participants the opportunity to adjust their responses to the probabilistic pattern. The provision of trial-by-trial feedback might be thought to favor a more analytic and intentional processing type in contrast to the passive and incidental processing that is characteristic of implicit learning. However, the probabilistic category structure seems to discourage the operation of an explicit rule-based system (see Smith & Grossman, 2008).

Prototype category learning conditions correspond more closely to the typical implicit learning conditions, in that participants learn distortions of a prototype without receiving any information about the category during training and thus without applying any strategies to discover it. In the test phase, for instance, participants might be asked to categorize novel patterns of dots (or artificial categories) that form random distortions of a category prototype. They are able to do so even though they cannot describe the basis of their judgements, namely the characteristic features of the categories. Another advantage of the prototype category abstraction tasks is that the structure of the to be learned categories is the same as the structure of most natural categories (i.e., with characteristic and not defining features) and can thus inform us on natural category learning as it occurs in incidental conditions in real life.

Finally, in the control of complex systems, participants are asked to control a dynamic system, such as a sugar production factory, where they have to learn to manipulate one or more variables (e.g., the number of workers) in order to achieve a desired outcome (e.g., a specific amount of sugar production). Again, they manage to control the system successfully without being able to describe the rules that determined the relationship between the input variables and the output of the system. Dynamic systems control tasks can inform us on many dynamic decision problems we perform in everyday life (e.g., firefighting). However, these tasks have been criticized as not highly representative paradigms of implicit learning (see e.g., Buchner et al., 1995), in that participants are aware from the beginning that they have to achieve a goal, making efforts and receiving feedback on the adequacy of these efforts, which contradicts the non-intentional mode of implicit knowledge acquisition. However, even though these learning conditions promote an explicit mode of learning, they do not exclude the possibility of implicit processing, especially when the explicit strategies prove ineffective.

As is clear from the above description, the default conditions in most (but not all) implicit experimental paradigms promote incidental knowledge acquisition, as they make no mention of the underlying rules or patterns of the stimuli and thus do not require the application of explicit strategies for their discovery and do not inform participants about the testing phase that follows. These conditions are thought to favor implicit learning and are closely related to the conditions of many real-life learning situations. In particular, implicit learning paradigms like the above map onto processes used in many everyday activities, such as language, categorization, decision making, judgement formation, and generalization, which often proceed under incidental conditions or result in knowledge that is not accompanied by conscious awareness. Research with tasks like the ones above has shown that participants are able to acquire rule-based, sequential, probabilistic, or simple associative patterns implicitly, or at least partly implicitly since a common case in both laboratory and everyday settings is that implicit learning may often co-exist with explicit learning. Notably, many researchers endorse the view that experimental tasks and methods do not satisfy the "process purity assumption" (Jacoby, 1991), in that every task (or method) involves both implicit and explicit processes (e.g., Litman & Reber, 2005; Merikle & Reingold, 1991; Nissen & Bullemer, 1987; Reingold & Merikle, 1988).

A difficult task for all methodologies used for disentangling implicit and explicit learning is to be able to unquestionably demonstrate the existence of different types of learning under different conditions that mimic -to a greater or smaller degree- learning in real-life conditions. All experimental techniques and measurement approaches used in implicit learning research ultimately aim at deepening our understanding of learning without awareness as it occurs in everyday life. In fact, the vast number of everyday paradigms of intuitive knowledge and unconscious processing was the stepping stone to a growing number of implicit learning studies, most of which have been conducted in artificial and carefully controlled laboratory settings, but by using stimuli with a structure that resembles the structure of material people learn in everyday situations (e.g., material with serial regularities). In addition, an increasing bulk of recent research is using less artificial stimuli that have the characteristics of meaningful material encountered in everyday life. Of course, more research work is needed on the generalizability of experimental findings to more naturalistic settings. Below, I review evidence of many different examples of implicit learning as they appear in various contexts, conditions, and populations.

Different contexts and applications of implicit learning

Apart from language acquisition, which is considered one of the most striking examples of implicit learning, other highly important types of human behavior and cognition may be accomplished through learning without conscious awareness in different everyday settings. As Polanyi (1966, p. 4) claims, “We can know more than we can tell”, a condition which he termed as ‘tacit knowledge’, that is, knowledge that cannot be verbalized and thus may be thought of as the product of implicit learning. Implicit or tacit knowledge encompasses our skills and experiences which may be acquired and applied without the involvement of language. For instance, we are often able to distinguish between members of different categories, type fluently, or recognize the face of a friend among other faces, without however being able to describe how we perform these tasks or provide the basis of our judgements. Similarly, people may be able to distinguish between different musical structures and styles, despite the fact that they might have no professional knowledge of music or be unable to explain their decisions (e.g., Rohrmeier & Rebuschat, 2012; Tillmann, 2005).

The application of implicit learning in a wide range of human life aspects has been corroborated by numerous research findings in different domains, such as social cognition (e.g., Frith & Frith, 2012; Greenwald & Banaji, 1995; Guivarch et al., 2017; Heerey & Velani, 2010; Lieberman, 2000), first and second language acquisition (e.g., Ellis, 1994; Robinson, 1996, 1997; Kerz et al., 2017; Li et al., 2013; Rebuschat & Williams, 2012), decision making, (Cohn et al., 2013; Raab & Johnson, 2008; Thakur et al., 2021), motor skills (e.g., Kal et al., 2018; Korman et al., 2018; Opitz et al., 2020; Stark-Inbar et al., 2016; Verburgh et al., 2016), music perception (e.g., Carrara-Augustenborg & Schultz, 2019; Daikoku, 2018; Daikoku et al., 2014; Rohrmeier & Rebuschat, 2012; Romano Bergstrom et al., 2012), categorization (e.g., Waldron & Ashby, 2001; Ziori & Dienes, 2008, 2012), and judgements on people’s age or personality (e.g., Lewicki et al., 1997; Lewicki et al., 1992).

Thus, implicit learning finds application in a variety of contexts and for various populations, including both healthy and clinical populations (such as people with neurological disorders), as well as with different age groups. And although initially implicit learning studies used only highly artificial stimuli, devoid of any meaning, research today uses meaningful material that may elicit different emotional states and activate participant’s goals, attention, and pre-existing knowledge, thus bringing implicit learning in the heart of everyday functioning. The wide applicability of unconscious processing, as instantiated by the case of implicit learning, in numerous domains of human functioning and in different settings highlights the power of the cognitive unconscious. This power is illustrated more clearly in the following sections.

Implicit learning of social skills. Our ability to detect complex regularities from our environments without conscious awareness is essential for the acquisition of social skills. From early infancy, we build on our social knowledge by constantly detecting cues which are associated with people’s actions, language, emotions, or intentions, all of which are fundamental for communication and the formation of social identity. This fascinating ability occurs automatically, in a fast and efficient fashion, without any instruction or intention to learn, and in such a way that we do not realize that we have learned something. It has been shown, for instance, that people make correct judgements about people’s personalities, which conform to behavioral regularities, without being able to report the basis of these judgements (e.g., Lewicki et al., 1992; Lewicki et al., 1997).

Implicit learning may be thought of as the equivalent of social intuition in the area of social cognition, with intuitive social cognition corresponding to the formation of implicit judgements and intuitive social action corresponding to implicit motor learning (Lieberman, 2000). More specifically, Lieberman (2000, p. 113) points out that “covariation detection and frequency detection are at the root of implicit learning. Intuitive social cognition and action also appear to be based on implicit covariation and frequency knowledge”. Lieberman (2000, p.111) also distinguishes between different types of intuitive social cognition, namely between intuitive (or implicit) “conceptual associations” on one hand and intuitive (or implicit) “sequential associations [that] are more consistently associated with accuracy” on the other.

In the area of social cognition, the investigation of implicit processes concerns mostly psychological constructs, such as attitudes, stereotypes, and self-concepts (Greenwald & Banaji, 1995; see also Kurdi & Banaji, 2022 for a review on implicit social cognition). The measures most frequently used in the social cognition research area are several types of priming (e.g., semantic, evaluative, and lexical decision priming), the Implicit Association

Test (IAT), as well as some more indirect tests (see Greenwald & Lai, 2020). Priming tasks are typical examples of implicit memory (a research area that, as mentioned above, influenced the onset of research in implicit learning to a great extent), as prior exposure to stimuli or experiences influence later attitudes or responses without effort or conscious awareness. The above measures map mostly onto Lieberman's "conceptual associations" or else implicit biases, such as racial or gender stereotypes that unconsciously affect our impression of people. The intuitive "sequential associations" may correspond more closely to traditional experimental paradigms of implicit learning that measure the unconscious acquisition of sequential knowledge, such as the SRT and AGL tasks.

Although the implicit learning literature does not have many examples of studies that accommodate the traditional implicit learning methodology for the investigation of unconscious social functioning, in the last few years there has been a growing research interest in that direction. For example, Norman and Price (2012) used a dynamic version of the SRT and AGL tasks to investigate the implicit learning of temporal sequences of body movement, namely of socially rich behavioral sequences. Their results showed that such naturalistic sequences with socially salient content may be learned implicitly. Similarly, Ivanchei et al. (2019) used socially relevant stimuli in an implicit learning paradigm known as hidden covariation detection. The results provided evidence of implicit learning of a covariation between a facial feature (i.e., women's hairstyle) and facial attractiveness ratings. Costea et al. (2022) have also found implicit learning of socially relevant stimuli using a dynamic version of a task that required control of a complex system. More specifically, the task required the interaction of participants with an avatar, which rendered it an appropriate task for the investigation of social functioning which, by nature, involves a highly interactive context. The study provided evidence of both implicit and explicit knowledge, a combination that is often encountered in real-life learning.

Advances of research on the intriguing role of implicit learning in social contexts will hopefully refine our understanding of both implicit learning and implicit social cognition.

First and second language acquisition and implicit learning. Language acquisition is among the most cited and self-evident paradigms of implicit learning in real life. Infants and children of preschool age acquire their language incidentally, without effort or intention to learn, and without conscious awareness of their acquired knowledge. Implicit learning paradigms like the AGL and SRT tasks mimic these incidental learning conditions quite effectively. Another example of implicit learning that approaches natural language acquisition more effectively is statistical learning (SL), which also uses artificial systems, but with a phrase structure that may include pseudowords instead of symbol sequences as those used in AGL. Statistical learning (SL) refers to the acquisition of probabilistic regularities of patterns found in our environments, such as the predictive dependencies between letters, syllables, or syntactic categories. Traditionally, SL research focused primarily on language acquisition with an increasing number of recent studies, however, highlighting the dominant role of SL in more functions of cognition, including vision, memory, and social cognition (for reviews, see e.g., Frost et al., 2019; Schapiro & Turk-Browne, 2015). In both implicit learning tasks and SL, participants acquire knowledge in a passive, unintentional way, without the application of analytical strategies. Despite their different origins and the slight differences that exist in their methodologies and interpretations, implicit learning and SL share common topics and concerns, with many authors often using the two terms as synonymous or even suggesting the unifying term of "implicit statistical learning" (see Christiansen, 2019).

Many studies that have used the above experimental paradigms have provided strong support for implicit learning even from infancy (e.g., Gomez & Gerken, 1999; Marcus et al., 1999; Saffran, 2003; Saffran & Kirkham, 2018). For instance, Gomez and Gerken (1999) presented 1-year-old infants with auditory tone sequences generated by a complex artificial grammar and found that they were able to learn them implicitly. In particular, they found that the infants acquired sensitivity to the sequential structure in that they were able to successfully distinguish between grammatically correct and incorrect sequences, as evidenced by infants' looking behavior. Most notably, Gomez and Gerken also found that infants were able to generalize their acquired knowledge, that is, to transfer knowledge of the trained vocabulary to sequences of a new vocabulary with the same underlying structure. Pacton at al. (2001) focused on bridging the gap between laboratory and everyday implicit learning and tested the generalizability of lab-based findings regarding language learning to a more naturalistic context. They found that school-aged children are able to learn orthographic rules early on, that is, long before they acquire them formally through explicit instruction.

Implicit learning and its distinction from explicit learning has also been investigated in the context of second language acquisition (SLA) research (e.g., N. Ellis, 1994, 2007; R. Ellis, 2005; Rebuschat, 2013, 2015; Rebuschat &

Williams, 2012). According to N. Ellis (1994, 2007), SLA entails both implicit and explicit processes and it is the combination of explicit instruction of grammar rules and incidental exposure to examples of such rules that is most effective for the acquisition of a L2. A challenging task and motivation of a growing number of empirical studies in the field of SLA is the attempt to determine which linguistic aspects (syntax, morphology, phonology, vocabulary) are best acquired implicitly (e.g., through incidental observation), which are enhanced by an explicit mode of learning (e.g., through explicit instruction or explicit rule searching), as well as how implicit and explicit processing may interact during learning. The answer to the above question would be of great benefit for the understanding of language learning in general and its relation to other cognitive abilities and consequently for the development of effective learning environments.

Implicit motor and perceptual skill learning. Many everyday activities which require practice for the development of mastery, such as playing games or sports, driving a car, or playing a musical instrument, rely on the acquisition of motor skills, without the necessary involvement of conscious awareness. The SRT task is an experimental paradigm that closely resembles and simulates the acquisition of such skills outside the lab. The serial regularity involved in the SRT task may be acquired not only by purely motor learning, that is, through the acquisition of sequences of correct button presses, but it may also entail perceptual learning, that is, the learning of sequences of visual stimuli and their positions. Despite their differences, motor sequence learning and perceptual learning are generally thought to proceed through similar routes, which correspond to the development of procedural learning (cf. Anderson, 1983), whereby performance improves considerably after a short period of practice. According to top-down theories of skill learning, which have a rather prominent place and long tradition in the field of motor learning (e.g., Anderson, 1983), at an initial stage performance relies on the exertion of effort and the application of explicit knowledge in the form of explicit instructions, or verbalization, whereas after practice performance becomes automated, faster, and less dependent on conscious awareness or working memory resources. However, the use of declarative or explicit knowledge at an initial stage of learning may not be a prerequisite for effective skill learning, in general, or motor learning, in particular. For instance, Kal et al. (2018) provided some evidence that implicit motor learning methods may be more effective than the use of explicit instructions in movement automaticity.

Many studies that have used the SRT task have shown that motor and perceptual skill learning corresponds to procedural learning that can occur without conscious awareness. However, more work is required toward the direction of disentangling the perceptual from the motor component in the SRT task and other perceptuomotor tasks or everyday settings, as well as towards assessing the contribution of implicit and explicit knowledge alone, and/or in synergy when this is the case, at the different stages of learning (For a more systematic discussion on the knowledge types acquired in SRT tasks and the various types of human behavior they can elucidate see e.g., Robertson, 2007 and Schorn & Knowlton, 2022).

As has been made clear from the discussion above, implicit learning is intrinsically related to the acquisition of complex associations and regularities, such as the rules involved in language learning, social interaction, perceptual and motor skills, that is, in skills that capture the complexity of everyday life. And although examining the neural substrates of implicit learning is beyond the scope of the present review, it is worth noting that studies on patients with neurological disorders, namely on patients with deficits in the above skills can deepen our understanding of implicit learning in general and its usefulness as a rehabilitation method in particular. Indeed, a great number of studies have provided evidence of a robust implicit learning system that remains spared in people with autism spectrum disorder (e.g., Foti et al., 2015; Zwart et al., 2018), dyslexia (Inácio et al., 2018; Pothos & Kirk, 2004), attention-deficit/hyperactivity disorder (e.g., Rosas et al., 2010), amnesia (Knowlton & Squire, 1994; Nissen & Bullemer, 1987), Alzheimer's disease (e.g., Klimkowicz-Mrowiec et al., 2008; Reber et al., 2003), and mental retardation (Atwell et al., 2003; Vinter & Detable, 2003). The profound deficits these patients demonstrate in explicit functioning make implicit processes a fruitful alternative route to the enhancement of their cognitive, social, and motor skills. Thus, intervention methods could promote more passive educational or rehabilitation programs, by exposing patients to correct examples of regularities rather than to explicit instruction of rules. It should be noted, though, that the existence of some contradictory findings with respect to the unimpaired implicit processes in the above disorders (e.g., Kahta & Schiff, 2016; Katan et al., 2017; Klinger at al., 2007; Laasonen et al., 2014) corroborates the necessity for further research on the topic, especially since it is often difficult to control for the explicit processes that may also be at play, at least to a certain extent, in people's performance in implicit learning tasks.

Top-down factors influencing implicit learning

Traditionally, implicit learning was equated with a bottom-up process that is unaffected by selective attention or any top-down guidance that might involve people's prior knowledge, goals, or motives (e.g., Hayes & Broadbent, 1988). However, more recent research has revealed that implicit learning may be influenced by selective attention and any factors that modulate it (e.g., Deroost et al., 2008; Hoffmann & Sebald, 2005; Jiang & Chun, 2003). The debate regarding the role of attention in implicit learning may be partly attributed to the different processing systems associated with the particular construct, such as a limited capacity system that requires effort or an executive control system, and a selective attention system. Most of the earlier studies of implicit learning focused on the impact of limited attentional resources and mental effort on the acquisition of implicit knowledge through the application of the dual task methodology (e.g., Dienes et al., 1995; Frensch et al., 1994; Jiménez, & Méndez, 1999). These and many more recent studies have shown that loading attentional resources with a secondary task interfered with explicit and not with implicit learning, suggesting that implicit learning proceeds in the absence of attention. However, many recent studies that have found an impact of attention on implicit learning have focused on the selective nature of attention, namely the preferential processing of the relevant vs irrelevant sensory input. This selectivity of attention has been shown to impact or even determine implicit learning to a great extent. In the sub-section that follows, some of the top-down factors that modulate and shape selective attention and have been shown to influence implicit learning are presented.

How affective states, prior knowledge, motives, and goals affect implicit learning. Although at the onset of implicit learning research, the vast majority of research work focused on the use of highly arbitrary and artificial stimuli, trying to leave out any meaning or previous knowledge activation, recent studies in the field have turned to more ecologically valid experimental paradigms implicating many top-down factors that may influence not only conscious but also unconscious processing. Such studies have provided ample evidence that various higher-level factors that are generic to human decisions and actions and are often used in the pursuit of understanding human cognition, such as people's prior knowledge, goals, motives, and affective states, may influence unconscious learning (e.g., Eitam et al., 2009; Eitam & Higgins, 2010, 2014; Pretz et al., 2010; Ziori & Dienes, 2008, 2015; Ziori et al., 2014).

All these factors may be considered as individualized, differentiating characteristics that lie in the heart of human thought and behavior, and, in that sense, it is of great importance to investigate their implicit or explicit underpinnings as well as their interplay with learning that occurs with and without conscious awareness. On Reber's evolutionary theory (1992, 1993), implicit processes have a longer and more robust history in the evolutionary continuum than the more recent advent of explicit processes and are thus thought to be more resistant to individual differences or, for that matter, to any factors that exert such a differentiating impact in comparison to their explicit counterparts.

A factor that exerts a differentiating influence on people's thoughts and behavior is their affective states. Moods and emotions are affective states with some distinctive characteristics, such as their duration, intensity, and cause specificity, with moods having a longer duration that may last from minutes to days, lower intensity, and an unspecified cause in comparison to emotions (see e.g., Ekman, 1999). The central place that affective states have in people's cognitive and social skills justifies the recent research interest in the interplay between them as well as in how affective states influence the content and quality of information processing.

Research on the relationship between implicit learning and affective states has resulted in mixed findings most likely due to methodological issues that have to do with the measures of conscious awareness and the manipulation of affective states. Thus, implicit learning of stimuli with emotional relevance is a relatively understudied yet very interesting research topic. A rather well-established research finding is that negative mood and affect lead to a narrowing of attention, which in turn promotes an analytical type of processing that gives emphasis on details (e.g., Rowe et al., 2007), that is, to a mode of processing that corresponds to explicit learning. By contrast, positive affective states lead to a broadening of attention that promotes global processing and focuses on relational information or what constitutes the bigger picture of the learning scene. Relatedly, according to the affect-as-information hypothesis, positive affective states are associated with relational knowledge, whereas negative affect is associated with details of specific stimuli (see e.g., Clore et al., 2001; Clore & Storbeck, 2006). Thus, a plausible way in which mood and affect influence implicit and explicit learning may be indirectly, through the differential effect of selective attention on the two types of learning.

In an SRT study, Shang et al. (2013) provided evidence in favor of the affect-as-information hypothesis above. In this study, participants' positive and negative affective states were induced via appropriate music pieces, which were used both before the SRT and for a shorter period during training to ensure a more sustained mood induction. For the assessment of the consciousness of knowledge, the researchers used both objective measures (i.e., a recognition test) and subjective measures [i.e., Dienes and Scott's (2005) knowledge attribution method]. In two experiments, they found that negative rather than positive affective states interfered with the unconscious learning of complex regularities of an SRT task, which involved integrative knowledge. By contrast, Bertels et al. (2013) found that implicit statistical learning was not affected by negative mood. More specifically, they explored the impact of negative vs neutral mood on visual statistical learning of shapes. For the manipulation of mood, they had participants listen to two stories of different emotional valence, and for the assessment of participants' knowledge and consciousness, they used direct and indirect measures (i.e., a four-choice task and a rapid serial visual presentation task) and subjective measures based on confidence ratings, respectively. Their results showed that explicit statistical learning was facilitated in the negative mood condition relative to a neutral condition, whereas implicit statistical learning was not affected by mood. Bertels et al.'s findings are in line with Reber's position about the robustness of implicit learning to individual differences (such as mood states).

Pretz et al. (2010) used an AGL and an SRT task to investigate the effect of mood on implicit learning and found that negative mood increased performance in the AGL task but did not influence learning in the SRT task, with the authors attributing the above discrepancy on the different knowledge structures involved in the two implicit learning tasks. In addition, the authors suggested that the SRT tasks might encourage a more implicit mode of processing in comparison to the AGL tasks. However, in the above study, the contribution of implicit and explicit learning in the two tasks is not clarified in that no additional measures of conscious awareness were used. This might be a reason that may explain the discrepancy between the findings of Pretz et al and the results of Shang et al. (2013) above. Another difference between the two studies that might explain the inconsistency in their results in terms of the effect of negative mood on the SRT task is their different methods of mood induction. As mentioned above, Shang et al. (2013) presented participants with different music pieces both before and during training in order to strengthen and sustain their effect throughout the long training phase of the SRT task, whereas Pretz et al. (2010) used affective photos which they presented for a quite shorter interval and only before training. Presumably, these methodological differences account for the different effect of mood manipulation on participants' performance in the two studies.

Apart from studies like the above, which used typical populations, many studies have investigated the relationship of affective states with implicit learning in patients with affective disorders that entail negative affect, like depression and bipolar disorder. These studies have led to mixed and inconclusive findings, most likely because of concomitant deficits in other cognitive processes that often accompany these disorders or because of differences in the severity or subtypes of the particular disorders (e.g., Abrams & Reber, 1988; Exner et al., 2009; Janacsek et al., 2018; Mörkl et al., 2016; Pedersen et al., 2009). For instance, some studies have found significant impairment of sequence learning in moderate to severe depression (Naismith et al., 2006), By contrast, Exner et al. (2009) found impaired implicit SRT learning only in patients with major depression that also had melancholic features, but not in participants with major depressive disorder but without melancholia, whose performance remained intact and equal to that of a control group. Similar results were obtained by Pedersen et al. (2009), who found intact implicit (and explicit) SRT performance in patients with remitted major depression, and impaired implicit sequence learning in patients remitted from melancholic major depression, although the above difference was not statistically significant, most probably because of the small sample size of the study. The above findings seem to support the possibility that the impairment of implicit learning in major depression is not due to negative mood per se, but to the anhedonia and diminished motivation or goal pursuit that characterizes the melancholic subtype of depression (see e.g., Fletcher et al., 2015; Padrao et al., 2013), which in turn may affect selective attention and thereby implicit learning.

The relationship of implicit learning with affective states has also been investigated through studies on the acquisition of unconscious emotional structures in the context of implicit reward learning, that is, in the context of unconscious acquisition of knowledge about the contingencies between a stimulus or a response and a reward (e.g., Bierman et al., 2005; Leganes-Fonteneau et al., 2018, 2019). Leganes-Fonteneau et al. (2018) found that participants' attention was directed toward stimuli associated with a higher probability of monetary reward rather than toward stimuli with a low-reward probability, and this occurred even for participants who had no conscious expectancies regarding the high-reward stimuli. In an earlier study, Bierman et al. (2005) utilized a dual AGL paradigm, in which participants were presented with sequences of symbols constructed by each of two grammars and were asked, on a trial-by-trial basis, to choose the sequence that would increase the possibility of earning money. What participants were unaware of was that sequences from one grammar always corresponded to a monetary reward, whereas sequences from the other grammar corresponded to a monetary punishment. The results showed that participants demonstrated a high degree of accuracy regarding the sequences leading to reward. However, this accuracy was not accompanied by any verbalizable knowledge of the correct rule. The above results provide supporting evidence in favor of the strong impact of motivational and reward signals on selective attention, which as recent research shows plays a determinant role in implicit learning.

Research on the association between stimuli or responses to stimuli and rewards can also inform us on the underlying mechanisms of addictions, whereby addiction-related cues acquire a rewarding power that shapes selective attention. For instance, Brevers et al. (2014) compared problem gamblers and controls in an AGL task, that is, in a decision-making task that involves uncertainty but no direct gambling. In the particular task, all participants were given explicit instructions about the existence of rules that they had to discover during training, a modification that enhances explicit processing in comparison with the standard, incidental version of the AGL task. The results showed that problem gamblers acquired knowledge of the artificial grammar but impaired in comparison to that of the control group, presumably because of the more explicit nature of the task. Furthermore, problem gamblers, in contrast to controls, demonstrated no metacognitive sensitivity towards (or conscious knowledge of) the grammar structure, namely no correlation between their confidence and performance. Analogous findings were obtained by another study of Brevers et al. (2013), in which problem gamblers were compared to controls while performing a task that involved direct gambling, namely the Iowa Gambling Task (IGT). Problem gamblers again demonstrated decreased metacognitive skills, as their low performance on IGT did not correspond to their high wagering decisions. Presumably, the uncertainty problem gamblers experience in more or less direct gambling-like situations has a motivational power that captures attention and drives behavior in a less conscious manner.

Another top-down factor that differentiates people is their pre-existing knowledge. The first studies in the implicit learning field avoided the activation of such knowledge, by using only meaningless and, to a great extent, semantically void stimuli, so as to prevent eliciting pre-existing associations that might facilitate a more reflective conscious processing. Over the last two decades, however, there has been an increase in implicit learning studies that use semantically rich stimuli that activate background knowledge (e.g., domain, cultural, and world knowledge), which plays a significant role in virtually all everyday tasks and cognitive processes. For instance, the most recent models of categorization incorporate previous knowledge in order to provide an efficient account of how both children and adults classify novel category exemplars (see e.g., Heit, 2001; Kimura et al., 2018). Relatedly, it has been shown that implicit knowledge of categories and artificial grammar classifications may be influenced by people's prior knowledge of categories or general world knowledge (e.g., Ziori & Dienes, 2008; Ziori et al., 2014).

In a modified version of the traditional AGL paradigm, Ziori et al. (2014) presented participants with sequences of European city names and told them that these sequences indicated the routes of an airline company. The training sequences were structured such that most inter-city routes corresponded to short distances. One group of participants was told that the company's benefit was to perform as many short-distance trips as possible and the other that long-distance trips were more profitable for the company. The above manipulation allowed us to examine how consistent and inconsistent general knowledge affected learning. The results showed that implicit learning can clearly be affected by people's general knowledge and, more specifically, that inconsistency between people's expectations and stimulus structure led to a clear advantage in implicit learning, as measured by Dienes and Scott's (2005) subjective method of participants' knowledge attributions. Similarly, in two category learning experiments, Ziori and Dienes (2008) found that people's prior knowledge of categories facilitated the acquisition of implicit knowledge of category features, as indicated by another subjective measure based on confidence ratings.

In a similar vein, a growing number of studies are in line with the notion that implicit learning corresponds to a selective process that may be influenced by participants' goals and motivation (Eitam et al., 2008; Eitam et al., 2009), pre-existing processing constraints (e.g., Leung & Williams, 2012; Rohrmeier & Cross, 2013), selective perceptual attention (e.g., Jiang, & Chun, 2001, 2003; Tanaka et al., 2008), and people's cultural expectations (e.g., Kiyokawa et al., 2012). In a series of experiments, Eitam et al. (2008, 2009) have shown that implicit learning was determined by participants' motivation and task relevance in that implicit learning emerged only when stimuli dimensions were task or goal relevant. Eitam et al. (2008) primed a goal that had to do with achievement, through a word-search task that included goal-related and goal-neutral words, in order to examine whether goal-directed attention would influence performance in a dynamic implicit learning task of controlling a complex system (a factory producing sugar). They found that unconscious goal pursuit facilitated implicit learning. The above findings were replicated in the second experiment of the study, which used a less dynamic or "intentional" implicit learning task, namely the SRT, as well as in a study (Gamble et al., 2014) that used an alternating SRT task, which is considered more "implicit" than the standard SRT task in that its regularities are more difficult to discover explicitly. More recently, Chon et al. (2018) have shown that participants motivated by fear of loss demonstrated enhanced implicit skill knowledge in a motor sequence learning task. In the domain of music, Rohrmeier and Cross (2013) found that AGL was affected by pre-existing processing constraints, in that melodic structures that were inconsistent with common melodic rules (namely, Narmour's principles) impaired implicit learning, as measured by participants' inability to report the acquired melodic rules.

Overall, affective states, prior knowledge, motives, and goals are highly influential individual characteristics that, to a great extent, determine human thought, choices, and decisions and have been shown to co-exist with and influence implicit learning. Selective attention seems to be a major mediating mechanism through which all the above top-down factors affect implicit learning in a variety of experimental paradigms and through the application of different measures of unconsciousness. Future research work on implicit learning would benefit from incorporating such top-down factors in its pursuit of disambiguating learning as it occurs in a meaningful, and socially, semantically, and affect-rich world.

Conclusions

From the discussion above, it should be obvious that unconscious cognitive processes play a pivotal role in cognition and behavior, including language acquisition, social cognition, perceptual and motor skills. The present review highlighted only some of the multiple facets of the powerful cognitive unconscious as specified through the implicit learning paradigm. Although implicit learning has lately become a vigorously researched topic in cognitive psychology, in particular, and in the cognitive and social sciences in general, further research is expected to enrich our knowledge of the implicit (and explicit) underpinnings of many aspects of everyday life and cognition. A main focus of the present paper was on the recent and growing research interest in top-down factors that older implicit learning studies ignored and which have more recently been shown to co-exist with and modulate unconscious processes, bringing the investigation of implicit learning closer to learning as it unfolds in real life.

A vast body of research has provided evidence of a robust implicit learning system that has primarily been investigated in the completely controlled experimental settings of the lab but may find multiple applications in real-life contexts and activities as well. It should be noted that implicit learning often proceeds in tandem with explicit learning in any given task or situation. The refinement of methodological tools and techniques should be able to delineate the weaknesses and strengths of the two types of learning, as well as the conditions that favor one over the other or the conditions that favor the blending and synergy of the two processes to the benefit of the outmost exploitation of our cognitive potential. The comparison and integration of different techniques both from the discipline of cognitive psychology and from other disciplines that touch on different aspects of implicit learning will contribute to a more inclusive understanding of the notion of the cognitive unconscious. Such an inclusive approach should benefit from a rich body of theoretical, methodological, and empirical knowledge accumulated from research on implicit processes in the fields of both learning and memory, that is, in two research fields that have followed two distinct and methodologically parallel routes, but with interesting intersections. Another area of implicit cognition that could broaden our perspective of unconscious processes, in general, is intuitive decision making (Kahneman, 2011). According to Kahneman (2011), intuitive decision making is based on System 1, which corresponds to a fast, automatic, and effortless system of thinking that is often more error-prone than System 2, that is, a slow, analytical, and deliberate type of decision and judgment making that relies on conscious reasoning. Although research in this domain emphasizes the speed of processing rather than the unconscious encoding of structural complexities, the exchange of knowledge and experience between the two research areas should enhance a more global view of the cognitive unconscious.

Despite the ample evidence for the robustness and power of implicit learning, only part of which was presented in the present paper, it shouldn't be concluded that learning without awareness outperforms explicit learning under all circumstances or in all populations. For instance, although numerous studies have shown that implicit learning is preserved in many neurological disorders, there are some neurological conditions, like Parkinson's disease, in which several lines of evidence suggest that implicit learning is rather impaired (see e.g., Clark et al., 2014), although not in all implicit learning tasks. In addition, there may be components of behavior and/or cognition that rely more on an automatic, fast, passive, unconscious mode of processing, and others that are favoured by a more analytical, slow, effortful, and conscious type of processing. Further studies investigating the environmental conditions, stimulus structures, knowledge representations, and neural underpinnings involved in the two types of processing are expected to shed more light on the nature of the fascinating cognitive unconscious, as well as on its strengths and limitations. Cognitive neuroscience has provided compelling evidence for the existence of an explicit system that is impaired in many neurological disorders and an implicit system that remains intact as well as for distinct neural circuitry involved in implicit and explicit learning tasks or in different structural aspects (e.g., rules vs similarity) in an implicit learning task. Further advances in neuroimaging methods in the context of implicit learning tasks and their contribution to the acquisition of more information on the robustness of implicit learning to the deficits and impairments that underlie many neurological disorders and thus cause difficulties in communication, behavior, and cognition are expected to be a valuable addition to the repertoire of scientific tools available for the planning of educational and rehabilitation programs.

Of equal importance, more sophisticated methodologies, measures, and experimental techniques, based on more naturalistic conditions and ecologically valid paradigms, should aim at further validating the results and conclusions reached by the bulk of implicit learning studies, which have primarily relied on more artificial stimuli, and thus at providing even stronger evidence of a powerful unconscious processing system, which may differ from a conscious, analytic system, but may as well interact with it in a synergistic way. A main concern of implicit learning research in the lab should be how its findings generalize or find applications in naturalistic contexts, where real-life stimuli, settings, demands, and needs are implicated and interrelated. When implicit learning research addresses domains like language and social skills, it is self-evident that it cannot overlook the interplay between top-down processing that may involve the application of explicit knowledge and bottom-up processing that is driven by the properties or the structure of the stimuli and functions independently of intention and awareness. On a more general account, a deepening in the understanding of the numerous factors and conditions that may influence unconscious (implicit) and conscious (explicit) processes of different populations and age groups is a challenging yet fruitful research direction that is expected to provide new insights into major aspects of human cognition.

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ΒΙΒΛΙΟΓΡΑΦΙΚΗ ΑΝΑΣΚΟΠΗΣΗ | REVIEW PAPER

Η δύναμη του γνωστικού ασυνείδητου: Η περίπτωση της άδηλης μάθησης

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ΛΕΞΕΙΣ ΚΛΕΙΔΙΑ

Ασυνείδητη γνώση,
Άδηλη μάθηση,
Ασυνείδητες διεργασίες,
Συνείδηση

ΣΤΟΙΧΕΙΑ ΕΠΙΚΟΙΝΩΝΙΑΣ

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ΠΕΡΙΛΗΨΗ

Το παρόν άρθρο εστιάζει στην ισχύ των ασυνείδητων διεργασιών εντός του πλαισίου της άδηλης μάθησης, μιας ερευνητικής περιοχής που έχει προσελκύσει εκτεταμένη προσοχή τις τελευταίες δεκαετίες. Πιο συγκεκριμένα, πραγματεύεται θεωρητικά ζητήματα που αφορούν σ’ αυτόν τον πολύπλευρο τύπο μάθησης που συμβαίνει χωρίς συνειδητή επίγνωση, και παρουσιάζει διάφορες εφαρμογές σε διαφορετικά μαθησιακά περιβάλλοντα και ερευνητικούς χώρους, καθώς και σε διαφορετικούς πληθυσμούς. Ένα ακόμη βασικό σημείο εστίασης αυτής της ανασκόπησης είναι οι σύγχρονες εξελίξεις στον τρόπο που κατανοούμε τους παράγοντες που επηρεάζουν την άδηλη μάθηση, συμπεριλαμβανομένων των κινήτρων, της προσοχής, των θυμικών καταστάσεων και της γενικής γνώσης. Το άρθρο τελειώνει με συμπεράσματα και γενικές αρχές που αντλούνται από την έρευνα γύρω από ένα φαινόμενο με εκτεταμένες εφαρμογές τόσο στο εργαστήριο όσο και στην καθημερινή ζωή και υπογραμμίζει την αναγκαιότητα περαιτέρω έρευνας που θα βελτιώσει τις μεθόδους που έχουμε στη διάθεσή μας για τη διάκριση μεταξύ συνειδητών και ασυνείδητων διεργασιών και θα παράσχει απαντήσεις σε άλυτα ζητήματα και αντιφατικά ευρήματα.