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DIFFERENTIAL OUTCOME TRAINING AND HUMANOID ROBOT FEEDBACK ON A VISUOSPATIAL GAMIFIED TASK

An experimental study investigating learning, affective social engagement cues and cognitive learning strategies

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Abstract

By combining Differential Outcome Training (DOT), the usage of unique stimulus-response pairings, and feedback from a humanoid simulated robot (SDK) this study aims to improve learning performance of subjects on a visuospatial gamified memory task. This is achieved by using the SDK as an interface for an algorithm that provides audiovisual, reinforcing feedback promoting engagement in a new dyadic setup for a gamified task. Additionally it enhances the differential outcome effect from the reward system of the gamified task that in turn improves learning. Learning performance was measured by percentage of correct responses on the gamified task and iMotions software, eye-tracking and Self Assessment Manikin-scale revealed affective cues and cognitive strategies. A total of 60 subjects participated in the experiment, and the results showed that subjects playing the gamified task in the DOT condition had significantly higher performance than those who did not. Qualitative analysis of the affective data revealed that participants assisted by the SDK had greater feeling of control and higher levels of valence when combined with DOT. The eye tracking revealed different cognitive strategies where a strategy that makes use of peripheral vision appeared to be most highly correlated with higher memory performance. The results imply that combining DOT with social robot feedback might be an effective way to improve learning, a finding of great significance for potential future clinical intervention of the setup in the context of memory training for patients with dementia and mild cognitive impairment.

Keywords

Human-robot interaction, gamified memory task, dementia, differential outcome theory, Furhat, engagement, digitalised treatments, robot assistance

DIFFERENTIAL OUTCOME TRAINING OCH FEEDBACK FRÅN EN HUMANOID ROBOT PÅ ETT VISUOSPATIALT KOGNITIVT SPEL

En experimentell studie som undersöker inlärning, affektivt socialt engagemang samt kognitiva inlärningsstrategier

Sammanfattning

Genom att kombinera *differential outcome training* (DOT), användandet av unika stimulus-respons par, med feedback från en social humanoid simulerad robot (SDK) syftar denna studie till att förbättra inlärnings- och minnesförmåga på ett digitalt visuospatialt spel. Denna studie föreslår en ny dyadisk setup för en digital *gamifierad* minnesuppgift som inkluderar DOT och SDK-feedback och hypotiserar att denna kombination ökar engagemang, vilket i sin tur förbättrar minnesförmåga. Detta uppnås genom att använda SDK som ett gränssnitt för en algoritm som ger audiovisuell, betingande feedback för att främja engagemang. Dessutom förstärker feedbacken *differential outcome effect* från belöningssystemet i spelet, vilket i sin tur förbättrar inlärningen. Inlärning mättes i denna studie genom antal korrekta svar räknat i procent i det visuospatiala spelet. Vidare användes iMotions-programvaran, eye-tracking och en *self assessment manikin*-skala för att analysera affektiva signaler och kognitiva strategier kvalitativt. Totalt deltog 60 försökspersoner i experimentet, varav resultaten visade att försökspersoner som spelade med DOT hade signifikant högre minnesförmåga än de som inte gjorde det. Vidare visade kvalitativ analys av affektiva data att deltagare som fick feedback av SDK hade större känsla av kontroll och kombinerat med DOT högre nivå av valens. Eye-tracking-data

avslöjade flera kognitiva strategier där perifert seende tycks vara mer korrelerad med högre minnesförmåga. Resultaten antyder att kombinationen av DOT med social robot-feedback är ett effektivt sätt att förbättra inlärning, vilket är av stor betydelse för potentiella framtida kliniska versioner av setupen i samband med minnesträning för patienter med demens och mild kognitiv funktionsnedsättning.

Nyckelord

Människa-robot interaktion, gamifierad minnesuppgift, demens, engagemang, digitaliserad demensvård, robotassistans.

Preface

This study was conducted as our bachelor thesis in the final year of the Cognitive Science BSc programme at University of Gothenburg spring 2022. It was equally carried out and divided between the authors. Markelius conducted the data analysis, and Sjöberg the practical experiments, and both were responsible for the corresponding parts of the report. The authors collaborated throughout the experiment, report writing and analysis, to be a part of the study mutually and jointly. This study is part of the STINT project *Engaging Humans in Gamified Memory Training using Humanoid Robots* as a collaboration of University of Gothenburg and Koç University, with the long-term goal of producing a sustainable research and education setup as well as laying the foundation for use of alternative digitalised technology (robots), as part of intervention memory training for mild to moderate dementia.

The authors wish to thank Dr. Robert Lowe and Bahram Salamat Ravandi for their supervising and insightful thoughts during the study as well as Martin Bergström for programming the TTT Booster Game used in the study. Extra thanks are also directed to Professor Dr. Soohyung Lee at Seoul National University for advice and support and to Sangbeom Kim for help with data analysis.

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List of abbreviations

AD: *Alzheimer's Disease*

DOT/DOE: *Differential Outcome Training/Effect*

NDOT: *Non-Differential Outcome Training*

HRI: *Human-Robot Interaction*

ISI: *Inter Stimulus Interval*

MCI: *Mild Cognitive Impairment*

SAM: *Self Assessment Manikin Scale*

SDK: *Simulated Furhat Robot (Simulated Development Kit)*

1 Introduction

Today every country in the world is experiencing a demographic shift with an increasingly ageing population. Improved healthcare and living standards on a global scale have made it possible for humans to live longer lives, and between 2015 and 2050, the proportion of the world's population over 60 years is expected to almost double from 12% to 22% (WHO, 2021). This has led to an increase in people living with Mild Cognitive Impairment (MCI) or dementia such as Alzheimer's disease (AD). In 2020, over 55 million people worldwide were living with dementia and this amount is expected to nearly double every 20 years, and to reach 78 million in 2030 and 139 million in 2050 (ADI, 2021). This will in turn increase the amount of people in need for treatments and therefore increase the demand for more effective interventions implemented on a larger scale and accessible to more people. Additionally, the ongoing COVID-19 pandemic affects the ability of seniors (those who are more susceptible to memory loss) to travel, a problem that is expected to continue for a long time (Cuffaro, 2020). This increases the demand for treatments to be available in home-settings and without the need of a clinician to create contamination-free and safe access. Digitalised gamified memory tasks offer great potential as a possible intervention to provide treatments on a larger scale and with improved accessibility (Sailer et al., 2020). Additionally, social assistive robots have potential to promote and improve learning and memory performance when offering feedback in combination with gamified tasks (e.g. Andriella et al., 2020). Implementation of Differential Outcome Training (DOT), the procedure when using unique stimulus-response pairings, has also been suggested to promote and increase memory performance (Vivas et al., 2018) for example on visuospatial cognitive tasks. This study concerns an experiment using the DOT methodology for a gamified memory task with feedback from a social robot. Much uncertainty still exists about the relationship between social feedback robots and DOT, and to the present day there has not been any research combining DOT and robots before according to the author's knowledge after extensive literature reviewing, a knowledge gap that this study aims to fill.

1.1 Objectives

To contribute to meet the above mentioned needs, this study proposes a new human/robot interactive setup for a visuospatial digitalised gamified task while implementing Differential Outcome Training (DOT). The study's initial goal was to investigate how participants' performance on a gamified memory task is affected by implementing an embodied Furhat robot (Furhat Robotics, 2021) compared to a simulated version of Furhat (SDK). However, due to technical issues with the Furhat robot during the experiment the condition was discontinued, and this study will solely investigate the SDK (see Appendix 1 for the results gathered for 7 participants in the Furhat condition before discontinuation). To provide embodied robots to all patients in future clinical interventions would be both difficult to achieve in terms of accessibility and costly on a large scale. Therefore the use of robot simulation (in this study the Furhat SDK), offers a potential effective solution to make robot interaction treatments more available. Many patients with MCI or dementia are either housebound or might have low mobility. If a simulator could give a beneficial effect, it could be a valuable alternative for reinforcing feedback with easier access than providing embodied robots for every intervention, especially within a mobile platform. The implementation of social feedback robots in the context of dementia treatment and for engagement have been increasing and in the last decades a number of researchers have sought to determine how to find optimal and effective implementations. Simulated robots used as avatar companions within affordable mobile technologies could be used within interventions, possibly then backed up by periodic use of the physical robot used in a specific facility. However, how subject memory performance and learning is affected by having a simulated robot as a feedback partner is yet unknown and this study aims to evaluate this with regard to playing a gamified memory task.

The proposed study involves using DOT combined with the simulated Furhat robot (SDK), to assist and provide feedback to facilitate social engagement as well as enhance the Differential Outcome Effect (DOE, the occurrence of association-pairs when implementing DOT) of the reward system of the game. The differential outcomes (rewards) provided by the gamified task

concerns pseudo-monetary reward while the Furhat SDK complements this with socially rewarding feedback consistent with that presented in the game, the robot is also believed to contribute with a social presence effect that would have a positive impact on learning (see section 2.2 Social Presence Theory). The DOT is included in the reward system of the gamified task and is intended to facilitate and improve learning and memory performance. DOT has previously been shown to improve learning and memory performance (Vivas et al., 2018) and it has potential to be beneficial if implemented as a future intervention for dementia treatment. Vivas et al. (2018) used DOT on a visuospatial task and found a DOE for performance accuracy (matching to sample) and this study aims to continue with a similar approach adapted to a gamified version instead and in combination with the robot feedback. Digitalised forms of memory tasks offer benefits such as precise therapy monitoring, adaptation to users' requirements and skills, and implementation at a large scale, possibly without a clinical therapist. Digitalisation of memory tasks additionally makes it possible for at-home treatments, increasing the accessibility, especially significant during COVID-19 because of the reduced mobility of elderly and dementia patients (Cuffaro, 2020). Ultimately, the setup is intended as a validation of a task to be used in a clinical cognitive intervention to meet the needs of an increased demand for digitalised forms of treatment for dementia such as AD and MCI. Since this study is part of the first initialization of the setup and the specific combination of robot feedback and DOT it will be conducted as a preclinical validation study to enable evaluation and improvement of the setup to later be used with respect to clinical participants. The components measured in this study, namely participants' learning performance, as well as cognitive and affective engagement with respect to DOT and robot presence are crucial for a successful future implementation. However, other components should additionally be investigated and researched before future clinical implementation.

Because this study is the first initialization of the setup, it is an important first step to allow for the possibility to evaluate and improve its various components for future studies and clinical implementations. The participants in this study are therefore limited to solely healthy individuals (not being a person with dementia). However, the experimental results are expected to produce insights into how to best configure future setups as they apply to persons with MCI or dementia. Andriella et al. (2018), conducted an experimental study investigating an Human-Robot

Interaction (HRI) setup for AD and MCI memory training that was tested and evaluated where DOE was detected for participants without cognitive impairments. The experiment was carried out with non-clinical subjects and with respect to different levels of interaction, feedback and challenge levels, similar to the different levels of the game and DOT in this study. As it is the first time this particular setup is tested and measured scientifically, it is of high importance to identify in an early stage what can be improved and optimised before testing it on patients with MCI. Furthermore, the parameters of the setup are scalable and can be adjusted for future clinical subjects, this includes both the feedback given by the robot as well as components of the gamified memory task and DOT. The objective of this experiment is to link to what extent implementation of DOT improves participants' learning and memory performance with respect to various components of the setup and how the robot feedback facilitates social and task engagement. Additionally, an objective of this research is to determine whether the DOT and SDK can prove to be an effective combination for improving learning in gamified memory tasks, providing significant and important contributions to the existing literature on the two phenomenons. This study aims to identify the potential interaction effects of HRI and DOT to improve learning and engagement. Finally, it also provides insight to various cognitive strategies to solve the gamified memory task, which can prove valuable for optimization and evaluation of the setup.

1.2 Question statements

i) Is there a differential outcome effect consisting of improved/faster learning accuracy on a gamified visuospatial memory task when implementing a DOT protocol in the game?

ii) How is learning performance on a gamified visuospatial task affected by the social presence effect and receiving reward feedback from a simulated robot, as compared to non-social reward feedback?

iii) Is the differential outcome effect on learning enhanced by the implementation of social reward feedback from a simulated robot?

1.3 Hypotheses

Hypothesis 1: Subjects' learning and memory performance (measured by percentage of correct game responses (CR)) in the gamified memory task is higher when playing the game under a differential outcome procedure than for a non-differential outcome procedure.

Hypothesis 2: Subjects' learning and memory performance (measured by percentage of correct game responses (CR)) in the gamified memory task is higher when receiving social reward feedback during the game from a simulated robot.

Hypothesis 3: The differential outcomes effect will be larger when social reward feedback is provided by a simulated robot, thus resulting in a positive interaction effect between the two variables.

2 Theory

The theories that are related to this study are addressed in the following section and are as follows: Differential Outcome Theory, Social Presence theory, Theories of engagement and dementia and Russell's circumplex model of affect.

2.1 Differential Outcome Theory

Differential Outcome Theory states that reward-related feedback unique to (differential with respect to) stimulus-response pairings has a positive effect on learning accuracy and rate of learning. When unique rewards are paired with a unique stimulus, learning appropriate responses to the stimulus is strengthened through the unique stimulus-reward associations, as compared to when the reward is not stimulus specific. Differential Outcome Effect (DOE) occurs when an individual forms association pairs between a stimulus and response, as well as simultaneous associations between a stimulus and its particular reinforcement (Goeters et al., 1992; Urcuioli, 2005). DOE was first introduced by Trapold (1970) who conducted an experiment where rats were taught to discriminate between two different noises. The results showed that rats with differential stimulus-response specific reinforcements had greater accuracy in discrimination compared to the rats in the control group with randomized reinforcers for each response. The effect was firstly tested on horses, pigeons and other non-human animals with results indicating that DOE is applicable for increased learning through associations and discrimination. Trapold's experiment led to further investigation of the theory, and it is assumed to exist in other animals used as models for understanding the learning and memory processes involved (Urcuioli, 2005).

McCormack et al. (2019) conducted a systematic meta-analysis review revealing a significant effect on learning when incorporating Differential Outcome Training (DOT) in tasks that applied to both animals, human children and adults. McCormack et al. developed a gamified psychology

task based on DOT for humans, where the results demonstrated a good experimental analogue for peoples' casual life, where different actions or stimuli lead to different consequences. The stimulus-specific reinforcements that DOT provides suggests enhancement of acquisition, faster learning and better accuracy. Furthermore, McCormack et al. (2019) observed medium-large effect sizes in regard to DOT, which provides strong evidence that DOE is effective to humans.

2.2 Social Presence Theory

Social presence Theory (SPT) was first introduced by Short et al. (1976) in the context of telecommunications, with the definition of social presence as "the degree of salience (i.e., quality or state of being there) between two communicators using a communication medium". Lowenthal (2010) accounts for how SPT continuously sought to explain on one end how people perceive other people as being present or being real and on another end how immersed people perceive themselves in a projected environment and how other people can perceive them. Some other definitions emphasise the emotional and interpersonal connection between communicators (Oztok, 2011). Lowenthal (2010) further connects SPT to learning and describes how it has become a central concept especially in online learning as a key component in theoretical frameworks for learning networks. Previous findings have revealed the importance of visual channels for strengthening communication media and how online learners project themselves as being online and present and suggests how that might improve learning. Similar mechanisms are believed to explain the feeling of being with another social entity that could then potentially also have a positive influence on learning combined with social HRI. The mechanism behind the theory can be described in terms of the environment. Increased social presence can be seen to create a more sociable, warm, and personal environment, whereas the opposite can be said of environments with less social presence, with for example less nonverbal and relational cues. The environment is said to be crucial for educational settings especially since learning often is seen as a social practice. The characteristics of the media is also of importance to increase the feeling of social presence, where a more multi-dimensional media often leads to increased social presence, such as video (including both audio and visual cues) as compared to solely audio (Lowenthal, 2010).

Social presence has previously shown significant importance in acceptance of social assistive robots in eldercare settings. The term often relates to the feeling of being accompanied by a social entity, and has been found to have a crucial role for the acceptance of both functional and conversational robotic agents. By measuring social presence in relation to acceptance or conversational expressiveness, earlier studies have connected the increased feeling of being in the presence of a social entity as having a positive impact on HRI (Heerink, 2009). This implies that by increasing the feeling of social presence of the robot in this study by its audiovisual feedback it might have a positive effect on acceptance of the robot as well as on learning. Additionally it might be of interest to connect the findings of DOE with social presence and a potential relationship between the two.

2.3 Engagement and dementia

One of the most important challenges of current research in cognitive interventions to aid memory training for patients with dementia is in terms of engagement. Engagement plays a crucial role to be able to make treatments meaningful, rewarding and to keep participants motivated to complete an intervention that might last over several weeks. Engagement in dementia is defined by Cohen-Mansfield et al. (2009) as "the act of being occupied or involved with an external stimulus." or by Nakamura and Csikszentmihalyi (2014) as "the sense of being positively absorbed in engaging activities." Additionally, Cohen-Mansfield et al. provides a theoretical framework for engagement in people with dementia and emphasises that engagement research is essential for the development of non-pharmacological dementia treatment and therapies. They propose the theoretical framework named the *Comprehensive Model of Engagement* for people with dementia, claiming that environmental attributes, human attributes, and stimulus attributes all influence stimulus engagement. As a result of the engagement, a shift in affect occurs, which determines the presentation of behaviour issues. The most significant characteristics of engagement, according to their research, are refusal, attention, and attitude. Because it combines refusal and attention, engagement time is a global metric that indicates an essential therapeutic component. They emphasise that future investigation is necessary to explore and, hopefully, dispel

the widely held belief that dementia inactivity is a fixed feature of the disease that cannot be treated. They also give a firsthand observational assessment of engagement of people with dementia where dimensions of engagement time, attention, attitude are included in the measurement.

Engagement has previously been studied in relation to psychological tasks including how it relates to visual attention, affective engagement and flow theory. Andriella et al. (2020) describe a framework on how to utilise assistive robots for facilitating engagement and patient-robot interaction (PRI) to improve learning in a clinical gamified task. Besides revealing the potential of using robots to improve engagement in memory training the authors also emphasise the need for further research on improving engagement in the context of patients with dementia and HCI. Doherty et al. (2018) investigates how engagement is interpreted, understood, and measured across human-computer interaction and emphasises its importance with respect to learning. Flow theory and social presence theory are often used to facilitate the analysis of interaction and engagement as a state of subjective experience. Engagement as a state of flow is defined as "optimal and enjoyable experience characterised by atractable challenge, immersion, control, freedom, clarity, immediate feedback, temporal insensitivity, and changes in one's sense of identity" and have often been used in the context of gamification (see section 3.2 Digitalised gamified memory training). Furthermore, engagement has also been described in terms of cognitive, emotional or behavioural components where emotional/affective engagement often is associated with perceived feelings such as interest or boredom. It has especially been related to the circumplex model of affect, where a high occurrence of valence and arousal have been related to engagement. Doherty (2018) also discusses engagement as a product of feedback and accounts for studies that have shown the influence of performance-related feedback that discovered that positive feedback encourages users to do better on tasks and how negative feedback did not create less engagement. They also emphasise how this previously has been shown in the context of immediacy signals exhibited by humanoid robots.

2.4 Russell's circumplex model

A circumplex model of affect was proposed by Russell (1980) as a method to measure affect and allowing psychologists to depict the structure of affective experience and to represent the cognitive structure behind affect and self-reported emotional states. It was proposed in contrast to theories of discrete basic emotions that often offer too simplified and unreliable ways to measure such a complex cognitive function such as affect. The circumplex model instead proposes that affective concepts can be seen as dimensions intercorrelated with each other that can be represented in a circular fashion representing the structure of self-assessed emotional experience. The original model consists of 4 scales ordered in a circle with the following dimensions; pleasure, excitement, arousal, distress, displeasure, depression, sleepiness, and relaxation. One of the scales would for example be pleasure in contrast to displeasure. The implications of using such a dimensional model of affect in contrast to a discrete model is that it offers a more realistic and reliable way aligned with how emotion actually is experienced in human beings (Feldman Barrett, 2001). Usually emotions are not experienced as discrete mental states clearly differentiated from each other but are rather ambiguous and overlapping experiences of several different mental states. There is also neurological support in favour of the Circumplex model of affect (Posner et al., 2005) and it has been widely used and adopted for psychology and affective research. The Self Assessment Manikin Scale is one of the specific measurements developed based on the Circumplex model of affect (Bradley & Lang, 1994).

2.4.1 Self Assessment Manikin Scale

Self Assessment Manikin scale (SAM) is a subjective, five-pointer scale which measures the participants' experienced emotions based on the Circumplex model of affect. SAM is a pictorial, non-verbal scale that has three levels which measures valence, arousal and dominance (Bradley & Lang, 1994). Valence is here regarded as an emotion of either positive or negative nature, arousal is accounting for calmness or excitement/distress, and dominance describes the feeling of being in control of the situation. The SAM scale is meant to reflect the idea of emotions as humans themselves know them and its purpose is to let the subjects assess their own emotions directly in regard to a stimulus or an event.

3 Earlier research

The experiment presented in this paper is mainly inspired by the study of DOT conducted by Vivas et al. (2018) as well as one by Andriella et al. (2020) where the former shows significant DOE on a visuospatial memory task and the latter how robot feedback can be implemented for dementia memory training. This study aims to adopt a new approach combining some elements from both studies and thus reveal how DOE and robot feedback together affect learning and memory game performance. In this section, among others, these two papers are discussed in detail with regard to this experiment.

3.1 Differential Outcome Effect

Miller et al. (2002) examined whether DOE (Differential Outcome Effect: the effect on learning induced by the DOT procedure based on pairing certain stimuli with certain rewards) is restricted to non-human animals, or if it is applicable to humans as well. They examined students aged between 18 and 38 years in an experiment with discrimination task of 15 japanese kanji characters with abstract meanings, so that they would be harder to form a visual association with. The characters had immediate “rewards” in the form of pictures in vibrant colours and outcomes with external prizes of an average value of $10. For the participants in the differential condition, each kanji character was always associated with a specific picture and prize. The results of the study showed a significant improvement in performance on the task with the DOT, the participants in the differential condition had a higher mean percentage of correct answers in comparison to the control group and partially differential condition (Miller et al., 2002). These findings indicate that

DOE is present in human adults and that DOT is a potentially effective intervention to improve learning for adults.

The task used in our experiment is inspired by a previous study by Vivas et al. (2018). Their study showed significant performance improvement of using DOT on a visuospatial working memory task in patients with AD and MCI. They tested three different groups of participants, one with AD, one with MCI and one control group, performing a visuospatial working memory task either under a DOT condition or under a NDOT condition. Performance of the task under the DOT condition was improved for all three groups. AD patients performed significantly above chance in the last block of trials only under the DOT condition but had overall worse performance relative to the other groups as expected due to significantly impaired spatial memory. However, this study included AD patients with more advanced cognitive deterioration than previous studies of DOE on AD, further suggesting its applicability and implications for patients on a wider range from mild to severe dementia.

3.1.1 Differential Outcome Effect and social contexts

Rittmo et al. (2020) examined differential outcomes training in social settings and conducted two experiments related to DOT and transfer of knowledge (how knowledge is transferred from learning to test phase). The first experiment supported the hypothesis that a transfer of knowledge, the occurrence of response selection given novel stimulus-response pairings via implicit inference (Rittmo et al., 2020), was obtained when using DOT in a social setting. The second experiment's purpose was to calculate the effect of the contrast between differential and non-differential outcomes within the social setting. The results from experiment two also indicated that a transfer of knowledge occurred within the social setting. The main findings of Rittmo et al. 's (2020) experiments suggested there are beneficial implications of DOT in a social setting (especially in the context of transfer of knowledge), which is also relevant to the study presented in this paper that also has a social dimension in terms of the robot feedback. If a similar beneficial effect can be observed it might be a cause of the same theory underlying the findings in Rittmos' study, namely the Associative Two-Process theory (ATP) – the suggested existence of a memory route where prospective outcome expectations can influence learning and decision making (Lowe & Billing,

2017). The results of the experiments suggested that ATP could apply in social contexts, however the main finding was that the transfer of control effect can apply in social contexts.

3.2 Digitalised gamified memory tasks

This study contains a gamified version of a visuospatial task (see section 4.2.1 TTT Booster Game). Gamification is defined as “the use of game design elements in non-game contexts” (Deterding, 2011) and is mainly used because of its potential to facilitate learning with motivational power and as an engaging and entertaining element. Memory training in the form of visuospatial tasks is a type of cognitive intervention treatment for persons with related memory loss, and by including game features it can allow for more engaging and entertaining clinical interventions with long-term cognitive and memory advantages. Sailer et al. (2020) emphasise that gamification is typically used to enhance rather than replace memory training and that good instructional content is a must for successful gamification. Additionally, the authors mean that gamification is meant to have a direct impact on learning practices and attitudes and a beneficial, indirect effect on learning outcomes.

Alves et al. (2018) discuss the relevance of flow, the feeling of deep engagement as a state, in a gameplay adaptation. Csikszentmihalyi (1997) defined two conditions for flow: “Perceived challenges of activity match and stretch the capabilities of the individual, thus producing an experience of being fully engaged in the task and acting on the height of their skills.”; and “the goals of the activity are explicit and reachable, and one received instant for their feedback for their progress on the activity”. Therefore, a state of flow might prove beneficial for gamified tasks due to increased enjoyment of said activity and has been studied as a means to explain and improve user engagement. By studying flow further, Alves et al. (2018) found that users have a higher self perceived flow state and scores when playing a game that adapts to their performance compared to adapting to their mental state. The subjects playing after the performance based adaptable protocol also had greater overall scores. Their findings show the benefits of measuring engagement (in the form of flow) for gamified tasks and how it is related to performance, motivating measuring flow as a unit of engagement and as an indicator of learning and performance in gamified tasks.

Andriella et al. (2020) also make use of a gamified memory task paired with robot interaction and show promising results of the implementation and combination of the two for patients with dementia. The task they use is a sorting tokes exercise, designed for people with Alzheimers and different stages of MCI and trains both memory, attention and motor functions. The study addressed in this paper is inspired by Andriella et al.'s (2020) experiment, but does however contribute with a different approach and methodology by adding the DOT as well as a different game that is digitalised and a more socially complex robot.

3.3 Assistive robot feedback

Several studies have sought to address the effect of feedback and learning and here we account for how it relates to social assistive HRI.

3.3.1 Feedback and Learning

Feedback and learning has been proven to be closely connected and there have been different ways to implement feedback to improve learning for different tasks. Luft (2013) reviewed how feedback correlated with learning in different neural circuits and described two types of learning processes, error-based learning and reinforcement learning. The former refers to learning via finely graded error information, which gives feedback that informs an error was made and the particular way the error was made, while the latter refers to learning affected by categorical rewards and punishments depending on a correct or incorrect response. Error-based learning and reinforcement learning have differences in regard to the learning processes that are involved, the former have been associated with implicit/procedural learning processes, and the latter with hypothesis-testing processes.

The gamified memory task used in this study is based on reinforcement learning, where the subjects learn which actions to take to maximise the outcome (reward) via trial and error. Luft (2013) further describes how in reinforcement learning the output is categorical, meaning either a correct answer is rewarded, or an incorrect response is punished (or in this study leading to an absence of rewards). Several neurological studies also support the importance of feedback to

improve learning and have clarified neurological underpinnings of the effect of feedback on exhibiting learning (Luft, 2013).

A study by Vollmeyer et al. (2005) concluded significant problem-solving task performance improvement by feedback and also how feedback increased strategy systematicity. The performance was not only improved in terms of final outcome, but also throughout the entire learning process. The feedback solely consisted of knowledge of how they performed and to what extent they responded correctly. The feedback however was not delivered through the interface of a robot and therefore our study seeks to investigate the combination of the game feedback and the robot feedback on learning, as a very different type of feedback delivery. Based on the social presence theory, the presence of the robot might exhibit the effect of the feedback even more. Most importantly, the implementation of DOT in the reward system of the game is also one of the most relevant components of the feedback in this study.

3.3.2 Human-Robot Interaction assistance

Andriella et al. (2020) describe a framework and present a cognitive robotic system designed to assist patients with mild dementia during brain-training sessions with successful results improving learning in a clinical gamified task. Besides showing the importance to memory training and how it can be improved with human-robot interaction the authors also emphasise the need for further research on improving engagement. Assistive robots have great potential as engaging tools for user interaction in the context of providing both home and on-site treatments with safer, non-contagious interaction and specialised assistance. Similar attempts have been made to use robotic assistance to increase the effectiveness of social and cognitive training interventions and make them more accessible in the context of people with dementia. A study by Chan et al. (2010) validated that the implementation of a socially assistive robot was effective for engaging people in a game and specifically feedback in the form of instructive and help phrases helped increase the participants' attention to the game.

Besides contributing to improved engagement and in turn learning, humanoid robots have proven to have great potential as assistive robots in dementia care for many other reasons. Ozdemir et al. (2021) suggest several promising ways social assistive robots can bring value based on previous

implementations, such as social and emotional support, companionship and practical help and assistance. They also identify the limitations in existing technologies and implementations in regard to the high cost of the hardware and prototypes of the embodied robots.

4 Method

The experiment followed a 2x2 independent groups experimental design (with SDK condition and control condition) with the following four conditions: 1) Differential Outcome Training (DOT), 2) Non-Differential Outcome Training (NDOT), 3) Differential Outcome Training with Simulated Robot (DOT SDK) and 4) Non-Differential Outcome Training with Simulated Robot (NDOT SDK). The 2 independent variables had 2 levels each: IV1: DOT vs NDOT and IV2: SDK vs Control. It was carried out with an expected large effect size, with respect to McCormacks' et al. (2019) meta-analysis (power = 0.8), (power calculation with MorePower 6.0.4) (Campbell & Thompson, 2012): N = 52 participants, divided in 4 groups (n = 13). The medium the experiment was performed on was a visuospatial gamified memory task with three difficulty levels (24 trials on each level) following the order: easy to medium to hard. The order of the challenge level was not considered an independent variable due to the purpose of retaining a natural setup to increase difficulty over trials. See section *4.2.1 TTT Booster Game*

Dependent variables were quantitatively measured and analysed based on data gathered from the game (accuracy: percentage of correct responses), together with evaluation based on measures of social engagement, such as Self Assessment Manikin Scale (SAM). Furthermore, samples were drawn from the iMotions data to understand potential memorization techniques and cognitive strategies based on eye tracking.

4.1 Participants

The participants were 60 young adults in the age between 19-35 (M = 23.93, SD = 2.82), where 33 participants were women and 27 were men. A total of eight participants were removed from the data analysis, one due to missing a break, and seven for being in the Furhat condition before it was discontinued. The criteria for inclusion of participants was healthy (not being a person with

memory loss) individuals between the age of 19-35. The sampling procedure was mainly carried out at the university campus of University of Gothenburg. Consent to participation in the experiment was ensured through an informed consent form (see Appendix 2). To ensure internal validity, the potential difference in participants' background was accounted for by randomising the condition groups to ensure limiting the potential influence of individual differences. Additionally, the DOT and NDOT conditions in the game were randomised for each participant as well. All the participants were compensated with a cinema ticket.

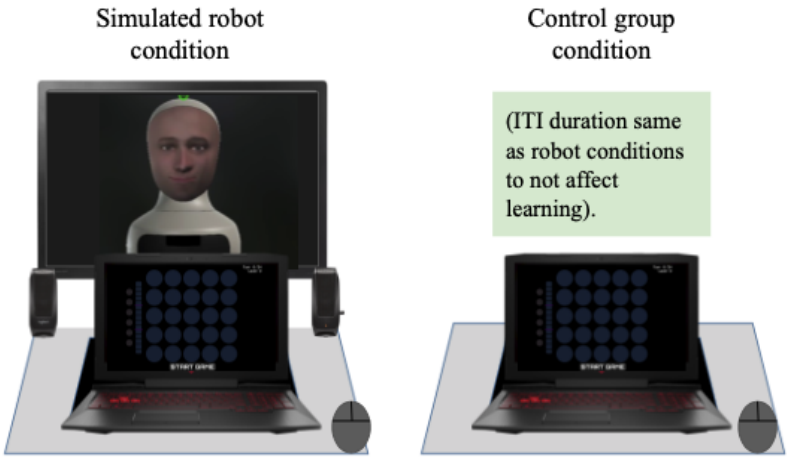
4.2 Equipment

Each participant was required to carry out the experiment on a laptop (HP Omen) with a keyboard and a bluetooth connected mouse. To calibrate the participants' eye movements and facial expressions, Smart Eye's AI-X eye tracker was used, connected to iMotions Software (version 9.2) which includes Facial Expression Analysis (FEA), based on inter alia Affectiva AFFDEX face reader code (iMotions, n.d.). Furthermore, the Unity Booster TTT game was used in the experiment, which is described in *section 4.2.1*.

Depending on the different conditions, the set-up had slight differences (See Fig. 1). For the control group, solely the equipment mentioned above was included. In the simulated robot condition, the Furhat SDK was shown on a monitor, standing on a pedestal behind the laptop. Speakers were connected to the monitor to enhance the simulated robot's voice.

Figure 1

Visualisation of the set up. See Appendix 3 for photographs.



4.2.1 TTT Booster Game

The game used in this experiment is a gamified version of the Vivas et al. (2018) task adapted to account for the different cognitive capabilities of the participants involved in the experiment. The game space consisted of cells in a 5x5 grid where stimuli, visualised as white dots, appeared in a sequence (level 1: 4 white cells, level 2: 6 white cells, and level 3: 8 white cells). As distractors, red and blue dots that are not a part of the stimuli sequence randomly appeared to tax working memory and to guard against potential ceiling effects in learning. To increase the cognitive workload further, the participant had to press the spacebar on the keyboard whenever a blue dot appeared. When the stimuli sequence was over, the participant chose between 2-4 (depending on the challenge level) response options. The correct response was the cell that a white dot was presented on during the current trial's stimuli sequence. The chance of guessing the correct response option was on level 1: 50%, level 2: 33%, and level 3: 25%. For each correct answer, the participant got an outcome (reward), which was either 1 coin, 3 coins, 1 diamond or 3 diamonds. The time between when the stimuli appeared and the response options were shown differed between 4 and 12 seconds, and was randomised for all trials, this was later stored as a variable in the data and is hereafter referred to as ISI (inter stimulus interval). In the beginning of each trial, the cell in the middle blinked in a bright green colour to attract attention.

The game had two different settings, the NDOT condition and the DOT condition. During the NDOT condition, the outcomes (rewards) in the game were randomised for each correct answer and not bound to its visuospatial position in the gridspace. During the DOT condition, the outcome was consistent with a specific stimulus position randomly assigned during the start of every condition, thus reinforcing the position in the gridspace with a unique outcome (see 2.1 Differential Outcome Theory). The response options used were always previously reinforced positions in the grid to reinforce the potential DOE. However, during level 1 and 2 when there were fewer than 4 response options, the formations were randomly chosen from the four reinforced positions after each trial.

See Appendix 4 for a visualisation of the TTT Booster Game.

4.2.2 Furhat

The embodied Furhat robot is a highly complex socially interactive humanoid robot head developed at Royal Institute of Technology in Stockholm (KTH). Its face can be changed into 22 animated customised versions via a projector inside the Furhat head that by 3D animation projects a translucent mask to create a face that feels alive as physically present. (Furhat Robotics, 2021). The speech can be customised to more than 200 voices in over 35 languages and varying regional dialects. In the experiment the *Matthew - Amazon Polly* voice was used with programmed customizations to enhance the pitch. When participants got a high reward in the game, the vocalisation was in a higher pitch and melodious, while getting an incorrect answer the vocalisation was in a lower pitch and monotone.

The simulated version of the Furhat robot (The Furhat SDK) is programmed and controlled via the application Furhat SDK Desktop Launcher. It is capable of the same wide range of facial expression, head movements and voices as the embodied version but is displayed via a 2D screen. For each specific reward, there were three possible feedback phrases for Furhat to vocalise, and they were randomised in each trial. The feedback was the same for both the DOT and NDOT condition, its purpose was to enhance which reward was given, and in turn enhance the DOE when present.

4.3 Pilot study

A pilot study with six participants was conducted before the first initialization of the experiment. The participants in the pilot study provided feedback on how to improve the experiment and allowed for evaluation and improvement. The experiment was revised after the pilot study by adding a trial level, a definition of how many trials each level consisted of, and a randomised amount of blue cells showing during each trial (varying from 2-4). More data was also collected in regard to the DOT/NDOT condition for separation purposes.

4.4 Procedure

The interactive scenario consisted of a setup where the participants conducted the gamified memory task via a laptop. The gamified memory task was carried out by the participants individually and after signing the consent form (see Appendix 2) they received instructions for the experiment procedure and game (see Appendix 5). The experiment leader repeated the information to ensure that the participant was fully aware of the task and the SDK was introduced to the participants if they were in the SDK condition. To get familiarised with the game, the participants played a test run of 10 short trials to ensure that they understood the game. Afterwards, their eye movements were calibrated with iMotions software, and the experiment was initialised. The game consisted of a total of 72 trials divided on three difficulty levels. After each game trial during the SDK condition, the participant received vocal performance feedback from the SDK (See Appendix 6). If the participant was in the control group, they did not receive any vocalised feedback, but instead had the same inter-trial interval (ITI) as not to affect learning. The sequence of trials were presented in blocks of 24 trials, with a break in between to reduce fatigue. During each break between the three levels of the game, the participants filled in the SAM-scale to evaluate their own affective experience of valence, arousal and dominance (control) with respect to the game and setup (See appendix 7). After finishing all of the challenge levels, the experiment leader/SDK (depending on condition: IV2) rewarded the participant with a cinema ticket. The experiment's duration was approximately 40 minutes.

4.5 Data collection and analysis

Quantitative data was collected through the game in the form of game performance (number of correct responses (CR)) for each trial of every challenge level of the game. The number of CRs were measured in percent per challenge level. Each challenge level was also divided into 4 blocks of 6 trials and CR was calculated for each block. Furthermore, the data was split up between different inter stimulus intervals (ISI) and analysed separately for each interval. Furthermore, the CR was also calculated separately with respect to ISI (either 4 or 12 seconds) and compared for the different conditions. The quantitative data was analysed using SPSS v.28.0.1.1 for descriptive

statistics as well as F-test and two-way-ANOVA for main and interaction effects. The statistical significance level was set at .05.

Qualitative data was collected through iMotions camera (eye tracking, facial expression). After evaluating participant eye tracking, an attempt was made to categorise different cognitive strategies by calculating the number of cell fixations over blocks. These data were also used in the analysis with respect to DOT, to the theory, quantitative data, and SAM. The data collected from the SAM-scale was summarised and analysed for monitoring and comparison of the participants' perceived emotional state both quantitatively and qualitatively.

4.6 Delimitations

In regard to participants, solely healthy individuals (not suffering from memory loss e.g. dementia/MCI) were participating in the experiment due to the study being pre-clinical (see discussion of implications in 1.1 Objectives and 6.3 Implications). Furthermore, the eye-tracking data that was collected was analysed from a sample of the best and worst performances (16 participants). To carry this out with respect to all videos would take approximately 40 hours per person and was therefore deemed prohibitively time consuming. Reaction time data was also gathered during the experiment to enable measuring subjects latency of response, however because no immediate difference could be seen depending on the conditions it was not used in the final results. Vivas et al. (2018) report a similar delimitation of the same reason in their study.

5 Results

By calculating the mean percent of CR per level, the mean accuracy was compared between the different conditions. *Table 1* shows the mean accuracy over the four different conditions for each level, and in the total accuracy for all levels. DOT condition shows a greater accuracy both in the control condition and in the sdk/robot feedback condition. A two-way between subjects ANOVA revealed statistical significance in the main effect of total accuracy between subjects in DOT condition compared to the NDOT condition, $F(1, 52) = 5.721$, $p = .021$, $\eta_p^2 = .107$. 95% CIs for DOT = [67.40, 76.63], and 95% CIs for NDOT = [56.21, 69.30]. The partial eta-squared reveals a medium-large effect size aligned with the estimated effect size used to determine sample size. There was no statistically significant main effect for subjects in the SDK condition compared to subjects in control condition (p = .635). There was no statistically significant interaction between the effects of DOT and robot feedback (IV1/IV2), $F(1, 52) = 2.262$, $p = .139$. *Figure 2* summarises the findings of mean accuracy over all conditions with percent of correct responses for each level.

Table 1

Mean accuracy: Percent correct responses (SD)

Condition	Level 1	Level 2	Level 3	Total
DOT	83.08 (10.29)	67.46 (16.11)	54.00 (15.15)	68.18 (12.86)
NDOT	78.62 (14.21)	62.77 (19.55)	52.85 (22.56)	64.74 (16.65)
SDK DOT	88.39 (8.64)	73.77 (10.46)	65.39 (12.61)	75.85 (8.65)
SDK NDOT	72.85 (16.01)	61.46 (17.88)	48.08 (19.51)	60.77 (16.17)

Figure 2

Mean accuracy (percent of correct responses) and standard error for each condition and level

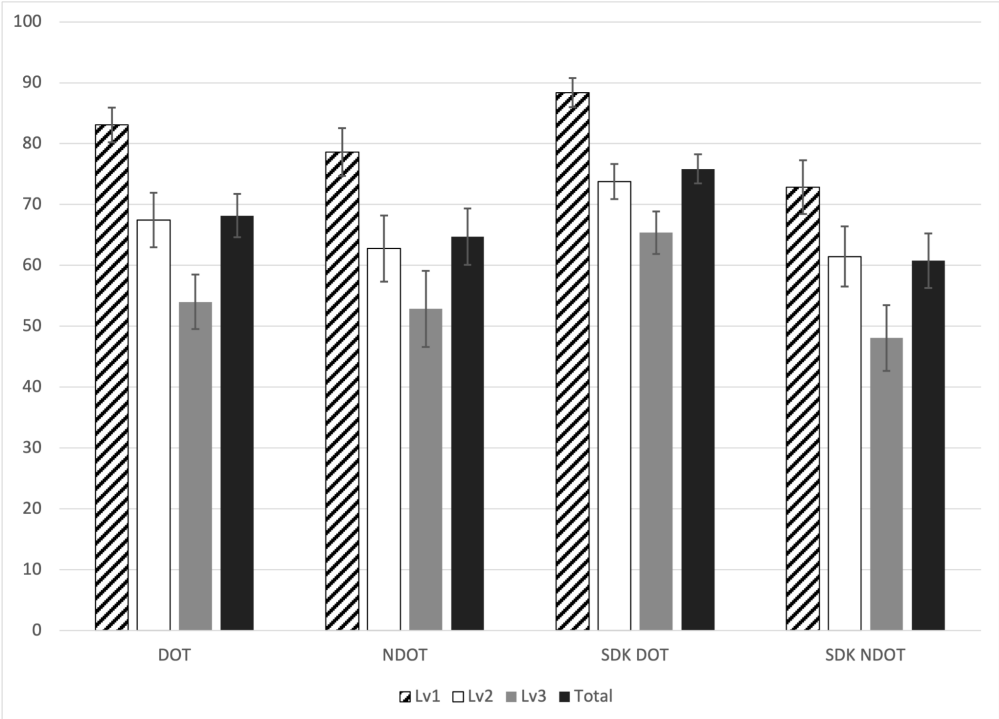


Table 2 shows the mean percent of total accuracy over all levels divided between ISI 4000 and ISI 12000 (inter stimulus intervals of 4 seconds compared to 12 seconds). A two-way ANOVA was conducted and revealed a statistical significant main effect of DOT for ISI 4000, $F(1, 156) = 9.796$, $p = .002$, $\eta_p^2 = .061$, 95% CIs DOT = [69.94, 78.75], NDOT = [59.47, 68.99], and for ISI 12000, $F(1, 156) = 4.788$, $p = .030$, $\eta_p^2 = .031$, 95% CIs for DOT = [64.81, 73.67], and 95% CIs for NDOT = [56.15, 66.98]. There was no statistically significant main effect of SDK compared to the control condition when dividing the accuracy in terms of ISI. Additionally, there was no statistically significant interaction between the effects of DOT and SDK feedback for total accuracy of ISI 4000 ($p = .055$) or ISI 12000 ($p = .137$).

Table 2

Mean accuracy wrt ISI. Percent correct responses (SD)

Condition	DOT	NDOT	SDK DOT	SDK NDOT	TOTAL
ISI 4000	69.74 (20.62)	65.87 (21.61)	78.95 (17.49)	62.59 (20.77)	69.29 (20.91)
ISI 12000	66.38 (21.48)	63.95 (25.24)	72.10 (17.45)	59.18 (22.77)	65.40 (22.20)

Further analysis split each level into blocks of 6 trials (4 blocks per level) to determine how mean accuracy evolves throughout each level. *Table 3* shows main accuracy split into blocks of trials. For tables for each level separately see Appendix 8. The main effect of DOT over each block showed statistical significance according to a one-way ANOVA for Level 1 Block 2, $F(1, 50) = 3{,}628$, $p = .010$, $\eta_p^2 = .125$, 95% CIs DOT = [80.96, 93.19], NDOT = [65.36, 82.02]. Level 1 Block 3 $F(1, 50) = 6{,}051$, $p = .017$, $\eta_p^2 = .108$, 95% CIs DOT = [79.82, 93.03], NDOT = [66.69, 82.00]. Level 2 Block 1, $F(1, 50) = 4{,}457$, $p = .040$, $\eta_p^2 = .082$, 95% CIs DOT = [65.39, 78.38], NDOT = [49.48, 69.68], and Level 3 Block 3 $F(1, 50) = 4{,}874$, $p = .032$, $\eta_p^2 = .089$, 95% CIs DOT = [53.77, 73.15], NDOT = [37.40, 58.67]. A visualisation of how performance changes over the blocks in each level can be seen in *Figure 3*.

Table 3

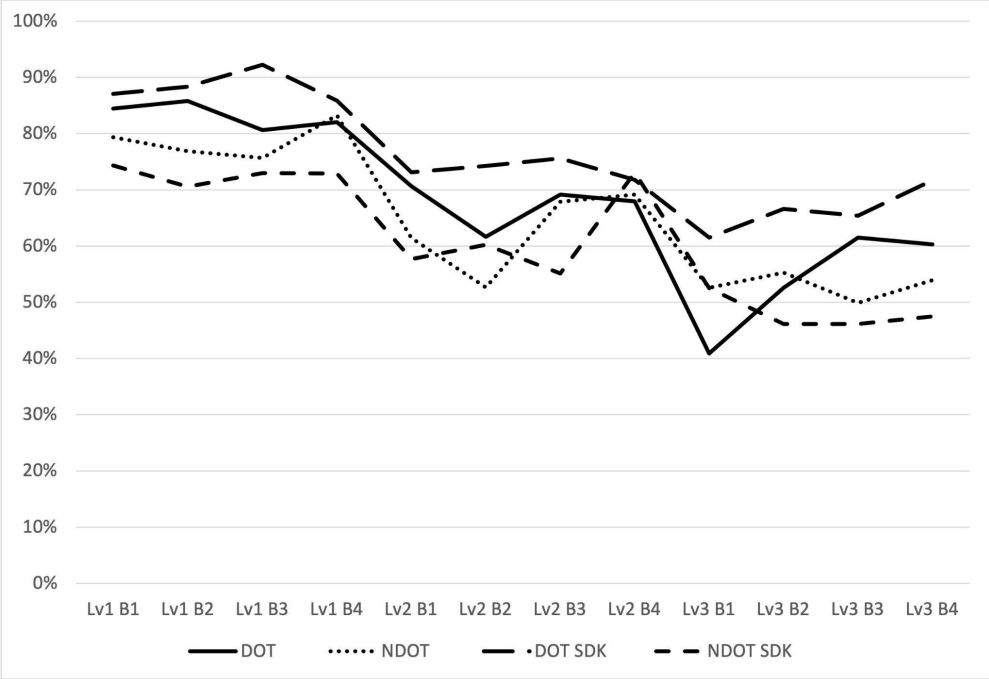
Mean accuracy over all conditions with respect to 4 blocks and DOT:

Percent correct responses (SD)

Condition	B1	B2	B3	B4
DOT Lv1	85.77 (13.05)	87.08 (15.13)	86.42 (16.35)	83.96 (20.17)
DOT Lv2	71.88 (16.08)	67.92 (22.51)	72.38 (23.98)	69.85 (14.78)
DOT Lv3	51.23 (20.53)	59.62 (18.95)	63.46 (23.99)	66.00 (28.40)
NDOT Lv1	76.85 (20.00)	73.69 (20.62)	74.35 (18.95)	78.08 (20.42)
NDOT Lv2	59.58 (25.00)	56.46 (25.88)	61.50 (26.18)	71.12 (19.72)
NDOT Lv3	52.58 (26.52)	50.73 (28.07)	48.04 (26.33)	50.69 (30.31)

Figure 3

Mean accuracy changes over 4 blocks in each of the 3 levels for each condition. Error bars omitted for visual clarity.



5.1 Self Assessment Manikin scale

The mean values for arousal, valence and control were calculated for each level in each condition resulting in 36 different values. Appendix 9 shows how the values for valence, arousal and control are distributed with respect to the different conditions. The results show that the highest levels of valence were found in the DOT SDK condition and particularly at level 1 over all conditions. The level of arousal was relatively consistent over all conditions and levels but reached a peak in DOT condition level 2. Dominance (or feeling of being in control) showed peak values over DOT SDK condition and at level 1 at DOT control condition. The feeling of dominance varied more in the DOT conditions but remained somewhat consistent in the NDOT conditions but was generally lower at level 3 on all conditions. A two-way between subjects ANOVA revealed a statistical

significant main effect in Dominance Level 1 between subjects in DOT condition compared to the NDOT condition, $F(1, 52) = 7.109$, $p = .010$, $\eta_p^2 = .116$, 95% CIs for DOT = [3.42, 4.01], and 95% CIs for NDOT = [2.56, 3.44]. Furthermore, a statistically significant interaction effect between the DOT and the SDK condition was detected on valence level 3 $F(1, 52) = 5.936$, $p = .018$, $\eta_p^2 = .099$, 95% CIs for DOT = [2.94, 3.63], and 95% CIs for NDOT = [2.47, 3.33].

5.2 Cognitive game strategies

The eye tracking data was collected through the iMotions software and analysed qualitatively by observing particular subjects with either notable high or low performance. In total a number of 16 subjects were analysed (the 2 highest and 2 lowest performance for each condition) By conducting sample analysis of two of the best performing and worst performing subjects in each condition, an attempt was made to categorise the strategies and conclude what strategies seemed most efficient for learning and memory performance. By summarising their gaze over the game grid a total of two main cognitive strategies could be identified; peripheral vision (PV) by fixating on certain spots of the game grid, or foveal vision (FV) to follow the sequence with the eye movements. Analysing eye tracking over the game grid allows for identification of different cognitive strategies and may contribute to evaluation of their efficiency with respect to learning. The implications of different strategies in regard to evaluation of the setup are further discussed in section 6.1.3 Discussion: Cognitive game strategies. See Appendix 10 for table over samples from the iMotions data.

6 Discussion

Hereby follows the discussion of this study examining how implementation of DOT and SDK feedback on a visuospatial gamified task affects learning in the form of game performance (CR) and subject affective experience. The results of this study are summarised as follows: a significant main effect of DOT on game performance was observed for participants both in the control and SDK condition, aligned with *Hypothesis 1* that subjects' learning and memory performance is improved by the implementation of DOT. Game performance was also measured in terms of ISI (inter stimulus intervals) and broken down into blocks, finding statistical significance on both different ISI as well as over some blocks (where learning could be observed in further detail). There was no statistical significant interaction effect between DOT and SDK hence *Hypothesis 2* and *3* could not be confirmed as subjects' learning and memory performance was not significantly higher when receiving SDK social reward feedback during the game. However, SAM-scale and eye-tracking yielded relevant results regarding participants' affective cues and cognitive strategies with respect to the game and learning.

6.1 Results

The results will be discussed in three parts, the first addressing the quantitative results of the CR and then the other two parts, the results from the SAM-scale and cognitive game strategies.

6.1.1 Memory task performance

The results show a statistically significant main effect of DOT on participant's game performance, indicating that there is a DOE occuring because of the differential reward system of the game. This effect is observed both in the condition with the SDK robot present and in the control condition. Furthermore, in the SDK robot condition the DOE leans towards being higher, however the interaction effect is not significant. The partial eta-squared indicated a medium-large effect size ($\eta_p^2 = .107$), aligned with the target effect size based on the study by McCormack et al.

(2019). Because the embodied Furhat experiment was cancelled there was not enough data to determine a potential interaction effect in that condition (see a summary of the results of the 7 participants in Appendix 1 for an indication of where the results might lean towards). The significance level of the interaction effect in the SDK condition is still close to significant, indicating that a potential interaction effect might be revealed with more participants and in the embodied Furhat condition. This is probable because the embodied Furhat might increase the social presence effect and result in larger difference compared to the control condition than the SDK solely, this will be further examined in future studies. The social presence effect might have been small to non-existent with the SDK, a highly relevant limitation of using the theory in this context. Biocca et al. (2003) argued there are limitations on using the social presence theory depending on the context, and that broader and more extensive definitions and measurements need to be investigated for it to be applicable to a wide range of contexts. They argue that measurements usually represent variables that are correlates or effects of social presence rather than social presence per se, a significant limitation of the theory, and that it might be a result of vague, overly broad, or circular definitions of social presence among others.

One interesting observation when analysing the total accuracy over all conditions was that by comparing the two NDOT conditions performance was lower for participants with SDK than in the control group, a reason that might contribute to the lack of main effect of SDK. It is possible to connect this to the role the feedback has on exhibiting/inhibiting a potential DOE. In the NDOT conditions participants did perform with less accuracy, probably because of DOE, and combined with reinforcing robot feedback this might have led to frustration or feeling of failure resulting in even worse performance. Even if previous literature did not find that negative feedback resulted in worse performance, this might have been the case in this experiment, though the difference between NDOT control and NDOT SDK was not so big. Future research could investigate the potential effect robot feedback might have in NDOT contexts as potentially inhibiting performance and learning. The results do not show statistical significance in terms of social presence effect of the SDK, however the results lean towards a potential presence effect that could show significance with an embodied robot and more subjects. Combined with the results of the

SAM scale that show a slightly more positive effect with regard to the SDK further studies might determine the role of social presence effect further.

The significant effect of the DOT was further observed when analysing the results with respect to inter stimulus interval (ISI). Having an ISI of 4 seconds led to higher memory performance in all conditions and over all levels in the game, indicating that it was easier to remember the sequence close to the stimuli compared to having to wait 12 seconds. Furthermore, the effect of DOT was higher with ISI 4 seconds than with ISI 12 seconds, suggesting that the DOE is affected by the lengths of ISI, something that can be further investigated in future studies and also adjusted and evaluated as a changeable parameter of the game. When analysing the performance broken down into blocks throughout the game it is possible to observe how subjects perform over time during the different levels. The results reveal that performance is somewhat constant within the levels themselves but is reduced for each level in all conditions. This could be a result of either fatigue or increased challenge level, or a combination of the two. Further investigations combining these results with affective data, such as galvanic skin response, eye tracking and SAM scale might provide some insights for the reason. The one condition showing most constant performance over all blocks in all levels is the DOT SDK condition, where DOE, social presence effect and reward feedback possibly facilitated and encouraged enough engagement and learning for the subjects to stay alert and perform well. They also had the overall best performance over all conditions in all levels. These results further imply the potential and effectiveness of combining a DOT with a social feedback robot for subjects' memory performance and engagement. Further studies might investigate if this effect will help subjects stay engaged also over time, if a potential future intervention might continue over many weeks of memory tasks or training.

Solely analysing CR for determining game performance was in this study deemed as a valid source because of the broad range of possible analyses that could be derived from the data (mean, blocks and ISI). However, reaction time data could also have been included as a complementary source of data to increase the dimension of the result and reliability. Understanding the DOE requires analysing the mechanisms behind it, and DOT as a theory consists of several complex components where scholars are divided in what gives rise to the actual effect. Some argue that expectations are of interest, and that differential response forms support the expectancy theory

account of the DOE, giving rise to the behaviour (Peterson 1980). Others arguments are more aligned with behavioural theories rooted in radical Skinner's ideas of rewards and behaviours. According to Goeters et al. (1992), behavioural theory rather than expectancy is a necessary component in describing the DOE, and that the answer to what gives rise to the effect can rather be found by simply accounting for a subject's behaviour rather than its inner workings. The lack of consensus concerning the DOT creates an obstacle in seeking to understand the mechanisms behind it and also to interpret results of studying the DOE as well as improving potential interventions making use of the theory. Further research is suggested to provide clearer answers to these questions.

6.1.2 SAM Scale

The participants filled in the SAM scale survey after each level in the game, resulting in the possibility to investigate and compare how subjects' self-perceived emotional state changed over time over the levels and in the different conditions. The survey consisted of three different scales; valence, arousal and dominance and subjects could state their level of each scale between 1-5 where 5 being high levels of valence, arousal and feeling of control. See Appendix 9 for figures of the results. Quantitative analysis of the results revealed significance for some levels and the other values were evaluated qualitatively to provide indications of emotional states and change. The values with statistical significance were control at level 1 on DOT condition compared to NDOT condition and an interaction effect on valence level 3 of SDK and DOT.

Generally, valence was high for the DOT condition in the beginning but was reduced over the levels, possibly suggesting boredom or fatigue. For NDOT valence is neutral throughout the levels, as might be expected since performance was not as good in the beginning and the increased challenge might not be perceived as big as a failure. The DOT SDK condition has the most constant high valence over all levels, suggesting that DOE in combination with receiving positive feedback helps keep the subjects in a positive mental state throughout the entire game. For the NDOT SDK condition valence reaches its lowest levels on the last level, suggesting that poor performance (because of no DOE) combined with the robot constantly pointing out they are not performing well might create a negative or frustrated state of mind throughout the game. Arousal

was somewhat constantly neutral for all conditions, the only peak that can be observed is in DOT condition level 2, maybe because of good performance and engagement creates a feeling of higher arousal. The game itself may not be emotionally arousing, at least not from the subject's own point of view. Further studies could include galvanic skin response as an alternative data source to determine how arousal might be correlated with affective engagement and response to robot feedback as well as game outcomes. For the feeling of control (dominance) it is remarkably higher for DOT conditions (both with and without SDK), especially in level 1, something also expected to be correlated with better performance. Control is especially high in the DOT combined with the SDK condition, suggesting that having the robot present might induce a feeling of control in the participants, possibly as a result of the social presence effect or because of the feedback that keeps stating the subject is performing well.

The results of the SAM scale are particularly interesting when combined with other affective data as a way to measure subjects' affective states when playing the game. Because of the subjective nature of the SAM scale it might not be adequate to be analysed alone to fully determine affective states, however in this state it offers some insightful suggestions that can be taken into consideration for future studies. Especially noteworthy is the improved perceived feeling of control the SDK combined with DOT might induce in participants as well as the high valence in the SDK DOT condition. These results are aligned with the suggestion that combining DOT and robot feedback in a future clinical intervention of memory training might not only improve memory performance, but also keep participants engaged, entertained and content with higher feelings of control and valence. Russell's Circumplex model, which serves as the theory behind the SAM scale, allows for classifying emotion in a multidimensional way, an approach that suits this scenario because of the broad types of felt emotion in the subjects and as proven by the results in this study. A potential future intervention might take SAM-scale data as input to the robot to adjust the feedback based on the subject's affective state. However, measuring emotion has some serious limitations, mainly with regard to the simplification of the complex phenomena human emotion is into something measurable on a scale. Additionally, only measuring emotion though one channel (SAM-scale) offers a limited representation of the actual emotion being present. Many recent studies suggest using a multimodal approach of measuring emotion instead, especially in learning environments (Kapoor and Picard 2005). A review by D'mello and Kory

(2015) identified several multimodal affect recognition systems, including for example audio and visual information, acted expressions and different measures of arousal such as physiological cues. Their review found that accuracy of the multimodal systems were superior to the simpler counterparts. The SAM-scale is therefore deemed as not enough to adequately measure affect, but should rather be considered an important component in a future multimodal system.

6.1.3 Cognitive Game Strategies

Owing to the complexity of the fixation-saccade patterns of behaviour it was considered that the most appropriate method for classifying strategies would be through inter-rater coding. Even if there was a difference between most of the subjects' use of strategies, a general trend could be identified where PV seemed to be more correlated to higher performance than sequence following (FV). In the PV strategy subjects fixated their gaze on a smaller area (only a fragment of the entire grid, such as a 2x2 dots, this strategy seemed to be mainly correlated with better performance. The other strategy, FV, on the other hand followed the sequence with the eye movements, resulting in a gaze constantly moving back and forth over the entire game grid. The reason why peripheral vision by fixating on smaller areas seems to be the most effective way for memorising the positions of stimuli might be because of reduced fatigue and cognitive load. Constantly following the sequence might lead to confusion, stress and reduced performance over time. The implications of these results are mainly how they contribute to increased understanding of cognitive strategies correlated with memory and learning and they might prove helpful to help future subjects perform well, stay engaged and improve learning also during possible clinical interventions. However, the results only show a trend and there is still a noteworthy variation between subjects. Future studies should find a way to quantify the cognitive strategies by calculating the number of gaze fixations over each block and level of the game. The number of fixations can then be analysed quantitatively together with a measure of game performance to determine if there is a significant correlation between gaze fixations (PV) and memory performance. The cognitive strategies are currently a working hypothesis and by continuing this research we hope to be able to draw more specific conclusions regarding their importance with respect to learning.

6.2 Method & Equipment

Limitations of the methodology are discussed with respect to components of the setup that might have interfered with the results and suggestions are made for future adjustments of those components. The experiment was conducted in a controlled setting with the same setup for each participant, in an independent group design. To account for the potential individual differences between subjects it would be of interest to replicate the study as a within-groups design to validate the results, and to generate individual learning curves for the different conditions respectively.

6.2.1 Equipment

When analysing the iMotions data it was found that the Smarteye AI-X eye-tracker was notably sensitive to movement, and when participants changed their position during the breaks it led to some eye movements not being detected. It was also sensitive to the angle of the face, if a participant were to tilt their head the data being collected were no longer as valuable. However, most of the eye-tracking recordings were adequate and deemed as reliable for analysis.

As mentioned in section *4.2 Equipment*, iMotions contains a Facial Expression Analysis (FEA). The purpose of using FEA was to gain insight if participants' explicitly expressed emotions in regard to the game and the SDK, to further analyse how the variables may have affected the participants emotionally. However, solely using a FEA might not be a reliable source due to the lack of ability to differentiate between similar emotions. To exemplify, if a participant laughed in frustration, the FEA regarded that as joy, even though it might have been a different emotion. Furthermore, different face characteristics and shapes, such as having down-turned lips were sometimes classified as anger even though individual calibrations were made . To be able to extract valid data from the FEA, it is essential to have equipment that can validate the emotions, for example galvanic skin sensors that can calculate the arousal of the participants in regard to stimuli and in general. Therefore, it is suggested to use further equipment that can support and validate the data from a FEA and to have a more multimodel approach to measure and interpret subjects' emotion. Because the FEA data contained the above mentioned limitations they were not used in the qualitative analysis in this study, however, future studies might compare them with the

SAM-scale data to find potential emotional patterns relating to engagement and game and memory performance.

6.2.2 TTT Booster Game

As mentioned in section *4.2.2*, the third level contained 4 different response options which were positioned at the same places each trial. This could potentially have led to the DOE disappearing for some participants in the DOT condition, due to focusing on the pattern of the response options, instead of the rewards, and therefore potentially interfering with the results. This could also have been a reason for some participants performing well in the NDOT condition; instead of focusing on sequence of stimuli, the participants may have started to focus on the different anticipated positions of the response options. One possible suggestion to eliminate such confoundings is to not randomise the response options over the whole game space, but to restrict the response options to different places, for example the four corners. The response options would in that case be more spread out, and it would be more difficult to see a pattern in the response options.

Furthermore, the outcomes (rewards) of the game could have been even more differential to further increase the DOE and to possibly investigate the performance difference according to different levels of differential outcomes. In the game there were four different outcomes: 1 coin, 3 coins, 1 diamond and 3 diamonds. Because of the similarity between the coins and diamonds, it could have been perceived as only two rewards with four different values by the subjects. It is suggested to use more differential outcomes, perhaps more abstract or even meaningful (such as objects with general emotional values), or even add an extra reward if the participant performs very well. Such an addition might enhance the feeling that the rewards make a meaningful difference to give the participants in the DOT condition the possibility to easily associate the response options with their outcomes.

Additionally, it may be of interest to make the game space smaller, from 5x5 to a 4x4 grid to highlight the corners of the game. The results suggest that the game is somewhat difficult for certain subjects and future interventions should consider adjusting the challenge not just through the levels but also by changing parameters such as the size of the grid. Minimising the game space is of interest for interventions with people with MCI that might not be as alert as young, healthy adults. The game is made to have changeable parameters such as space, challenge level, number of

distractors and so on, allowing for adjustments, fine-tuning and personalisation of the game that might prove beneficial for future interventions. Even though potential limitations could be identified, the results in this experiment are deemed to be reliable in terms of measurements of the dependent variable, but after adjustments, future studies might find stronger/additional support of the hypotheses.

6.2.3 Feedback from Furhat

The Furhat robot and SDK are adaptable and able to be pre-programmed in diverse characteristics and give different types of feedback depending on outcomes of the game, performance of the subject and/or the emotional state of the subject; meaning it can be made to implement DOT systematically. This allows for precise monitoring of the implementation of DOT on learning as well as adaptation of the feedback based on participant needs. Even though the robot/SDK in this study was non-interactive, meaning the conversation was one-way only, it is still capable of providing insights of its possible influence as an assistive partner on learning and can be implemented with an interactive nature in future interventions of the setup. Possible critique to use an interactive robot suggests that a pre-recorded human could give the same type of feedback and social presence effect and that therefore the use of a robot is not necessary. However, there are several reasons for using an interactive robot instead of a pre-recorded human being displayed on a screen or giving feedback in real life. For instance, due to (1) the human factor of making a mistake in real life and not giving the same response for each participant, and (2) the uncanniness of a human vocalising the same phrases over and over again. Furthermore, as a future clinical intervention, the robot or the simulator can be implemented on a big scale and be accessible to more, contamination free treatments and possibly even completely without a clinician, therefore allowing for extensive treatments available for more people and meeting the needs of a higher demand for dementia treatments.

The results suggest that the participants who were accompanied by the SDK (and a potential similar effect with the embodied robot) had a higher accuracy in performance when in the DOT SDK condition, compared to those in the control condition, even if the interaction effect was not significant, a trend towards such an effect could be observed. However, it is still uncertain if it is a social presence effect that makes the participant perform better, with the feeling of being

monitored or judged, or if it is only the vocal feedback that reinforces the rewards and highlighting when the participant is doing well. A limitation of this study is to not be able to differentiate between the potential source of effect the SDK gives rise to, this can be further investigated in future studies of the setup. It is possible both of these effects will be increased by using the Furhat robot compared to the SDK, since it might be perceived more as a social entity and take up more space in the setup than simply the robot being displayed on the screen. However, if the difference is not big between the SDK and the Furhat, this implies that the SDK could be a suitable option to replace or complement clinical interventions with the robot, therefore allowing for more accessible feedback if only a screen is needed to set up the feedback system. This could allow for SDK interventions in home settings where the embodied robot could be difficult to implement.

6.3 Implications

The main implications of this study is the potential effective combination of DOT and receiving vocal feedback from a humanoid robot on improving learning and memory performance. This finding can be beneficial for future clinical intervention versions of the setup used in this study for patients suffering from dementia and MCI. Additionally, the cognitive strategies identified with the eye tracking data could be quantified and together with the performance data provide insightful knowledge on cognitive strategies related to learning. This is relevant not only to research about learning in different contexts but also for implementation using similar approaches.

The data collected in the SDK condition and the few who partook in the Furhat condition is of interest due to showing similar results, which hints that a future implementation of either or both can be of use in clinical and casual settings. With the future study of the Furhat condition this can be of value for increased accessibility of memory training robot assistance, in home settings and possibly also in a mobile version. The digitalised visuospatial game used in this study proved to be an appropriate medium for creating a DOE in subjects, implying that the format and components of the game can be further utilised in similar settings. The different parameters of the entire setting, including the game, the SDK/robot and the DOT are all scalable and adjustable, which is

of great importance to allow for personalization and adjustments to future specific needs and contexts, including patients from mild MCI to severe dementia such as AD.

6.4 Further studies

For further studies and interventions it is suggested to keep investigating different aspects of the setup to improve and provide insights of its various components. Since the embodied robot condition in this study was cancelled the first priority would be to investigate and compare the control, SDK and embodied Furhat conditions to determine how social presence effect, feedback and performance is affected by receiving feedback either from an embodied or simulated robot. This is of particular interest since future interventions might include simulated or mobile versions of the setup and to ensure similar positive effects of the feedback is essential for such an intervention. Additionally, it would be of interest to continue researching the audiovisual feedback in more detail and the specific role of for example vocalisation alone as a reinforcer of the DOE. For example, to use a non-humanoid robot to get a better understanding if it is solely the vocalisations that exhibit the DOE or if it is because of the social humanoid presence.

One potential aspect that could be promising to include in the context of a setup such as the one presented in this study is an algorithm created to mimic voices (Jia et al., 2019), for example a relative of the subject. Such an intervention could prove to be particularly of interest for patients with MCI and could create a feeling of familiarity and less uncanniness when hearing a well known voice. The interaction with the robot in this study was solely one-way, meaning the robot gave feedback to the subject but there was no two-way interaction available. Future studies of the setup are proposed to implement a human-robot interaction framework called “robot in the loop”, where a two way communication is available as well as other aspects. This type of setup could allow for the possibility to code phrases that adapt to the participants' performance. Words of affirmation could be added when being close to reaching the top of the reward bar, or when having several incorrect answers in a row giving tips and it could be possible for the participant to ask the robot questions about the game and have conversations with it during the breaks. The robot could also be programmed to provide backchanneling cues (such as non-verbal vocalisations (‘mhm’,’

ah-ha’) verbal expressions (‘yea’,’ right’) or using facial expressions, nodding, returning smiles) to promote engagement as well as providing social motivational and reinforcing feedback, interactive game state and reward feedback and also modulating the challenge level of the game based on participants' needs. Backchanneling cues is of particular interest as a way to improve engagement and could be researched and measured according to connection events as previously done by Türker et al. (2017) at Koç University. They have also offered to provide their expertise and methodology in regard to this setup and future studies will therefore be conducted as a collaboration including their expertise in HRI and backchanneling.

7 Conclusion

This paper reported the results of an experimental study showing a significant effect of DOT on memorising positions of stimuli in a digitalised visuospatial memory task. It also addressed how simulated robot feedback can be included in a setup for such a task as a way to exhibit the DOE and to influence subjects' affective engagement with e.g. the social presence effect. Although there was no statistically significant interaction effect for game performance (CR) between the combination of DOT and feedback from a simulated robot, a trend could be identified which showed higher accuracy in the DOT SDK group overall. The experiment also revealed and investigated subjective affective experience based on a circumplex model of emotion, cognitive strategies based on eye-tracking as well as how various components of the game affected performance. The affective data from the SAM-scale revealed promising results on how the SDK had a positive influence on participants affective engagement in the DOT condition, an important component in the setup. The implications of the study is mainly in terms of how the combination of DOT and simulated robot feedback might prove promising for effectivising and improving learning and memory performance on visuospatial gamified memory tasks. This is of interest due to an increasing demand for treatments for memory loss such as dementia or MCI. With an increasingly ageing population as well as an ongoing pandemic, digitalised memory training with DOT combined with social embodied robots could prove important to assist patients that may be homebound or having reduced mobility. Future research is suggested to investigate performance differences of implementing embodied compared to simulated robots as well as mobile versions of the setup, as well as investigating the specific role of audiovisual feedback and two-way HRI with backchanneling cues.

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Appendices

Appendix 1: Furhat indications

Table 9

Mean accuracy Furhat embodied condition (7 participants): Percent correct responses (SD)

Condition	Level 1	Level 2	Level 3	Total
DOT	87.33 (11.15)	66.67 (10.97)	69.33 (19.63)	74.44 (13.84)
NDOT	78.25 (12.84)	62.25 (11.33)	50.00 (14.63)	63.50 (11.74)

Mean accuracy of CR for the condition with the embodied Furhat robot were also calculated and followed the same trend as the SDK (DOT *M* = 74.44, *SD* = (13.84)) and (NDOT *M* = *63.50, SD* = (11.74)), but because the experiments with the robot were interrupted the data was not used in the analysis.

Appendix 2: Written consent form

Agreement on participation / consent form

The undersigned approves participation in the experiment conducted by Alva Markelius and Sofia Sjöberg for their bachelor thesis supervised by Robert Lowe and Bahram Salamat Ravandi at the Department of Applied IT, University of Gothenburg. The purpose of the study is to conduct research concerning human/robot interaction and the experiment is part of the STINT project *Engaging Humans with Memory Loss in Gamified Memory Training w/ the use of Humanoid Robots*.

Please read the following list carefully and sign the document to consent with the following statements:

1. I agree that the use of my data will be anonymous and used for data collection and research at University of Gothenburg, according to GDPR law for research, see chapter 4, 3§, in Law 2018:218.

2. I understand that during the experiment iMotions software will be used to record video and audio data of my face and voice. The video will be analyzed solely by Markelius and Sjöberg and their supervisors, my identity will remain anonymous.

3. After the experiment is completed, I agree on not telling anyone what was done or the purpose of the study until the thesis is published.

4. I understand that my participation in the research is completely voluntary and that I may choose to stop participating at any time. My decision to stop participating, or to refuse to answer particular questions, will not affect my relationship with the researchers, University of Gothenburg, or any other group associated with this project. In the event that I withdraw from the study, all associated data collected will immediately be deleted wherever possible.

If you have questions about the research in general, how your data is collected and stored or your role in the study, you can contact the researchers Alva Markelius: gusmarkeal@student.gu.se or Sofia Sjöberg gussjosoj@student.gu.se, or their supervisor Robert Lowe robert.lowe@ait.gu.se.

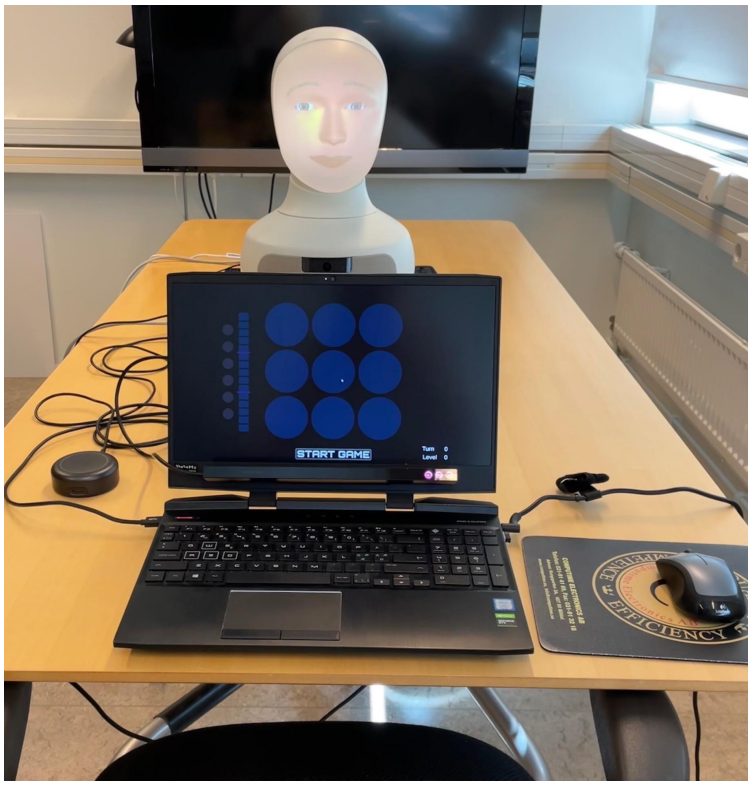
_____ _____

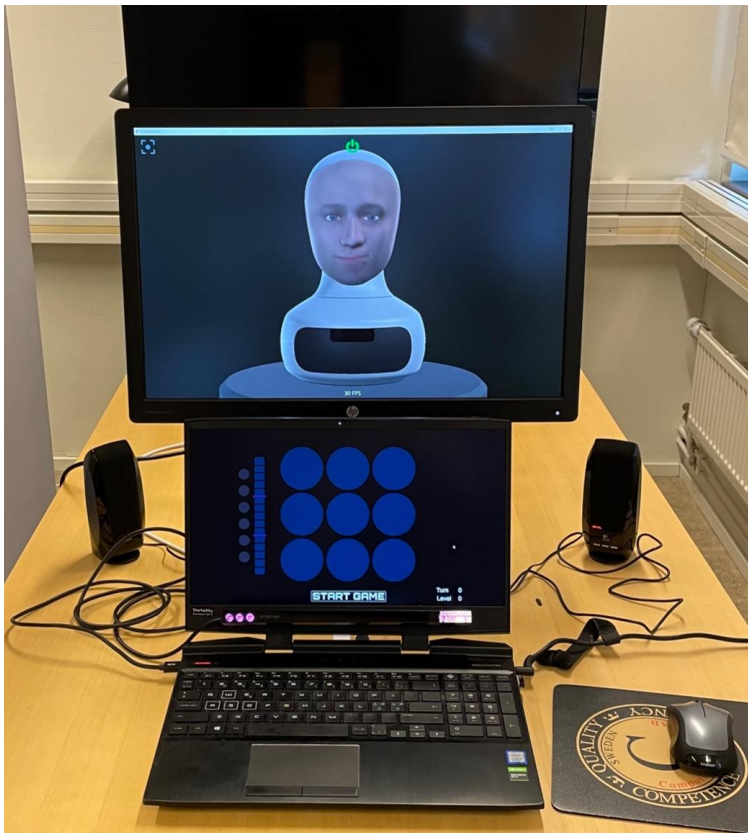
Signature Date

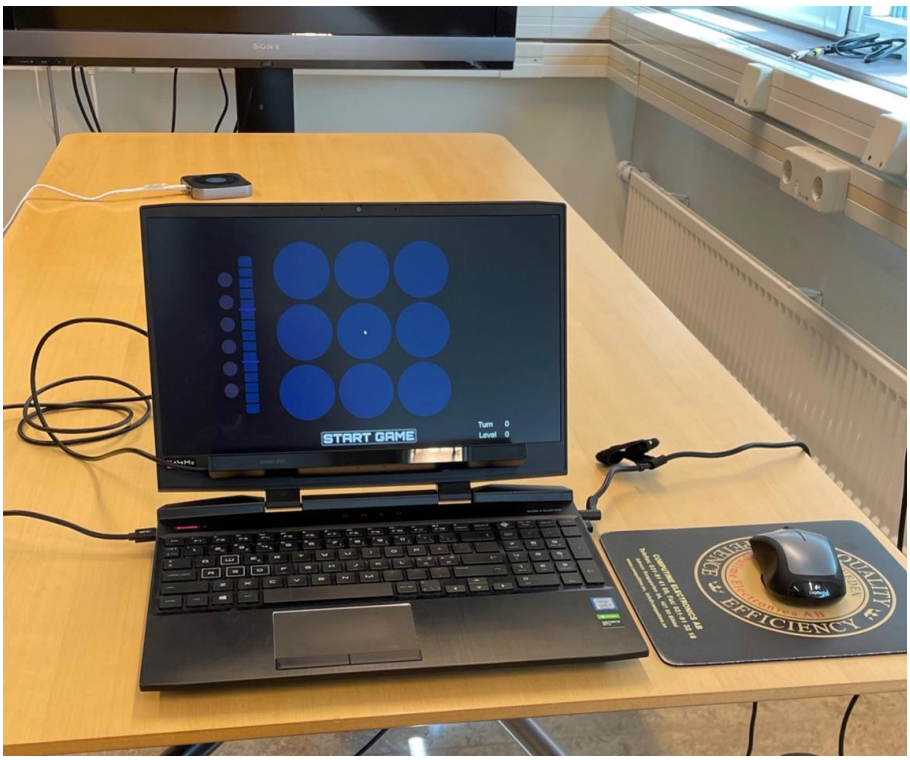
_____

Name

Appendix 3: Pictures of the set-up







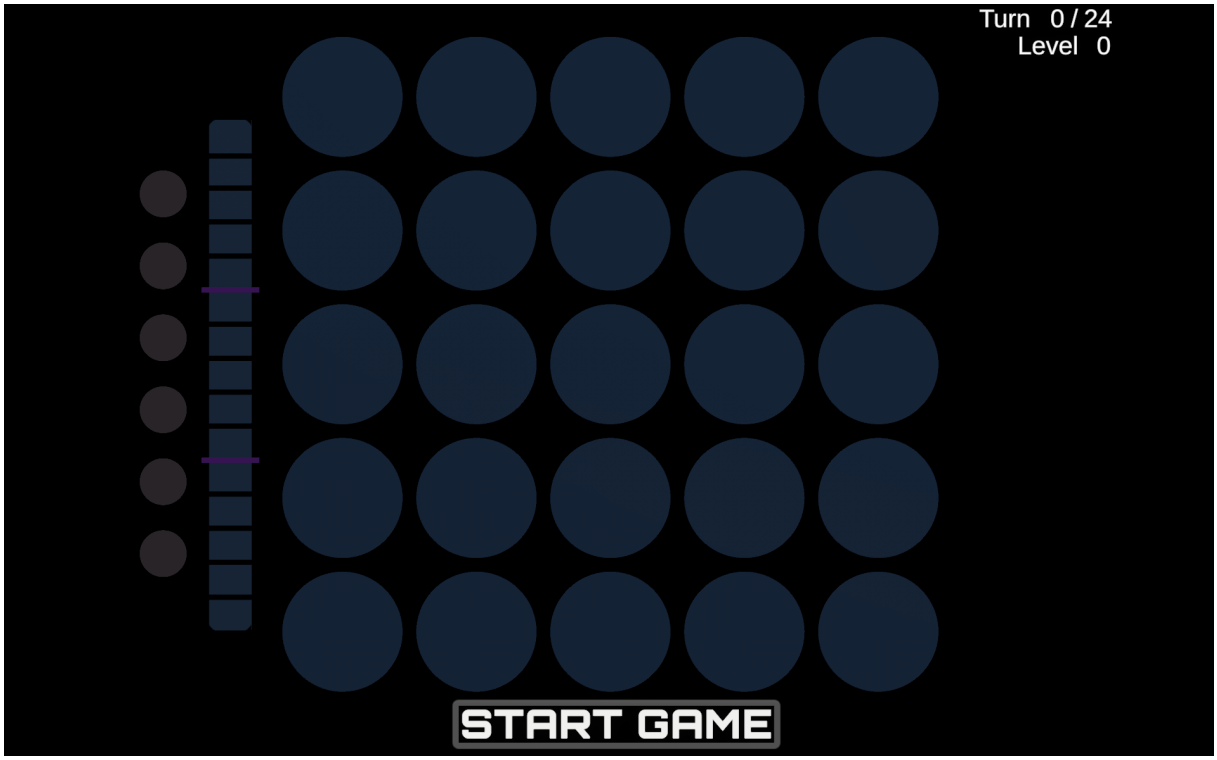
First picture: Set up with the Furhat Robot

Second picture: Set up with the Furhat SDK

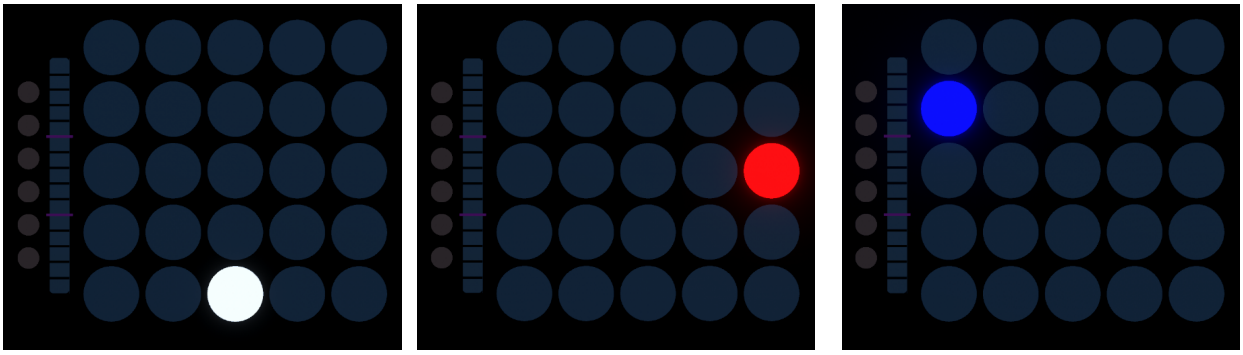
Third picture: Set up for the control group

Appendix 4: TTT Booster game visualisation

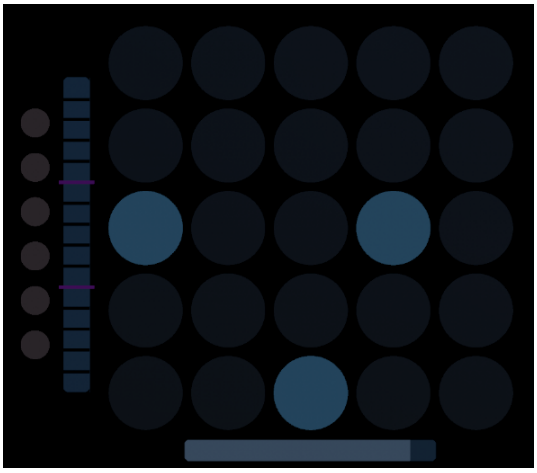
Starting page:



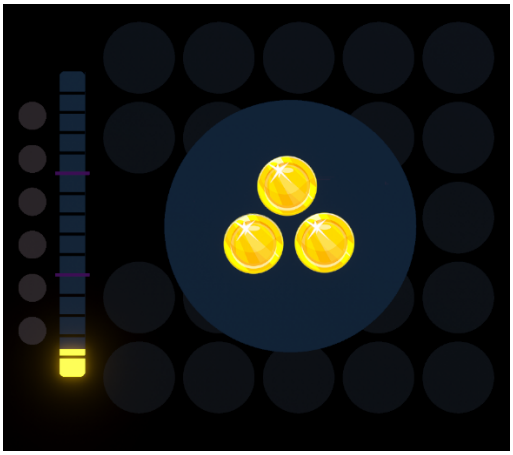
Visualisation of stimuli:

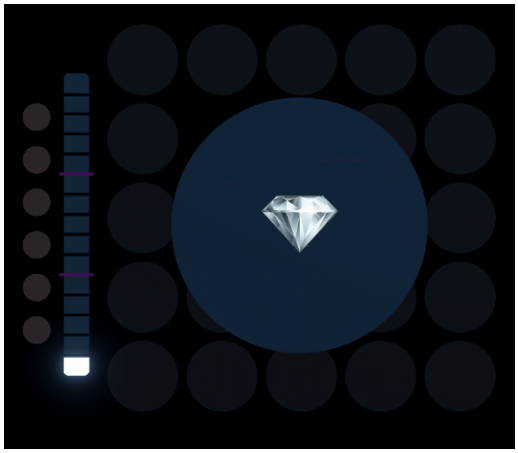


Response options:



Examples of rewards when getting a correct answer:





The different rewards that was possible to receive:

Appendix 5: Task instructions

English version:

In this experiment, you will play a game where you have to memorize a sequence of stimuli.

- The game is a grid of round cells, during the game a sequence of illuminating white cells/stimuli will appear on the grid. Try to memorize the position of the WHITE cells.
- Other coloured cells/stimuli will also appear, and if BLUE, press the SPACEBAR immediately.
- After the sequence is done, you will be presented with different response options, and you will have to choose which a white cell was presented on, in the previous sequence. Note: There is only one correct option and you will have 5 seconds to give your response.
- There is a reward bar on the left, if you fill it up enough times, Furhat *(or, if the participant is in the control group: the experiment leader)* will decide if you will get a prize (based on your engagement and performance).
- The game has three challenge levels, after you have completed a level, you will answer a few questions on a scale about your current emotional state in regard to the game.
- If you have any questions, you may ask them now, or when the experiment is done. Please try to not ask any questions during the experiment.

Swedish version:

Välkommen!

Detta experiment går ut på att spela ett spel, där du kommer att behöva memorera sekvenser av stimuli

- Spelat utförs på ett rutnät av runda celler. Under spelet kommer en sekvens av vita celler/stimuli att visas på rutnätet. Försök att memorera positionen av de VITA cellerna.

- Stimuli med andra färger kommer också att visas, om du ser ett BLÅTT stimuli, tryck på MELLANSLAGSTANGENTEN direkt.

- Efter att sekvensen är klar kommer du att få olika svarsalternativ i form av grå framstående celler. Du måste välja vilken av dessa som en vit cell presenterades under sekvensen du nyss såg genom att trycka med muspekaren på “rätt” cell. Observera att endast ett av svarsalternativen var presenterat i sekvensen. Du har 5 sekunder på att ge ditt svar.

- Till vänster om rutnätet finns det en “reward bar”, som visar dina framsteg. Om du fyller upp denna tillräckligt många gånger, kommer Furhat (eller experimentledaren i kontrollgruppen) att bestämma om du får ett pris (baserat på din prestation och engagemang)

- Spelet har tre svårighetsnivåer. Efter varje nivå du fullföljt, kommer du att få fylla i en skala angående ditt nuvarande emotionella tillstånd gentemot spelet och du kommer få ta en kort paus innan nästa nivå.

- Om du har några frågor, ställ dem gärna nu eller efter att experimentet är klar. Var god försök att inte ställa frågor under experimentets gång.

Lycka till!

Appendix 6: Feedback signals

The following outcomes were vocalised by Furhat or the SDK depending on the outcome the participant received, if they had an incorrect answer, or if the participant did not give an answer in time. The different outcomes were randomised in regard to the respective outcome that the participant received.

Outcome 1 - One coin:

"Yes, one coin"

"Huh, you got a coin"

"Hmm, good work"

Outcome 2 - Three coins:

"Wow, excellent! Three coins"

"Whoa, you got three coins!"

"Oh yes, jack-pot!"

Outcome 3 - One diamond:

"Aha, one diamond!"

"Okay! You got a diamond"

"Yes, well done"

Outcome 4 - Three diamonds:

"Wow, you got three diamonds!"

"Outstanding! So many diamonds"

"Yess! Brilliant!

Outcome 5 - Incorrect answer:

"Incorrect, keep fighting!"

"Try to stay focused!"

"Noo, try again!"

"Come on, you can do it!"

Outcome 6 - Time out:

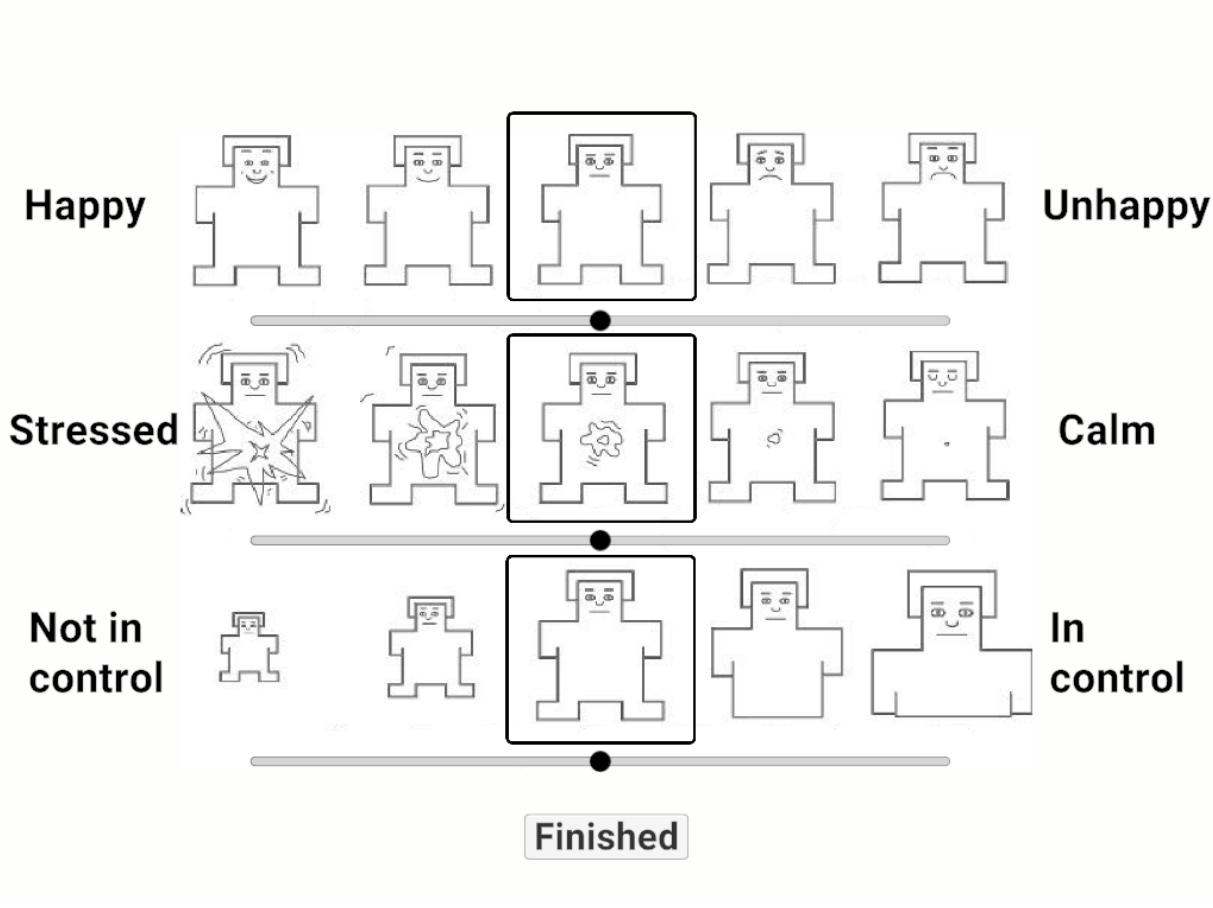
"Uh, time out!"

"Time out, be faster!"

"Oh no, pick up speed"

"Huh, catch up"

Appendix 7: Visualisation of SAM scale



Appendix 8: CR over blocks for each level

Table 4

Mean accuracy Level 1 wrt 4 blocks: Percent correct responses (SD)

Condition	Lv1 B1	Lv1 B2	Lv1 B3	Lv1 B4
DOT	84.46 (14.36)	85.77 (17.82)	80.62 (19.04)	82.08 (17.19)
NDOT	79.38 (20.59)	76.85 (19.86)	75.69 (14.46)	83.23 (21.56)
SDK DOT	87.08 (12.05)	88.38 (12.48)	92.23 (11.03)	85.85 (23.33)
SDK NDOT	74.31 (19.90)	70.54 (21.68)	73.00 (23.14)	72.92 (18.62)

Table 5

Mean accuracy Level 2 wrt 4 blocks: Percent correct responses (SD)

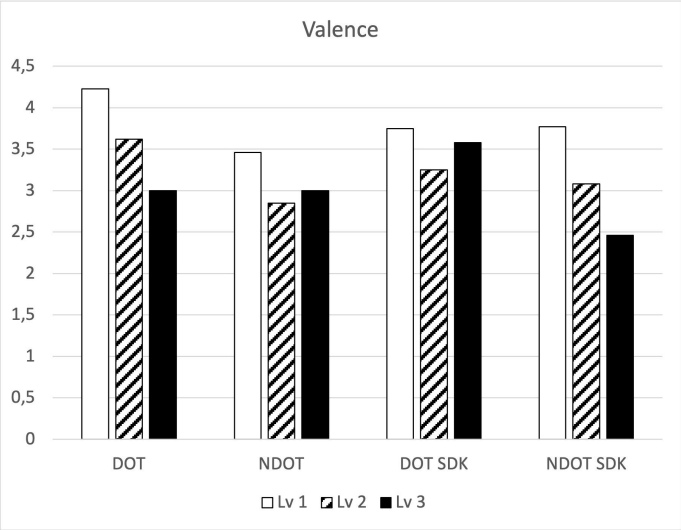
Condition	Lv2 B1	Lv2 B2	Lv2 B3	Lv2 B4
DOT	70.62 (16.80)	61.62 (23.93)	69.15 (25.38)	67.92 (17.19
NDOT	61.46 (27.53)	52.69 (28.73)	67.85 (30.13)	69.15 (19.00)
SDK DOT	73.15 (15.90)	74.23 (19.93)	75.62 (23.04)	71.77 (12.31)
SDK NDOT	57.69 (23.17)	60.23 (23.21)	55.15 (20.82)	73.08 (20.99)

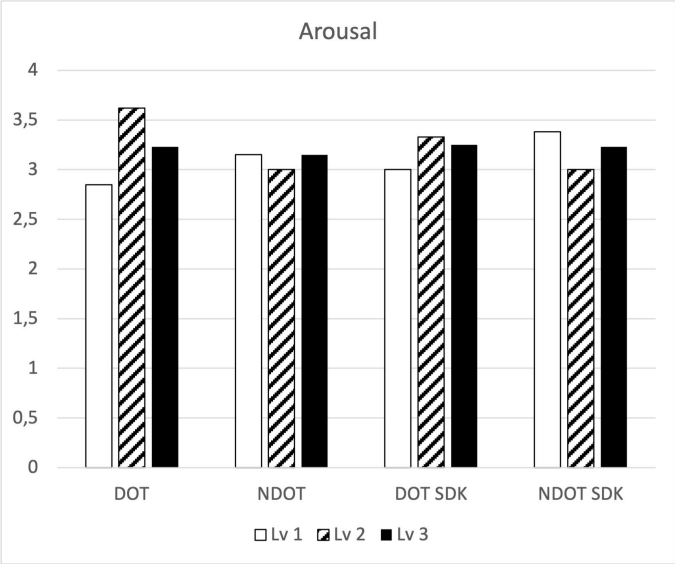
Table 6

Mean accuracy Level 3 wrt 4 blocks: Percent correct responses (SD)

Condition	Lv3 B1	Lv3 B2	Lv3 B3	Lv3 B4
DOT	40.92 (18.75)	52.62 (19.15)	61.54 (28.26)	60.31 (29.90)
NDOT	52.62 (26.21)	55.31 (30.60)	49.92 (22.59)	53.92 (30.52)
SDK DOT	61.54 (17.22)	66.62 (16.59)	65.38 (19.82)	71.69 (26.76)
SDK NDOT	52.54 (27.90)	46.15 (25.69)	46.15 (30.44)	47.46 (30.98)

Appendix 9: SAM scale result





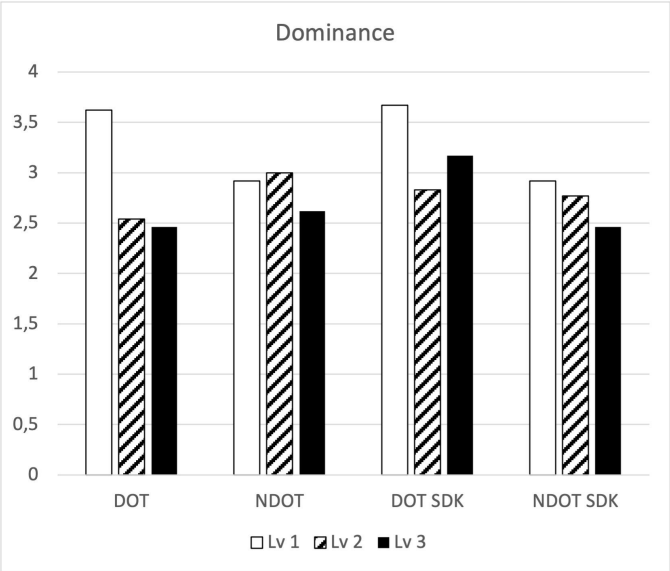


Table 7

Mean values for SAM scale Control Condition

Condition	Valence	Arousal	Dominance
DOT Lv1	4.23	2.85	3.62
DOT Lv2	3.62	3.62	2.54
DOT Lv3	3.00	3.23	2.46
NDOT Lv1	3.46	3.15	2.92
NDOT Lv2	2.85	3.00	3.00
NDOT Lv3	3.00	3.15	2.62

Table 8

Mean values for SAM scale SDK Condition

Condition	Valence	Arousal	Dominance
DOT Lv1	3.75	3.00	3.67
DOT Lv2	3.25	3.33	2.83
DOT Lv3	3.58	3.25	3.17
NDOT Lv1	3.77	3.38	2.92
NDOT Lv2	3.08	3.00	2.77
NDOT Lv3	2.46	3.23	2.46

Appendix 10: Sample from iMotions

The following table is a sample of 16 participants, the 2 best and worst for each condition. Their eye movements were analysed over blocks of 6 trials, resulting in 12 blocks in total. Peripheral vision (PV) = 0, and Foveal vision (FV) = 1.

ID	Condition	% (accuracy)	1B1	1B2	1B3	1B4	2B1	2B2	2B3	2B4	3B1	3B2	3B3	3B4
4146	DOT C	88	1	1	0	0	0	0	0	0	1	1	0	1
4181	DOT C	43	0	1	1	0	1	1	1	1	1	0	0	0
4145	DOT C	84	0	0	0	0	0	0	0	0	0	0	0	0
4111	DOT C	56	1	0	1	0	0	0	1	1	1	1	1	0
4262	DOT SDK	86	1	1	1	1	1	1	1	1	1	1	1	1
4203	DOT SDK	60	0	0	0	0	0	0	0	0	0	0	0	0
4202	DOT SDK	85	1	1	0	1	1	1	1	1	1	1	1	1
4205	DOT SDK	61	0	0	1	0	1	1	1	1	0	1	0	1
4183	NDOT C	95	1	0	0	0	0	0	0	0	0	0	0	0
4144	NDOT C	35	0	0	0	0	0	0	1	0	0	1	1	1
4191	NDOT C	86	0	0	0	0	0	1	1	1	0	0	0	0
4122	NDOT C	43	1	1	1	0	1	1	0	1	0	1	1	1
4212	NDOT SDK	87	0	0	1	1	0	0	0	0	0	0	1	0
4211	NDOT SDK	33	1	1	1	1	1	1	1	1	1	1	1	1
4251	NDOT SDK	86	1	0	1	1	1	1	0	1	1	1	1	1
4267	NDOT SDK	46	1	1	1	1	1	1	1	1	1	1	1	1