

# Chapter 3

## Individual Differences in Implicit Learning: Current Problems and Issues for Research

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### ABSTRACT

*This chapter reviews research on whether individual differences in psychometric intelligence, working memory, and other less investigated variables, such as emotion and personality, affect implicit learning, with particular focus on Reber's evolutionary theory and Kaufman's dual-process theory for implicit learning. The review shows that while the null effects of psychometric intelligence on implicit learning seems robust as both theories claim, those of working memory were unclear due to methodological insufficiency. For the effects of emotion and personality, further investigation is needed as studies in this direction have just begun to proliferate. The chapter concludes that the research findings on the effects of these individual difference variables on implicit learning are still inconclusive, except for psychometric intelligence, and provides suggestions for future research.*

### INTRODUCTION

Individual differences (IDs) in implicit learning have been a neglected area of research. Empirical studies were rather sporadic and focus was on psychometric intelligence during the 1990s. Findings have been evaluated according to Reber's (1993; Reber & Allen, 2000) evolutionary theory of implicit learning where he argued that IDs in psychometric intelligence (and other variables such as affect) should contribute only to variability in explicit but not implicit learning. However,

recent interest in the dual-process theory of cognition (e.g., Kaufman, 2011; Kaufman, DeYoung, Gray, & Brown (2011); Kaufman, DeYoung, Reis, & Grey, 2011; Stanovich & Toplak, 2012) shed new light on IDs in other variables such as Working Memory (WM), emotion and personality in the implicit learning literature, and begin to provide empirical findings on the effects of these variables on implicit learning. The aim of this paper, then, is to review the recent findings of the effects of these ID variables on implicit learning and to provide state of the art research

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with special references to two prominent theories of IDs in implicit learning. In so doing, the paper, after providing brief characteristics of implicit learning, considers theoretical treatments of IDs in implicit learning, especially focusing on Reber's (1993; Reber & Allen, 2000) evolutionary theory of implicit learning and Kaufman's (2011) dual-process theory of intelligence. Then, reviews of empirical research on the two most investigated areas of research with relation to implicit learning, psychometric intelligence and WM, are provided in addition to other less investigated areas such as emotion and personality. Before concluding, some issues for further research are provided each for psychometric intelligence, WM, and emotion and personality.

## **BACKGROUND**

Implicit learning, learning without awareness of learning processes and/or learning outcomes, has been extensively studied in cognitive psychology (see Perruchet, 2008; Pothos, 2007; Shanks, 2005 for recent reviews). Two learning tasks have been employed in the implicit learning literature: artificial grammar (AG) learning and serial reaction time (SRT) tasks (see Nissen & Bullemer, 1987 and Reber, 1967 for representative studies). Since participants typically cannot verbalise the contents of rules or regularities underlying stimuli but nevertheless show learning in both tasks, the nature of their learning is argued to be implicit.

In the typical AG learning task, participants are presented with a series of digits (e.g., XVXXV) without information on the existence of rules, or "grammar", that underlie such digits. They are just asked to memorise the digits. After training, they are told of the existence of the rules and asked to judge the grammaticality of test digits as well as to indicate the content of such rules. Participants' performance on the grammaticality judgment is above chance (thus showing evidence of learning).

In the typical SRT task, the screen is divided into quadrants and a stimulus appears in one of the quadrants. Participants are required to press keys corresponding to each location. A sequence of a stimulus follows a fixed pattern and participants do not know of its existence. After repeated exposure to this fixed pattern, reaction time (RT) on the fixed pattern decreases. Later a random sequence of a stimulus is inserted into the key-pressing trial. Since participants' RTs on this random pattern significantly increases, it is argued that they have learned the fixed pattern of the stimulus sequence.

One of the characteristics of implicit learning is the nature of acquired knowledge: tacit complex knowledge, largely unavailable to consciousness at the point of learning itself (not "after" the learning; see Reber, 1989). Although the amount of research on the implicit nature of implicit learning has proliferated in the literature, this issue of the implicitness of learned knowledge and/or learning processes has not been settled. This is largely because of methodological problems on how to measure participants' awareness of the learning processes and/or the learning outcomes at the point of learning, or more generally, during learning (Nakamura, 2013a, b; Shanks & St. John, 1994).

Reber (1993; Reber & Allen, 2000), from an evolutionary point of view (described below), provided other characteristics of implicit learning: lesser influences by IDs such as psychometric intelligence on implicit learning, compared with explicit learning. Although this issue of IDs has been less investigated, compared with the vast amount of research on the first issue, investigation into the individual variability of implicit learning is necessary for clarifying the (dissociable) nature of implicit learning (from the explicit learning) and thus the paper provides a view on the individual variability in implicit learning, particularly focusing on the relation between intelligence and implicit learning, and its relations to other cognitive-conative-affective abilities<sup>1</sup>

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