Predicting Experienced Presence Exploring Large Mazes in VR

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***Abstract*—**

I. Introduction

investigate the influence of subjectively reported presence on body movements in VR

why it is interesting to look at objective predictors of presence experience. Do people that experience presence behave differently in VR? Poses questions to the ecological validity of virtual reality as an investigative tool in cognitive science with first applications in cognitive neuroscience.s

II. Methods

Participants. Thirty-two healthy participants (aged 21–45 years, 14 men) took part in the experiment. All participants gave written informed consent to participation and the experimental protocol was approved by the local ethics committee (protocol: GR_08_20170428). Three participants were excluded from data analysis due to incomplete data or difficulties in complying with the task requirements.

The Invisible Maze Task. Participants freely explored an interactive sparse invisible maze environment by walking and probing for virtual visual wall feedback with their hand, delivered by a virtual reality (VR) headset. Four different mazes (Fig. 1 B) were explored in three consecutive runs. Upon collision of the hand with an invisible wall, an illuminated white disc was displayed 30cm behind the collision point parallel to the invisible wall (Fig. 1 C). Due to the complexity of the technical details, please consult [2]. In summary, the task required participants to explore mazes to build a spatial representation of the maze layout.

Assessing experienced presence. In the current work, we were interested in the subjectively reported experience of presence. Therefore we analyzed the first item on Igroup's presence questionnaire, i.e. 'In the computer generated world I had a sense of "being there"' rated from 'not at all' to 'very much' [7], [8].

Statistical Analyses. We computed an ordinary least squares regression entering IPQ presence score as the dependent variable using R [5]. For the predictors, we first computed the participant average and then entered: movement velocity, time-on-task, number of wall touches, sketch map accuracy, video game experience, sex, perspective taking and orientation ability, sense of direction into the regression model. For an explanation of each predictor, pleas consult [2]. To reduce over-fitting and increase the possible insight of our results for other researcher, a stepwise model selection procedure based on Akaike's information criterion (AIC) was computed using 'stepAIC' of package 'MASS' [3], [4]. Ultimately, the reduced model of three predictors was assessed in terms of the predictive accuracy of the model. Therefore, a cross-validation with 5 folds was computed to obtain a robust mean absolute error [1], [6]. With 29 participants comprising the analyzed data, each training fold consisted of either 23 or 24 participants with either 5 or 6 participants in the evaluated test fold.

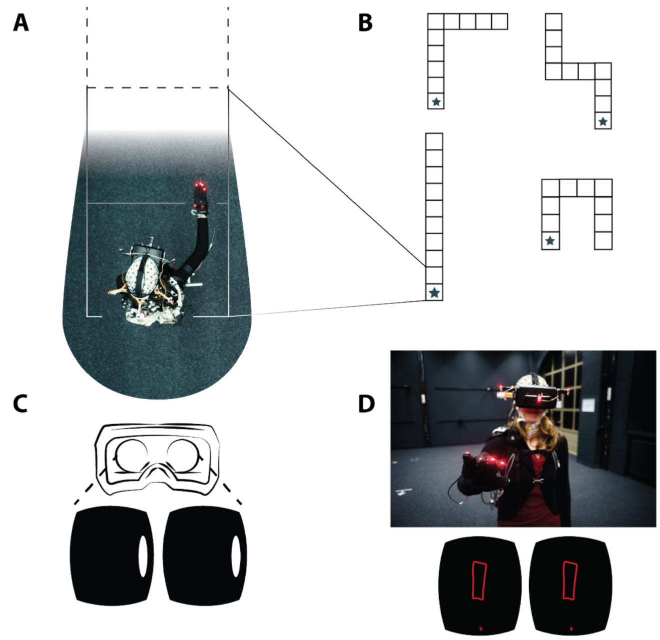

Fig. 1. Invisible Maze Task, **A** Participant from a birds eye view. **B** Participants are instructed to explore four different mazes and return to the start. **C** First-person view in binocular ””VR optics”” of a wall touch. **D** Top: Participants draw a top-down view of the explored maze. Participant is equipped with 160 channels wireless EEG, head-mounted virtual reality goggles and LEDs for motion capture. Bottom: drawn sketch map. Find a detailed description in [2].

III. Results

Video Game Experience, Gender and Perspective Taking predict experienced Presence. Running stepwise model selection resulted in three predictors being kept, explaining 53,4% of the variation in experienced presence ($F_{(3,25)} = 11.69, p < .001$, adjusted $R^2 = .534$). Participants' predicted

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presence is equal to 8.15 - 1.2 (Video Game Experience) + 2.61 (SEX) - 0.02 (PTSOT) where sex is coded as 1 = Male, 2 = Female, video game experience is higher in higher scores and perspective taking ability is worse in higher scores. Video game experience ($t = -4.7, p < .001$), sex ($t = 5.6, p < .001$) as well as perspective taking ability ($t = -2.52, p < .05$) were significant predictors of presence.

Predicting Presence. Training the three predictor model above for each of five different folds of the data and evaluating its performance on the held-out fold yields a combined average .76 mean absolute error. Hence, using video game experience, sex as well as perspective taking ability we can predict experienced presence to within three-quarters of a point accuracy.

IV. Discussion

presence and accuracy of motor behavior, problem because non-continouous metric, cite myself, moderated by learning/difficulty, clustering approaches

presence is best predicted by video game experience and sex (there is evidence of sex and videogame influence in slater work etc.). Interestingly, in our experiment video game experience negatively impacts presence reported on the general item of the IPQ. This may be due to the overly simplistic visuals of the virtual world. Participants with significant video gaming experience might perceive the world as too artificial.

explore exit interviews and use in discussion!

Disentangling Presence.

Sense of ownership, sense of agency etc.

Outlook.

Increasing the resolution of the investigation to finely resolved analysis in space. Motion capture allows us to do that.

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