Babeș-Bolyai University
Faculty of Psychology and Educational Sciences
Applied Cognitive Psychology Doctoral School

IMPLICIT LEARNING OF SOCIAL INFORMATION: IMPLICATIONS FOR THE AUTISM SPECTRUM DISORDERS

Extended summary of the Doctoral thesis

Author: Ph.D. candidate,
Andrei Răzvan COSTEA

Scientific coordinator:
Professor Adrian OPRE Ph.D.

CLUJ-NAPOCA
2022

ABSTRACT

The implicit learning deficit (IL) autism (ASD) hypothesis assumes that these individuals have problems in social interactions because they fail to unconsciously (implicitly) learn regularities from their environment. In the first chapter, we discuss data showing that individuals with ASD compensate for this deficit by consciously learning regularities in IL tasks. We further suggest that this compensatory processing is less efficient when operating with complex surface stimuli. The methodological objective is to create IL paradigms with increased external validity for social functioning. The theoretical objective is to determine whether autistic traits predict deficits in IL of cognitive structures instantiated by socio-emotionally relevant surface stimuli. In the third chapter, we will present our own line of research. In the three studies, we attempted to increase the external validity for social functioning of well-known research paradigms; specifically, the Serial Reaction Times Task -study 1; Dynamic Systems Control Task - study 2; Artificial Grammar Learning (AGL) task – in study 3. In contrast to the literature on this topic, we observed that the level of autistic traits predicts a deficit in the acquisition of cognitive structures instantiated by socio-emotional stimuli, in the AGL task. This result will be interpreted as evidence that individuals with high autistic traits show a tendency to use compensatory processing when completing the AGL task. The final chapter outlines future directions for developing an expanded cognitive model of social deficits in ASD.

Keywords: *unconscious cognitive processes; implicit learning; autism spectrum disorders; compensatory cognitive processing; external validity; social functioning*

TABLE OF CONTENTS

1 THEORETICAL BACKGROUND[1]

1.1 Overview of the Theoretical Background

According to the DSM 5 (American Psychiatric Association, 2013), persons diagnosed with ASD are characterized by social communication impairments in multiple contexts and restrictive, repetitive patterns of behavior interests or activities. We start this summary by briefly presenting the overarching arguments that constitute the conceptual scaffolding of our work that is placed in the larger field of cognitive-behavioral research focused on ASD. Thus, in THEORETICAL BACKGROUND, we acknowledged that even nowadays, ASDs continue to be a great challenge for cognitive scientists; and that this is because many of the disorder`s mechanisms still elude scientific enquiry. It is, nevertheless, a common desiderate that a more nuanced understanding of the cognitive features which generate the ASD symptomatology will inform the design of more efficient interventions. Accordingly, a marked deficit in social cognition seems to be a core deficit in ASD however, the underlying cognitive processes which might determine-it are still insufficiently understood (Travers et al., 2010).

Since the seminal work of Reber (1967), numerous scholars provided evidence suggesting that human learning can be placed on an implicit – explicit continuum. IL is thus defined as a cognitive process which enables the non-intentional acquisition of regularities and covariances from the

[1] Parts of this chapter were published as:

Costea, A. R. (2018). Can Compensatory Processing Account for the Performance of Individuals with Autism Spectrum Disorders in Implicit Learning Tasks? A Focused Mini-Review. *Studia Universitatis Babes-Bolyai-Psychologia-Paedago*gia, 63(2), 5-25.

Costea, A. R., Jurchiș, R., Visu-Petra, L., Cleeremans, A., Norman, E., & Opre, A. (2022). Implicit and explicit learning of socio-emotional information in a dynamic interaction with a virtual avatar. *Psychological research*, 1-18.

Pamparău, C., Costea, A., Jurchiș, R., Vatavu, R. D., & Opre, A. (2022, May). Experimental Evaluation of Implicit and Explicit Learning of Abstract Regularities Following Socio-Emotional Interactions in Mixed Reality. In *2022 International Conference on Development and Application Systems* (DAS) (pp. 150-154). IEEE.

environment. The acquired knowledge is often unavailable to awareness or intentional control but, as indicated by behavioral change, it reaches some form of mental representation (Cleeremans et al., 1998; Cleeremans & Jimenez, 2002; Reber, 1967, 1989, 1993). In this context, research suggests that implicitly learned information serves as a cognitive substrate which supports the feelings of intuition (Mealor & Dienes, 2013). Moreover, implicitly learned information is regarded by some authors (Lieberman, 2000; Norman & Price, 2012; Raab & Johnson, 2008) as a cognitive substrate of both social intuition and social cognition. Lieberman (2000) suggests that social intuition involves making rapid judgments about the emotions, personality, intentions, attitudes, and skills of others; the author further notes that such "*judgments are often based on the perception of sequences of various forms of nonverbal cues, including subtle facial expressions, body postures, and nonverbal gestures*' (Liberman, 2000, p. 111).

Given that individuals diagnosed with an ASD manifest an observable social intuition deficit, researchers investigated if a suboptimal functioning of IL could account for it. The current literature on the topic provides mixed results. Thus, Foti et al. (2015) conducted a meta-analytic review. The authors identified 11 studies examining the functioning of IL in individuals with an ASD by using five standard experimental paradigms and concluded that "*individuals with ASD can learn implicitly, supporting the hypothesis that implicit learning deficits do not represent a core feature in ASDs*" (Foti et al. 2015, p. 8). However, in the paragraphs below we will address two comments concerning this conclusion.

First, because they combined all research methods in a single meta-analysis (in a one-size-fits-all manner), Foti et al. (2015) assume that IL is a general capacity. However, this assumption is at odds with a consistent corpus of empirical findings. The extant literature on the boundary conditions for IL clearly shows that we cannot implicitly extract regularities from all categories of stimuli to the same extent. For instance, participants with TD automatically learn a task-irrelevant artificial grammar when it is instantiated by evolutionary relevant stimuli (human faces), but not when it is instantiated by evolutionary irrelevant stimuli - buildings (Eitam et al., 2014), but see also Dienes and Altmann (1997); Jiménez et al. (2020) or Scott and Dienes (2010) for further evidence on the dependency of IL on the characteristics of the surface stimuli. Closer to the social domain, Ziori and Dienes (2015) found that an artificial grammar was learned less when it structured sequences of faces (56% classification accuracy), compared to the same grammar that structured letter strings (64% accuracy; Dienes & Scott, 2005b). In a direct comparison, Norman and Price (2012) found less learning of an artificial grammar that structured sequences of body postures compared to the same grammar when it structured letter sequences (53% vs 58% classification accuracy). Further evidence comes the related field of statistical language learning, which is often assumed to occur, partially, implicitly. Li et al. (2022) have found that young adults with a high level of autistic traits are able to extract statistical regularities from non-social auditory input (pure tones), but not from socially relevant auditory input (Chinese disyllables), bringing further support for the stimulus-dependent operation of implicit/statistical learning.

Second, Foti et al. (2015) reach the conclusion that individuals with ASD can learn implicitly because they failed to gather evidence showing that they cannot – instead, as we have discussed in the subsection titled "***Error! Reference source not found.***" the absence of evidence for an effect d oes not equal with having evidence of absence for the respective effect – this inference bias further legitimates our research proposal.

Accordingly, despite the lack of behavioral evidence supporting the IL deficit in ASD hypothesis, this thesis assumes a compensatory processing framework (see Livingston & Happé, 2017). Briefly, according to this framework, compensatory processing occurs when a typical behavioral functioning (or performance in a cognitive task) is achieved through the recruitment of additional cognitive and/or neurobiological resources which are not normally recruited by individuals with TD. After reviewing literature suggesting that individuals with ASD compensate in some Theory of mind, Reasoning, and Category learning tasks, we analyzed evidence of compensatory processing in the IL research. In this sense, a series of more recent investigations provide contrasting evidences with the conclusion of Foti et al. (2015). For instance, Zwart et al. (2017) recorded the brain activity while individuals with ASDs or TD completed a standard IL paradigm. Their behavioral data indicated a lack of between-groups differences however, electroencephalographic data indicated that the TD group's learning style was mostly incidental (as indexed by an increased N2b component) and, in contrast, the ASD group's learning style was mostly intentional (as it was highlighted by an increased P3 component). Authors suggest that the intact behavioral performance of individuals with ASD was sustained by – as we interpret - a compensatory strategy (i.e., the intentional learning style) and while this processing style is an effective in simple/artificial tasks, it may "*adversely affect learning in complex social situations*" (Zwart, et al., 2017, p. 9) or more naturalistic tasks.

We assume that, if present, an IL deficit in ASD would play a central role especially in the learning of socially relevant information, where – because of their perceptual complexity – the potential compensatory processing strategies might cease being effective. Very important to note is the fact that none of the studies included in the meta-analysis of Foti et al. (2015) investigated IL in a socially relevant context. Based on the above-mentioned scientific data, we emphasized that in order to formulate stronger conclusions, researchers should optimize the ecological validity for social functioning of the experimental tasks intended to assess the functioning of IL in ASD. Few studies in the literature present such research tools that can reliably assess the IL of socially relevant information. In this context, we will next introduce our chief objectives.

1.2 Objectives of the thesis

1.2.1 The methodological objective

We aim to develop instrumental vehicles that are able to induce learning and reliably assess its implicit-explicit nature while employing socially relevant surface stimuli under the form of emotional facial expressions.

1.2.2 The theoretical objective

We aim to assess if participants' levels of autistic traits can predict a deficit in the – implicit and explicit – acquisition of knowledge from our socially relevant IL tasks.

To follow the methodological and the theoretical objectives, in this thesis, we conducted a number of six individual experiments that are grouped in three studies.

2 ORIGINAL RESEARCH CONTRIBUTIONS[2]

2.1 Overview of the Studies

We are now going to present our original research that constitutes our attempt to pursue the above-mentioned objectives. Specifically, in this doctoral work, we have assumed the development of

[2] Parts of this chapter were published as:

experimental tasks that were intended to assess the IL of cognitive structures instantiated by socio-emotional components. Each of the three experimental studies that will be presented in this chapter will focus on adapting to induce implicit social learning of one of the mainstream IL experimental paradigms that were presented in Section **Error! Reference source not found.**, "***Error! Reference source not found.***", namely; The SRT task (study 1), the DSC task (Study 2 with experiments 2a, 2b, 2c and 2d) and finally the AGL task (Study 3). Whenever these modified paradigms will induce IL, we will also assess the relationship between participants' learning performance and their level of autistic traits (by using both NHST and Bayesian tests).

2.2 Study 1. The Relation Between Autistic Traits and the Implicit and Explicit Learning in a (Socio-Emotional) Serial Reaction Time [(s-e)SRT] Task

2.2.1 Introduction

In the present study, we intend to take a tentative step toward the design and construction of a more ecological paradigm for studying IL in an emotionally relevant context. Because, on the one hand, it employs surface stimuli under the form of emotional facial expressions and because, on the other

---

Costea, A. R. (2018). The relationship between implicit learning of cognitive structures with socio-emotional components and subthreshold autistic traits. *Journal of Evidence-Based Psychotherapies*, *18*(2), 131-141.

Costea, A. R., Jurchiș, R., Visu-Petra, L., Cleeremans, A., Norman, E., & Opre, A. (2022). Implicit and explicit learning of socio-emotional information in a dynamic interaction with a virtual avatar. *Psychological research*, 1-18.

Pamparău, C., Costea, A., Jurchiș, R., Vatavu, R. D., & Opre, A. (2022, May). Experimental Evaluation of Implicit and Explicit Learning of Abstract Regularities Following Socio-Emotional Interactions in Mixed Reality. In *2022 International Conference on Development and Application Systems* (DAS) (pp. 150-154). IEEE.

Pamparau, C., Vatavu, R.-D., Costea, A. R., Jurchis, R., & Opre, A. (2021). XR4ISL: Enabling Psychology Experiments in Extended Reality for Studying the Phenomenon of Implicit Social Learning. 20th International Conference on Mobile and Ubiquitous Multimedia, 195–197.

Pamparău, C., Vatavu, R.-D., Costea, A. R., Jurchiş, R., & Opre, A. (2021). MR4ISL: A Mixed Reality System for Psychological Experiments Focused on Social Learning and Social Interactions. Companion of the 2021 ACM SIGCHI Symposium on Engineering Interactive Computing Systems, 26–31. https://doi.org/10.1145/3459926.3464762 hand, is an adaptation of the classical SRT task (Nissen & Bullemer, 1987), our task is dubbed the socio-emotional Serial Reaction Time (s-e)SRT task.

2.2.1.1 Objectives

First, our methodological objective is to investigate if abstract knowledge of a complex second-order conditioning sequence of facial emotional expressions can be learned implicitly. We hypothesize that:

- (H1) Participants will learn the social contingencies embedded in the (s-e)SRT task;
- (H2) Learning will be implicit (i.e., participants completing a task with complex contingencies will not have the ability to intentionally control the acquired knowledge).

Second, our theoretical objective is to investigate the link the autistic traits and the implicit and explicit learning of cognitive structures instantiated by socio-emotional components in the (s-e)SRT task. Thus, we hypothesize that:

- (H3): the level of autistic traits will negatively predict participants' ability to - implicitly and explicitly - acquire structural knowledge from our (s-e)SRT task.

2.2.2 Method

2.2.2.1 Participants

We estimated our sample size based on the power needed to test H3, because it has a smaller expected effect size than that of H1 or H2. Fifty-four participants would be sufficient to test H1 and H2, according to Fu et al. (2010). However - importantly, concerning the power needed to test H3 - because we tested if participants' level of autistic traits negatively predicted their ability to acquire structural knowledge from our (s-e)SRT task by recruiting participants from the general population, we expected this effect to be small. Thus, our power analysis indicated that a simple linear regression with a small effect size f^2 = 0,02 would be statistically significant at an α of 0,05 with a statistical power of 1-β = .80 in a sample of 395 participants. Crucially, for reasons that will be discussed in Section 2.2.3.2 "*H1: Evidence of learning*", the data collection process was stopped after 52 (45 women, m_{age} = 21 years, *sd* = 3.15) undergraduate students recruited from Babeș-Bolyai university participated in the experiment.

2.2.2.2 Self-report instruments

The Subthreshold Autistic Traits Questionnaire (SATQ; Kanne et al., 2012) is a 24-item screening questionnaire with answers given on 4-point Likert scales. This instrument was chosen because, unlike some other measures of ASD screening (e.g., The Autism Spectrum Quotient AQ; Baron-Cohen et al., 2001), the SATQ was specifically constructed to assess the presence of subthreshold autistic traits in the general population (Kanne et al., 2012). For this study, we translated the instrument into Romanian and subjected it to a retroversion procedure; the resulting items are listed in Supplementary material **Error! Reference source not found.**. The translated v ersion revealed good split-half reliability properties (Chronbach's α = 0.75; 95% CI = .66 - .82).

2.2.2.3 Apparatus

The cinematic 3D design of the stimuli (the human avatar with dynamic facial cues) were designed in iClone (*3D Animation Software for Character Animator | IClone*, n.d.) according to the guidelines provided by the Facial Action Coding System FACS (Ekman et al., 2002). The experiment was coded in PsychoPy (Peirce et al., 2019) and ran on Windows computers.

2.2.2.4 Task

2.2.2.4.1 The Acquisition phase:

In our version of the task, the letters were replaced with videos of dynamic facial emotional expressions. On each trial, a cinematic virtual 3D human avatar dynamically morphed from a neutral pose into a preset emotional facial expression instantiating either Fear, Joy, Disgust, or Surprise – for a graphic representation of these emotional facial expressions, see Figure 1 below.

Figure 1. The surface stimuli used in this study; from left to right, the emotional facial expressions represent states instantiating: Joy, Sadness, Surprise, and Disgust.

Unknown to the participants, the transition of facial emotional expressions followed the two second-order conditioning sequences (SOC) taken from Fu et al. (2010). As, instead of letters, we used videos of facial emotional expressions, the letter '*D'* was replaced by '*Fear'*; the letter '*F'* by '*Joy'*; '*K'* by '*Disgust'* and '*J'* by '*Surprise'*. The resulting structures for the two SOC sequences are presented in Table 1 below.

Table 1. The structure of the emotional SOC sequences

SOC 1	*Surprise – Disgust – Joy – Surprise – Sadness – Joy – Sadness – Disgust – Surprise – Joy – Disgust - Sadness*

SOC 2	*Surprise - Disgust - Sadness - Joy - Disgust - Surprise - Sadness - Disgust - Joy - Sadness - Surprise - Joy*

A potential limitation of IL experiments that apply the SRT task is that participants might not extract abstract knowledge but mere motor sequences of responses (Bischoff-Grethe et al., 2004; Meier & Cock, 2010; but, for a different perspective, see Grafton et al., 1998). We control for this potential vulnerability by asking participants to press the spacebar (as quickly and as accurately as possible) in response to only one target facial expression of the four. For instance, in block one participants were instructed to press the spacebar only when the avatar's facial expression is that of "Joy"; in block two, only when the avatar's facial expression is that of 'Surprise', etc. Throughout the acquisition phase, all four facial expressions were independently targeted in two blocks. Crucially, if participants develop abstract representations of the acquisition SOC, we expect that they will be able to automatically predict the appearance of the target facial expression based on the SOC structure and consequently improve their RTs across the acquisition trials.

The acquisition phase consisted of of 768 trials; however, participants responded to one target facial expression / block; therefore, their RTs were measured in only 192 trials. The passive trials automatically transitioned after 2000 milliseconds. Our stimuli followed the acquisition SOC for 87.5% trials and the transfer SOC for the remainder of 12.5% trials. Half of the participants completed the acquisition phase with SOC1 as the acquisition sequence and SOC2 as the transfer sequence, while the other half completed the acquisition phase conversely. Each block started at a random point in the learning sequence. Thirty seconds of rest breaks occurred between every two blocks. Response latencies were measured from the onset of the fixation cross to a correct key press. We operationalize learning as the difference in RTs between the acquisition and the transfer sequences. The description of the methods to assess the implicit/explicit status of learning will be discussed in the next subsection.

2.2.2.4.2 The Test phase:

After the completion of the acquisition phase of the (s-e)SRT task, participants were informed that the stimuli followed specific rules but, their actual conditional relations remained undisclosed to them. An adapted version of the Process Dissociation Procedure (PDP) (Destrebecqz & Cleeremans, 2001; Jacoby, 1991) was used to evaluate the nature of the judgement knowledge. Furthermore, subjective measures of awareness were used to evaluate the implicit – explicit character of the acquired structural knowledge. Their response options were adapted based on Dienes and Scott (2005b).

2.2.2.5 Procedure

Participants were initially invited to give their informed consent; then, they completed the acquisition phase of the (s-e)SRT task; following this activity, they completed the Test phase (comprised of the PDP and subjective response basis attributions); lastly, they completed an electronic version of the Subthreshold Autistic Traits Questionnaire (SATQ; Kanne et al., 2012).

2.2.3 Results

2.2.3.1 The operationalization of the variables for data analysis

- Sequence learning: Evidence of learning was considered if the RTs of the acquisition sequence will decrease significantly more than the RTs of the transfer sequence as the task progresses.
- Unconscious judgement knowledge: We will draw the conclusion that participants had acquired unconscious judgement knowledge from the task in the situation in which they will not be able to generate a significantly lower number of triplets identical with the acquisition sequence in the Exclusion task than in the Inclusion task.
- Unconscious structural knowledge: The existence of unconscious structural knowledge is inferred if, in trials in which participants use implicit attributions (i.e., Guess and Intuition), they are able to accurately use their judgement knowledge (i.e., by including significantly more responses that conform to the acquisition sequence in inclusion than in exclusion; see, e.g., Fu et al., 2010, 2018).
- The levels of autistic traits: is indexed by participants' scores on the SATQ.

2.2.3.2 H1: Evidence of learning

A within-subject ANOVA, with block (1-8) and sequence (acquisition vs. transfer) as independent variables yielded a significant effect of block $F(7.357) = 48.536$, $p < .001$, $\eta^2_p = .488$. This suggests that participants improved their RTs as the task progressed (see

Figure 2 below). However, the effect of sequence was not significant $F(1, 51) = 1.298$, $p = .260$, $\eta^2_p = .025$. This suggests that participants did not respond faster the acquisition than the transfer sequence.

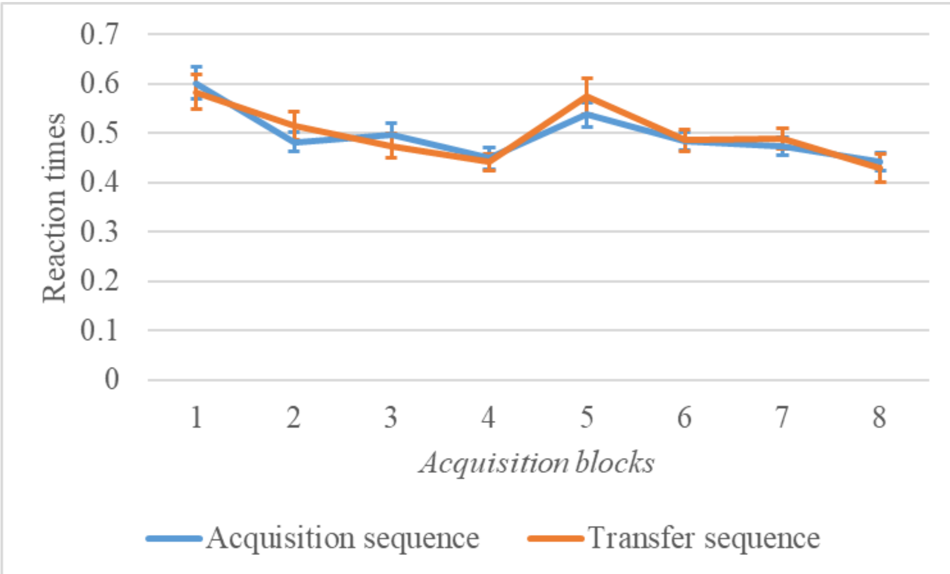

Figure 2. Represents the RTs for the acquisition sequence and the transfer sequence across the training blocks. The error bars represent 95% CI.

2.2.3.3 H2: Evidence of IL

The testing of the second hypothesis was prevented by the lack of evidence suggesting that learning occurred in the task.

2.2.3.4 H3: The relations between autistic traits and learning in the (s-e)SRT task

Due to the fact that we were unable to show that the task induced learning, the testing of H3 would not be theoretically meaningful.

2.2.4 Discussion and bridge to the next study

In this chapter, we detailed our – for now, unsuccessful - efforts to develop an experimental task that increases the ecological / external validity for social functioning on the basis of the SRT task. In short, we failed to observe evidence that this task induces implicit or explicit learning. Because of this result, and motivated by the relative artificiality of the way in which participants interact with our task, we will next motivate our second study.

Specifically, one of the present study's limitations is related to the artificial interactions between the participants and the task. Put differently, in our implementation, participants responded to a predetermined SOC sequence. The sequence remained unchanged, regardless of participants' RTs. This characteristic differentiates our task from the manner in which IL processes likely contribute to our day-to-day functioning. In brief, here we suggest that if we intend to evaluate IL with a high degree of external validity for social functioning, this goal, by itself, obliges us to construct evaluation contexts (i.e., experimental paradigms) that maximally resemble the manner in which this process likely operates in real life. Motivated by this objective, in the next section, we will present our efforts to develop an IL instrument that immerses participants in a dynamic interaction with the task (such as it happens in natural social interactions), that is, the Dynamic systems control task (Berry & Broadbent, 1995)

Table of Contents

2.3 Study 2. The Relation Between Autistic Traits and the Implicit and Explicit Learning in a Realistic (Socio-Emotional) Dynamic Systems Control [(s-e)DSC] Task

2.3.1 General Introduction

We capitalize on several recent developments from the fields of Cognitive Psychology, in implicit cognition research - and Computer Science, in Mixed Reality and natural user interfaces based on gesture and voice input, to maximize our external validity for social functioning in the assessment of IL. By assuming an iterative approach, "Study 2a: The Construction of the (s-e)DSC Task in 2D" will develop and test the task in a 2D environment; Afterward, studies 2b and 2c will implement it in an Augmented Reality (AR) setup. The results that will be presented in this last study will enable study 2d to assess the relationship between participants levels of autistic traits and their IL functioning, as assessed by their performance on our socially relevant, Mixed Reality task [AR[4](s-e)DSC].

2.3.2 Study 2a: The Construction of the (s-e)DSC Task in 2D

2.3.2.1 Introduction

We start from the observation that in both real-life and experimental environments, information is being exchanged in loops. Specifically, in most cases of real-life interaction, an individual's behavior determines or encourages a response from the social environment; in addition, the individual typically reacts again to the response of the social environment, thus perpetuating a loop of information exchange. Similarly, in experimental contexts, a participant's behavior determines a response from the research paradigm (e.g., advancing to the next stimulus), to which the participant typically reacts again, thereby perpetuating a loop of informational exchange.

However, the loops through which information is exchanged in most IL tasks are fundamentally different from those in which information is exchanged in social environments. Specifically, in the real-world environment, if an individual behaves in different manners, s/he should expect different responses, that is, information is being exchanged via feedback-driven interactive loops (Becchio et al., 2010). On the contrary, in most IL paradigms, participants respond to overly complex, predefined sequences of stimuli which, crucially, do not adapt in reaction to their responses – i.e., information is being exchanged via non-interactive loops. For instance, in the acquisition phase of the AGL task, participants are exposed to a predetermined list of letter strings; there is no modulation in the behavior of the task or of the stimuli as a consequence of participant's behavior. Here, we emphasize that an instrument that aims to assess the role of IL in social interactions – besides using socially relevant surface stimuli - should also simulate the dynamic, feedback-driven manner in which information is being exchanged in such environments. One example of such a method is the classic Dynamic Systems Control (DSC) task (Berry & Broadbent, 1984, 1995) – which was initially presented in Subsection **Error! Reference source not found.** of this thesis.

We suggest that while Berry and Broadbent's (1984) task implements interactive loops of informational exchange, its use of linguistic labels as surface stimuli keeps it abstract in a way that severely limits its relevance to the social domain.

2.3.2.1.1 Objectives and hypotheses

The main objective of this study was to determine whether IL can be involved in the acquisition of the complex regularities present in a situation involving dynamic interaction with a life-like virtual agent. Based on the previous DSC studies (e.g., Dienes & Fahey, 1998), our hypotheses were that:

- (*H1) participants will acquire the regularity*;
- (*H2*) *they will possess accurate judgement knowledge;*
- (*H3) their accurate judgement knowledge will be based both on unconscious structural knowledge and on conscious structural knowledge*.

2.3.2.2 Method

2.3.2.2.1 Participants

Because it has a smaller expected effect size than that of *H1* and *H2*, we determined our sample size considering the statistical power needed to test *H3*. We expected a small to medium effect size for the unconscious learning effect stipulated by *H3*, based on previous studies that used similar methods to measure conscious and unconscious knowledge (e.g., Fu et al., 2010, 2018). Our power analysis indicated that a one-tailed test can detect a potential difference between two paired means (i.e., within-subjects design) that has an effect size of *Cohen's* $d_z = 0.3$ with a statistical power of $1\text{-}\beta = .8$ in a sample of 71 participants. Note that for the other hypotheses, we expected large or medium to large effect sizes (for H1, a $d_z = 0.798$ based on Dienes & Fahey, 1998; for H2, a $\eta^2_p = .329$, based on Fu et al., 2010; for the conscious learning effect stipulated by H3, a $d_z = 0.67$, based on Fu et al., 2010), and 71 participants provided a statistical power > 99% for all these effects. Therefore, we aimed for a sample size of at least 71, but, as participants were rewarded with partial course credit, a higher number of persons enrolled. A total of 115 first-year undergraduate students in psychology from the Babeș-Bolyai University, (99 female, $m_{age} = 19.74$, $sd = 1.27$) participated in this research.

2.3.2.2.2 Apparatus

The stimuli were designed with iClone Version 7.2 (*3D Animation Software for Character Animator | IClone*, n.d.) the JavaScript experiment was coded in PsychoPy / PsychoJs (Peirce et al., 2019) and ran on the Pavlovia.org servers (*Pavlovia*, n.d.).

2.3.2.2.3 The task

In a within-group design, we used a two-step task with a learning phase and an awareness test phase. In the learning phase, participants were presented with a socially relevant environment that made it possible to quantify the on-line acquisition of knowledge. In the awareness test phase, we assessed the implicit/explicit status of the acquired knowledge.

The stimuli and materials

Participants interacted with a cinematic virtual avatar that could display a range of seven emotional facial expressions (see **Error! Reference source not found.**) and transitioned from one facial e xpression to the next in a fluid motion comprised in fixed intervals of 30 frames, each lasting 500 milliseconds, see Figure 3 below.

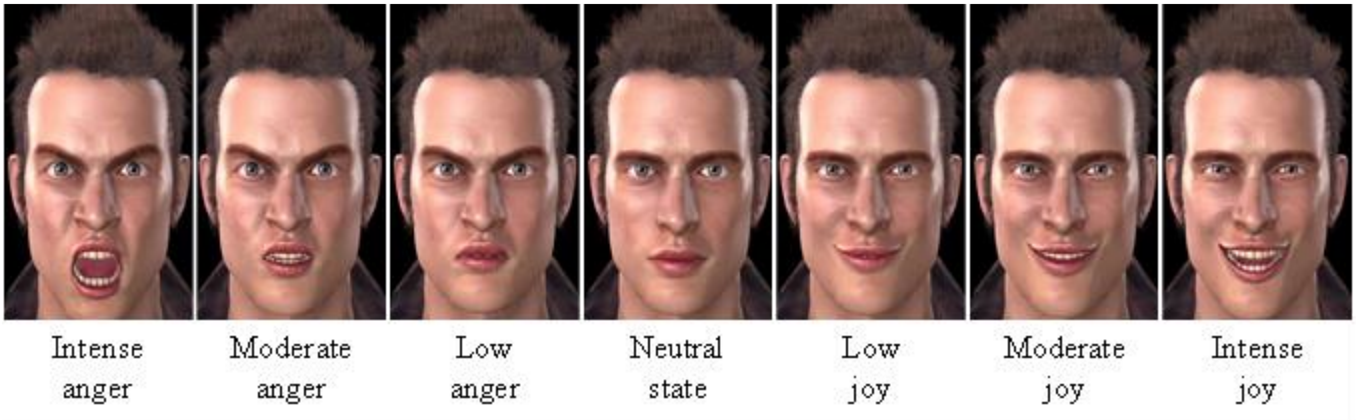

Figure 3 The seven facial expressions used in this study

The learning phase

Participants were informed that they will interact with a fictional character from an unknown culture who is able to display only a limited number of facial expressions and is unable to regulate his facial expressions. They were further instructed that the avatar attends an important task in which he must not express intense facial expressions - neither positive nor negative - and that their task is to assist him in regulating his emotions, aiming to get him into the Neutral state as many times as possible. Crucially, undisclosed to participants, their interaction with the avatar was mediated by a complex rule, that will be detailed in the subsection below.

The abstract rule

To describe our implementation of the equation, it is first necessary to present the fact that each of the avatar's 7 possible facial expressions, as well as each of the participants' seven possible response options were assigned a constant position within a looped numerical sequence; for a graphical representation, see the Figure 4 below. The starting point of the sequence was set on position 0 (i.e., Intense anger) however, transitions within the sequence could be made in both a clockwise and an anticlockwise direction. Participants were not directly exposed to, or made aware of, the existence of this sequence.

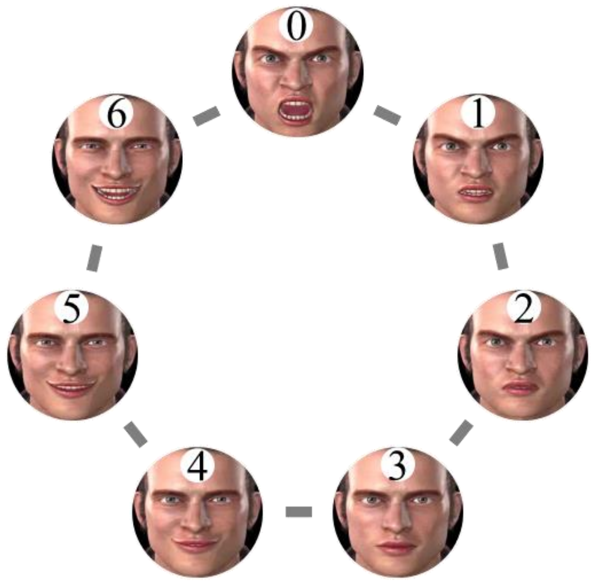

Figure 4. The abstract looped numerical sequence. It depicts both the avatar's possible facial expressions and the participants' possible response options. Intense anger = position 0, Moderate anger = position 1, Low anger = position 2, the Neutral state = position 3, Low joy = position 4, Moderate joy = position 5 and, Intense joy = position 6.

To determine the avatar's facial expression on any given trial (i.e., $Av.\ Exp._{t}$), the task was programmed to compute the equation "$Av.\ Exp._{t} = 0 + [Av.\ Exp._{t-1} + (Av.\ Exp._{t-1} - P.\ Resp._{t-1})]$" where, "$Av.\ Exp._{t}$" denotes the Avatar's expression in the current trial; "*0"* represents the starting point of the stimulus set; "$Av.\ Exp._{t-1}$" represents the Avatar's expression in the previous trial and "$P.\ Resp._{t-1}$" represents the Participant's response in the previous trial.

The result of the equation indicated the direction and length of the pathway that the task moved within the looped sequence - starting from position 0 - to select the avatar's facial expression in the current trial. The task was programed to move within the sequence in a clockwise direction if the result was a positive number and vice versa if the result was a negative number. Participants were instructed to regulate the avatar's facial expression in the Neutral state as many times as possible. Thus, all instances in which "$Av.Exp._t = 0 + 3$" or, "$Av.Exp._t = 0 – 4$" were considered *On-target trials* because, according to these results, the avatar will morph into the Neutral facial expression. For a possible interaction sequence between a participant and the task across the first three trials of a block, see the Table 2 below.

Table 2. Simulates how the equation mediates the interaction between a participant's responses and the avatar's facial expressions

Event order	**Event description**	**Equation**
1	Avatar's expression in trial 1 is I*ntense anger*	$Av.\ Exp._{t1}$ = 0 [i.e., Intense anger]
2	If participants' response in trial 1 is N*eutral*	$P.\ Resp._{t1}$ = 3 [i.e., Neutral]
3	Computation of the required change in position	$Change_{t2} = 0 + [Av.\ Exp._{t1} + (Av.\ Exp._{t1} - P.\ Rresp._{t1})]$
		$Change_{t2}$ = 0 + [0 + (0 – 3)]
		$Change_{t2}$ = 0 + [0 + (– 3)]
		$Change_{t2}$ = 0 + (-3)
4	The location moves three positions counterclockwise, starting from zero	$Change_{t2}$ = -3
5	**Outcome**: Avatar's expression in trial 2 is *low joy*	$Av.\ Exp._{t2}$ = 4 [i.e., Low joy]
6	If participants' response in trial 2 is *intense joy*	$P.\ Resp._{t2}$ = 6 [i.e., Intense joy]
7	Computation of the new state by the algorithm	$Change_{t3} = 0 + [Av.\ Exp._{t2} + (Av.\ Exp._{t2} - P.\ Resp._{t2})]$
		$Change_{t3}$ = 0 + [4 + (4 – 6)]
		$Change_{t3}$ = 0 + [4 + (– 2)]
		$Change_{t3}$ = 0 + 2
8	The location moves two positions clockwise, starting from zero	$Change_{t3}$ = +2

9	**Outcome**: Avatar's expression in trial 3 is *low anger*	$Av.\ Exp.t3$ = 2 [i.e., Low anger]
10	If participants' response in trial 3 is *moderate anger*	$P.\ Resp._{t3}$ = 1 [Moderate anger]
11	Computation of the new state by the algorithm	$Change_{t4} = 0 + [Av.\ Exp._{t3} + (Av.\ Exp._{t3} - P.\ Resp._{t3})]$ $Change_{t4}$ = 0 + [2 + (2 – 1)] $Change_{t4}$ = 0 + [2 + (1)] $Change_{t4}$ = 0 + 3
12	The location moves three positions clockwise, starting from zero	$Change_{t4}$ = +3
13	**Outcome**: Avatar's expression in trial 4 is *Neutral*	$Av.\ Exp._{t4}$ = 3 [i.e., Neutral]

Note. *The table describes the events from three consecutive trials. Av. Exp.*$_{tx}$ *– the avatar's expression in trial x. P. Resp.*$_{tx}$ *– participants' response in trial x; Change*$_{tx}$ *– the change in position within the looped sequence, required for reaching the avatar's state in trial x*

Noteworthy, our task has no specific input – specific output mapping; therefore, task habituation cannot explain performance improvements. The learning phase was structured as a self-paced seven alternative forced choice task (7AFC) and consisted of 300 trials divided to ten equal blocks, with 30 seconds rest breaks between each of them.

The awareness test phase

The main goal of this phase was to determine whether participants had acquired accurate unconscious and conscious knowledge about the equation (structural knowledge). To this end, we employed an extensively used subjective measure of awareness, called *knowledge attribution* (Dienes & Scott, 2005a; Fu et al., 2010, 2018; Norman et al., 2011, 2016, 2019; Waroquier et al.,

2020) which was used in the context of a *Process Dissociation Procedure* (PDP; Jacoby, 1991; Destrebecqz & Cleeremans, 2001).

The avatar's seven facial expressions were randomly presented twice in both the inclusion and the exclusion tasks. If participants regulated the avatar to the target state on significantly more trials in inclusion vs. exclusion, we would conclude that they had acquired accurate judgement knowledge. Participants were required to indicate the subjective attribution of their response after each trial of the PDP. Under the form of a 4-alternative forced choice (4AFC) with *Guess*, *Intuition*, *Rules,* and *Memory* as response options. The *Guess* and *Intuition* response options denote that participants attribute their answer to unconscious structural knowledge (hereinafter *implicit attributions)* whereas the *Rules* and *Memory* response options denote that participants attribute their answer to conscious structural knowledge (hereinafter, *explicit attributions*). Participants were presented with explanations of these response options after each trial of the PDP (see Table 3 below) and were asked to choose the option that they think best describes what they relied on when they gave the previous answer.

Table 3. Definition of the Self-reported decision strategies

Guess	*Your answer had no basis whatsoever. You could have just as well flipped a coin to decide.*
Intuition	*You felt that your answer was correct, but you have no idea why you felt this. That is, you had a feeling that by responding with that facial expression, you were regulating John in the Neutral state - but you do not know what that impression was based on.*
Rules	*Your answer was based on a rule (or on a fragment of a rule) that you know consciously, and you can describe if we ask.*
Memory	*Your answer was based on the fact that you consciously remember that by responding with that facial expression you were bringing John in the Neutral state.*

In the following section, we present the specific sequence of instructions and tasks that were administered to the participants.

2.3.2.2.4 Procedure

In brief, participants were first asked to give their written informed consent prior to completing the experimental activities. Second, they were asked for their demographic information. Third, they completed the learning phase and, fourth, they completed the awareness test phase. The entire experiment lasted around 25 minutes. After the awareness test phase was completed, participants were thanked for their involvement in this research and were given the contact information of the principal investigator to address their potential questions.

2.3.2.3 Results

2.3.2.3.1 The operationalization of the variables for data analysis

- Learning: Evidence of learning was considered if the number of On-target trials increased with practice (i.e., as the task progressed).
- Unconscious judgement knowledge: We will draw the conclusion that participants had acquired unconscious judgement knowledge from the task in the situation in which they will not be able to generate a significantly lower number of On-target trials in the Exclusion than in the Inclusion task.
- Unconscious structural knowledge: The existence of accurate unconscious structural knowledge is inferred if, in trials in which participants use implicit attributions (i.e., Guess and Intuition), they are able to accurately use their judgement knowledge (i.e., by

including significantly more responses that conform to the learned equation in inclusion than in exclusion; cf., e.g., Fu et al., 2010, 2018).

In the following, we will first analyze whether participants acquired knowledge of the regularity. Then, we analyze whether they possess accurate judgement knowledge. Last, we assess whether their accurate judgement knowledge is based both on unconscious structural knowledge and on conscious structural knowledge.

2.3.2.3.2 (H1) Evidence of learning

The raw dataset generated for this study is available on the Center for Open Science repository (osf.io/q9bac). If participants acquired knowledge from the task, we would expect an increase of the number of *On-target trials* as the task progressed. A one-way repeated measures ANOVA revealed a significant effect of *Block* (1-10, within-subjects) on the number of *On-target trials*, $F(9,114) = 38.33$, $p < .001$, $\eta^2_p = .252$. A follow up repeated measures t-test indicated that participants generated significantly more *On-target trials* in the *10th acquisition block* ($m_{proportion} = .309$, $sd = .198$) than in the *1st acquisition block* ($m_{prop.} = .135$, $sd = .106$), $t(114) = -9.05$, $p < .001$, *Cohen's d* = 0.84. Altogether, these results clearly show that learning had occurred during the task (see the Figure 5, below).

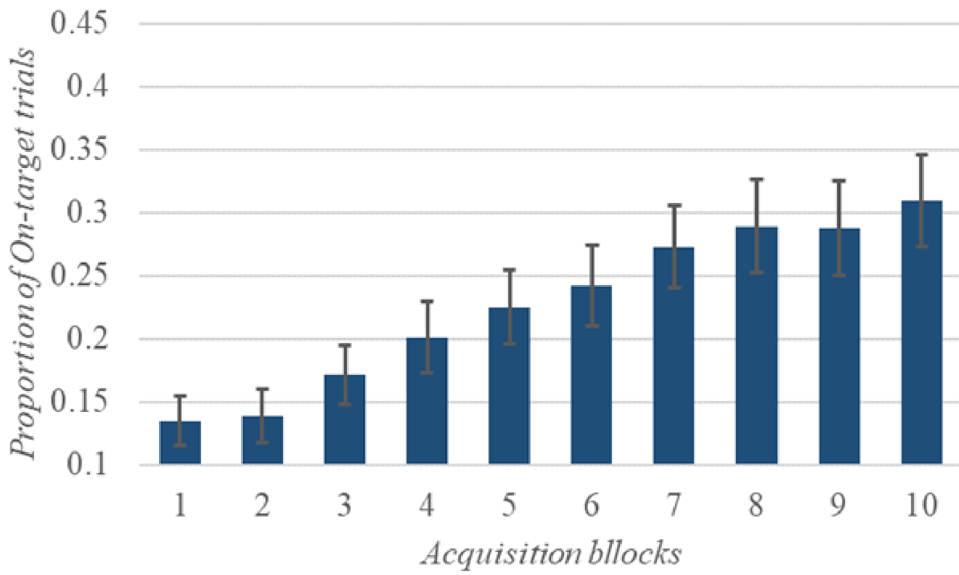

Figure 5. The mean proportion of On-target trials (I.e., the trials in which participants managed to bring the emotional facial expression of the avatar in the Neutral state) generated across the acquisition blocks. Error bars depict 95% CIs.

2.3.2.3.3 (H2) Evidence for accurate judgement knowledge

To determine whether participants possessed accurate judgement knowledge, we compared the number of *On-target trials* from the inclusion task with those from the exclusion task. Thus, a mixed ANOVA assessed the effects of *Instruction* (within-subjects: inclusion vs. exclusion) and *task order* (between-subjects: inclusion–exclusion vs. exclusion–inclusion) on the number of *On-target trials* generated in the test phase. We found a significant *Instruction* effect, $F(1, 113) = 107.01$, $p < .001$, $\eta^2_p = .486$, indicating that participants generated significantly more *On-target trials* in the inclusion ($m_{prop.} = .357$, $sd = .220$) than the exclusion ($m_{prop.} = .104$, $sd = .098$) task. We failed to detect either a significant *Task order* effect, $F(1, 113) = .61$, $p = .435$, $\eta^2_p = .005$, or a significant *Instruction* by *Task order* interaction effect $F(1, 113) = .07$ $p = .794$, $\eta^2_p = .005$. These results suggest that participants acquired accurate judgement knowledge from the task.

2.3.2.3.4 (H3) Evidence for accurate conscious and unconscious structural knowledge

After having established that participants possessed accurate judgement knowledge, we now analyze to what extent it is based on unconscious and/or on conscious structural knowledge.

Following established analytical strategies in IL research (Norman & Price, 2012; Ziori & Dienes, 2015), we combined the Guess and Intuition response attributions to create *Implicit attributions* scores, and the Rules and Memory attributions to create the *Explicit attributions* scores. Roughly half of the total responses were based on *Implicit attributions* (in inclusion, $m_{prop.} = .528$, $sd = .306$ and in exclusion, $m_{prop.} = .465$, $sd = .368$) and the other half were based on *Explicit attributions* (in inclusion, $m_{prop.} = .472$, $sd = .306$ and in exclusion, $m_{prop.} = .535$, $sd = .368$).

We then analyzed the accuracy of participants' judgement knowledge depending on the conscious/unconscious status of their structural knowledge. First, we assessed whether participants had accurate judgement knowledge when they reported that their responses were based on explicit structural knowledge. For responses based on *Explicit attributions*, a paired sample *t* test indicated that participants generated significantly more *On-target* trials in the inclusion ($m_{prop.} = .558$, $sd = .347$) than the exclusion task ($m_{prop.} = .072$, $sd = .114$), $t(96) = 13.02$, $p < .001$, $d = 1.32$. The analyses above indicate that participants had accurate judgement knowledge on trials where they reported relying on conscious structural knowledge.

We then assessed whether participants had accurate judgement knowledge when they reported that their responses were based on unconscious structural knowledge. For responses based on *Implicit* *attributions*, a paired sample *t* test indicated that participants generated significantly more *On-target trials* in the inclusion ($m_{prop.}$ = .200, *sd* = .209) than the exclusion task ($m_{prop.}$ = .130, *sd* = .156), *t*(87) = 2.88, *p* = .006, d_z = 0.31. Collectively, the analyses indicate that participants had accurate judgement knowledge on trials where they reported relying on unconscious structural knowledge – when they reported basing their answers on an intuition or, even when they indicated that they had chosen them at random.

2.3.2.4 Discussion and bridge to the next study

The present study is one of the first to propose a task for assessing the role of IL in interactive situations with socially relevant surface stimuli. Furthermore, by employing one of the most versatile measures of awareness that was used in the DSC research up until this point, we provide evidence that, similar with other well-established IL tasks (e.g., the AGL and SRT task), our (s-e)DSC task indeed produces implicit knowledge, along with a significant amount of explicit knowledge". In the paragraph below, we will offer a conceptual "bridge" – that is intended to connect the results presented in this study, to the foundation of the next one.

In order to investigate the relationship between participants' ability to implicitly learn social information and their level of autistic traits, we first need to develop a task that assesses IL in a manner that is as similar as possible to the way in which this process is supposed to function in real-life environments. To this end, the development of our version of the (s-e)DSC task is a notable contribution. However, it still preserves a significant sense of artificiality. Specifically, as opposed to the how we exchange information in real-life social interactions (i.e., spoken language, gestures, etc.), in the current version of the task, participants interacted with the avatar by means of mouse clicks. Furthermore, the sense of artificiality was also preserved in the current task as the virtual avatar was represented as a miniature on a computer screen, thus diverging with the size of the real-life social partners. Fortunately, recent developments from the computer sciences offer a plethora of tools to address both of these limitations and thus, increase the external validity of our task even further. In sum, by capitalizing on the results presented in Study 2a, the purpose of the Study 2b was to develop a version of the (s-e)DSC task in an immersive environment that resembles natural social interactions and enables participants to engage in the interaction with the avatar by using naturally occurring means of communication such as language and gesture making.

2.3.3 Study 2b: The Implementation of the (s-e)DSC task in Augmented Reality (Pilot 1)

2.3.3.1 Introduction

Our chief goal for this chapter was to develop a research tool, able to assess the functioning of IL upon socially relevant surface stimuli in a manner that is as close as possible to a genuine social interaction. For this reason, we undertook an interdisciplinary approach, and constructed our research paradigm in augmented reality (AR). The product of this development project will bear the name Augmented Reality for (socio-emotional) Dynamic Systems Control [AR^4(s-e)DSC] task. Besides the specifications that were discussed in Study 2a, this task will also attempt to satisfy two additional requirements, as follows:

- RQ1: Display a naturalistic presence of a social partner. As discussed above, there are relatively few IL paradigms that employ socially relevant stimuli. Moreover, in virtually all currently available research, testing is performed using standard PC displays - which hardly mimic social interactions in real environments. In contrast, we are going to maximize the external validity of our MR4ISL model by creating a Mixed Reality experience in which participants will interact with a dynamic, photorealistic human character at real scale.

- RQ2: Allow naturalistic means of interacting with the virtual partner. In most of the currently available assessment instruments, participants respond by means of WIMP-like interactions (i.e., user interfaces composed of windows, icons, menus, and pointing) - again, departing from the manner in which information is being exchanged in the real social environment. In contrast, our MR4ISL model will be equipped with speech processing capabilities and participants will be able to interact with the virtual interlocutor by voice input.

2.3.3.1.1 Hypotheses

Similarly with Study 2a, here we hypothesized that:

- *(H1) participants will learn the social contingencies embedded in the task;*
- *(H2) learning will be implicit (i.e., participants will perform better than would be expected at the chance level even when they will declare knowledge unawareness).*

2.3.3.2 Methods

2.3.3.2.1 Participants

To determine the sample size needed to test *H1*, we looked at the learning effect of Study 2a. There, we observed that participants generated significantly more *On-target trials* in the *10^{th} acquisition block* ($m_{proportion}$ = .309, *sd* = .198) than in the *1^{st} acquisition block* ($m_{prop.}$ = .135, *sd* = .106), $t(114) = -9.05$, $p < .001$, *Cohen's d* = 0.84. Thus, our power analysis indicated that a one-tailed test can detect a potential difference between two paired means (i.e., within-subjects design) that has an effect size of *Cohen's* d_z = 0.84 with a statistical power of 1-β = .80 and an α = .05 in a sample of 11 participants.

Second, the sample size needed to test H2 was also based on our results from Study 2a. There, we observed an unconscious learning effect of Cohen's d of 0.24. Thus, our power analysis indicated that a sample of 109 participants would be needed to test for this effect with a statistical power of 1-β = .80 and an α = .05. However, for reasons that will be discussed in subsection 0, the data collection process was stopped after 60 ($m._{age}$ = 19.8; *sd* = 0.81) psychology undergraduate students underwent this research in exchange for partial course credits.

2.3.3.2.2 Apparatus

We implemented MR4ISL 2.0 using the second-generation Microsoft HoloLens HMD with an ARMv8 architecture, 65GB UFS 2.1 flash and 4GB LPDDR4x DRAM memory and running Windows 10. We used Visual Studio 2019, Unity3D, Windows Software Development Kit for Windows 10 and Universal Windows Platform (UWP). Gesture recognition and voice commands were implemented with the technology built into the HoloLens SDK. The source code of our application is accessible for download at: http://www.eed.usv.ro/mintviz/projects/ISELMIR/.

2.3.3.2.3 *The task*

The training phase

The purpose of this phase was to teach participants to interact with the holograms. First, to deploy the task, participants were instructed to pronounce the voice command “Go!”. Then, the participant was asked to look at their hands and notice their augmented version see the Figure 6 below.

Figure 6. A screenshot of the MR4ISL application running on the HoloLens mixed reality headset, depicting a participant's real and virtual hands.

Next, the participant was informed that the blue spheres placed above the index fingers would have to touch the holograms in order to interact with them. As illustrated in Figure 7, five blue cubes numbered 1 to 5 appeared on the scene. The participant was tasked to make them disappear by touching them in ascending order.

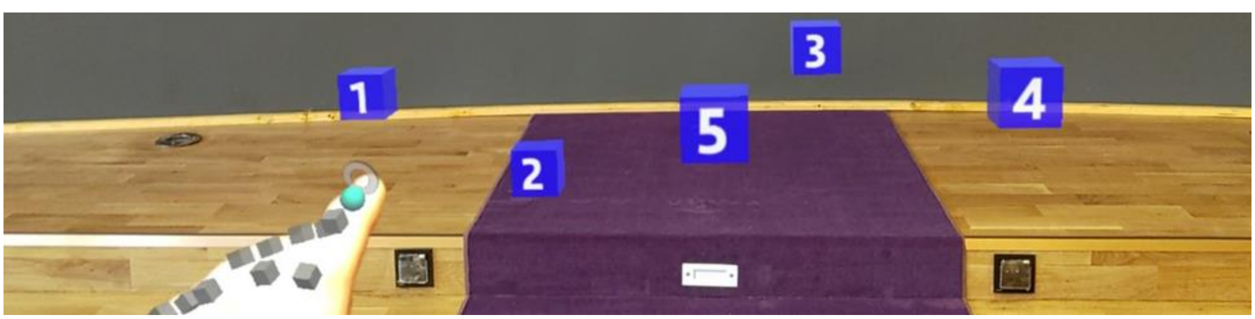

Figure 7. A view of a participant's hands as they go through the training phase of the experiment.

The Acquisition phase

This experiment followed the logic of Experiment 2a. Differently however, here, the cover story was that we investigate how colors help people regulate their emotions. Participants were informed that Kevin – their virtual partner - will change his emotional state only as a reaction to the colors that he is being shown and, that their most important task is to figure out Kevin's preferences for colors aiming to regulate and maintain him in a calm emotional state in as many trials as possible. The acquisition task consisted in 10 blocks of 30 trials, and the interaction between participants and the task was mediated by the same abstract set of rules as the ones implemented in Study 2a. The succession of emotional facial expressions that were presented to the participants can be observed in Figure 8 below.

Figure 8. The range of emotional facial expressions that can be displayed by the avatar during the experiment.

The test phase

Participants responded to a task consisting of 28 generation trials. On each, they were presented with one of Kevin's seven facial expressions and asked to indicate a response that would regulate his facial expression in the neutral state. Once the response was given, we evaluated the implicit/explicit nature of the structural knowledge which sustained that decision by taking subjective measures of awareness (Dienes & Scott, 2005; Scott & Dienes, 2008). The response options (Guess, Intuition, Rules, and Memory) appeared alongside their definitions (see Table 3) in the center of the visual field in a scene emptied of any other graphic elements. Participants pronounced their response option.

2.3.3.2.4 Procedure

Initially, participants gave their written informed consent. The procedure started with the training phase, continuing with the acquisition phase, and finalizing with the testing phase.

2.3.3.3 Results

2.3.3.3.1 The operationalization of the variables for data analysis

- **Learning**: Evidence of learning was considered if the number of On-target trials increased with practice (i.e., as the task progressed).
- **Unconscious structural knowledge**: The existence of unconscious structural knowledge is inferred if, in trials in which participants use implicit attributions (i.e., Guess and Intuition), they are able to generate significantly more On-target trials than would be expected at the chance level.
- **Conscious structural knowledge:** The existence of conscious structural knowledge is inferred if, in trials in which participants use explicit attributions (i.e., Rules and Memory), they are able to generate significantly more On-target trials than would be expected at the chance level.

2.3.3.3.2 H1. Evidence of learning

A one-way, repeated measures analysis of variance (one way ANOVA) revealed a significant effect of practice on the number of On-target trials, $F(9, 59) = 2.04$, $p = .033$, $\eta^2_p = .023$, indicating that participants improved their ability to control the avatar's emotional state as the task progressed (see Figure 9 below).

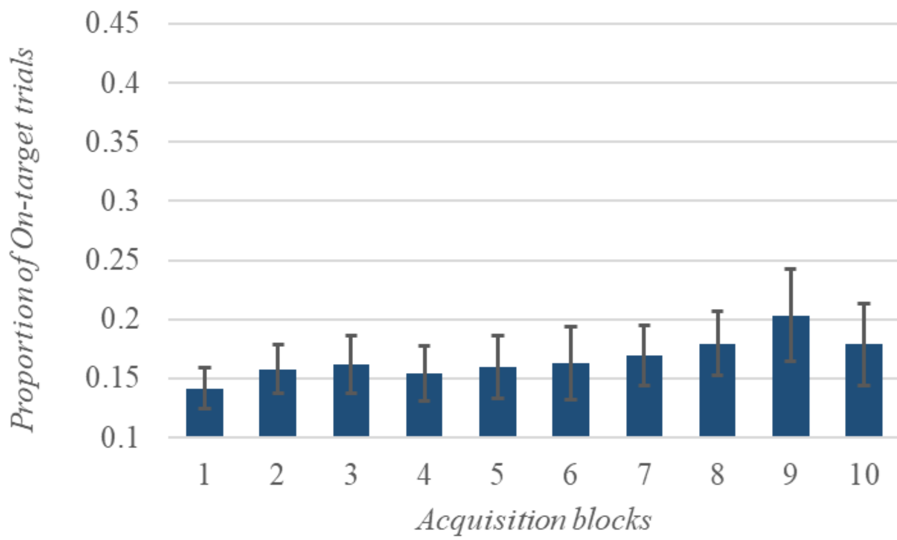

Figure 9. Depicts the average proportion of On-target trials (i.e., responses that regulated the avatar to the Neutral state), generated over the acquisition blocks. Error bars depict 95% Cis.

2.3.3.3.3 H2) Evidence of IL

Responses attributed to Guess, and Intuition were collapsed to create implicit attribution scores; responses attributed to Rules and Memory were collapsed to create explicit attribution scorers. To analyze the type of learning that was induced by our task, we compare the responses based on implicit or explicit response attributions with the accuracy that would be expected at the chance level. For this, we initially need to determine the chance level. Specifically, given that in each trial of the generation task, participants had 7 response options of which only one was correct, the chance level is set at .142. A one-sample *t* test indicated that responses attributed to conscious response bases (i.e., Rules and Memory) were significantly above chance level, $t(55) = 5.57$, *p*

<.001, $d = -0.744$. This result indicates that participants acquired a significant amount of explicit knowledge from the task. However, contrary to our expectation, another one sample *t* test indicated that responses attributed to unconscious structural bases (i.e., Guess and Intuition), were not significantly above chance level, $t(56) = -1.95$, $p = .97$, $d = -0.258$, $B_{h(0,.029)} = 0.16$. This result shows that participants did not acquire unconscious knowledge from the task.

2.3.3.4 Discussion

In this implementation, participants interacted with a holographic animated avatar that could display various facial expressions. Participants were informed that the study was investigating the manner in which colors help people regulate their emotions; and that their task is to get the avatar to display a neutral facial expression in as many trials as possible. Unbeknownst to them, a complex regularity mediated their interaction. The task induced only a minimal amount of explicit learning and – very importantly – failed to induce IL. To achieve our goals, it is necessary to continue developing the experimental design of the AR^4(s-e)DSC task so that it will induce IL. The updated version of it, and our extended rationale for updating-it, will be presented in the experiment below.

2.3.4 Study 2c: The Development of the AR^4(s-e)DSC Task (Pilot v.2.0)

2.3.4.1 Introduction

The results of Study 2b are surprising because it employed a very similar method with the one presented in Study 2a yet failed to induce IL. The differences in participants' response options were identified as a potential factor that could account for these different results. Specifically, in the first version (Study 2a, which successfully produced IL) participants interacted with the avatar by indicating different facial expressions. In other words, they responded to facial expressions with other facial expressions. In contrast, in the second experiment (Study 2b) participants responded by choosing a specific color.

Changing the way in which the participant responded (through indicating a color vs. a facial expression), likely primed different strategies and cognitive processes. More precisely, colors, in the context of a social interaction, do not carry inherent, intrinsic meaning. For example, there is no a priori reason to differentiate between the color yellow and the color green in the context of realistic social interactions. Conversely, the emotional tonality of our responses is naturally, in the ecological environment, relevant to the responses we will receive from the interaction partners. So, it is possible that, having to make a series of arbitrary associations between colors and expressions of the avatar, the participants resorted to explicit, analytical strategies for encoding these associations – for example, to have explicitly tested hypotheses related to the correct answers and to have relied predominantly on explicit memory for the retention of these responses. Motivated by our intriguing results and based on the previous arguments, we decided to edit participant response options and make them more similar to the ones of the Study 2a and re-run the study in AR.

2.3.4.1.1 Hypotheses

- *(H1) participants will learn the social contingencies embedded in the task;*
- *(H2) learning will be implicit (i.e., participants will perform better than would be expected at the chance level even when they will declare knowledge unawareness).*

2.3.4.2 Methods

2.3.4.2.1 Participants

We estimated our sample size based on the same logic that was used in Study 2b. The data acquisition process was stopped after thirty undergraduate psychology students (m_{age} = 19.54 years sd = 0.83) participated in exchange for partial course credits.

2.3.4.2.2 Apparatus

The apparatus used in this study is identical with the one described in Study 2b.

2.3.4.2.3 The task

The training, acquisition and test phases respected the same methodological specifications as the one described in Study 2b. Differently, here, to facilitate the acquisition of implicit knowledge, we adopted the cover story and response options of Study 2a and implemented in the Augmented Reality environment of Study 2b, see Figure 10 below.

Figure 10. The animated avatar used in both implementations of the experimental model. In the initial implementation (left side), participants had the task of interacting with the avatar by showing it one of the displayed colors. In the improved implementation of the model (right side),

participants could interact with the avatar by showing it one emotional facial expression at a time

2.3.4.2.4 Procedure

The procedure of this experiment was identical with the one of Study 2b.

2.3.4.3 Results

2.3.4.3.1 The operationalization of the variables for data analysis

The operationalization of the variables was exactly the same with the one presented in Study 2b.

2.3.4.3.2 H1: Evidence of learning

A repeated measures ANOVA revealed a significant effect of practice on the number of trials in which participants were able to regulate the facial expression of the avatar in the target state $F(9,252) = 7.68$, $p < .001$, $\eta^2_p = 0.215$. Also, consistent with our predictions, a within-subjects t-test detected that participants regulated the avatar's facial expression to the target state in significantly more trials in the 10th acquisition block ($m = 9.45$) than in the first acquisition block ($m = 4.38$): $t(28)= 4.24$, $p < .001$, $d = 0.79$. These results indicate a learning process in which participants improved their ability to control the avatar's emotional state as the task progressed (see Figure 11 below).

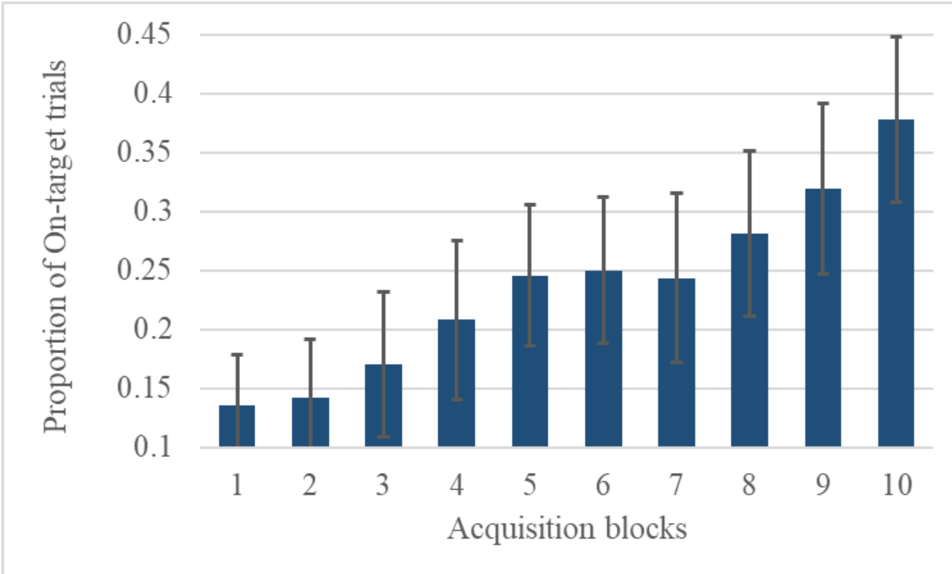

Figure 11. Depicts the average proportion of On-target trials (i.e., responses that regulated the avatar to the Neutral state), generated over the 10 acquisition blocks. Error bars represent 95% CIs.

2.3.4.3.3 H2: Evidence of IL

Consistent with how we proceed in the previous two experiments, for each participant we aggregated test phase responses that were attributed to guessing and intuition to create implicit attribution scores. Similarly, we aggregated responses attributed to rules and memory to create explicit attribution scores. We observed that 48.8% of responses were assigned to implicit response bases, while 50.2% were assigned to explicit response bases.

A one sample *t*-test indicated that responses assigned to conscious response bases (rules and memory) were significantly more accurate than would have been expected at the chance level, $t(28) = 6.94$, $p < 0.001$, $d = 1.289$. This result indicates that participants acquired a significant amount of explicit structural knowledge from the task. Furthermore, a second one sample *t-test* indicated that the accuracy of responses attributed to unconscious structural bases (guess and intuition) was also significantly higher than the one that would have been expected at the chance level, $t(28) = 3.32$, $p = 0.001$, $d = 0.62$. This result indicates that, in addition to a significant amount of conscious structural knowledge, participants also acquired unconscious structural knowledge from the task; in other words, we can confirm that this knowledge improved their performance in the test phase in the absence of subjective awareness.

2.3.4.4 Discussion and bridge to the next study

In the current study, we developed a research instrument which evaluates the IL of cognitive structures instantiated by socially relevant surface stimuli in augmented reality. Participants interacted with a holographic avatar and were able to gradually increase their ability to control the interaction even in the circumstances in which they were not aware of the rules that structured it.

On a final note (for this experiment), given that the current model of the task was able to induce both implicit and explicit learning, we can continue with our investigative approach and assess the relationships between the level of autistic traits and ISL. For this purpose, we carried out a separate study, as will be detailed in the subsections below.

2.3.5 Study 2d: The Relation Between Autistic Traits and Learning in the AR^4(s-e)DSC task

2.3.5.1 Introduction

Over the last three experiments, we developed a research instrument which successfully induced learning of cognitive structures instantiated by socio emotionally relevant surface stimuli in an augmented reality setup – this experimental paradigm will allow us to pursue our theoretical objective for the present study:

2.3.5.1.1 Objective and hypotheses

We aim to assess the relationship between autistic traits and the implicit and explicit learning of cognitive structures instantiated by socio-emotional components in the AR^4(s-e)DSC task. Thus, we hypothesized that:

- **H1:** participants will learn the social contingencies embedded in the task;
- **H2:** learning will be implicit *(i.e., participants will perform better than would be expected at the chance level even when they will declare knowledge unawareness).*
- **H3:** participants' levels of autistic traits will negatively predict their ability to - implicitly and explicitly - acquire structural knowledge from our AR^4(s)DSC task.

2.3.5.2 Method

2.3.5.2.1 Participants

To test these hypotheses, we set-up a Bayesian stopping rule, terminating the data collection process as soon as we observed good enough evidence for the third experimental hypothesis (if B < 3) or for its null model (if B < 0.33). This decision was taken after we have collected 122 datasets.

2.3.5.2.2 Self-report instruments

Ritvo Autism and Asperger Diagnostic Scale (RAADS-14), is a 14-item screening questionnaire which measures the presence of symptoms on the autism spectrum (Eriksson et al., 2013). Our retroverted version revealed acceptable psychometric properties (Chronbach's $\alpha = 0.65$).

2.3.5.2.3 Apparatus

We used two Microsoft HoloLens 2 headsets running the MR4ISL 2.0 application, respectively two laptops to administer the questionnaires that measured autistic traits.

2.3.5.2.4 The task

We measured the IL performance by using the previously developed mixed reality application (for details, see

Study 2c:)

2.3.5.2.5 Procedure

After offering their informed consent, participants completed the ISL measurement task using the MR4ISL app. As detailed in the previous experiment, participants first went through a familiarization/training phase, then an acquisition/learning phase, in which they regulated the emotional state of the avatar by indicating an emotional expression. In the test phase, participants were instructed to regulate the state of the avatar, while also reporting the level of awareness of the knowledge that allowed them to do so - by choosing one of the response basis attribution options of: Guess, Intuition, Rules or, Memory. After completing the AR^4(s-e)DSC task, participants completed the RAADS-14, which assessed the level of their autistic traits.

2.3.5.3 Results

2.3.5.3.1 The operationalization of the variables of data analysis

For this project, we implemented a within-group quasi-experimental design with repeated measures. Next, we specify the operationalization of our variables;

- **The amount of task-induced learning:** indexed by the number of trials in which participants were able to adjust the avatar to the neutral state during the acquisition phase.
- **Explicit learning:** indexed by the difference between participants' accuracy in the test phase and chance level in trials in which they indicated that they based their responses on explicit decision strategies (rules and memory).
- **IL:** indexed by the difference between participants' accuracy in the test phase and chance level on trials in which they indicated that they based their responses on implicit decision strategies (guessing and intuition).
- **The level of autistic traits:** indexed by the total score obtained following the application of the RAADS-14 questionnaire.

2.3.5.3.2 H1: Evidence of learning

A repeated measures ANOVA revealed a significant effect of practice on the number of On-target trials $F(121, 9) = 28.48$, $p < .001$, $\eta^2_p = 0.19$. Also, a preplanned within-subjects t-test detected that participants regulated the avatar's facial expression to the target state in significantly more trials in the 10^{th} acquisition block ($m = 8.75$; $sd = 6.06$) than in the first acquisition block ($m = 3.98$; $sd = 2.85$): $t(121)= 8.14$, $p < .001$, $d = 0.73$. Consistent with the results obtained in

Study 2c: these results indicate that participants engaged in a learning process in which they improved their ability to control the avatar's emotional state as the task progressed (see Figure 12 below).

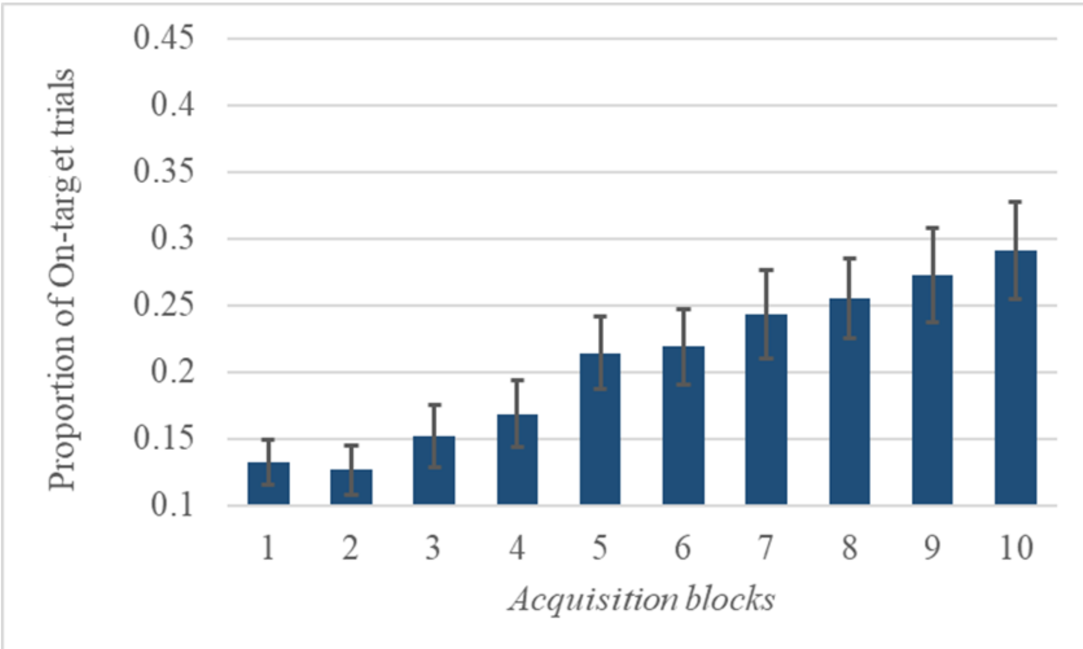

Figure 12. Depicts the average proportion of On-target trials (i.e., responses that regulated the avatar to the Neutral state), generated over the acquisition blocks. Error bars represent 95% CIs.

2.3.5.3.3 H2: Evidence of IL

Participants had a level of accuracy above chance when they reported that they relied on subjectively implicit response bases (m = .18, sd = .159), $t(117) = 2.63$, $p = .004$, $d = 0.242$, as well as when they reported that they relied on subjectively explicit response bases, (m = .452, sd = .278), $t(119) = 12.22$, $p < .001$, d = 1.12

2.3.5.3.4 *H3: The relations between autistic traits and learning in the AR⁴(s-e)DSC task*

We performed a simple linear regression with participants' RAADS-14 scores as IV and their overall accuracy in the test phase as DV. The model was not significant, R^2 = 0.000, F(1, 135) = 0.061, p = .806. We found good enough evidence against a deficit associated with participants levels of autistic traits: b = -0.055%, SE = 0.223, t = -0.246, p = .806, $B_{N\ (1.02:\ 0.51)}$ = 0.092. Put differently, we found that a 1-point increase in the RAADS-14 score is associated with a 0.06% decrease in participants accuracy in the test phase; however crucially, this relationship was not statistically significant and, furthermore, our Bayesian analyses revealed that our data are 0.09 times more likely to support the alternative than the null hypothesis – by convention, this base factor is regarded as providing good enough evidence for accepting the null hypothesis.

2.3.5.4 Discussion and Bridge to the next study

The results of our experiment confirm that the AR^4(s-e)DSC application induces and can reliably measure implicit and explicit social learning. Importantly for the aims of this thesis, we collected data indicating the absence of an association between the level of autistic traits and IL of socio-emotional information. To interpret these results, we suggest that performance in the DSC can be sustained by executive functions such as planning and working memory - because the very structure of this task allows for explicit hypothesis testing. The participant can voluntarily and consciously plan a certain response, which will turn out to be correct or not depending on the obtained feedback. Further, if the feedback indicates that the answer was correct, the participant can voluntarily choose to retain these answers (i.e., mappings between his response and the state of the dynamic system) for future interactions.

Motivated by our results and the suggestion above, we will next proceed to test the possible association between the functioning of IL and the levels of autistic traits in a research paradigm that – because it does not provide on-line feedback - does not allow for as many compensatory processing - that is, a socio-emotionally relevant (s-e)AGL task.

2.4 Study 3: The Relation Between Autistic Traits and the Implicit and Explicit Learning in a (Socio-Emotional) Artificial Grammar Learning (s-e)AGL Task

2.4.1 Introduction

We suggested that a potential reason for which we did not observe our hypothesized effect in the previous study has to do with the very essence of the DSC task. Specifically, because participants interact with a live agent, they receive on-line feedback on their performance; In turn, this feedback is likely to offer the knowledge base for conscious hypothesis testing, supporting an optimal task performance in the case of both individuals with high or low levels of autistic traits. We suggested that the chances to observe a potential IL deficit in individuals with elevated levels of autistic traits would increase in a task that does not offer participants live feedback on their performance – such a task is the AGL paradigm. This last suggestion sets the context to formulate our objectives for the current study.

In the present study we aim to provide a preliminary investigation of the relationship between autistic traits and the implicit and explicit learning of cognitive structures instantiated by socio-emotional components in a (socio-emotional) Artificial Grammar Learning [(s-e)AGL] task. To this end, we hypothesize that:

- **H1:** participants will learn the social contingencies embedded in the task;

- **H2:** learning will be implicit *(i.e., participants will perform better than would be expected at the chance level even when they will declare knowledge unawareness).*
- **H3:** participants level of autistic traits will negatively predict their ability to - implicitly and explicitly - acquire structural knowledge from our (s-e)AGL task.

2.4.2 Methods

2.4.2.1 Participants

We ceased the data collection after we observed good enough evidence for (if B > 3) or against (if B < 0.33) for H3. In the present investigation, the stopping rule was satisfied after we have collected data from a total number of 282 participants (210 = female, 1 = prefer not to say; overall m_{age} = 19.43, *sd* = 3.35).

2.4.2.2 Self-report instruments

The Subthreshold Autistic Traits Questionnaire (SATQ; Kanne, Wang, & Christ, 2012) is a self-report questionnaire where each of the 24 items is rated on a four-points Likert scale. In our sample, SATQ had an acceptable quotient of internal consistency (Crombach's α = 0.71); participants' m_{score} = 23.85 (*sd* = 8.26).

2.4.2.3 Apparatus

The stimuli used in the off-line version of the experiment were taken from the NimStim database (Tottenham et al., 2009), and the experiment was programmed in OpenSesame (Mathôt et al., 2012). Because our agreement for using the NimStim stimuli prohibited us to display them over the internet, for the on-line version of the experiment, we selected a different set of emotional facial expressions from Lundqvist et al. (1998) and the experiment was programed with Gorilla.sc (Anwyl-Irvine et al., 2020). For a graphic representation of the surface stimuli that were employed by the two versions of the task, see Figure 13 below.

Figure 13. Depicts the emotional facial expressions taken from NimStim (Tottenham et al., 2009) and used in the off-line task (top row) respectively the emotional facial expressions taken from the KDEF (Lundqvist et al., 1998) and used in the on-line version of the task (bottom row).

2.4.2.4 The task

2.4.2.4.1 The acquisition phase

We constructed our version of the (s-e)AGL task by adapting the letter strings from experiment 2 of Scott and Dienes (2008). For a graphical representation of the original grammar, see a reconstruction in Figure 14 below.

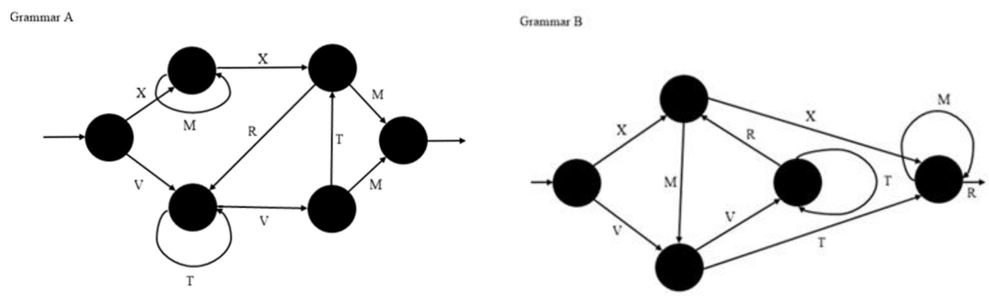

Figure 14. Depicts a graphical representation of the two acquisition grammars that were used in this study.

In our version of the task, letters were replaced by images of facial emotional expressions, thus, X was replaced by “Fear”, “M” by “Joy”, “R” by “Disgust”, “T” by “Calm”, “V” by “Anger” (for a graphic representation of a string, see Figure 15 below).

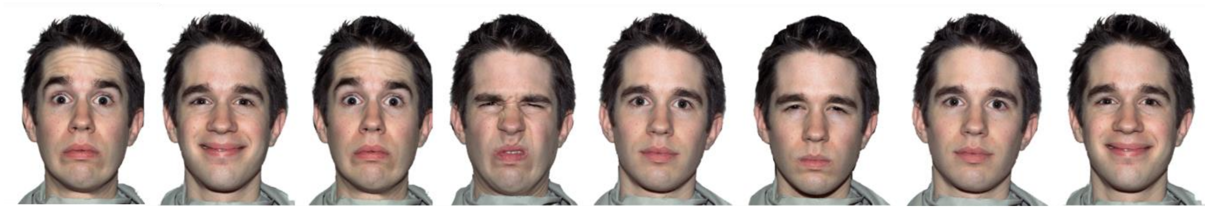

Figure 15. Depicts a gramatical string constructed on the basis of Grammar A.

Participants were exposed to 15 strings of facial expressions which appeared consecutively on the display. Each covered approximately 34 millimetres in width and 52 millimetres in height. Strings were between 5 and 9 facial expressions in length. Each string was repeated four times and stayed on the screen for 12 seconds. Participants were instructed to memorise the strings and were not informed of the presence of any underlying grammatical structure. Roughly half of the participants completed the acquisition phase with strings following Grammar A and, for counterbalancing purposes, the other half completed the acquisition phase with strings following Grammar B.

2.4.2.4.2 The test phase

After completing the acquisition phase, participants were then informed that they will be presented a random succession of 20 strings which respected grammar A and 20 strings which respected grammar B. For each string, they had to indicate whether or not it follows the rules from the previous phase. Following each response, we took subjective measures of awareness by asking participants to choose one of the options below:

Table 4. Definitions of response basis given to participants

Guess	You have no basis whatsoever for your response. You could have as well flipped a coin to decide.
Intuition	You feel that your response is correct, but you don't know why it is correct. That is, you have an impression, a feeling, that the string obeys the rules or that it doesn't obey the rules, but you don't know what the basis of this feeling is.
Familiarity	You answered based on the fact that the string – or a part of it – is familiar (if you responded YES), or unfamiliar (if you responded NO), but you have no idea why it is familiar or unfamiliar for you.
Rules	Your response is based on a certain rule (or fragments of rules) that you have learned consciously and that you could describe, if you would be asked to.
Remembering	Your response is based on the fact that you consciously remember having seen this string, or fragments of it, earlier (if you responded YES); or you consciously remember not having seen the string or fragments of it (if you responded NO).

Note. Definitions are similar adaptations based on the work of Dienes and Scott (2005),

2.4.2.5 Procedure

Participants were initially asked to give their informed consent. Subsequently, they completed the computerised version of the (s-e)AGL task (starting with the acquisition phase and finishing with the test phase). Lastly, they completed the SATQ.

2.4.3 Results

2.4.3.1 H1: Evidence of learning

A one sample *t* test revealed that participant's accuracy in the test phase (m = 60.38%, sd = 12.198) was significantly higher than the one expected at chance (i.e., 50%), $t(281) = 14.3$, $p < .001$, d = 0.85 offering strong evidence that overall learning occurred in the task.

2.4.3.2 H2: Evidence of IL

A one sample *t* test revealed that participants' accuracy for the trials where they indicated explicit response bases - i.e., responses based on Rules and Remembering attributions – (m = 65.86 sd = 22.68) was significantly higher than chance level, $t(253) = 11.14$, $p < .001$, $d = 0.7$, suggesting that explicit learning occurred in the task. Also, a one sample *t* test revealed that participants' accuracy for the trials where they indicated unconscious response bases - i.e., responses based on Guess, Intuition and Familiarity attributions – (m = 57.88% sd = 13.24) was significantly higher than the one expected at the chance level, $t(278) = 9.95$, $p < .001$, $d = 0.595$, offering solid ground to argue that IL also occurred in the task.

2.4.3.3 H3: The relation between the autistic traits and learning in the (s-e)AGL task

The distribution of priors for testing this hypothesis was estimated by employing the Ratio-of-scales heuristic (Dienes, 2019). According to its rationale, we determined that our maximum regression slope can be modelled as: (100 – 50) / (72 – 0) = 0.7. Thus, similarly with the manner in which we proceeded in the previous study, for our purposes, we model a normal distribution with the mean of half the maximum regression slope and a standard deviation as half of the mean. Finally, our Bayes factor was noted as $B_{N(-0.35: 0.175)}$.

First, we performed a simple linear regression with participants' SATQ scores as IV and their overall accuracy in the test phase as DV. The model was significant, R^2 = 0.018, F(1, 280) = 4.997, *p* = .026. We found good evidence for a deficit associated with participants levels of autistic traits: *b* = -0.2%, *SE* = 0.087, *t* = -2.24, *p* = .026, $B_{N(0.35: 0.175)}$ = 3.98. Hence, we found that a 1-point increase in the SATQ score predicts a decrease of 0.2% in participants test phase accuracy. Moreover, our Bayesian analyses revealed that our data are almost 4 times more likely to support the alternative than the null hypothesis. By convention, this Bayes factor is good enough evidence to accept the experimental hypothesis.

Crucially, because we did obtain evidence of a learning deficit associated with autistic traits, in the next lines we will analyse how varied levels of autistic traits differently affect implicit and explicit processing strategies. Thus, we performed a second, simple linear regression with participants' SATQ scores as IV and their accuracy on implicit structural knowledge in the test phase as DV. The model was not significant, R^2 = 0.002, F(1, 277) = 0.45, *p* = .502. We found good enough evidence against a deficit associated with participants levels of autistic traits: *b* = -0.07%, *SE* = 0.098, *t* = -0.672, *p* = .502, $B_{N(0.35: 0.175)}$ = 0.215. Hence, we found that a 1-point increase in the SATQ score is associated with a 0.07% decrease in participants accuracy in the test phase on implicit structural knowledge; however crucially, this relationship was not statistically significant and, furthermore, our Bayesian analyses revealed that our data are only 0.2 times more likely to support the alternative than the null hypothesis – by convention, this Bayes factor is regarded as providing good enough evidence for accepting the null hypothesis.

Finally, we performed a third, simple linear regression with participants' SATQ scores as IV and their accuracy on explicit structural knowledge in the test phase as DV. In the frequentist approach, the model was not significant, $R^2 = 0.011$, $F(1, 252) = 2.92$, $p = .089$. However crucially, in a Bayesian approach, we found good enough evidence for a deficit associated with participants levels of autistic traits: $b = -0.3\%$, $SE = 0.178$, $t = -1.708$, $p = .089$, $B_{N(0.35: 0.175)} = 3.01$. Hence, we found that a 1-point increase in the SATQ score is associated with a 0.3% decrease in participants accuracy in the test phase on the basis of explicit structural knowledge. Furthermore, our Bayesian analyses revealed that our data are 3 times more likely to support the alternative than the null hypothesis. By convention, this is good enough evidence to accept the alternative hypothesis.

2.4.4 Discussion

In this study, we aimed to assess the relationship between the ability to implicitly and explicitly learn cognitive structures instantiated by socio-emotional components and the level of autistic traits in individuals from the general population. To assess participants' levels of autistic traits, we administered a translated version of the SATQ (Kanne et al., 2012). To induce implicit and explicit learning of socioemotional components we modified a standard version of the AGL task.

Our results indicate that the (s-e)AGL task induced both implicit and explicit learning. Concerning our theoretically relevant objective, our results confirmed our hypothesis. Specifically, in stark contrast compared to the findings from the literature, we found that a 1-point increase on the SATQ is associated with a 0.2% decrease on the overall test phase accuracy. We accepted the alternative hypothesis as our Bayesian analyses indicated that the collected data is 4 times more probable under it than under the null hypothesis. The fact that we collected evidence suggesting that, even in the general population, autistic traits predict a learning deficit in our version of the tasks, is interpreted as a significant finding because it fundaments expectations that this effect size would be substantially higher in clinical samples.

The scientific community holds that individuals with ASD do not have an IL deficit largely on the basis of evidence which failed to show a difference in the overall learning effect between individuals with and without an ASD (c.f., Foti et al., 2015). However, because our results massively contradict the mainstream conclusion of the literature, we set out to investigate the source of this deficit in a finer grained manner. Specifically, our analyses indicated that an increase level of autistic traits does not predict a decrease in the test phase on the basis of implicit structural knowledge. Instead, key, we found that a 1-point increase on the SATQ predicts a 0.3% decrease in the test phase accuracy on the basis of explicit structural knowledge. We interpret this result as participants with increased levels of autistic traits exhibiting a more pronounced tendency to rely on false rules than participants with lower levels of autistic traits. This interpretation is consistent both with the IL literature at large and, in particular, with a compensatory processing account of learning.

2.4.4.1 Conclusion

Two-hundred-and-eighty-two participants underwent the (s-e)AGL task in which letters were replaced by emotional facial expressions. Participants acquired knowledge of the underling grammar, both explicitly and implicitly. Furthermore, their level of autistic traits (as assessed by a translated version of the SATQ) negatively predicted their overall accuracy in the test phase. Interestingly, this accuracy deficit seems to be caused by an unsuccessful compensatory processing strategy – by directing explicit learning processes over content that would probably be acquired better implicitly

3 GENERAL DISCUSSION AND CONCLUSIONS[3]

3.1 An Overall Perspective on our Results Evaluating the Relation Between Autistic Traits and the Ability to Implicitly and Explicitly Acquire Cognitive Structures Instantiated by Socio-Emotional Components.

In Study 2, Experiment 2d we confirmed that the level of autistic traits does not predict participants' ability to implicitly or explicitly acquire knowledge from the AR[4](s-e)DSC task. However, Study 3 reached a radically different conclusion in that our evidence confirmed that the level of autistic traits does predict an impairment in participants' ability to acquire knowledge from the (s-e)AGL task and furthermore, that this impairment is caused by their responses based on explicit decision strategies. The next paragraph is intended to integrate our apparently incompatible results in a more coherent perspective.

We start from the fact that IL is not a unitary construct. As previously suggested (Gebauer & Mackintosh, 2007; Salthouse et al., 1999), it is likely that implicit and explicit acquisition of knowledge in the AGL paradigm is supported by different cognitive processes than the implicit and explicit acquisition of knowledge in the DSC task. We further suggest that these different

---

[3] Parts of this chapter were published as:

Costea, A. R. (2018). Can Compensatory Processing Account for the Performance of Individuals with Autism Spectrum Disorders in Implicit Learning Tasks? A Focused Mini-Review. Studia Universitatis Babes-Bolyai-Psychologia-Paedagogia, 63(2), 5-25.

Costea, A. R. (2018). The relationship between implicit learning of cognitive structures with socio-emotional components and subthreshold autistic traits. *Journal of Evidence-Based Psychotherapies*, *18*(2), 131-141.

Costea, A. R., Jurchiș, R., Visu-Petra, L., Cleeremans, A., Norman, E., & Opre, A. (2022). Implicit and explicit learning of socio-emotional information in a dynamic interaction with a virtual avatar. *Psychological research*, 1-18.

Jurchis, R., Costea, A. & Opre, A. (accepted) Implicit processes in therapy in (Arthur Reber and Rhiannon Allen eds) The cognitive unconscious: the first 50 years. Oxford University Press.

Pamparău, C., Costea, A., Jurchiș, R., Vatavu, R. D., & Opre, A. (2022, May). Experimental Evaluation of Implicit and Explicit Learning of Abstract Regularities Following Socio-Emotional Interactions in Mixed Reality. In *2022 International Conference on Development and Application Systems* (DAS) (pp. 150-154). IEEE.

constraints on the cognitive system determines that individuals with increased levels of autistic traits can engage in compensatory processing in some tasks, but not in others. Put differently, IL tasks that use complex socio-emotionally relevant surface stimuli, but give live performance feedback [such as the AR^4(s-e)DSC], allow to all participants – including to those with more elevated levels of autistic traits – to engage in a learning style characterized by deliberate hypothesis testing. Case in point, the participant can voluntarily and consciously plan a certain response, which will turn out to be correct or not depending on the feedback that s/he receives. Further, if the feedback indicates that the answer was correct, the participant can voluntarily choose to retain these answers for future interactions. Thus, individuals with higher autistic traits could compensate for a potential deficit in the AR^4(s-e)DSC by an increased engagement of conscious hypothesis testing processes. However, when a task employs complex, socio-emotionally relevant surface stimuli and, crucially, does not display live performance feedback – such as the (s-e)AGL, the learning deficit of individuals with increased levels of autistic traits becomes apparent. We speculate that this is because their natural tendency to engage in a learning process based on explicit hypothesis testing cannot iteratively improve their performance in the absence of feedback. On a final note, it seems that, just by evaluating the relationship between the subthreshold autistic traits and the implicit and explicit learning of socio emotional components we started to confirm the suggestion formulated by Zwart et al. (2017), that even individuals with increased autistic traits seem to be "too *eager to learn*". We interpret this eagerness as a compensatory learning strategy under the form of explicit hypothesis testing that indeed seems to "*adversely affect learning in complex social situations*" (Zwart, et al., 2017, p. 9).

In the introductory chapter we stressed that, while we are interested in developing clinical applications for individuals on the autistic spectrum, the focus of the work constituting this thesis falls on the methodological contributions. Now, after we have presented and discussed our original research, we feel that some potential investigative directions will give the reader a general sense of how this work could progress to more applied topics for the ASD – we deal with this in the subsection below.

3.2 Implications for Future Research

If the IL deficit in ASD hypothesis will receive more substantial support in samples composed of individuals with a clinical diagnosis of an ASD, this line of research has the potential to shed some light on the cognitive mechanisms which might explain part of the social cognition impairments in ASD. More specifically, this line of research could help integrate findings on the abnormal sensory processing (Crane et al., 2009; Marco et al., 2011) with findings on the deficits in implicit theory of mind (Baron-Cohen et al., 1985; Senju, 2012; Senju et al., 2009; White et al., 2011) in a more comprehensive cognitive model which might explain a significant part of the social difficulties of individuals with ASDs.

3.3 An Overall Perspective on Our Contributions

Here, we attempt to emphasize our contributions by following the silver lining of our thesis. Accordingly, we start by presenting our contribution from the first chapter. Thus, from a theoretical standpoint, the scientific literature began to shift away from viewing ASD as a group of disorders characterized by a series of deficits and toward viewing individuals with this disorder as being neurodiverse (Lewin & Akhtar, 2021). Anecdotally, this idea can be illustrated by viewing these individuals as being *different*, and not as having a *deficit*. However, despite the fact that his perspective started to gain traction in in recent years, numerous research domains still investigate

ASD in terms of their '*deficits*'. In fact, even the investigative niche of evaluating the functioning of IL in ASD still operates from this vantage point. To the best of our knowledge, our published work from the theoretical chapter (Costea, 2018a) is the first scientific work to conceptualize the functioning of IL in ASD through a compensatory processing framework.

Moving further to the first experiment of this thesis, we remind the reader that here we attempted to develop the (s-e)SRT task. To the best of our knowledge, this is the first study to employ surface stimuli under the form of kinematic, realistic, facial expressions, bringing our research one step closer to the habitual mode of processing this information in the real social environment.

The second study has a number of contributions. First, experiment 2a is the first DSC study to employ trial by trial subjective measures of awareness (i.e., response attributions and the PDP); thereby, offering a more precise perspective on the way in which explicit knowledge, as well as implicit knowledge, contribute to task performance in this paradigm. This contribution was extensively presented in our publication, (Costea et al., 2022). Second, by capitalizing on the results presented in Study 2a, the purpose of the Study 2b and 2c was to develop a version of the (s-e)DSC task in an immersive environment that resembles natural social contexts and enables participants to engage in an interactive learning context with a realistic human scaled avatar. Thus, to the best of our knowledge, out AR^4(s-e)DSC task is the first experimental paradigm that successfully induced implicit and explicit learning in mixed reality. It is also, to the best of our knowledge, the first task to bypass traditional means of data collection (i.e., mouse clicks and key presses) and instead implement naturally occurring means of communication such as speech recognition and gesture making. These contributions were presented in our publications, Pamparău et al., (2021a; 2021b and 2022). Experiment 2d is the first study to conclusively show that the level of autistic traits does not predict an IL impairment in the DSC task. Especially when coupled with our findings from the third study, this finding becomes important in generating a more holistic perspective on the types of tasks in which individuals with ASD might engage in compensatory processing.

The third study, as presented in Costea (2018b) is the first experimental investigation to show that autistic traits can predict a learning deficit in the AGL task. Furthermore, besides providing results that are incompatible with the mainstream conclusion of the literature on the functioning of IL in ASD, this investigation offers tentative support to the compensatory processing framework in the relationship between IL and autistic traits. Finally, we conclude by suggesting that our findings could foster novel research avenues into the role that IL might play in different conditions characterized by atypical social functioning, as presented in our publication, Jurchiș et al. (2022). In the subsection below we will attempt to draw our general conclusions.

3.4 General Conclusion

The overarching objective of the present thesis was to advance our knowledge of a potential IL deficit in ASD. In this regard, we began an ongoing multistage research project. In it, we first managed to adapt several classical IL task, so as to induce IL of socio-emotional regularities. Using these paradigms, we then found evidence for the absence of a predictive relationship between subclinical levels of autistic traits and IL assessed with a task that offered opportunities for using explicit learning strategies – i.e., the AR^4(s-e)DSC task. However, we found evidence that autistic traits predict a learning deficit when the task better stimulated incidental, implicit, acquisition – the (s-e)AGL task. The results provide preliminary evidence for the hypothesis of a deficit in implicit social learning in ASD. Building on these findings, we proposed several future research directions for progressing at the clinical level and testing an extended cognitive model of the social impairments in ASD.

Bibliographical references

3D Animation Software for Character Animator | iClone. (n.d.). IClone Home. Retrieved August 30, 2022, from https://www.reallusion.com/iclone/default.html

Anwyl-Irvine, A. L., Massonnié, J., Flitton, A., Kirkham, N., & Evershed, J. K. (2020). Gorilla in our midst: An online behavioral experiment builder. *Behavior Research Methods*, *52*(1), 388–407.

Baron-Cohen, S., Wheelwright, S., Skinner, R., Martin, J., & Clubley, E. (2001). The autism-spectrum quotient (AQ): Evidence from asperger syndrome/high-functioning autism, males and females, scientists and mathematicians. *Journal of Autism and Developmental Disorders*, *31*(1), 5–17.

Becchio, C., Sartori, L., & Castiello, U. (2010). Toward you: The social side of actions. *Psychol*, *19*(3), 183–188. https://doi.org/doi: 10.1177/0963721410370131

Berry, D. C., & Broadbent, D. E. (1984). On the relationship between task performance and associated verbalizable knowledge. *Q. J. Exp. Psychol*, *36*(2), 209–231. https://doi.org/doi: 10.1080/14640748408402156

Berry, D. C., & Broadbent, D. E. (1995). Implicit learning in the control of complex systems. In *Complex problem solving: The European perspective* (pp. 131–150).

Bischoff-Grethe, A., Goedert, K. M., Willingham, D. T., & Grafton, S. T. (2004). Neural substrates of response-based sequence learning using fMRI. *Journal of Cognitive Neuroscience*, *16*(1), 127–138.

Cleeremans, A., Destrebecqz, A., & Boyer, M. (1998). Implicit learning: News from the front. *Trends in Cognitive Sciences*, *2*(10), 406–416. https://doi.org/10.1016/S1364-6613(98)01232-7

Cleeremans, A., & Jimenez, L. (2002). Implicit Learning and Consciousness: A Graded, Dynamic Perspective. In R. M. French & A. Cleeremans (Eds.), *Implicit Learning and Consciousness: An Empirical*. Psychology Press.

Costea, A. R. (2018a). CAN COMPENSATORY PROCESSING ACCOUNT FOR THE PERFORMANCE OF INDIVIDUALS WITH AUTISM SPECTRUM DISORDERS IN IMPLICIT LEARNING TASKS? A FOCUSED MINI-REVIEW. *Studia Universitatis Babes-Bolyai-Psychologia-Paedagogia*, *63*(2), 5–25.

Costea, A. R. (2018b). The relationship between implicit learning of cognitive structures with socio-emotional components and subthreshold autistic traits. *J. Evid-Based Psychother*, *18*(2), 131–141. https://doi.org/doi: 10.24193/jebp.2018.2.18

Costea, A. R., Jurchiș, R., Visu-Petra, L., Cleeremans, A., Norman, E., & Opre, A. (2022). Implicit and explicit learning of socio-emotional information in a dynamic interaction with a virtual avatar. *Psychological Research*. https://doi.org/10.1007/s00426-022-01709-4

Dienes, Z. (2019). How Do I Know What My Theory Predicts? *Advances in Methods and Practices in Psychological Science*, *2*(4), 364–377. https://doi.org/10.1177/2515245919876960

Dienes, Z., & Altmann, G. (1997). *"Transfer of implicit knowledge across domains: How implicit and how abstract." in How implicit is implicit* (learningD C. Berry, Ed.). Oxford University Press.

Dienes, Z., & Scott, R. (2005a). Measuring unconscious knowledge: Distinguishing structural knowledge and judgement knowledge. *Psychol Res*, *69*(5–6), 338–351. https://doi.org/doi: 10.1007/s00426-004-0208-3

Dienes, Z., & Scott, R. (2005b). Measuring unconscious knowledge: Distinguishing structural knowledge and judgment knowledge. *Psychological Research*, *69*(5), 338–351. https://doi.org/10.1007/s00426-004-0208-3

Eitam, B., Glass-Hackel, R., Aviezer, H., Dienes, Z., Shoval, R., & Higgins, E. T. (2014). Are task irrelevant faces unintentionally processed? Implicit learning as a test case. *Journal of Experimental Psychology: Human Perception and Performance*, *40*(5), 1741.

Ekman, P., Friesen, W. V., & Hager, J. C. (2002). *Facial Action Coding System. Manual and Investigator's Guide*. Research Nexus.

Eriksson, J. M., Andersen, L. M., & Bejerot, S. (2013). RAADS-14 Screen: Validity of a screening tool for autism spectrum disorder in an adult psychiatric population. *Molecular Autism*, *4*(1), 49. https://doi.org/10.1186/2040-2392-4-49

Foti, F., Crescenzo, F. D., Vivanti, G., Menghini, D., & Vicari, S. (2015). Implicit learning in individuals with autism spectrum disorders: A meta-analysis. *Psychological Medicine*, *45*(5), 897–910. https://doi.org/10.1017/S0033291714001950

Fu, Q., Dienes, Z., & Fu, X. (2010). Can unconscious knowledge allow control in sequence learning? Conscious. *Cogn*, *19*(1), 462–474. https://doi.org/doi: https://doi.org/10.1016/j.concog.2009.10.001

Fu, Q., Sun, H., Dienes, Z., & Fu, X. (2018). Implicit sequence learning of chunking and abstract structures. *Conscious. Cogn*, *62*, 42–56. https://doi.org/doi: 10.1016/j.concog.2018.04.010

Gebauer, G. F., & Mackintosh, N. J. (2007). Psychometric intelligence dissociates implicit and explicit learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *33*(1), 34–54. https://doi.org/10.1037/0278-7393.33.1.34

Grafton, S. T., Hazeltine, E., & Ivry, R. B. (1998). Abstract and effector-specific representations of motor sequences identified with PET. *Journal of Neuroscience*, *18*(22), 9420–9428.

Jiménez, L., Oliveira, H. M., & Soares, A. P. (2020). Surface features can deeply affect artificial grammar learning. *Consciousness and Cognition*, *80*, 102–919. https://doi.org/10.1016/j.concog.2020.102919

Kanne, S. M., Wang, J., & Christ, S. E. (2012). The Subthreshold Autism Trait Questionnaire (SATQ): Development of a brief self-report measure of subthreshold autism traits. *Journal of Autism and Developmental Disorders*, *42*(5), 769–780.

Lewin, N., & Akhtar, N. (2021). Neurodiversity and deficit perspectives in The Washington Post's coverage of autism. *Disability & Society*, *36*(5), 812–833. https://doi.org/10.1080/09687599.2020.1751073

Li, X., Bai, X., Conway, C. M., Shi, W., & Wang, X. (2022). Statistical learning for non-social and socially-meaningful stimuli in individuals with high and low levels of autistic traits. *Current Psychology*, 1–11.

Lieberman, M. D. (2000). Intuition: A social cognitive neuroscience approach. *Psychological Bulletin*, *126*(1), 109.

Livingston, L. A., & Happé, F. (2017). Conceptualising compensation in neurodevelopmental disorders: Reflections from autism spectrum disorder. *Neuroscience & Biobehavioral Reviews*, *80*, 729–742.

Lundqvist, D., Flykt, A., & Öhman, A. (1998). Karolinska directed emotional faces. *Cognition and Emotion*.

Mathôt, S., Schreij, D., & Theeuwes, J. (2012). OpenSesame: An open-source, graphical experiment builder for the social sciences. *Behavior Research Methods*, *44*(2), 314–324.

Mealor, A. D., & Dienes, Z. (2013). The speed of metacognition: Taking time to get to know one's structural knowledge. *Consciousness and Cognition*, *22*(1), 123–136.

Meier, B., & Cock, J. (2010). Are correlated streams of information necessary for implicit sequence learning? *Acta Psychologica*, *133*(1), 17–27.

Nissen, M. J., & Bullemer, P. (1987). Attentional requirements of learning: Evidence from performance measures. *Cogn. Psychol*, *19*(1), 1–32. https://doi.org/doi

Norman, E., & Price, M. C. (2012). Social intuition as a form of implicit learning: Sequences of body movements are learned less explicitly than letter se- quences. *Advances in Cognitive Psychology*, *8*(2), 121–131.

Norman, E., Price, M. C., & Jones, E. (2011). Measuring strategic control in artificial grammar learning. *Consciousness and Cognition*, *20*(4), 1920–1929.

Norman, E., Scott, R. B., Price, M. C., & Dienes, Z. (2016). The relationship between strategic control and conscious structural knowledge in artificial grammar learning. *Conscious. Cogn*, *42*, 229–236. https://doi.org/doi: 10.1016/j.concog.2016.03.014

Norman, E., Scott, R. B., Price, M. C., Jones, E., & Dienes, Z. (2019). *"Can unconscious structural knowledge be strategically controlled?". In Implicit learning: 50 Years on* (C. A., A. V., & M., Eds.). Routledge.

Pamparău, C., Costea, A., Jurchiș, R., Vatavu, R.-D., & Opre, A. (2022). Experimental Evaluation of Implicit and Explicit Learning of Abstract Regularities Following Socio-

Emotional Interactions in Mixed Reality. *2022 International Conference on Development and Application Systems (DAS)*, 150–154.

Pamparau, C., Vatavu, R.-D., Costea, A. R., Jurchis, R., & Opre, A. (2021). XR4ISL: Enabling Psychology Experiments in Extended Reality for Studying the Phenomenon of Implicit Social Learning. *20th International Conference on Mobile and Ubiquitous Multimedia*, 195–197.

Pamparău, C., Vatavu, R.-D., Costea, A. R., Jurchiş, R., & Opre, A. (2021). MR4ISL: A Mixed Reality System for Psychological Experiments Focused on Social Learning and Social Interactions. *Companion of the 2021 ACM SIGCHI Symposium on Engineering Interactive Computing Systems*, 26–31. https://doi.org/10.1145/3459926.3464762

Pavlovia. (n.d.). Retrieved September 2, 2022, from https://pavlovia.org/

Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., & Lindeløv, J. K. (2019). PsychoPy2: Experiments in behavior made easy. *Behav. Res. Methods*, *51*(1), 195–203. https://doi.org/doi: 10.3758/s13428-018-01193-y

Raab, M., & Johnson, J. G. (2008). *Implicit learning as a means to intuitive decision making in sports. Intuition in judgment and decision making, 119-133*.

Reber, A. S. (1967). Implicit learning of artificial grammars. *Journal of Verbal Learning and Verbal Behavior*, *6*(6), 855–863. https://doi.org/10.1016/S0022-5371(67)80149-X

Reber, A. S. (1989). Implicit learning and tacit knowledge. *Journal of Experi- Mental Psychology: General*, *118*(3), 219.

Reber, A. S. (1993). *Implicit learning: An essay on the cognitive unconscious*. Oxford University Press.

Salthouse, T. A., McGuthry, K. E., & Hambrick, D. Z. (1999). A Framework for Analyzing and Interpreting Differential Aging Patterns: Application to Three Measures of Implicit Learning. *Aging, Neuropsychology, and Cognition*, *6*(1), 1–18. https://doi.org/10.1076/anec.6.1.1.789

Scott, R. B., & Dienes, Z. (2010). Knowledge applied to new domains: The unconscious succeeds where the conscious fails. *Consciousness and Cognition*, *19*(1), 391–398.

Tottenham, N., Tanaka, J. W., Leon, A. C., McCarry, T., Nurse, M., Hare, T. A., Marcus, D. J., Westerlund, A., Casey, B. J., & Nelson, C. (2009). The NimStim set of facial expressions: Judgments from untrained research participants. *Psychiatry Research*, *168*(3), 242–249.

Travers, B. G., Klinger, M. R., Mussey, J. L., & Klinger, L. G. (2010). Motor-linked implicit learning in persons with autism spectrum disorders. *Autism Research*, *3*(2), 68–77.

Waroquier, L., Abadie, M., & Dienes, Z. (2020). Distinguishing the role of conscious and unconscious knowledge in evaluative conditioning. *Cognition*, *205*, 104460.

Ziori, E., & Dienes, Z. (2015). Facial beauty affects implicit and explicit learning of men and women differently. *Front. Psychol*, *6*, 1124. https://doi.org/doi

Zwart, F. S., Vissers, C. T. W., van der Meij, R., Kessels, R. P., & Maes, J. H. (2017). Autism: Too eager to learn? Event related potential findings of increased dependency on intentional learning in a serial reaction time task. *Autism Research*, *10*(9), 1533–1543.