Exploring the Effect of Environmental Interaction on Belief Change Towards Climate Change: A Virtual Reality Approach

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Abstract

Climate change is a major global threat, with estimates predicting up to 14.5 million additional deaths by 2050. Misinformation about it contributes to confusion, doubt, and political inaction. Virtual reality (VR), with its immersive and interactive qualities, has shown to be a promising tool for misinformation correction. Building on the study by Erisen et al. (2024), which found that VR can increase climate change belief and reduce skepticism, the present study explores whether user engagement and avatar presence further enhance these effects. A mixed quasi-experimental longitudinal design was used, with data collected at four time points across three conditions: a VR condition with a text-based correction, a VR condition featuring a human avatar delivering the correction, and a social media condition used as control. The final sample consisted of 87 participants. The measures included items on climate change belief and skepticism assessed via surveys, and user engagement measured through the number of teleportations in the VR environment. No significant effects were found for teleportation frequency or avatar presence on climate change belief or skepticism. These findings align with previous research and suggest that simple measures of interaction, such as teleportation and avatars, may not be sufficient to enhance the effectiveness of VR-based misinformation correction. The results underscore the need for additional research on how specific features of VR environments impact attitude change and engagement.

Introduction

The European Commission clearly states, "[C]limate change is a serious matter and it affects us all," emphasizing that, "We need climate action now, or these impacts will only intensify" (Consequences of Climate Change, n.d.). Defined by NASA, climate change refers to long-term shifts in typical weather conditions. Pushed by human action, these changes have a wide range of impacts (Cermak, 2024). An analysis done by the World Economic Forum (2024) estimates an additional 14.5 million deaths due to climate change by 2050, highlighting only one of many consequences, stressing the need for action. Still, climate change misinformation is circling in new and traditional media, having a crucial role in explaining climate change to the general population and leading to, among others, political stagnation or the dismissal of climate change mitigation policies (Stubenvoll & Marquart, 2018; Treen et al., 2020).

Climate change misinformation

The Global Risks Report 2024 ranked misinformation and extreme weather conditions as the most severe global risks for society. Assigning it a significant influence on the political and societal divide (World Economic Forum, 2024). Climate change misinformation, a form of misinformation mentioned before, is defined as erroneous information regarding climate change (Sethi, 2024). Multiple explanations exist for the development of climate change misinformation. It ranges from a sincere misunderstanding to assumptions based on inaccurate or partial evidence. Even though it might be an honest mistake of individuals or organizations, the consequences can still be horrendous (Sethi, 2024). Adding to the risk of misinformation to society is that in every category of information, misinformation spreads more quickly, deeply, and widely than the truth on social media (Vosoughi et al., 2018).

There are two main types of climate change misinformation narratives: climate denial and climate delayism. The first is an older form of misinformation, denying either climate change as a whole or human activity accelerating climate change. A newer, more prevalent form is climate delayism. It consists of different tactics to weaken and undermine evidence. This rather new narrative took over 70% of climate denial posts on YouTube, making it current and acute. These posts foster confusion and doubt about scientific data (Sethi, 2024).

People generally tend to encode new information in context with the information they have already learned, processed, and stored in their long-term memory and naturally assume all new information is true. Corrective evidence that challenges false information that makes up their prior beliefs and knowledge is frequently disregarded (Jang et al., 2019). Additionally, it is exceptionally hard to clear up false information after people have internalized it (Lewandowsky, Ecker, Seifert, Schwarz, & Cook, 2012, as cited in Cook, 2019). Even if people are aware that the information they encounter is false, they are still prone to be influenced by it (Thorson, 2016, as cited in Cook, 2019). Furthermore, if the person feels their worldview is threatened, the false information is prone to backfire and be reinforced (Hart & Nisbet, 2012, as cited in Cook, 2019). Therefore, it is necessary to investigate on how to battle the spread of misinformation.

One approach to combating misinformation on social media is to assign responsibility to companies, who in turn implement fact-checking software, as Facebook did with the label "Fake News" on posts containing misinformation (Sethi, 2024; Levin, 2017, as cited in Cook, 2019). Another more effective approach is debunking. Generally, literature recommends keeping the same degree of factuality as the misinformation; the person should be able to exchange false facts with true facts (Ecker et al., 2015, as cited in Cook, 2019). Additionally, research shows that providing graphical information is more effective than text-based information (Nyhan &

Reifler, 2018, as cited in Cook, 2019). Examples of such graphical information include infographics, data visualizations, and educational videos, which are increasingly used in public communication (Cook, 2019). Given these findings, immersive technologies such as virtual reality (VR) offer a promising platform to communicate corrective information more effectively. One way of delivering such content is through fully immersive VR environments that allow for a highly engaging user experience.

Virtual Reality

The particularities of VR offer many opportunities to combat climate change misinformation, as evidenced in various studies. A study by Huang et al. (2020) utilized immersive VR to visualize forests of the future in an immersive virtual reality environment for experts, policymakers, and the public to experience, as VR technologies are becoming more mainstream. Furthermore, a study by Meijers et al. (2023) discovered that in comparison to magazine articles or videos, immersive VR achieved the highest amount of spatial presence, emotional responses, bodily responses, and life-like feel in experiencing climate change consequences. A similar study by Thoma et al. (2023) consolidates these findings by confirming that immersive VR environments showing climate change consequences are more likely to lead to attitude change in comparison with traditional media.

Various theories and frameworks underly these findings. Immersive, interactive experiences may lead to increased engagement, as well as a stronger sense of presence, compared to traditional media formats such as videos or articles, which are expected to be less effective in fostering empathy (Meijers et al., 2023; Thoma et al., 2023). Additionally, immersive and interactive experiences may lead to a greater sense of embodiment and body ownership, which in turn increases perspective-taking and sharing another person´s experiences.

Both have been found to enhance compassion and cognitive empathy. But no significant signs for an increase in emotional empathy were found (Martingano et al., 2021; Sora-Domenjó, 2022).

Building on these findings, Erisen et al. (2024) investigated the potential of immersive VR to combat climate change misinformation and reduce climate change skepticism among participants. The researchers used VR to let the participants experience future climate change scenarios, focusing on the rising sea level and increasing temperatures. The longitudinal study explored several aspects, including emotional engagement, presence in VR, and the role of avatars. The findings showed that particularly VR interventions utilizing avatars significantly reduced climate change skepticism and increased climate change belief, highlighting VR's potential as an effective medium for misinformation correction. However, the study lacked a deeper exploration of engagement within the VR environment. The present study aims to add there, focusing on engagement and interactivity in VR.

Engagement and interactivity in VR are part of the user experience. Interactivity refers to the extent to which users can influence and navigate the VR environment, often through physical actions or control mechanisms such as joysticks or hand tracking (Wang et al., 2020). In contrast, engagement is a broader concept that describes the user's psychological investment, encompassing their attention, immersion, and emotional involvement (Brockmyer et al., 2009, as cited in Anderton et al., 2024). One common form of interaction in many commercial VR applications is teleportation. This locomotion technique allows users to instantly shift positions within the virtual space, offering an alternative to physical walking (Anderton et al., 2024). However, teleportation has also been found to reduce realism and disrupt spatial presence compared to more naturalistic movement methods. Anderton et al. (2024) reviewed commercial

VR applications and found that while teleportation remains one of the most frequently used locomotion techniques, its use may hinder full immersion and user embodiment, especially when not paired with intuitive design. These insights highlight the need to examine not only whether users interact with VR, but how they do so, and whether those interactions foster engagement and belief change. In the present study, teleportation frequency was used as a measurement of user engagement, offering a measurable way to explore whether higher levels of interactivity enhance the effectiveness of misinformation correction.

The interactivity effects model (Shin et al., 2012) revealed that interactivity in a VR environment has great influence on the attitude, intentions and engagement (Wang et al., 2020). A study by Kosa and Johnson-Glenberg (2023) consolidate by examining the combined effects of interactivity, immersion, and meaningful content in VR gaming, finding a long-term stress reduction and subsequently showing the potential of VR for long-term positive effects.

Research Questions

Building on these findings and replicating the study by Erisen et al., (2024), the present study will focus on measuring engagement in VR through the amount of teleportations and retesting significant items. The research questions to be addressed are:

RQ1: To what extent does the level of interaction with the VR environment influence participants' climate change skepticism?

RQ2: To what extent do avatars in VR environments effectively combat climate change misinformation?

To answer these research questions, a mixed experimental design featuring longitudinal data collection will be utilized. A VR study allowing participants to explore different climate change scenarios and engage with them via teleportations will be used, and a pre-test as well as three post-tests capturing, among other objectives, climate change skepticism and belief in climate change will be implemented to evaluate a change in these objectives over the course of three weeks.

Methods

Participants

A sample of 43 participants was recruited through convenience sampling, mainly from the researcher's social network. Additionally, 44 participants from a parallel master thesis study, using the same experiment, were added, resulting in a total of 87 participants for the analysis. The sample comprises 43 persons with the self-assigned gender female, and 41 with the self-assigned gender male, as well as three people without a self-assigned gender. The participant ages were calculated based on the reported birth year and ranged from 16 to 73 ($M = 27.5$, $SD = 10.89$). The inclusion criteria was over 16 years old. Participants reported a relatively high level of education overall ($M = 6.28$, $SD = 1.26$), with most having completed at least some university or a university degree. Educational levels ranged from “some secondary school” to “graduate or professional degree.” All participants took part voluntarily after being fully informed about the experiment procedure, risks, and benefits. Ethical approval, with the application number 250312, was obtained from the University of Twente BMS ethics committee beforehand. One participant was excluded because they only completed the pre-test.

Materials

The materials used in this experiment stem from the Erisen et al. (2024) experiment and will be discussed in the following paragraphs. First, the focus will be on the differences between the original study by Erisen et al. (2024) and this study. A major difference, due to a lack of time and lab resources, was to change the experiment design into a quasi-experimental structure. This way, participants were recruited specifically for VR or Social Media conditions. The purpose was to optimize the time spent in the BMS lab. Additionally, half of the VR participants participated in the experiment in a private setting, e.g., their living room. Lastly, slight alterations were made to the survey, such as correcting spelling mistakes.

The surveys were conducted and distributed using the platform Qualtrics. The first part of the pre-test survey was to obtain informed consent. The informed consent section of the survey is provided in Appendix B. Only if that was obtained were the different items tested. A complete overview of all items tested can be found in the Erisen et al. (2024) paper; in the following, only items relevant to this study will be discussed will be discussed. Since this experiment also contributes to a data pool and the data will be shared beyond this dissertation, more data were collected than needed for this study. Apart from demographics and explorative research, this study focuses on the items measuring climate change belief, trend skepticism, and attribution skepticism from Poortinga et al. (2011).

Climate change belief was measured with two items, "*To what extent do you agree or disagree with the statement 'I am uncertain that climate change is really happening.'?",* with answer option from "strongly disagree" to "strongly agree" coded from 1 to 5; and the dichotomous item "*As far as you know, do you personally think that the world's climate is changing or not?*" having the answer options "Yes, it is changing", "No, it is not changing" and "Don´t know". The belief items are positively coded, meaning a higher score indicates lower belief in climate change.

Climate change skepticism is split into two types of items: impact skepticism and attribution skepticism. For impact skepticism, the items are: *"To what extent do you agree or disagree with the statement 'The seriousness of climate change is exaggerated?'"* and *"To what* *extent do you agree or disagree with the statement 'It is uncertain what the effects of climate change will be?'"* For attribution skepticism, the items are: *"To what extent do you agree or disagree with the statement 'Most scientists agree that humans are causing climate change?'"* and *"Thinking about the causes of climate change, which of the following best describes your opinion?"*, with the answer options ranging from "Climate change is entirely caused by natural processes", "Climate change is mainly caused by natural processes", "Climate change is partly caused by natural processes and partly caused by human activity", "Climate change is mainly caused by human activity", to "Climate change is completely caused by human activity", coded from 1 to 5. All other skepticism items have answer options ranging from "strongly disagree" to "strongly agree", coded from 1 to 5. The attribution skepticism items are negatively coded, meaning a higher score indicates less skepticism, whereas the impact skepticism items are positively coded, with higher scores indicating greater skepticism.

One survey was used for the social media condition (SM), which randomly and evenly distributed the participants into the female or male social media condition. Another survey was utilized for the VR conditions, randomly and evenly distributing the participants into either VR with the avatar (VRA), and then avatar gender female or male, or VR without an avatar but with text (VRT), and then either a female or male voice speaking the text. The items in the questionnaires were also tailored to the conditions, hence only participants in the VR condition were asked about their presence in VR, etc.

A variety of materials were needed for the experiment. For the social media condition, a laptop was used to make the survey mentioned above available to the participants. Furthermore, the "Misinformation Game" was utilized to provide the participant with a social media environment. For VR conditions, in addition to the laptop for the survey, either the BMS lab with the included equipment, the Oculus Quest 2 headset, or a gaming laptop with the same model Oculus Quest 2 Headset was utilized. The actual climate change scenario environment was run using the Meta application. A Fitbit Charge 3 Fitness/Activity tracker was used to measure the participants' heart rate in the VR conditions.

Procedure

After agreeing on a time slot and meeting with the participant, informed consent was obtained as the first part of the pre-test survey. Following this, the participants filled in the pre-test and were then distributed into their respective conditions, according to the randomization in the survey, as mentioned earlier.

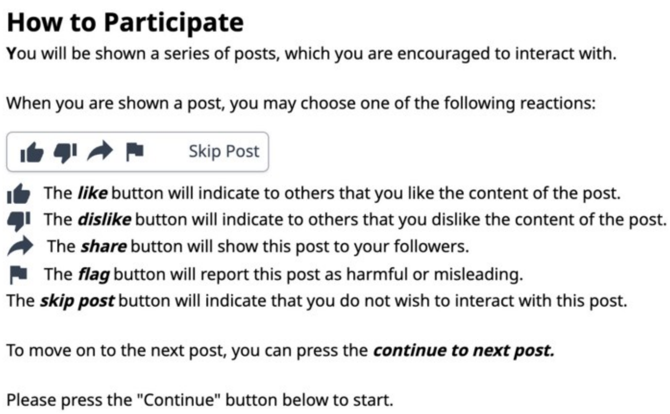
Participants assigned to the social media condition were provided with a link to the Misinformation Game in the pre-test survey and used that to access the game and interact with it. After the game opened, an introductory screen appeared, explaining the game to the participants. The instructions are visible in Figure 1. Afterwards, the game provided seven social media posts, showing pictures of climate change scenarios from the VR environment and providing correcting information. An example post can be seen in Figure 2. The simulator took the participants approximately three to five minutes to complete. No intervention by the researcher was required during the intervention. Only after completing the Misinformation Game, the participants were instructed to call the researcher to continue with the first post-test.

In the VR conditions, the participants were provided with a wristband to measure their HR. The wristband was placed on the participants' left wrist, approximately one centimeter above their wrist bone. The participants then received further information on the VR intervention. The information consisted of a briefing on the use of the controller, including an explanation of the buttons and joysticks; the button on the right controller were the index finger rests is needed for choosing the language and the gender of the avatar or voice in the VR application, depending on the assigned condition, as well as rating the VR experience still in the application immediately after the experiment. Additionally, an explanation of the teleporting function was given. Participants could teleport if they tilted the joystick on their right controller forward in the direction of the ground. If, by doing so, a blue circle appeared on the ground, the participants could proceed with the joystick movement and teleport their avatar into the circle. By doing so, participants would be able to explore more of the environment, even though teleportation only works over short distances. Lastly, a reminder was given that participants could remove the headset at any time if they felt unwell or did not want to continue. After starting the VR experience and selecting the menu options, as described earlier, the participants began in a coastal environment. The first part of the scenario focused on the impact of rising sea levels and featured a hurricane destroying a coastal community. The second part focused on droughts affecting farmland and featured a devastating fire that destroyed the farmland environment. Example pictures from the environment are shown in Figure 3. The VR experience took approximately 3 minutes to complete. Immediately after the condition, the participants were invited to participate in the first post-test.

The entire lab session, including the pre- and first post-tests and the intervention (either VR or social media), lasted up to 30 minutes. Approximately three days after the experiment, participants received an email to the account they had shared during the experiment with the second post-test. Finally, approximately three weeks after the experiment, the participants received the last survey via email.

Figure 1

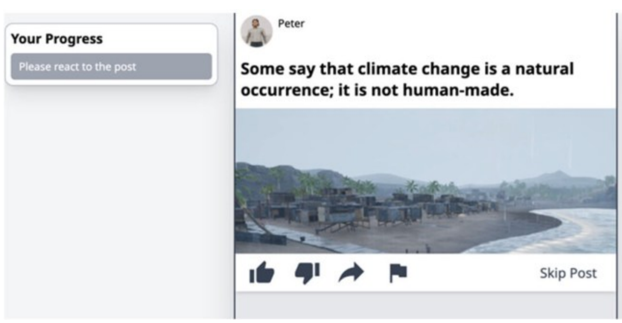
Instruction page of the Misinformation Game



Note. Reprinted from *Exploring the effectiveness of virtual reality in combating misinformation on climate change* by E. Erisen, F. Yildirim, E. Duran, B. Şar, & I. Kalkan, 2024, *Political Psychology, 00*, 1–29 (https://doi.org/10.1111/pops.13057). © 2024 International Society of Political Psychology.

Figure 2

Example posts from the Misinformation Game



Note. Adapted from *Exploring the effectiveness of virtual reality in combating misinformation on climate change* by E. Erisen, F. Yildirim, E. Duran, B. Şar, & I. Kalkan, 2024, *Political Psychology, 00*, 1–29 (https://doi.org/10.1111/pops.13057). © 2024 International Society of Political Psychology.

Figure 3

Screenshots from the VR experience; with and without an avatar

Note. Adapted from *Exploring the effectiveness of virtual reality in combating misinformation on climate change* by E. Erisen, F. Yildirim, E. Duran, B. Şar, & I. Kalkan, 2024, *Political Psychology, 00*, 1–29 (https://doi.org/10.1111/pops.13057). © 2024 International Society of Political Psychology.

Data Analysis

The data sets were downloaded from Qualtrics and processed locally using Excel and R version 4.5. The utilized R code can be found in Appendix C.

During the experiment, each participant was assigned two different participant IDs. Using an ID mapping sheet, these IDs were matched and consolidated into a single, uniform identifier per participant to ensure consistency across all datasets. Duplicate entries from a participant who completed the pre-test twice were merged into a single entry by calculating the mean of their responses across both attempts. Following, only the relevant variables were selected, and all datasets were merged into a single wide-format dataset, which was then reshaped into long format for analysis. The two attribute-based skepticism items were reverse-coded to ensure uniformity, so that higher scores consistently reflected greater skepticism.

First, descriptive statistics were computed, including the mean and standard deviation for the dependent variables, as well as frequency tables and visualizations for the demographics and conditions. Using the ggplot function, boxplots were computed to provide an overview of the data and visually check for potential outliers.

Subsequently, Cronbach's alpha was calculated to assess the internal consistency of the belief and skepticism items. As the analysis did not indicate sufficient reliability, all items were treated individually in the following analyses. Additionally, the dichotomous variable ccbelief_dic was excluded at this stage due to insufficient variance in the responses.

To answer the first research question, linear mixed-effects models were computed. All dependent variables were tested separately. The independent variables were the conditions (between subjects), the time point (within subjects), and the number of teleportations per participant. The participant IDs were included for random effects. Participants without teleportation data and participants in the social media condition were excluded. The VRT condition and time point T0 (pre-test) served as the reference.

Another set of linear mixed-effects models was fitted to answer the second research question. All dependent variables were tested separately. The fixed effects in this case were the VR conditions (VRA and VRT), as well as the time point (within subjects). The participant IDs were included for random effects. Participants in the Social Media condition were excluded. The VRT condition and time point T0 (pre-test) served as the reference.

Lastly, for explorative research, another set of linear-mixed effects models was conducted, comparing all conditions. Further information and the results are to be found in Appendix D.

Following, model diagnostics and assumption checks were run to check whether linear mixed-effects models were appropriate. Residual plots and Q-Q plots were computed to assess the assumption of normality and homoscedasticity of the residuals. Cook´s distance measure with a threshold of 0.5 was used to conduct an outlier analysis, identifying influential cases. Additionally, the performance package in R was utilized to identify potential violations of the model assumptions.

Results

To provide an overview of the descriptive results, mean scores for each survey item across all time points and conditions are visualized in Figure 4. Overall, the values remained relatively stable, with only minor fluctuations between the time points. Some small deviations following the intervention are visible, but no clear or consistent patterns indicating a possible trend were observable across the conditions. The scores were very similar across the groups, and differences between conditions were smaller than the within-group variations. Furthermore, the standard deviation error bars suggest substantial overlap across the groups. Across all items, the overall scores were relatively low, indicating low levels of climate change skepticism in general. The mean values of the dependent variables ranged from 1 to 2.5 on 5-point scales, indicating low levels of climate change skepticism and high levels of climate change belief. Table 1, containing the descriptive statistics for the dependent variables computed per condition and time point, can be found in Appendix E.

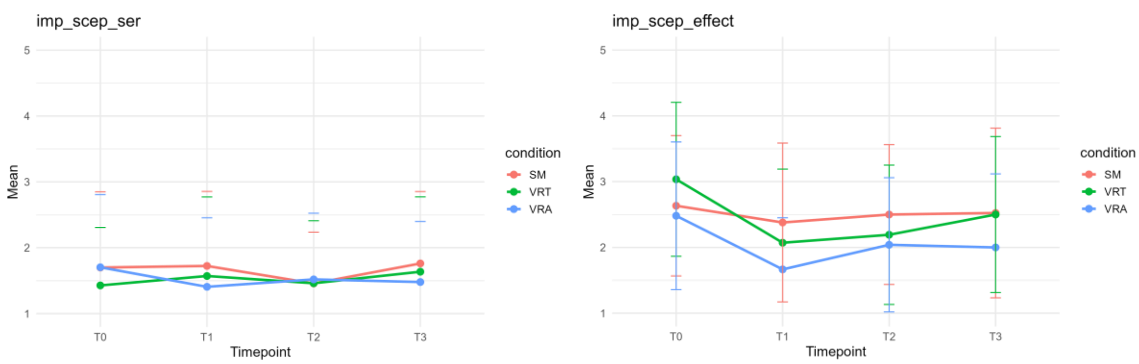
The Cronbach's alpha for a scale containing the four skepticism items ranged from .57 to .62 across time points, which falls below the reliability cut-off score of .7, indicating that the scale is unreliable. Subsequently, the items are reported separately. The full Cronbach´s alpha test results are in Appendix F.

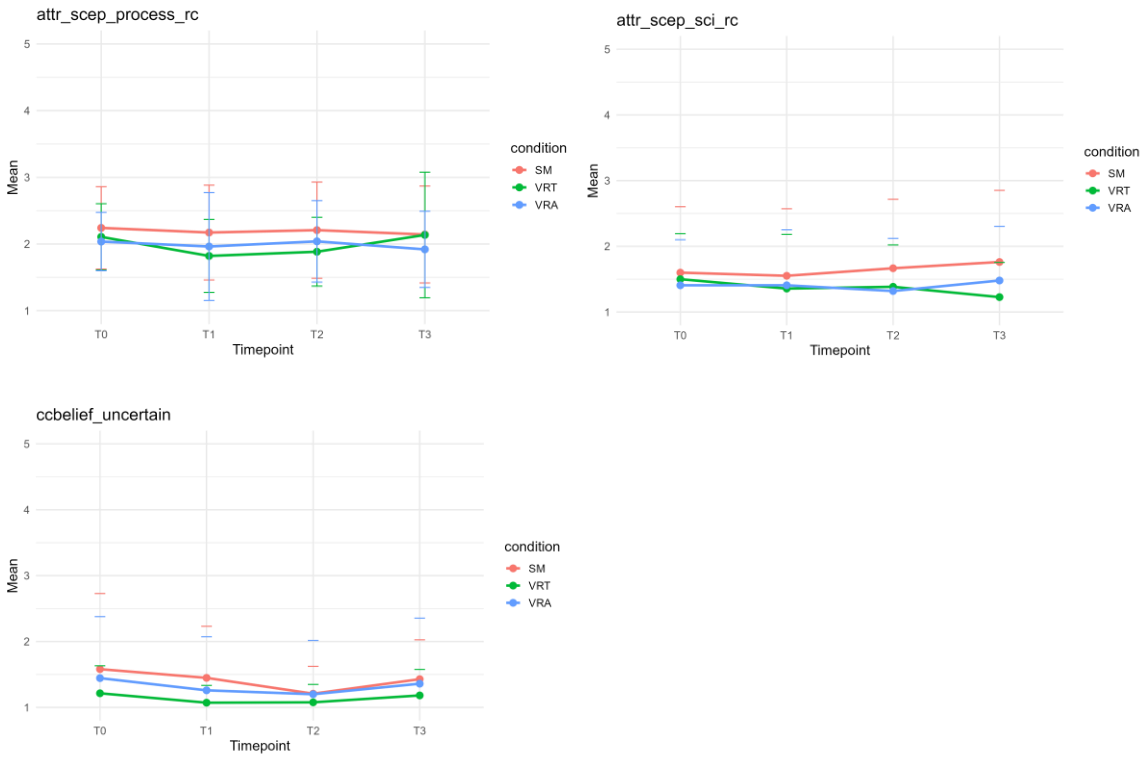
The dichotomous belief item ccbelief_dic was excluded from further analysis due to too little variance. Across all four timepoints and three conditions (N = 342 total responses), 333 responses (97.4%) were "yes" indicating a belief in climate change, with 9 responses (2.6%) being "no" indicating no belief in climate change.

Figure 2 displays the distribution of teleportation frequency. As can be seen, the vast majority of participants did not utilize the teleportation function. Of the 55 participants in the VR conditions, 20 participants used the teleportation function at least once, and 35 did not teleport.

Figure 4

Mean scores on belief and skepticism across all time points by condition

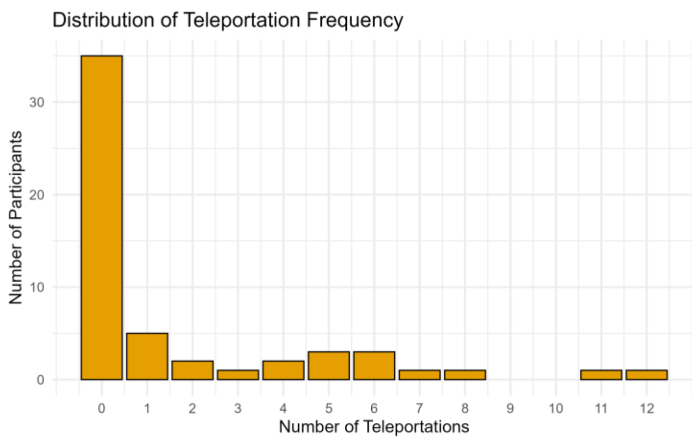




Note. The variable *attr_scep_process_rc* refers to the process-related item from the attribution skepticism scale. The suffix "_rc" indicates that this item was reverse-coded. The variable *attr_scep_sci_rc* reflects the attribution skepticism item concerning scientists and was also reverse-coded. *Imp_scep_effect* denotes the item addressing skepticism about the potential effects of climate change, and *imp_scep_ser* reflects skepticism about the seriousness of climate change. *Ccbelief_uncertain* represents the belief-related item assessing uncertainty about the existence of climate change.

Figure 2

Distribution of Teleportation Frequency



RQ1

To answer the first research question, linear mixed models were computed for each dependent variable within the VR conditions (VRT and VRA). For *climate change belief uncertainty*, no significant interaction between time and frequency of teleportation (measured as number of teleportations) was found (b = -0.04 to -0.14, SEs = 0.17–0.18, $ps \geq .395$). However, teleportation frequency significantly predicted belief uncertainty, with participants who teleported three times ($b = 1.22$, $SE = 0.35$, $p = .001$) or eight times ($b = 0.97$, $SE = 0.35$, $p = .008$) reporting higher uncertainty.

A similar pattern was observed for *procedural skepticism*, where the interaction between time and teleportation frequency was not significant (b = 0.03 to 0.21, SEs = 0.13–0.18, $ps \geq .097$). Nonetheless, teleportation counts of three ($b = 1.12$, $SE = 0.48$, $p = .024$) and eight ($b = 1.12$, $SE = 0.48$, $p = .024$) were associated with significantly higher skepticism scores.

For *scientific skepticism*, the interaction between time and teleportation was also not significant (b = -0.10 to -0.30, SEs = 0.17–0.18, $ps \geq .092$), but teleporting eight times significantly predicted increased skepticism ($b = 1.08$, $SE = 0.50$, $p = .036$).

For *sincerity skepticism*, no significant interaction was observed (b = -0.24 to -0.44, SEs = 0.17–0.18, $ps \geq .070$), though teleportation counts of three ($b = 2.57$, $SE = 0.73$, $p = .001$) and eight ($b = 2.32$, $SE = 0.73$, $p = .003$) were significant positive predictors.

Finally, for *effectiveness skepticism*, no significant interaction was found (b = -0.02 to -0.96, SEs = 0.24–0.26, $ps \geq .058$). However, teleporting eleven times significantly predicted higher skepticism ($b = 1.52$, $SE = 0.75$, $p = .049$). This may reflect participant-specific variance, and it is worth noting that the p-values were close to the conventional threshold of .05.

RQ2

To address the second research question, separate linear mixed models compared the avatar condition (VRA) to the non-avatar condition (VRT). For *climate change belief uncertainty*, no significant main effect of condition was found ($b = 0.23$, $SE = 0.18$, $p = .208$), and no significant interaction effects were observed.

For *procedural skepticism*, the main effect of condition was not significant ($b = -0.07$, $SE = 0.17$, $p = .678$), nor were any interaction terms. Similarly, for *scientific skepticism* ($b = -0.09$, $SE = 0.20$, $p = .585$) and *sincerity skepticism* ($b = 0.28$, $SE = 0.28$, $p = .324$), neither the main effect nor interaction terms were significant.

For *effectiveness skepticism*, the main effect of condition was marginally non-significant ($b = -0.55$, $SE = 0.29$, $p = .058$), and no timepoint interactions reached significance.

Model Fit and Assumption Checks

To evaluate model fit and test the assumptions of linear mixed models, diagnostic checks were conducted for each model. The normality of residuals was assessed using Q–Q plots and Shapiro–Wilk tests. Across nearly all models, the assumption of normally distributed residuals was violated ($p < .001$), which was also evident in the Q–Q plots included in Appendix G.

The assumption of homoscedasticity was met in most models, as indicated by non-significant test results. However, the model predicting belief uncertainty in the second research question showed evidence of heteroscedasticity ($p = .001$). An outlier analysis using Cook's Distance (threshold = 0.5) identified a small number of influential cases in several models. Specifically, one outlier was detected in the belief and sincerity skepticism models for RQ1, and up to five outliers were found in the sincerity skepticism model for RQ2. Taken together, the residual diagnostics indicated that model fit was generally insufficient.

Discussion

The present study aimed to expand on the findings of Erisen et al. (2024) by investigating the role of engagement in VR-based interventions aimed at correcting climate change misinformation. This study examined whether virtual reality can reduce climate change skepticism and belief uncertainty by correcting misinformation, with a particular focus on the effects of avatar presence and user engagement, measured through teleportation frequency. A longitudinal quasi-experimental design with linear mixed models was utilized.

Overall, the analyses did not reveal significant effects of teleportation frequency, used as a measure for engagement with the VR environment, on participants' climate change beliefs or skepticism. Furthermore, no significant differences in belief or skepticism were found between participants in the VR condition with an avatar present and those in the condition without an avatar. Lastly, the exploratory comparisons between the two VR conditions and the social media condition also found no significant effects.

To answer the first research question, *to what extent does the level of interaction with the VR environment influence participants' climate change skepticism,* the results indicate that the number of teleportations did not significantly affect participants' beliefs or skepticism. Possible explanations and limitations of these findings are addressed in the following sections.

Similarly, for the second research question, *to what extent do avatars in VR environments effectively combat climate change misinformation*, no significant effects were observed for the presence of avatars in enhancing the effectiveness of misinformation correction on climate change attitudes.

Erisen et al. (2024) similarly found no significant effect of avatar presence on climate change belief or skepticism. As in the present study, the internal consistency of the belief and skepticism scales was low, as indicated by Cronbach's alpha. Consequently, individual items were analyzed separately in both studies.

Interpretation of Findings

The absence of significant changes in the dependent variables, climate change belief and the various types of skepticism, can partly be explained by participants' already high belief in climate change and low climate change skepticism. As shown in Figure 4, mean values for belief and skepticism items were close to the scale maximum, suggesting a ceiling effect (Poortinga et al., 2011). This finding is consistent with Erisen et al. (2024), who also reported high pre-existing belief scores. Furthermore, participants with established pro-climate attitudes may be less receptive to corrective information, particularly when the intervention does not introduce sufficient emotional or cognitive dissonance (Meijers et al., 2023; Hoekstra et al., 2024). The lack of significant effects for avatar presence also aligns with Erisen et al. (2024) findings who also did not found a significant effect for the presence of avatars.

Teleportation, used in this study as a measurement for engagement, did also not predict meaningful changes in belief or skepticism scores. While teleportation is a widely used locomotion technique in VR due to its simplicity, it tends to reduce realism and disrupt spatial presence when compared to more natural movement methods (Anderton et al., 2024). Confirming this, participants in the present study reported that teleportation felt unnatural and disconnected from real-life navigation, which may have weakened its psychological impact. As noted by Kosa and Johnson-Glenberg (2023), VR engagement is influenced not only by behavioral interaction, but also by immersion and emotional resonance. Therefore, the teleportation frequency as a measure for engagement might not have adequately captured the user engagement necessary for attitude change.

While no significant effects were found for avatar presence, this finding should still be taken into account. Although avatars are often said to enhance message persuasiveness by increasing perceived social presence, the basic form of embodiment used in this study might not have been strong enough to create that effect. Prior research suggests that the persuasive power of avatars depends on features such as realism, behavioral responsiveness, and interactivity (Martingano et al., 2021; Sora-Domenjó, 2022). In this case, the avatar merely delivered the corrective information without dynamic interaction or personalization. As a result, participants may not have experienced the avatar as a socially engaging source. These findings are in line with Erisen et al. (2024), who similarly found no advantage of avatar presence in their VR misinformation intervention. Taken together, the present findings suggest that while VR holds promise as an immersive platform, meaningful belief change likely requires more than minimal interactivity or passive exposure, particularly in already motivated and well-informed participants.

Limitations

Several methodological limitations should be considered when interpreting the findings of this study. First, model diagnostics revealed violations of key assumptions, most notably the assumption of normally distributed residuals. These violations occurred in nearly all models and likely reflect the low variance in participants' responses, particularly on the climate change belief item. As shown in the descriptive plots (see Figure 4), belief scores were already high at baseline, which limited the possibility of detecting change. Although linear mixed-effects models are considered robust to moderate deviations from normality (Schielzeth et al., 2020), such violations weaken the reliability of inferential tests and increase the likelihood of spurious significance.

Second, the teleportation variable, used as a measurement for engagement, presents interpretation challenges. Each teleportation count was treated as a separate predictor in the models, but several values (e.g., three or eight teleportations) were recorded by only a single participant. As a result, the statistically significant associations at those levels are likely driven by individual participant variance rather than generalizable trends. These results should therefore be interpreted with caution and are not considered meaningful evidence of an engagement effect.

Third, outlier diagnostics using Cook's Distance identified several cases with high influence on model estimates. In particular, outliers were present in models assessing belief uncertainty and sincerity-related skepticism. These cases were retained to preserve the integrity and size of the dataset, but their influence may have further limited the stability and generalizability of the results.

Further limitations relate to the design and implementation of the teleportation feature. It was only possible to teleport over relatively short distances, and the mechanism functioned only when the joystick was tilted toward the ground and a teleportation circle appeared. If no circle appeared, the attempt failed and the avatar did not move. These failed attempts were not recorded, resulting in an underestimation of participants' actual engagement with the feature.

In addition, part of the study was conducted in private settings, which introduced technical inconsistencies. These included reduced graphical quality, longer loading times, and, in one case, a crash of the VR environment. Such factors may have negatively affected the VR experience and limited the sense of immersion for participants who completed the experiment in a private setting.

Another key limitation was the generally low number of teleportations observed across participants (see Figure 2). This could be attributed to insufficient instruction on how to use the function, as well as to user discomfort. Several participants reported that teleportation felt "unnatural" and that they would have preferred to walk freely. One participant explicitly questioned the purpose of the feature, stating they could not perceive its usefulness. Additionally, spatial constraints within the VR environment may have reduced the appeal or functionality of teleportation. These factors likely contributed to limited engagement, thereby weakening the validity of teleportation count as an indicator of interaction.

It is also important to acknowledge that teleportation reflects only one form of interaction in VR. As previously discussed, there are various modes of engagement, including object manipulation, movement-based exploration, and dialogic interaction (Anderton et al., 2024). Therefore, the lack of significant effects for interaction measured through teleportation should not be generalized to all types of interactivity in virtual environments.

Moreover, the sample consisted predominantly of highly educated participants. Since education has been shown to correlate strongly with climate change belief (Hoekstra et al., 2024), this may have introduced bias and contributed to ceiling effects, further limiting the detection of change across conditions.

A technical limitation occurred during the distribution of the second post-test. A scheduling error in the automated mailing system caused some participants to receive the follow-up survey up to five days later than planned. Additionally, some participants delayed responding. As a result, the intended measurement intervals of three days and three weeks post-intervention could not be consistently maintained across participants.

Finally, although heart rate data were initially collected for physiological analysis, the data were ultimately excluded due to technical issues. The heart rate monitors did not consistently record data across sessions, resulting in substantial data loss and rendering this measure unusable for the current analyses.

Directions for future research

From these limitations arise a multitude of directions and suggestions for future research. A more diverse and larger sample is expected to be beneficial in retesting the research questions, replicating the findings and improving generalizability. In particular, recruiting participants with lower baseline belief in climate change and higher levels of climate skepticism could help avoid ceiling effects and allow for greater sensitivity in detecting changes following misinformation interventions (Hoekstra et al., 2024).

Furthermore, engagement and interactivity still offer many interesting opportunities for misinformation correction that should be explored. One way of replicating and expanding the present study would be to implement a function to record the joystick movements in order to also record the teleportation attempts. Another approach could be to upgrade the teleportation function in the VR environment to enhance immersion and make the use of the function more intuitive. Alternatively, the implementation of a different, more intuitive function to engage with VR would be recommended, for example, implementing the option to walk through the VR environment would add a new, more natural way of interaction. Perhaps the walking distance could be measured and added as a new variable for measuring engagement in VR.

Additionally, the findings of the present study could help refine the study design developed by Erisen et al. (2024). Future studies may benefit from implementing more naturalistic interaction mechanisms, offering clearer onboarding instructions for participants unfamiliar with VR, and ensuring more consistent scheduling of post-test assessments. Moreover, physiological data such as heart rate variability could be incorporated alongside self-report measures to provide a more comprehensive understanding of participants' emotional and cognitive responses. Although heart rate data could not be analyzed in this study due to technical issues, future research should revisit this approach under more controlled conditions.

Overall, implementing these improvements may contribute to a better understanding of the psychological and experiential mechanisms behind belief change misinformation correction using VR environments.

Conclusion

The present study explored the effects of user engagement and avatar presence in virtual reality on climate change belief and skepticism. Although no significant effects were found, the study provides valuable insights into the methodological and conceptual challenges of researching misinformation correction in immersive environments, highlighting limitations and offering directions for future research. This work contributes to the ongoing development of effective VR-based interventions aimed at promoting accurate understanding of climate change.

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Appendix A

AI Statement

During the preparation of this work, the author used Word and the included grammar check function to spell and grammar check the written work. Grammarly was also used to check the spelling and grammar of the work, as well as for phrasing recommendations. Furthermore, the author utilized Microsoft Copilot to assist with refining text and providing feedback. Additionally, ChatGPT was used to evaluate and improve the R code, as well as find solutions for errors. ChatGPT was also used for additional help with interpreting the results, structuring, and finding phrases for the Discussion section. After using these tools, the author reviewed and edited the content as needed and took full responsibility for the content of the work.

Appendix B

Informed Consent

UNIVERSITY OF TWENTE.

Dear Participant,
Thank you for considering participation in our research study. We appreciate your interest. Before making your decision, we kindly ask you to read the information provided below. This sheet aims to give you a clear understanding of the research project, including its objectives, benefits, potential risks, and the process of participation. If you have any questions or concerns, please contact the researcher before agreeing to participate.

Purpose of the Research: This study seeks to explore public attitudes towards environmental issues across various media. By participating, you will contribute valuable insights to this area of scientific research. The first session will take you approximately 20-25 minutes and involve answering survey questions before and after receiving information on a computer screen, whereas the online surveys to be filled out a week and a month after today's session will each take approximately 12-15 minutes to complete.

Benefits and Risks of Participating: By participating in this study, you will contribute to advancing knowledge in the field of environmental attitudes. You will be rewarded with a 10 Euro bol. gift card or Sona points. Otherwise, there are no direct benefits to you for participating in this study, but your participation will help us better understand information processing and decision making mechanisms. There are no known risks associated with participating in this study. If, however, you experience any discomfort or distress during your participation, you may withdraw from the study at any time without any penalty or loss of benefits.

Ethics Approval: This research project has been reviewed and approved by the Ethics Committee of the Faculty of Behavioural and Management and Social Sciences at the University of Twente. This approval ensures that the research is conducted in accordance with ethical principles and guidelines.

Procedures for Withdrawal: Participation in this study is voluntary. If you decide to participate, you may withdraw at any time without any penalty or loss of benefits. If you choose to withdraw from the study, your data will be removed from the analyses.

Collection and Processing of Personal Information: Upon completing all sessions of the study, your data will be anonymized. Therefore, once the study is over, the research team will no longer be able to identify you and delete your data. After you complete the first session of the study today, we will ask you one last time if you wish to continue. Should you choose to withdraw at this point, we will promptly delete all data associated with your participation.

Usage of Data and Confidentiality: The data collected during this study will be used solely for research purposes. The data will be stored anonymized to protect your privacy. The data will be stored securely, and access to it will be restricted to authorized researchers. Data may be archived for future research use. If the research data are published, no personally identifiable information will be included.
Retention Period: The research data will be retained for at least 10 years after the completion of the study in accordance with the data retention policy of our organization. We emphasize that all data is stored without any personal identifiers, ensuring complete anonymity and the absence of any personally identifiable information.

Contact Information: If you have any questions or concerns about this study, please contact the researcher: Marie Sophie Kaiser at m.s.kaiser@student.utwente.nl or the researcher's supervisor: Dr. Funda Yildirim: f.yildirim@utwente.nl If you have any complaints about the study, please contact the Ethics Committee of the Faculty of Behavioural and Management and Social Sciences at the University of Twente: ethicscommittee-bms@utwente.nl

Do you agree to all the statements below? Please choose "Yes" or "No" down below the statements.

- I have read and understood the information hereby provided on the study.
- I consent voluntarily to be a participant in this study and understand that I can withdraw from the study at any time, without having to give a reason and without any consequences.
- I am aware that I can contact the researcher in case I have any concerns or questions about the study.
- I agree that my answers will be saved and used for the purpose of the study and research.
- I understand that my responses will be anonymous, and only anonymous versions of the data will be presented, stored or shared.
- I confirm that I possess a sufficient level of proficiency in English and that I am at least 16 years old.
- I give my consent to taking part in this study.

○ Yes

○ No

Appendix C

R Code

Script 1: Descriptive Statistics

```
### descriptive statistics
library(readxl)
library(dplyr)
library(tidyr)
library(stringr)
library(janitor)
library(ggplot2)
library(psych)
library(flextable)
library(officer)
library(readr)

# load dataset (long format!)
df <- read.csv("analysis_data_long.csv") %>%
  mutate(part = as.character(part),
    condition = factor(condition, levels = c("SM", "VRT", "VRA")),
    timepoint = factor(timepoint, levels = c("T0", "T1", "T2", "T3")))%>%
    filter(!is.na(condition))  # Exclude rows with missing condition

# Add reverse-coded skepticism variables
df <- df %>%
  mutate(
    attr_scep_process_rc = 6 - attr_scep_process,
    attr_scep_sci_rc = 6 - attr_scep_sci)

# Load teleportation data
teleport_df <- read_excel("teleport_df.xlsx")

teleport_df <- teleport_df %>%
  mutate(n_teleports = as.numeric(n_teleports)) # Ensure n_teleports is numeric

## demographics
demographics <- df %>%
  filter(timepoint == "T1") %>% # data from P1 = T1
  select(part, condition, gender, yob, edu) %>%
  distinct() %>%
  mutate(age = 2025 - as.numeric(yob), # birthyear to age
    gender = factor(gender),
    edu = factor(edu))
```

```
summary(demographics)

# reverse code attribute scepticism items
  # goal that high scep scores mean high scepticism in the participants
df <- df %>%
  mutate(
    attr_scep_sci_rc = 6 - attr_scep_sci,
    attr_scep_process_rc = 6 - attr_scep_process)


# cronbach's alpha skepticism (ChatGPT)
timepoints <- c("T0", "T1", "T2", "T3")

for (tp in timepoints) {
  df_tp <- df %>% filter(timepoint == tp)
  # Subset skepticism-related items
  alpha_data <- df_tp %>%
    select(attr_scep_process_rc, attr_scep_sci_rc, imp_scep_ser, imp_scep_effect)
  # Compute reliability
  print(psych::alpha(alpha_data))}


# descriptive statistics DVs
items <- c("ccbelief_uncertain", "ccbelief_dic", "attr_scep_process_rc",
           "attr_scep_sci_rc", "imp_scep_ser", "imp_scep_effect")

descriptives <- df %>%
  select(part, timepoint, condition, all_of(items)) %>%
  pivot_longer(cols = all_of(items), names_to = "item", values_to = "value") %>%
  group_by(item, timepoint, condition) %>%
  summarise(
    n    = sum(!is.na(value)),
    mean = round(mean(value, na.rm = TRUE), 2),
    sd   = round(sd(value, na.rm = TRUE), 2),
    min  = ifelse(n > 0, min(value, na.rm = TRUE), NA),
    max  = ifelse(n > 0, max(value, na.rm = TRUE), NA),
    .groups = "drop") %>%
  filter(n > 0) %>%
  arrange(item, timepoint, condition)

print(descriptives, n = Inf)
View(descriptives)


# Create APA-style flextable
descriptives_table <- descriptives %>%
```

```
  mutate(across(where(is.numeric), ~ round(., 2))) %>%  # ensure all numeric values are rounded
  flextable() %>%
  set_header_labels(
    item = "Item",
    timepoint = "Timepoint",
    condition = "Condition",
    n = "N",
    mean = "Mean",
    sd = "SD",
    min = "Min",
    max = "Max") %>%
  autofit() %>%
  theme_booktabs() %>%
  fontsize(size = 11, part = "all") %>%
  padding(padding = 4, part = "all") %>%
  set_table_properties(layout = "autofit", width = 0.75)


### plots DVs
# Define variables to plot
dv_items <- c("ccbelief_uncertain", "ccbelief_dic",
              "attr_scep_process_rc", "attr_scep_sci_rc",
              "imp_scep_ser", "imp_scep_effect")

# Function to plot DV with fixed y-axis scale
plot_dv <- function(var) {
  summary_stats <- df %>%
    filter(!is.na(.data[[var]])) %>%
    group_by(condition, timepoint) %>%
    summarise(M = mean(.data[[var]], na.rm = TRUE),
      SD = sd(.data[[var]], na.rm = TRUE),
      .groups = "drop")

  p <- ggplot(summary_stats, aes(x = timepoint, y = M, color = condition, group = condition)) +
    geom_line(linewidth = 1.2) +
    geom_point(size = 3) +
    geom_errorbar(aes(ymin = M - SD, ymax = M + SD), width = 0.1) +
    labs(title = var, y = "Mean", x = "Timepoint") +
    ylim(1, 5) +  # fixed axis
    theme_minimal(base_size = 14)
    ggsave(filename = paste0(var, "_plot_standardized.png"), plot = p, width = 8, height = 5)}

# Apply to all DVs
invisible(lapply(dv_items, plot_dv))

### Plot Teleportation data
```

```
ggplot(teleport_df, aes(x = n_teleports)) +
  geom_bar(fill = "#E69F00", color = "black") +
  scale_x_continuous(breaks = 0:max(teleport_df$n_teleports, na.rm = TRUE)) +
  labs(title = "Distribution of Teleportation Frequency",
    x = "Number of Teleportations",
    y = "Number of Participants") +
    theme_minimal(base_size = 14)

# save plot
ggsave("teleportation_distribution_standardized.png", width = 8, height = 5)
```

Script 2: LMMs

```
### Linear Mixed Models
library(lme4)
library(lmerTest)
library(dplyr)
library(readr)
library(ggplot2)
library(performance)
library(see)
library(influence.ME)
library(readxl)

# Load main analysis dataset
df <- read.csv("analysis_data_long.csv") %>%
  mutate(
    part = as.character(part),  # ensure consistent type for join
    timepoint = factor(timepoint, levels = c("T0", "T1", "T2", "T3")),
    condition = factor(condition, levels = c("SM", "VRT", "VRA"))) %>%
  filter(!is.na(condition))  # exclude participants without a condition

# Load and merge teleportation data
teleport <- read_excel("teleport_df.xlsx") %>%
  mutate(part = as.character(part))  # match ID type

# Merge
df <- df %>%
  left_join(teleport, by = "part")

# Reverse code attribute skepticism items
df <- df %>%
  mutate(
    attr_scep_sci_rc = 6 - attr_scep_sci,
    attr_scep_process_rc = 6 - attr_scep_process)
```

```
## RQ1
# VR with teleportation as predictor
df_vr <- df %>% filter(condition %in% c("VRT", "VRA"))%>%
  mutate(condition = factor(condition, levels = c("VRT", "VRA")))  # VRT as reference

model_rq1_uncertain <- lmer(ccbelief_uncertain    ~ timepoint * condition + n_teleports + (1 |
part), data = df_vr)
model_rq1_process   <- lmer(attr_scep_process_rc  ~ timepoint * condition + n_teleports + (1 |
part), data = df_vr)
model_rq1_attr      <- lmer(attr_scep_sci_rc      ~ timepoint * condition + n_teleports + (1 | part),
data = df_vr)
model_rq1_ser       <- lmer(imp_scep_ser          ~ timepoint * condition + n_teleports + (1 | part),
data = df_vr)
model_rq1_effect    <- lmer(imp_scep_effect       ~ timepoint * condition + n_teleports + (1 |
part), data = df_vr)

## RQ2
#Comparison of VRA and VRT to check effect of avatars

model_rq2_uncertain <- lmer(ccbelief_uncertain    ~ timepoint * condition + (1 | part), data =
df_vr)
model_rq2_process   <- lmer(attr_scep_process_rc  ~ timepoint * condition + (1 | part), data =
df_vr)
model_rq2_attr      <- lmer(attr_scep_sci_rc      ~ timepoint * condition + (1 | part), data = df_vr)
model_rq2_ser       <- lmer(imp_scep_ser          ~ timepoint * condition + (1 | part), data = df_vr)
model_rq2_effect    <- lmer(imp_scep_effect       ~ timepoint * condition + (1 | part), data =
df_vr)

# explorative looking at effectiveness of VR conditons in comparison to SM
model_ex_uncertain <- lmer(ccbelief_uncertain    ~ timepoint * condition + (1 | part), data = df)
model_ex_process   <- lmer(attr_scep_process_rc  ~ timepoint * condition + (1 | part), data = df)
model_ex_attr      <- lmer(attr_scep_sci_rc      ~ timepoint * condition + (1 | part), data = df)
model_ex_ser       <- lmer(imp_scep_ser          ~ timepoint * condition + (1 | part), data = df)
model_ex_effect    <- lmer(imp_scep_effect       ~ timepoint * condition + (1 | part), data = df)


# View summaries
summary(model_rq1_uncertain)
summary(model_rq1_process)
summary(model_rq1_attr)
summary(model_rq1_ser)
summary(model_rq1_effect)

summary(model_rq2_uncertain)
summary(model_rq2_process)
summary(model_rq2_attr)
```

```
summary(model_rq2_ser)
summary(model_rq2_effect)

summary(model_ex_uncertain)
summary(model_ex_process)
summary(model_ex_attr)
summary(model_ex_ser)
summary(model_ex_effect)
```

Script 3: model fit/assumption checks:

```
### Assumption Checks/ Model fit
library(lme4)
library(lmerTest)
library(performance)
library(sjPlot)
library(see)

# Create output folder
output_folder <- "diagnostics_outputs"
if (!dir.exists(output_folder)) {
  dir.create(output_folder)}

# Helper function to save plot with consistent path
save_plot <- function(model, name) {
  png(filename = file.path(output_folder, paste0("diagnostics_", name, ".png")),
      width = 8, height = 6, units = "in", res = 300)
  print(check_model(model))
  dev.off()}


# Save plots
save_plot(model_rq1_uncertain, "rq1_uncertain")
save_plot(model_rq1_process,   "rq1_process")
save_plot(model_rq1_attr,      "rq1_attr")
save_plot(model_rq1_ser,       "rq1_ser")
save_plot(model_rq1_effect,    "rq1_effect")

save_plot(model_rq2_uncertain, "rq2_uncertain")
save_plot(model_rq2_process,   "rq2_process")
save_plot(model_rq2_attr,      "rq2_attr")
save_plot(model_rq2_ser,       "rq2_ser")
save_plot(model_rq2_effect,    "rq2_effect")

save_plot(model_ex_uncertain,  "ex_uncertain")
save_plot(model_ex_process,    "ex_process")
```

```
save_plot(model_ex_attr,       "ex_attr")
save_plot(model_ex_ser,        "ex_ser")
save_plot(model_ex_effect,     "ex_effect")

# Model list
models <- list(
  RQ1_uncertain = model_rq1_uncertain,
  RQ1_process   = model_rq1_process,
  RQ1_attr      = model_rq1_attr,
  RQ1_ser       = model_rq1_ser,
  RQ1_effect    = model_rq1_effect,
  RQ2_uncertain = model_rq2_uncertain,
  RQ2_process   = model_rq2_process,
  RQ2_attr      = model_rq2_attr,
  RQ2_ser       = model_rq2_ser,
  RQ2_effect    = model_rq2_effect,
  EX_uncertain  = model_ex_uncertain,
  EX_process    = model_ex_process,
  EX_attr       = model_ex_attr,
  EX_ser        = model_ex_ser,
  EX_effect     = model_ex_effect
)

# Run and save assumption check results
results <- lapply(models, function(m) {
  list(
    normality        = check_normality(m),
    homoscedasticity = check_heteroscedasticity(m),
    outliers         = check_outliers(m))})

sink(file.path(output_folder, "assumption_checks_all_models.txt"))
print(results)
sink()
```

Appendix D

Explorative Analysis

For explorative research, another set of linear-mixed effects models was conducted, comparing all conditions. The fixed effects in this case were the three conditions, namely VRA, VRT, and the control condition SM, as well as the time point (within subjects). The participant IDs were included for random effects. The SM condition and time point T0 (pre-test) served as the reference.

For climate change belief uncertainty, no significant interaction effects were found (b = 0.06 to 0.11, SEs = 0.23–0.25, $ps \geq .664$), though a trend toward lower uncertainty was observed in the VRT condition compared to SM (b = -0.36, SE = 0.19, p = .06).

For procedural skepticism, no significant effects were found for either VRT (b = -0.15, SE = 0.17, p = .372) or VRA (b = -0.22, SE = 0.17, p = .196) relative to SM.

Similarly, for sincerity skepticism, neither VR condition differed significantly from SM (VRT: b = -0.26, SE = 0.27, p = .348; VRA: b = 0.02, SE = 0.27, p = .944).

For effectiveness skepticism, the VRT condition significantly predicted lower scores at the first post-test (b = -0.73, SE = 0.31, p = .02) and second post-test (b = -0.66, SE = 0.32, p = .042). No significant effects were observed for the VRA condition at any time point: T1 (b = -0.58, SE = 0.31, p = .066), T2 (b = -0.29, SE = 0.33, p = .374), and T3 (b = -0.42, SE = 0.33, p = .211).

Appendix E

Descriptive Statistics Dependent Variables

Table 1

Descriptive Statistics for the Dependent Variable attr_scep_process_rc

Condition	Time	*N*	*Mean*	SD	*min*	*max*
SM	Pre-T	31	2.24	.62	1	4
SM	T1	29	2.17	.71	1	4
SM	T2	24	1.67	1.05	1	4
SM	T3	21	2.14	.73	1	4
VRT	Pre-T	28	2.11	.50	1	3
VRT	T1	28	1.82	.55	1	3
VRT	T2	26	1.88	.52	1	3
VRT	T3	22	2.14	.94	1	5
VRA	Pre-T	27	2.04	.44	1	3
VRA	T1	27	1.96	.81	1	5
VRA	T2	25	2.04	.61	1	3
VRA	T3	25	1.92	.57	1	3

Note. The column “Time” displays the corresponding test. “Pre-T” stands for pre-test, “T1” for the first post-test, and so on.

Table 2

Descriptive Statistics for the Dependent Variable attr_scep_sci_rc

Condition	Time	*N*	*Mean*	SD	*min*	*max*
SM	Pre-T	30	1.60	1.00	1	5
SM	T1	29	1.55	1.02	1	4
SM	T2	24	1.67	1.05	1	4
SM	T3	21	1.76	1.09	1	4
VRT	Pre-T	28	1.50	.69	1	3
VRT	T1	28	1.36	.83	1	5
VRT	T2	26	1.38	.64	1	3
VRT	T3	22	1.23	.53	1	3
VRA	Pre-T	27	1.41	.84	1	5
VRA	T1	27	1.96	.81	1	5
VRA	T2	25	1.32	.80	1	4
VRA	T3	25	1.48	.82	1	4

Note. The column "Time" displays the corresponding test. "Pre-T" stands for pre-test, "T1" for the first post-test, and so on.

Table 3

Descriptive Statistics for the Dependent Variable imp_scep_effect

Condition	Time	*N*	*Mean*	SD	*min*	*max*
SM	Pre-T	30	2.63	1.07	1	5
SM	T1	29	2.38	1.21	1	5
SM	T2	24	2.50	1.06	1	4
SM	T3	21	2.52	1.29	1	5
VRT	Pre-T	28	3.04	1.17	1	5
VRT	T1	28	2.07	1.12	1	5
VRT	T2	26	2.19	1.06	1	4
VRT	T3	22	2.50	1.19	1	5
VRA	Pre-T	27	2.48	1.12	1	5
VRA	T1	27	1.67	.78	1	4
VRA	T2	25	2.04	1.02	1	4
VRA	T3	25	2.00	1.12	1	4

Note. The column “Time” displays the corresponding test. “Pre-T” stands for pre-test, “T1” for the first post-test, and so on.

Table 4

Descriptive Statistics for the Dependent Variable imp_scep_ser

Condition	Time	*N*	*Mean*	SD	*min*	*max*
SM	Pre-T	30	1.70	1.15	1	5
SM	T1	29	1.72	1.13	1	5
SM	T2	24	1.46	.78	1	4
SM	T3	21	1.76	1.09	1	5
VRT	Pre-T	28	1.43	.88	1	4
VRT	T1	28	1.57	1.20	1	5
VRT	T2	26	1.46	.95	1	5
VRT	T3	22	1.64	1.14	1	5
VRA	Pre-T	27	1.70	1.10	1	5
VRA	T1	27	1.41	1.05	1	5
VRA	T2	25	1.52	1.00	1	4
VRA	T3	25	1.48	.92	1	4

Note. The column “Time” displays the corresponding test. “Pre-T” stands for pre-test, “T1” for the first post-test, and so on.

Table 5

Descriptive Statistics for the Dependent Variable ccbelief_uncertain

Condition	Time	*N*	*Mean*	SD	*min*	*max*
SM	Pre-T	31	1.58	1.15	1	5
SM	T1	29	1.45	0.78	1	4
SM	T2	24	1.21	.41	1	2
SM	T3	21	1.43	.60	1	3
VRT	Pre-T	28	1.21	.42	1	2
VRT	T1	28	1.07	.26	1	2
VRT	T2	26	1.08	.27	1	2
VRT	T3	22	1.18	.39	1	2
VRA	Pre-T	27	1.44	.93	1	5
VRA	T1	27	1.26	.81	1	5
VRA	T2	25	1.20	.82	1	5
VRA	T3	25	1.36	.99	1	5

Note. The column "Time" displays the corresponding test. "Pre-T" stands for pre-test, "T1" for the first post-test, and so on.

Appendix F

Cronbach´s Alpha Results

```
Reliability analysis
Call: psych::alpha(x = alpha_data)

  raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd median_r
      0.53       0.6    0.58      0.28 1.5 0.083    2 0.59     0.25

    95% confidence boundaries
         lower alpha upper
Feldt     0.34  0.53  0.67
Duhachek  0.37  0.53  0.69

 Reliability if an item is dropped:
                     raw_alpha std.alpha G6(smc) average_r  S/N alpha se
attr_scep_process_rc      0.43      0.46    0.43      0.22 0.86    0.109
attr_scep_sci_rc          0.33      0.42    0.34      0.19 0.71    0.121
imp_scep_ser              0.39      0.50    0.45      0.25 0.99    0.112
imp_scep_effect           0.66      0.70    0.62      0.44 2.33    0.056
                     var.r med.r
attr_scep_process_rc 0.058 0.093
attr_scep_sci_rc     0.016 0.171
imp_scep_ser         0.043 0.171
imp_scep_effect      0.009 0.483

 Item statistics
                      n raw.r std.r r.cor r.drop mean   sd
attr_scep_process_rc 86  0.63  0.73  0.60   0.45  2.1 0.53
attr_scep_sci_rc     85  0.72  0.77  0.70   0.48  1.5 0.81
imp_scep_ser         85  0.73  0.71  0.57   0.38  1.6 1.05
imp_scep_effect      85  0.59  0.50  0.18   0.13  2.7 1.13

Non missing response frequency for each item
                        1    2  2.5    3    4    5 miss
attr_scep_process_rc 0.07 0.73 0.01 0.17 0.01 0.00 0.01
attr_scep_sci_rc     0.64 0.27 0.00 0.06 0.02 0.01 0.02
imp_scep_ser         0.66 0.20 0.00 0.04 0.08 0.02 0.02
imp_scep_effect      0.11 0.44 0.00 0.15 0.25 0.06 0.02

Reliability analysis
Call: psych::alpha(x = alpha_data)

  raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd median_r
      0.62      0.63    0.57       0.3 1.7 0.065  1.8 0.66     0.28

    95% confidence boundaries
         lower alpha upper
Feldt     0.47  0.62  0.73
Duhachek  0.49  0.62  0.75

 Reliability if an item is dropped:
                     raw_alpha std.alpha G6(smc) average_r  S/N alpha se
attr_scep_process_rc      0.59      0.60    0.52      0.34 1.52    0.076
attr_scep_sci_rc          0.46      0.47    0.38      0.23 0.89    0.096
imp_scep_ser              0.50      0.52    0.43      0.27 1.08    0.090
imp_scep_effect           0.62      0.63    0.54      0.36 1.69    0.066
                      var.r med.r
attr_scep_process_rc 0.0153  0.29
attr_scep_sci_rc     0.0024  0.24
imp_scep_ser         0.0067  0.29
imp_scep_effect      0.0114  0.33
```

```
 Item statistics
                     n raw.r std.r r.cor r.drop mean  sd
attr_scep_process_rc 84  0.57  0.65  0.44   0.34  2.0 0.7
attr_scep_sci_rc     84  0.75  0.76  0.67   0.53  1.4 0.9
imp_scep_ser         84  0.76  0.72  0.60   0.46  1.6 1.1
imp_scep_effect      84  0.66  0.62  0.39   0.31  2.0 1.1

Non missing response frequency for each item
                        1    2    3    4    5 miss
attr_scep_process_rc 0.20 0.64 0.13 0.01 0.01 0.03
attr_scep_sci_rc     0.73 0.19 0.02 0.04 0.02 0.03
imp_scep_ser         0.74 0.10 0.07 0.05 0.05 0.03
imp_scep_effect      0.35 0.44 0.07 0.11 0.04 0.03

Reliability analysis
Call: psych::alpha(x = alpha_data)

  raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd median_r
      0.57      0.62    0.59      0.29 1.6 0.077  1.8 0.57      0.3

    95% confidence boundaries
         lower alpha upper
Feldt     0.40  0.57  0.70
Duhachek  0.42  0.57  0.72

 Reliability if an item is dropped:
                     raw_alpha std.alpha G6(smc) average_r  S/N alpha se
attr_scep_process_rc      0.41      0.43    0.39      0.20 0.77    0.111
attr_scep_sci_rc          0.33      0.40    0.36      0.18 0.67    0.127
imp_scep_ser              0.60      0.64    0.56      0.37 1.75    0.074
imp_scep_effect           0.63      0.65    0.58      0.39 1.89    0.068
                     var.r med.r
attr_scep_process_rc 0.039  0.30
attr_scep_sci_rc     0.032  0.27
imp_scep_ser         0.020  0.30
imp_scep_effect      0.016  0.33

 Item statistics
                     n raw.r std.r r.cor r.drop mean   sd
attr_scep_process_rc 75  0.71  0.77  0.68   0.53  2.0 0.62
attr_scep_sci_rc     75  0.78  0.79  0.72   0.55  1.5 0.84
imp_scep_ser         75  0.59  0.59  0.36   0.23  1.5 0.91
imp_scep_effect      75  0.63  0.57  0.33   0.22  2.2 1.05

Non missing response frequency for each item
                        1    2    3    4    5 miss
attr_scep_process_rc 0.16 0.65 0.17 0.01 0.00 0.14
attr_scep_sci_rc     0.72 0.16 0.07 0.05 0.00 0.14
imp_scep_ser         0.71 0.19 0.04 0.05 0.01 0.14
imp_scep_effect      0.25 0.45 0.09 0.20 0.00 0.14

Reliability analysis
Call: psych::alpha(x = alpha_data)

  raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd median_r
       0.6      0.62    0.61      0.29 1.7 0.069  1.9 0.66     0.32

    95% confidence boundaries
         lower alpha upper
Feldt     0.45   0.6  0.72
Duhachek  0.47   0.6  0.74

 Reliability if an item is dropped:
```

```
                     raw_alpha std.alpha G6(smc) average_r  S/N alpha se
attr_scep_process_rc      0.57      0.59    0.55      0.32 1.44    0.079
attr_scep_sci_rc          0.49      0.49    0.42      0.25 0.98    0.089
imp_scep_ser              0.37      0.43    0.38      0.20 0.76    0.118
imp_scep_effect           0.66      0.67    0.59      0.40 2.04    0.061
                     var.r med.r
attr_scep_process_rc 0.046 0.364
attr_scep_sci_rc     0.019 0.279
imp_scep_ser         0.036 0.094
imp_scep_effect      0.014 0.420

 Item statistics
                      n raw.r std.r r.cor r.drop mean   sd
attr_scep_process_rc 68  0.57  0.65  0.46   0.33  2.1 0.75
attr_scep_sci_rc     68  0.69  0.74  0.65   0.45  1.5 0.86
imp_scep_ser         68  0.80  0.79  0.71   0.57  1.6 1.04
imp_scep_effect      68  0.66  0.56  0.33   0.26  2.3 1.20

Non missing response frequency for each item
                        1    2    3    4    5 miss
attr_scep_process_rc 0.18 0.65 0.13 0.03 0.01 0.22
attr_scep_sci_rc     0.69 0.19 0.06 0.06 0.00 0.22
imp_scep_ser         0.65 0.21 0.06 0.06 0.03 0.22
imp_scep_effect      0.28 0.41 0.04 0.24 0.03 0.22
```

Appendix G

Model diagnostics and assumption checks

Figure 6

Diagnostics RQ1

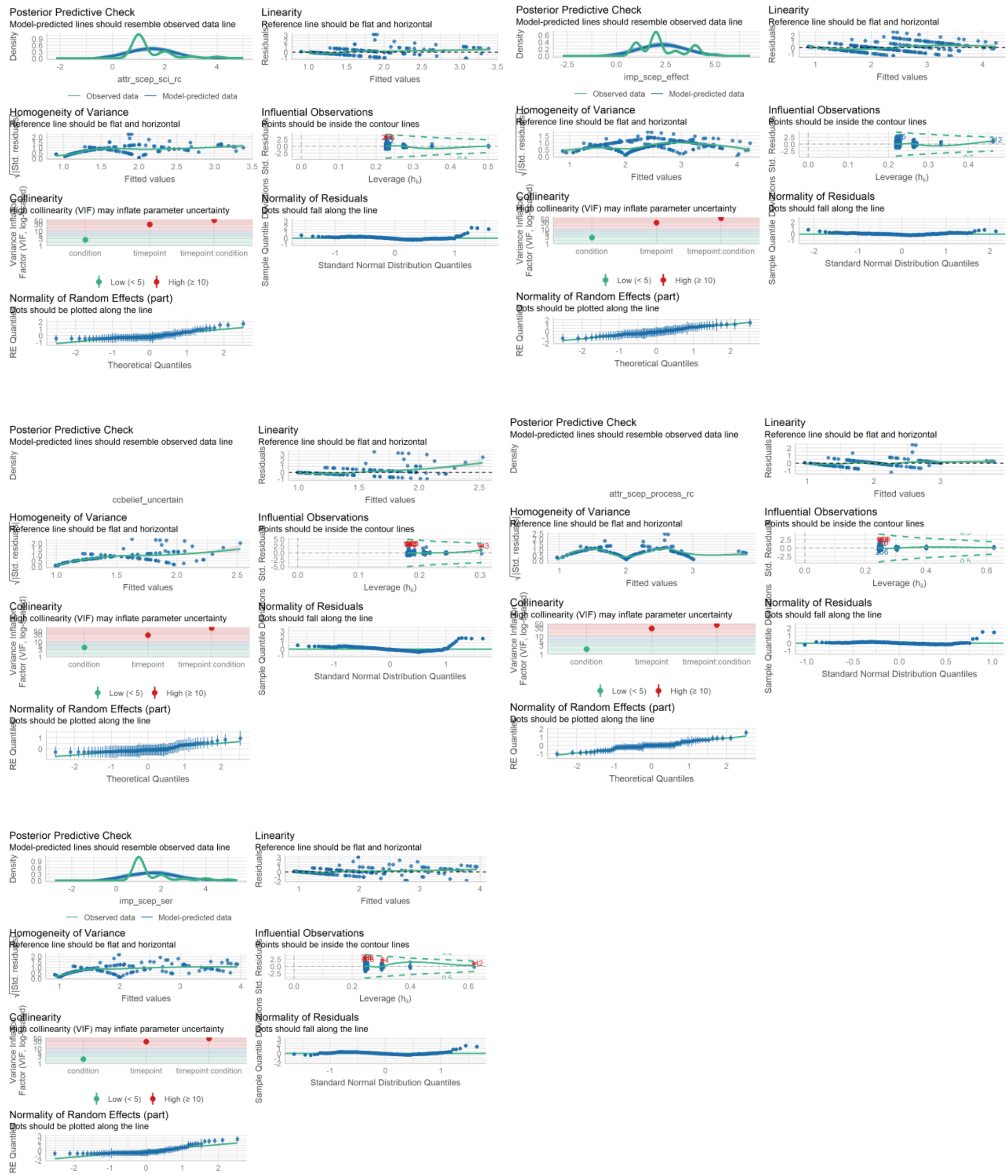
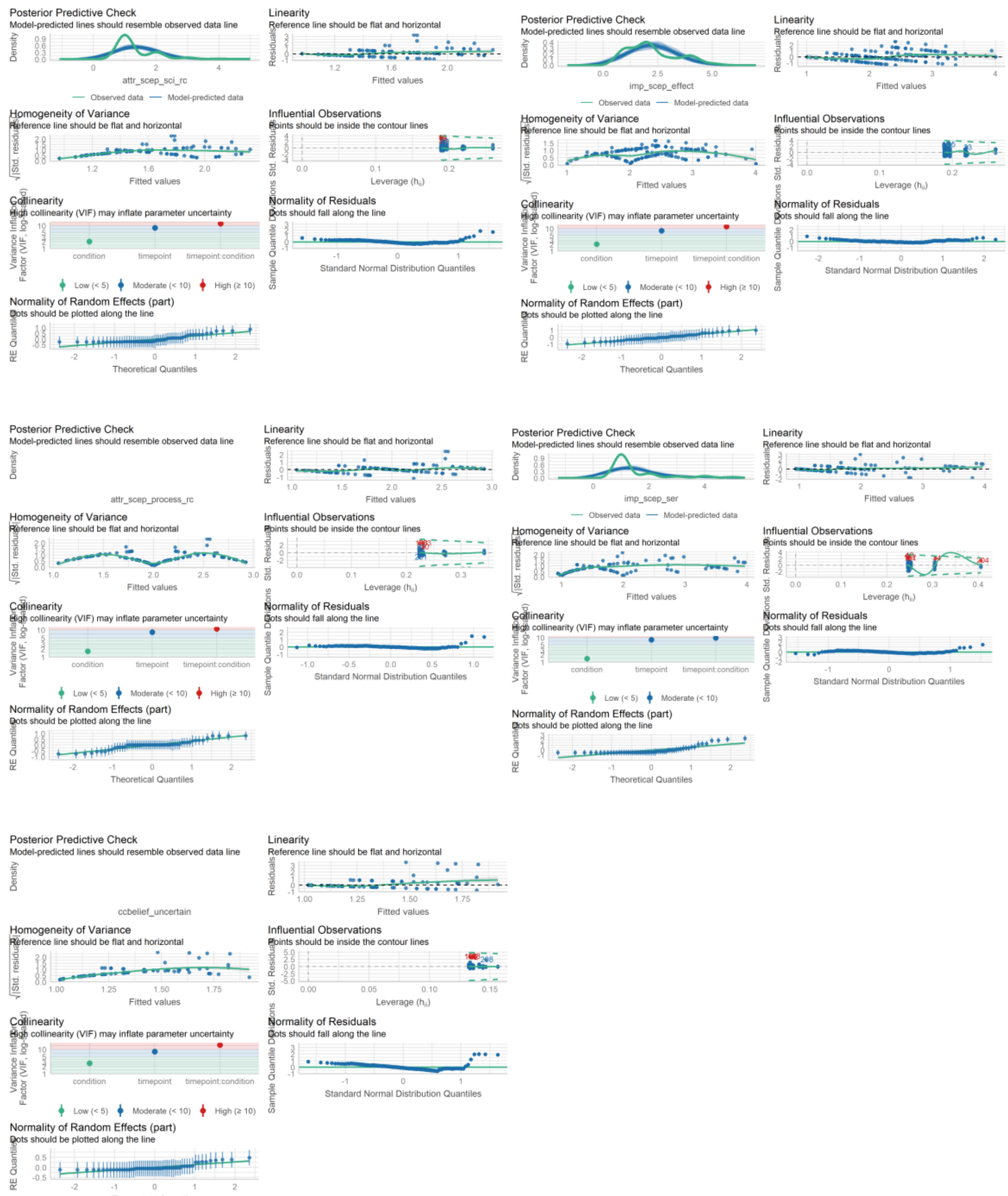


Figure 4

Diagnostics RQ2

Figure 5

Diagnostics explorative analysis



Print output assumption checks/ model fit:

$RQ1_uncertain
$RQ1_uncertain$normality
Warning: Non-normality of residuals detected (p < .001).

$RQ1_uncertain$homoscedasticity
OK: Error variance appears to be homoscedastic (p = 0.064).

$RQ1_uncertain$outliers
1 outlier detected: case 12.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model).

$RQ1_process
$RQ1_process$normality
Warning: Non-normality of residuals detected (p < .001).

$RQ1_process$homoscedasticity
OK: Error variance appears to be homoscedastic (p = 0.597).

$RQ1_process$outliers
2 outliers detected: cases 133, 203.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model).

$RQ1_attr
$RQ1_attr$normality
Warning: Non-normality of residuals detected (p < .001).

$RQ1_attr$homoscedasticity
OK: Error variance appears to be homoscedastic (p = 0.129).

$RQ1_attr$outliers
OK: No outliers detected.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model)

$RQ1_ser
$RQ1_ser$normality
Warning: Non-normality of residuals detected (p < .001).

$RQ1_ser$homoscedasticity
OK: Error variance appears to be homoscedastic (p = 0.166).

$RQ1_ser$outliers

1 outlier detected: case 18.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model).

$RQ1_effect
$RQ1_effect$normality
Warning: Non-normality of residuals detected (p < .001).

$RQ1_effect$homoscedasticity
OK: Error variance appears to be homoscedastic (p = 0.464).

$RQ1_effect$outliers
OK: No outliers detected.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model)

$RQ2_uncertain
$RQ2_uncertain$normality
Warning: Non-normality of residuals detected (p < .001).

$RQ2_uncertain$homoscedasticity
Warning: Heteroscedasticity (non-constant error variance) detected (p = 0.001).

$RQ2_uncertain$outliers
4 outliers detected: cases 12, 106, 161, 198.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model).

$RQ2_process
$RQ2_process$normality
Warning: Non-normality of residuals detected (p < .001).

$RQ2_process$homoscedasticity
OK: Error variance appears to be homoscedastic (p = 0.546).

$RQ2_process$outliers
3 outliers detected: cases 20, 133, 203.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model).

$RQ2_attr
$RQ2_attr$normality
Warning: Non-normality of residuals detected (p < .001).

$RQ2_attr$homoscedasticity

OK: Error variance appears to be homoscedastic (p = 0.094).

$RQ2_attr$outliers
3 outliers detected: cases 18, 35, 52.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model).

$RQ2_ser
$RQ2_ser$normality
Warning: Non-normality of residuals detected (p < .001).

$RQ2_ser$homoscedasticity
OK: Error variance appears to be homoscedastic (p = 0.144).

$RQ2_ser$outliers
5 outliers detected: cases 18, 34, 161, 162, 204.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model).

$RQ2_effect
$RQ2_effect$normality
Warning: Non-normality of residuals detected (p < .001).

$RQ2_effect$homoscedasticity
OK: Error variance appears to be homoscedastic (p = 0.438).

$RQ2_effect$outliers
OK: No outliers detected.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model)

$EX_uncertain
$EX_uncertain$normality
Warning: Non-normality of residuals detected (p < .001).

$EX_uncertain$homoscedasticity
Warning: Heteroscedasticity (non-constant error variance) detected (p = 0.001).

$EX_uncertain$outliers
6 outliers detected: cases 12, 143, 144, 161, 216, 253.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model).

$EX_process
$EX_process$normality
Warning: Non-normality of residuals detected (p < .001).

```
$EX_process$homoscedasticity
OK: Error variance appears to be homoscedastic (p = 0.766).

$EX_process$outliers
3 outliers detected: cases 20, 188, 258.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model).


$EX_attr
$EX_attr$normality
Warning: Non-normality of residuals detected (p < .001).

$EX_attr$homoscedasticity
OK: Error variance appears to be homoscedastic (p = 0.130).

$EX_attr$outliers
3 outliers detected: cases 18, 52, 286.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model).


$EX_ser
$EX_ser$normality
Warning: Non-normality of residuals detected (p < .001).

$EX_ser$homoscedasticity
OK: Error variance appears to be homoscedastic (p = 0.077).

$EX_ser$outliers
5 outliers detected: cases 18, 34, 142, 216, 286.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model).

$EX_effect
$EX_effect$normality
Warning: Non-normality of residuals detected (p < .001).

$EX_effect$homoscedasticity
OK: Error variance appears to be homoscedastic (p = 0.439).

$EX_effect$outliers
OK: No outliers detected.
- Based on the following method and threshold: cook (0.5).
- For variable: (Whole model).
```