sustainability

MDPI

Article

The Efficacy of Virtual Reality on Climate Change Education Increases with Amount of Body Movement and Message Specificity

Anna C. M. Queiroz [1,*], Géraldine Fauville [2], Adina T. Abeles [1], Aaron Levett [1] and Jeremy N. Bailenson [1]

[1] Stanford University; acmq@stanford.edu (A.C.M.Q.) abeles@alumni.stanford.edu (A.T.A.); alevett@alumni.stanford.edu (A.L.); bailenso@stanford.edu (J.N.B.)
[2] University of Gothenburg; geraldine.fauville@gu.se (G.F.)
* Correspondence: acmq@stanford.edu (A.C.M.Q.)

Abstract: Climate change impacts are felt globally, and the impacts are increasing in severity and intensity. Developing new interventions to encourage behaviors that address climate change is crucial. This pre-registered field study investigated how the design of a virtual reality (VR) experience about ocean acidification could impact participants' learning, behavior, and perceptions about climate change through the manipulation of the experience message framing, the sex of voice-over and the pace of the experience, and the amount of participants' body movement. The study was run in 17 locations such as museums, aquariums, and arcades in the U.S., Canada, U.K., and Denmark. The amount of body movement was a causal mechanism, eliciting higher feelings of self-efficacy while hindering learning. Moreover, linking the VR narrative about ocean acidification linguistically to climate change impaired learning compared to a message framing that did not make the connection. As participants learned more about the experience, they perceived the risks associated with ocean acidification as higher, and they were more likely to engage in pro-climate behavior. The results shed light on the mechanisms behind how VR can teach about ocean acidification and influence climate change behavior.

Keywords: virtual reality; climate change; education

Citation: Queiroz, A.C.M.; Fauville, G.; Abeles, A.T.; Levett, A.; Bailenson, J.N. The Efficacy of Virtual Reality on Climate Change Education Increases with Amount of Body Movement and Message Specificity. *Sustainability* **2023**, *15*, x. https://doi.org/10.3390/xxxxx

Academic Editor(s):

Received: date
Revised: date
Accepted: date
Published: date

1. Introduction

Climate change is fueling the increase in frequency and intensity of extreme events such as heat waves, storms, wildfires, and droughts [1,2]. While human activity and the resultant emissions are responsible for the increased carbon dioxide concentrations in the atmosphere that lead to global warming and climate change [3,4], the ocean has mitigated atmospheric concentrations by absorbing an estimated 40% of carbon dioxide emissions since the Industrial Revolution [5]. This absorption, however, has led to decreasing ocean water pH, a process referred to as ocean acidification (OA), resulting in a disruption of the seawater chemistry which impacts, among others, shell-forming marine organisms and the ecosystems that depend on them [6–8]. Even with a growing scientific understanding of the scale of the problem, most people are not familiar with ocean acidification, and have not experienced its adverse effects on marine life, making it harder to understand and less likely that people would take steps to address the issue [9].

Human actions can also both reduce the future effects of climate change through mitigation behaviors and prepare for the unavoidable impacts through adaptive behaviors. Interventions can encourage climate change-related behaviors, such as learning more about climate change, demanding policy action, and preparing one's home for flooding or wildfires. Broadly, we refer to these behaviors as climate change actions, and there have been multiple studies on understanding and increasing climate change actions among various populations [10–14].

Work on climate change puts forth several frameworks that seek to explain the factors impacting one's climate change behavior, such as the social amplification of risk framework [11,13], the protective action decision model [12], and the protection motivation theory [10]. To better identify the factors that motivate climate change behavior, van Valkengoed and Steg [14] conducted a meta-analysis of 106 papers, including all these frameworks. They identified 13 main factors, including trust in government, risk perception, climate change belief, knowledge, and outcome efficacy. The authors highlighted the need to explore how the factors interrelate and jointly influence behavior, and to investigate the mediation effect risk perception can have between learning and climate change behavior.

Although research on climate change behavior is vast, a recent meta-analysis on behavioral interventions to promote household action on climate change showed small and short-termed effects [15], pointing out the need for new forms of interventions [16]. In the last decade, there has been a significant increase in the adoption of virtual reality (VR) in several contexts, such as schools, libraries, museums, and informal learning programs, with at least 10 million VR headsets sold in 2021 [17]. This technology allows new ways of communication, perception, and interaction with content, leveraging the power of communication mainly through its capacity to trigger emotions [18]. This affordance, coupled with the endless simulation possibilities, and strict ability to control the experience and to record users' verbal and nonverbal behavior (such as body movement and gaze shift), has led to several researchers using VR in climate-related education [19] and human behavior research [20].

Although much remains to be discovered about the potential role VR can play in broad climate change education and behaviors, recent media and design comparison studies have shown the benefits of using VR instead of computer monitors on some of the factors identified by van Valkengoed and Steg [14], such as knowledge [21–25], risk perception [26], involvement with nature [26], positive and negative affect [27], pro-environmental behavior [19,28–30], trust [31], and factors related to learning, such as self-efficacy toward science [22,32,33].

Beyond the general effect of using VR as a medium, it is crucial to delve deeper and understand the interaction between specific design elements and the mechanisms through which VR could impact the factors motivating climate change behaviors, such as learning and risk perception. Learning about climate change is complex [34]. It involves dealing with a large amount of abstract information, connecting different subjects, such as chemistry, geography, mathematics, and biology, and ultimately, trusting in the information received [34,35].

The Cognitive Load Theory [36] explicates three cognitive demands that are involved in learning processes: extraneous cognitive load (processing information not relevant to the learning goals); intrinsic cognitive load (processing information relevant to the learning goals), and germane cognitive load (learner's effort to construct schemas about the information being processed). Stimulus-rich multimedia environments often requires greater cognitive effort to process visual, auditory, and textual information, impeding learning [37,38]. Hence, multimedia environments should reduce extraneous cognitive load to avoid unnecessary cognitive overload to impact information processing [36,39].

One principle shown to reduce processing load and improve attention and learning is segmenting the message in meaningful blocks [40–42]. Adding pauses to segment a VR experience could, however, break the feeling of presence, i.e., the phenomenon of behaving and feeling as being in the virtual environment [43]. While Ahn and colleagues [44] found that segmentation had little effect on presence or information recall, Mayer and colleagues [45] reviewed 13 media comparison studies and concluded that more than pauses, adding generative learning activities or asking questions during pauses in the delivery of VR lessons can enhance learning outcomes. Hence, we hypothesized that participants in conditions where the content is segmented, by adding pauses between scenes to reflect on the content, will score higher for learning than participants in non-segmented conditions (H1). Since breaking the experience flow can harm the feeling of presence in VR, we hypothesized that participants in non-segmented conditions will score higher for presence than participants in segmented conditions (H2). Moreover, we investigated the effects of segmentation on factors motivating climate change behavior through the following research question (RQ1): What are the impacts of segmenting content on behavior, risk perception, concern, causes, and beliefs about increased carbon dioxide emissions, and self-efficacy?

Recent studies using VR to teach OA have shown that users' movement in VR underlie the media effects on knowledge gains [21] and self-efficacy toward learning [22]. Research from multiple backgrounds has demonstrated that body movement is essential in learning [46–52], in creating social and psychological attachments to the environment [53], and inducing attitude and behavior change [54]. Markowitz and colleagues [21] suggest that moving in a virtual space meaningful to the learning activity helps participants elaborate and understand the consequences of climate change, leading to learning gains. Moreover, because the brain is constantly making predictions about body movement and the environment [55,56], the motor and visual exploration of the environment in VR can increase the sense of agency (i.e., the feeling of being in control of one's own actions and environmental outcomes; [57]), which in turn influence self-efficacy towards learning [22,58]. Because of that and the unique VR affordances, allowing users to walk around and move during the experience, we designed the current study to compare the effects on climate change learning and behavior of having the experience seated versus standing up, being able to walk around. In this sense, we hypothesized that participants having a standing-up experience that allows them to walk around, will score higher for learning, behavior, risk perception, concern, causes and beliefs about increased carbon dioxide emissions, presence, self-efficacy, and trust than participants in seated conditions (H3).

The processes involved in learning about climate change can be influenced not only by the pedagogy of the experience but also by non-verbal aspects of the information [59]. For example, studies have shown that when exposed to new information, we are constantly reasoning about the informant's characteristics (such as physical appearance, voice, and gestures) and the implications of the information received [35]. When receiving information from a computer, particularly in rich media environments such as animations and VR experiences, reasoning about the informant becomes more complex, as the informant is not a person but a computer-simulated environment, and the human characteristics that we used to reason about the source of information are absent or transformed. These aspects influence how much we trust and learn the information.

Research on human-computer interaction has demonstrated that impact of the sex of the computer's voice (male or female) is influenced by the gender of the participants themselves [60–62] and gender stereotypes [63]. Some studies have shown that participants trusted information more when it was received from a male compared to a female voice-over [64,65]. Moreover, Khashe and colleagues [66] argued that adults might be more inclined toward pro-environmental requests made by a female computer voice, while Liu [67] did not find a difference between human voice-over sex on changing participants' climate change beliefs. Hence, we hypothesized that participants in conditions with a female voice-over will score higher for learning than participants in male-voiced conditions (H4); that participants' reported self-efficacy comparing female-voiced and male-voiced conditions will be gender dependent, with women scoring higher than males in female-voiced conditions and vice versa (H5); and that participants in male-voiced conditions will score higher for trust than participants in female-voiced conditions (H5). To investigate the effects of voice-over sex on the other factors influencing climate change behavior and learning, we posed the following research question: What are the impacts of the sex of the voice-over on risk perception, concern, causes, and beliefs about increased carbon dioxide emissions (RQ2) and on presence (RQ3)?

In addition, the way individuals engage with climate change depends on the framing of the issue at stake (i.e., how the message emphasizes aspects of the information and resonates with the audience's knowledge and values) [68–73]. Although a loss-framed message might trigger a greater intention to act upon environmental issues [74], this framing may be moderated by the degree of uncertainty associated with climate change. Morton and colleagues [71] showed that a loss-framed message coupled with high uncertainty reduced pro-environmental intentions. In contrast, high uncertainty coupled with a gain-framed message yielded greater positive pro-environmental intentions. Investigating framing in VR, Ahn and colleagues [75] found that growing a virtual tree (gain framing) was more effective in promoting pro-environmental behavior than cutting down a virtual tree (loss framing). On the one hand, focusing on the process of OA instead of Climate Change could reduce the complexity of the topic being learned, positively influencing how participants feel able to learn (self-efficacy). However, on the other hand, it taps into unfamiliar concepts that could make it more difficult to learn, and negatively influence self-efficacy [76]. Moreover, the term climate change has been extensively linked with negative outcomes by the media, resulting in a negative valence associated with the term[77]. Hence, to investigate the effects of message framing on self-efficacy, we posed RQ4: What is the impact of message framing on self-efficacy?

Finally, political opinions have been shown to influence how climate change messages are interpreted, with a conservative political view being more correlated with casting doubts on messages framed as climate change than neutral messages [78,79]. Cooke and Kim [80] have shown that when OA is explained in connection to climate change, people tend to politicize the message, mainly because of their unfamiliarity with OA and lack of connection with the ocean. The process of misinterpreting scientific information to fit it to their political and psychological biases is called motivated reasoning, which, in the case of climate change, is stronger among politically conservative individuals [81]. In terms of learning, Guilbeault and colleagues [82] found that polarizing the message significantly reduced social learning. We then hypothesized that compared to participants in an ocean acidification framing condition, participants in a climate change framing condition reporting a more liberal political view will score higher for behavior, risk perception, trust, learning, concern, causes and beliefs about increased carbon dioxide emissions than participants reporting more conservative political views (H7).

Given the multifaceted aspect of climate change learning and behavior and increasing VR use to depict environmental issues, it is crucial to understand better how the design of the VR experience relates to climate change learning and behaviors. In this context, this study's objective is threefold: a) understand how the design of the VR experience can influence some of the factors indicated in the literature as influencing climate change behavior (namely, risk perception, trust, beliefs, concern about the ocean, and knowledge; RQ1: segmentation effects, and RQ2: voice-over effects) and other aspects related to climate change behavior in VR, such as presence (RQ3: voice-over effects) and self-efficacy toward science learning (RQ4: message framing effects); b) identify the relationship between body movement in VR, learning, and self-efficacy towards science learning, and; c) explore how knowledge, beliefs, risk perception, and trust relate to climate change behavior and each other after a VR experience about OA (RQ5 and RQ6). Hence, we manipulated design elements in VR that the literature indicated could impact these factors, namely: movement, framing, voice-over, and segmentation. The hypotheses and research questions were pre-registered at (https://osf.io/5rkmb). Visual representations of the data recording procedure, VR equipment used, and conditions are shown in Figure 1.

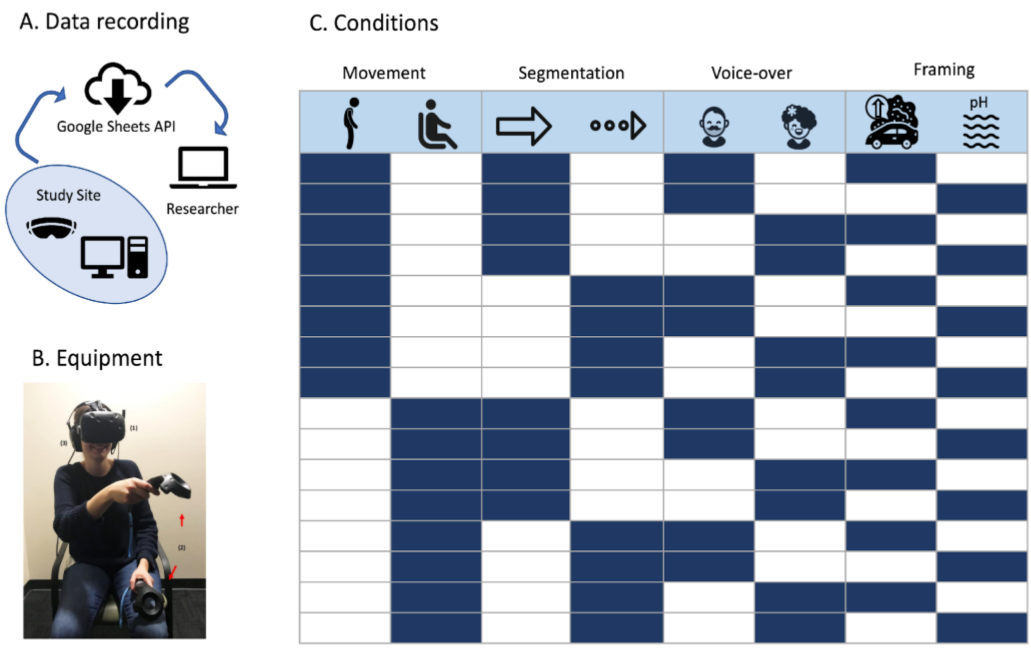

Figure 1. Study setup and conditions. **A**: Data recording procedure: participants' subjective and movement data were recorded in real-time to the cloud in a secure server using Google Sheets API, then accessed through the researcher's computer. B: Equipment used in the study: (1) HTC Vive headset, (2) Hand controllers, (3) Headphones. C: Combinations of the manipulation variables in a 2x2x2x2 design. Colored cells show the presence of the manipulation: movement (seated vs. standing), experience segmentation (non-segmented vs. segmented), voice-over (male vs. female), and framing (climate change vs. OA).

2. Materials and Methods

2.1. Developing remote data collection

This study was run in schools, universities, museums, aquariums, VR arcades, libraries, and foundations from 17 locations across the U.S., U.K., Canada, and Denmark. The Institutional Review Board approved the procedures and materials. Participants were students or visitors that voluntarily joined the study. Docents on each study site informed the participants about the study procedures. They also helped participants use the VR equipment and go through the assigned version of the Stanford Ocean Acidification Experience (SOAE). Participants that gave consent had their data collected and recorded in real-time to an online spreadsheet. The system collected data on participants' assigned condition, location, answers to questionnaires, headset and hand controller orientation (yaw, pitch, roll), headset and hand controller translation (x, y, z coordinates), button clicks, and experience length. Every 0.25 seconds, this data was snapshotted and stored in program memory, periodically flushed to a Google Sheet with the unique participant ID via the Google Sheets API [83]. Once current in-memory data was successfully written to the spreadsheet, it would be cleared from local program memory. In the case of a failed write (e.g., temporary network connection failure), the data whose write failed would be preserved in the local program memory and included in future write attempts. In the rare instance of network failure without restoration by the end of the experience, such that there was either no data or incomplete data written to the participant's Google Sheet, the participant's data were excluded from the analysis. Similarly, if the participant did not complete the study for any reason, their data were excluded from the analysis. In total, 127 out of 432 participants' data was excluded due to incomplete data. Because conditions were randomly assigned, docents would not know if the participant would need a chair or not (seated or standing conditions) until the experience had already begun. As a result, some study sites would restart the experience if they did not have a chair available at that time, or for museum visitors who did not feel comfortable sitting, which would be registered as incomplete data. This remote data collection method was also used to record which of the conditions the user was randomly assigned. Also, it was used to record specific user behavior, including their responses to the pre- and post-tests and their physical interactions with the VR experience (e.g., "touching" the exhaust pipe in the opening city scene).

2.2. Stanford Ocean Acidification Experience (SOAE) versions

SOAE is an eight-minute-long, interactive computer graphics piece that teaches about OA's causes, processes, and outcomes. Through the experience, participants observe firsthand the effects of ocean acidification on the ocean. They watch cars' exhaust pipes releasing carbon dioxide molecules (Figure 2A), push a molecule, watching it flying to the sky, and watch a carbon dioxide molecule react with a water molecule to create a carbonic acid molecule (Figure 2B). They then embody a scientist and measure the health of a coral reef by counting and placing flags beside sea snails (Figure 2C). Finally, they experience the consequent degradation of a rocky reef and its marine life (Figure 2D). The original experience is available at https://stanfordvr.com/soae/.

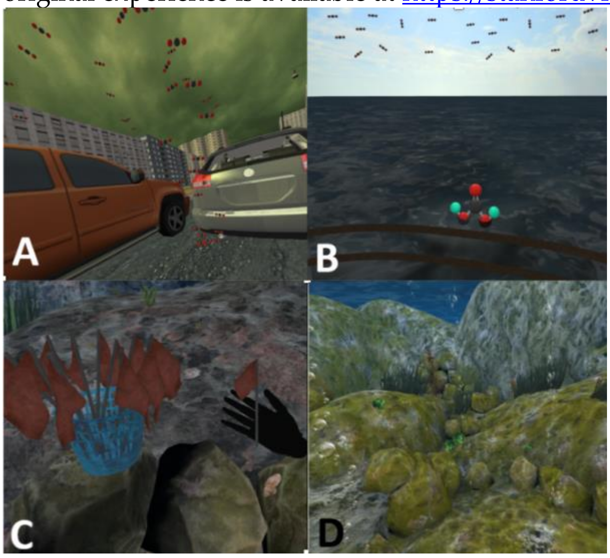

Figure 2. The Stanford Ocean Acidification Experience images. A: Visualizing carbon dioxide molecules spilled by vehicle exhaust pipes. B: representation of the chemical reaction between a carbon dioxide and a water to create carbonic acid molecule. C: flags used to count sea snails in a healthy coral reef. D: unhealthy coral reef.

Sixteen versions of SOAE were created, combining the manipulation variables: movement, segmentation, framing, and narration. For the movement manipulation, participants in the standing conditions walked around a four-square meters area and used hand controllers to perform interactive tasks and receive haptic feedback (hand controllers' vibration). In the seated condition, all those activities occurred, except the participant remained seated and used virtual lasers to interact with distant virtual objects. In the segmented condition, we included three-seconds pauses after some passages 20-seconds pauses between four different content blocks. During the 20-second pauses, participants were prompted to think about what they had just learned in that block while the screen turned black. To manipulate the framing of the message, in the climate change condition, the experience title was "Ocean Acidification, a Climate Change Problem," and the narration mentioned climate change a couple of times during the experience. In the OA framing condition, the title was "Ocean Acidification, a Carbon Dioxide Emission Problem," and the narration did not link OA to climate change. For the voice-over manipulation, we created versions of SOAE narrated by a woman and a man. The experience was piloted with university students, who provided qualitative feedback about the experience and the length of the pauses in the segmented versions of the experience that influenced final study design.

2.3. Measuring subjective variables

Participants answered pre-test and post-tests while in VR, using the hand controllers to choose options or input values. All participants answered the same questions. The pre-test included demographic questions (age, gender, race/ethnicity, education level, VR use frequency), how well the participant understood English, and how much they believed they knew about OA. After answering the pre-test, participants were randomly assigned to one of the conditions. After that, they answered the post-test, also in VR. It included eight questions to measure learning (adapted from the International Ocean Literacy Survey; [84]) and one question to measure each of the following: concern about the health of the ocean, causes of OA, the severity of OA (risk perception), beliefs about increased carbon dioxide emissions in the atmosphere, self-efficacy towards science learning, how much they believed to know about OA, presence, and trust in the information they received during the experience. These questions were developed in consultation with marine and social scientists engaged in climate change research. As a measure of climate change behavior, they were asked to read, and then to decide whether or not to sign a petition to support investments in research about OA mitigation strategies. We used this measure to indicate engagement with climate change and support for meaningful measures to address OA. Participants could use the hand controller to handwrite in VR and sign the petition. Finally, they were asked to select where they placed themselves on a political spectrum from left/liberal to right/conservative. The questionnaires were piloted with participants of a national climate change event, who gave feedback on their understanding of the questions, length of the questionnaire and link between the question and the construct being investigated. Questions and their respective coding are shown in Table 1. A composite of the learning questionnaire was created by averaging the eight learning questions' scores.

Table 1. Subjective measures' questions.

Variable	Question	Coding
Learning	1.The ocean absorbs and stores which of the following from the atmosphere?	0 (incorrect) or 1 (correct)
Learning	2. Which of the following causes ocean acidification?	0 (incorrect) or 1 (correct)
Learning	3. Which of the following is a result of human-caused carbon dioxide emissions?	0 (incorrect) or 1 (correct)
Learning	4. Clams, oysters, and other marine organisms use the carbon dissolved in the ocean to:	0 (incorrect) or 1 (correct)
Learning	5. The formula for carbonic acid is:	0 (incorrect) or 1 (correct)
Learning	6. Which human activity contributes a significant amount to greenhouse gas emissions?	0 (incorrect) or 1 (correct)
Learning	7. What can scientists observe in the rocky reef off the coast of Naples, Italy?	0 (incorrect) or 1 (correct)
Learning	8. How does ocean acidification impact all shelled species?	0 (incorrect) or 1 (correct)
Subjective knowledge	After this experience, how much, if anything, would you say you know about ocean acidification?	5-point Likert scale: 1 (nothing) to 5 (a great deal)
Concern	How concerned, if at all, are you about the health of the ocean?	5-point Likert scale: 1 (not at all) to 5 (extremely)
Risk perception	How serious of a problem do you think the increased amount of carbon dioxide in the atmosphere is for the health of the ocean?	5-point Likert scale: 1 (not at all) to 5 (extremely)
Beliefs	Do you think the amount of carbon dioxide in the atmosphere has been going up over the past 100 years, or do you think this has not been happening?	4-point Likert scale: 1 (definitely not) to 4 (definitely yes)
Causes	The increased amount of carbon dioxide in the atmosphere was caused . . .	Ordinal response. 1) mostly by natural causes; 2) about equally by things people did and natural causes; 3) mostly by things people did.
Self-efficacy	How confident are you that you can understand most complex material in science courses?	5-point Likert scale: 1 (not at all) to 5 (extremely)
Presence	To what extent did you feel you were really inside the virtual world?	5-point Likert scale: 1 (not at all) to 5 (very strongly)
Trust	How much do you trust the information that you got from this virtual reality experience?	5-point Likert scale: 1 (not at all) to 5 (completely)
Political view	Some people talk about politics in terms of left, center, and right. On a left-right scale from 0 to 6, with 0 indicating extreme left (or extreme liberal) and 6 indicating extreme right (or extreme conservative), where would you place yourself?	From 1 (extreme right/conservative) to 7 (extreme left/liberal)
Petition	People have started the following petition to ask the international community to take action to combat ocean acidification. Please read the petition. You will then have an opportunity to sign it. TELL THE UNITED NATIONS: IT IS TIME TO ADDRESS OCEAN ACIDIFICATION Dear Secretary General Guterres, Right now, the ocean absorbs about a quarter of all carbon dioxide emissions, and this carbon dioxide changes the chemistry of the ocean. Without intervention, the ocean's acidity level is expected to more than double by 2100. This will negatively impact shellfish, coral reefs, and all the people and organisms around the globe that	0 (not signed) or 1 (signed)

depend on them. It is time for the United Nations to take meaningful steps to address ocean acidification.
With scientific and technological advancements we, as a global community, can address this pressing issue. Please dedicate significant funding to support an international research agenda that aims to address and understand the threats we face from ocean acidification.
You can sign this petition in the space below by holding down the trigger button. Signing this petition is completely optional, and your decision to sign or not sign will not affect your ability to continue participation in the research. Finally, your name will not be collected by us or connected with e any of your survey responses.

2.4. Measuring movement

Participants' orientation (yaw, pitch, roll), head translation (x, y, z), and controller translation (x,y,z) were tracked and recorded throughout the experience every 0.25 seconds. Movement data was cleaned and processed using Python, Pandas, and NumPy. We followed Won and colleagues [85] and Li and colleagues [86] methods for movement analysis in VR. Using the headset and hand controllers' x, y, and z coordinates, we calculated the total amount of translation, normalized them per second, and calculated head and hands' yaw, pitch, and roll standard deviation. Figure 3 shows visual representations of yaw, pitch, roll, and translation.

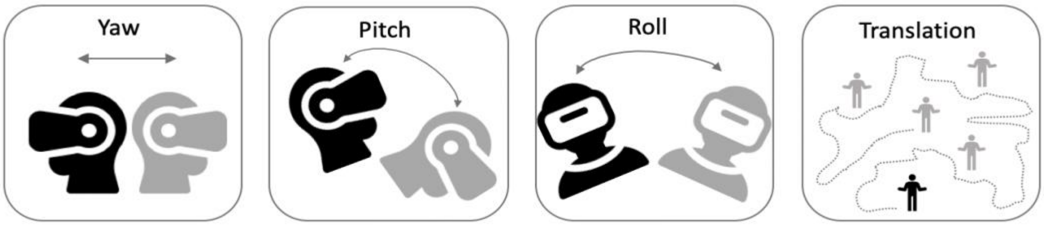

Figure 3. Body movements: Yaw, Pitch, Roll, and Translation.

2.5. Statistics

We estimated parameters from several linear mixed effect models to test the pre-registered hypotheses, investigate the research questions, and run exploratory analyzes. All models included the random effects of location, included all manipulation variables as predictors, and controlled for gender, age, VR use, English proficiency, political view, and education. We estimated parameters from generalized linear mixed models predicting behavior (signing or not a petition supporting investment in OA research). The analyses were carried out in R Studio software. We used the "lmerTest" [87] package to run the regressions, which reports Satterthwaite approximations for degrees of freedom and p-values. Linear mixed effect models were inspected for the assumptions of linearity, homoscedasticity, normality of residuals' distribution, and independence using the package "sjPlot"[88] Additionally, models were tested for multicollinearity, using the package "car"[89] to measure the variance inflation factor (VIF) of each variable in the model. No multicollinearity of concern was found (VIF < 5)[90]. We used the package "effectsize"[91] to calculate effect sizes. For linear mixed-effects models, partial eta squared ($\eta^2{}_p$) with a 90% confidence interval (CI)[92] was computed using Sums-of-Squares [91]. For generalized mixed-effects models (models predicting climate change behavior) and ordinal logistic regressions (models predicting causes attributed to OA), standard coefficients were reported along with 95% CI. Our research questions and hypotheses testing did not involve interactions. For example, to investigate the voice-over gender effects on the variables of interest, we ran LMER models predicting the dependent variable of interest from the manipulated variable "voice-over sex" (predictor). The predictor always had two factors (in this case, male [n = 149] and female voice-over [n = 156]). The models were controlled for the other manipulations and its factors, participants' demographics and included the random effects of location. Hence, we did not test all of the two, three and four-way interactions.

Finally, we ran mediation analyses using the package "mediation", reporting nonparametric bootstrap confidence intervals with the percentile method to investigate the relationships between the factors motivating climate change behavior. A priori power analyses including linear mixed effect models with two tails, alpha probability error of 0.05, H1 ϱ^2 (rho squared) of .115 [93], H0 ϱ^2 of 0, 15 predictors (predictor with two factors, controlling for the other three manipulations variables with two factors each, and seven demographics variables), and 95% power showed a lower critical R^2 of 0.025, and upper critical R^2 of 0.10 and indicated a sample size of 260. A type 2 ANOVA was run on the LMER models' output to generate type 2 sums of squares ANOVA tables of fixed effects. A priori power analysis of the ANOVA tests, including Cohen's $f = 0.20$, alpha probability error of 0.05, two groups and 95% showed a sample size of 328.

2.6. Participants

A total of 305 complete and valid responses were included in the data analysis. Participants' age mean was 23.83 years old (*SD* = 13.71, min = 11, max = 73), and their demographics are shown in Table 2.

Table 2. Participants' location, gender, and race.

Country	**N = 305**	**Gender**	**N = 305**	**Race**	**N = 305**
U.S.	262 (85.9%)	Woman	171 (56%)	Afro-American	16 (5.2%)
Denmark	20 (6.6%)	Man	132 (43.3%)	Chinese	15 (4.9%)
Canada	16 (5.2%)	Other	2 (0.7%)	Filipino	3 (1.0%)
U.K.	7 (2.3%)			Hispanic / Latinx	11 (3.6%)
				Indian	10 (3.3%)
				Japanese	3 (1.0%)
				Korean	4 (1.3%)
				Mexican	11 (3.6%)
				Middle Eastern	10 (3.3%)
				Native American	7 (2.3%)
				Southeast Asian	15 (4.9%)
				White	176 (58%)
				More than one	7 (2.3%)
				Decline to answer	8 (2.6%)
				Unknown	9 (3.0%)

3. Results

Means and standard deviations of the subjective measures per manipulated variable are shown in Table 3. Table 4 shows the correlations between the variables. A summary of the pre-registered hypotheses and research questions along the corresponding data analyses and conclusions are shown in Appendix A.

Table 3. Means and standard deviations of subjective measures per manipulated variable.

Variables	**Segmentation**				**Movement**				**Voice-over**				**Framing**			
	Non-segmented (n = 140)		**Segmented (n = 165)**		**Seated (n = 92)**		**Standing (n = 213)**		**Female (n = 156)**		**Male (n = 149)**		**Climate Change (n = 159)**		**Ocean Acidification (n = 146)**	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Learning	0.77	0.21	0.79	0.23	0.83	0.18	0.76	0.23	0.77	0.23	0.79	0.22	0.76	0.23	0.80	0.21
Self-efficacy	3.34	0.93	3.34	1.00	3.09	0.95	3.45	0.96	3.30	0.92	3.38	1.02	3.33	0.98	3.35	0.96
Behavior	0.81	0.39	0.84	0.37	0.91	0.28	0.79	0.41	0.84	0.37	0.82	0.39	0.86	0.35	0.80	0.40
Presence	3.76	0.87	3.80	0.91	3.58	0.92	3.87	0.86	3.70	0.90	3.87	0.88	3.75	0.88	3.81	0.91
Trust	4.13	0.78	4.10	0.78	4.01	0.72	4.16	0.80	4.10	0.76	4.12	0.80	4.12	0.81	4.10	0.74
Concern	3.96	0.90	3.98	0.88	4.00	0.85	3.96	0.91	3.94	0.87	4.01	0.91	4.03	0.90	3.90	0.88
Risk perception	4.37	0.70	4.39	0.76	4.46	0.62	4.35	0.78	4.38	0.70	4.38	0.77	4.41	0.71	4.35	0.76
Beliefs	3.66	0.54	3.74	0.52	3.73	0.47	3.69	0.56	3.66	0.58	3.75	0.46	3.73	0.52	3.68	0.54

* *M* and *SD* are used to represent mean and standard deviation, respectively. Variables ranges: Learning (0-1), Self-efficacy (1-5), Behavior (0-1), Presence (1-5), Trust (1-5), Concern (1-5), Risk-perception (1-5), Beliefs (1-4).

Table 4. Means, standard deviations, and correlations with confidence intervals.

Variable	***M***	***SD***	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Knowledge	0.78	0.22								
2. Self-efficacy	3.34	0.97	.14*							
			[.02, .24]							
3. Presence	3.78	0.89	.01	.18**						
			[-.10, .12]	[.07, .28]						
4. Trust	4.11	0.78	.11	.23**	.25**					
			[-.00, .22]	[.12, .33]	[.15, .36]					
5. Concern	3.97	0.89	.32**	.21**	.29**	.30**				
			[.21, .41]	[.10, .32]	[.18, .39]	[.19, .40]				
6. Risk perception	4.38	0.74	.27**	.20**	.18**	.40**	.58**			
			[.16, .37]	[.09, .30]	[.07, .29]	[.30, .49]	[.50, .65]			
7. Beliefs	3.70	0.53	.36**	.16**	.12*	.26**	.39**	.48**		
			[.26, .46]	[.05, .27]	[.00, .22]	[.16, .37]	[.29, .48]	[.38, .56]		
8. Behavior	0.83	0.38	.14*	.07	-.00	.21**	.21**	.25**	.21**	
			[.03, .25]	[-.04, .18]	[-.12, .11]	[.10, .32]	[.10, .32]	[.14, .35]	[.10, .31]	
9. Political view	4.39	1.26	.23**	-.10	-.12*	.09	.19**	.31**	.22**	.14*
			[.12, .33]	[-.21, .01]	[-.23, -.00]	[-.02, .20]	[.08, .30]	[.20, .41]	[.11, .33]	[.03, .25]

* *M* and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$. The number on the header of the third to the 10th column refers to their corresponding variable listed in the first column (e.g., 5 refers to 5. Concern).

Segmenting the experience did not influence the outcomes (RQ1). No differences between the segmented and non-segmented conditions were found for the subjective measures investigated (learning (F (1, 276) = .28, p = .599, $\eta^2{}_p$ < .01, 90% CI [.00,.00]); self-efficacy (F (1, 292) = .04, p = .845, $\eta^2{}_p$ < .01, 90% CI [.00,.01]); presence (F (1, 292) = .04, p = .837, $\eta^2{}_p$ < .01, 90% CI [.00,.01]); concern (F (1, 287) = .01, p = .941, $\eta^2{}_p$ < .01, 90% CI [.00,.02]); risk perception (F (1, 292) = .01, p = .935, $\eta^2{}_p$ < .01, 90% CI [.00,.00]); trust (F (1, 290) = .25, p = .614, $\eta^2{}_p$ < .01, 90% CI [.00,.02]); beliefs (F (1, 292) = 1.69, p = .194, $\eta^2{}_p$ < .01, 90% CI [.00,.03]) and behavior ($\chi 2(1)$ = 0.691, p = 0.406 , std. coef = 0.30, 95% CI [-0.42, 1.02])).

Male voice-over elicited higher feelings of presence but did not influence factors motivating climate change behavior (RQ2 and RQ3). Participants in the male voice-over conditions reported feeling more present than participants in the female voice-over conditions (F (1, 292) = 4.61, p = .033, η^2_p = .02, 90% CI [.00,.05]). No difference between the narration conditions were found for the factors motivating climate change behavior (risk perception (F (1, 292) = .53, p = .466, η^2_p < .01, 90% CI [.00,.02]); trust (F (1, 289) = .68, p = .409, η^2_p < .01, 90% CI [.00,.02]); beliefs(F (1, 292) = 1.11, p = .294, η^2_p < .01, 90% CI [.00,.02]); behavior(χ2(1) = 0.924, p = 0.336 , std. coef = -0.36, 95% CI [-1.08, 0.37])).

The framing of the experience did not influence self-efficacy (RQ4) but focusing the message on OA yielded higher learning than linking it to climate change. There was no significant difference between the framing conditions on self-efficacy (F (1, 292) = .01, p = .938, η^2_p < .01, 90% CI [.00,.00]). Participants in the OA framing conditions scored significantly higher for learning than participants in the climate change framing conditions (F (1, 278) = 7.37, p = .007, η^2_p = .03, 90% CI [.00,.06]). The scores means per question assessing learning, per framing condition, are shown in Figure 4.

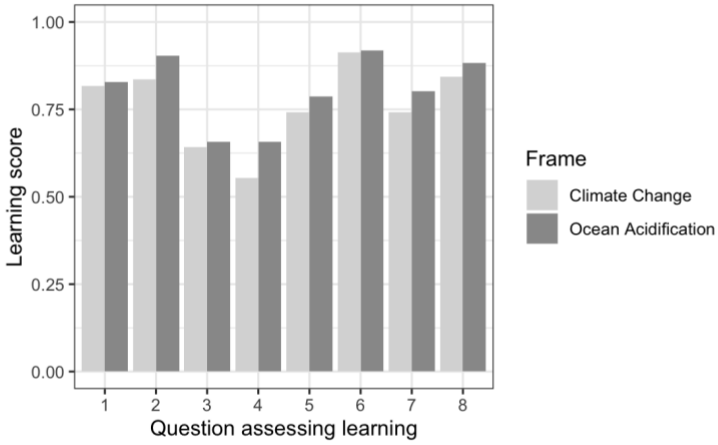

Figure 4. Learning scores per framing condition. Questions' wording is shown in Table 1.

Learning was positively associated with participants' risk perception, concern, self-efficacy, causes, and beliefs about OA (RQ5). Results of the linear mixed effect models including learning as a predictor showed significant effects of learning on risk perception (F(1, 292) = 8.49, p < .01, η^2_p = .03, 90% CI [.01,.07]); concern about the ocean (F(1, 255) = 16.49, p < .001, η^2_p = .06, 90% CI [.06,.11]), self-efficacy towards science (F(1, 292) = 6.68, p = .010, η^2_p = .02, 90% CI [.00,.06]), causes of OA (estimate = 2.37, p = 0.006, std. coef = 0.53, 95% CI [0.15, 0.91]), and beliefs about OA (F(1, 292) = 27.15, p < .001, η^2_p = .09, 90% CI [.04,.14]). No direct effects of learning were found on climate change behavior (χ2(1) = 0.587, p = 0.444 , std. coef = 0.15, 95% CI [-0.23, 0.54]), presence (F(1, 244) = 2.05, p = .154, η^2_p < .01, 90% CI [.00,.04]), and trust (F(1, 259) = 3.28, p = .071, η^2_p = .01, 90% CI [.00,.04]).

Learning about OA indirectly influenced climate change behavior via risk perception (RQ6). To test van Valkengoed and Steg's (2019) suggestion that learning would indirectly influence behavior via risk perception, we ran a causal mediation analysis including behavior as an outcome, learning as a predictor, risk perception as a mediator, and political view, English proficiency, and education as covariates. Results showed that risk perception fully mediated the relationship between learning and behavior (*ACME* = .10, p = .002, 95%CI [.03, .19]; *ADE* = .12, p = .378, 95%CI [-.13, .36], *Total Effect* = .219, p = .104, 95% CI [-.04, .45]).

Trust in the information received in the VR experience indirectly influenced behavior via risk perception. To test van Valkengoed and Steg's (2019) that risk perception would mediate the relationship between trust and behavior, we ran a causal mediation analysis, including behavior as an outcome, trust in the information as a predictor, and risk perception as a mediator. Political views, English proficiency, and education were included as covariates. Results showed that risk perception fully mediated the relationship between trust and behavior (*ACME* = .03, *p* = .016, 95%CI [.01, .06]; *ADE* = .06, *p* = .056, 95%CI [-.01, .13], *Total Effect* = .096, *p* = .004, 95% CI [.03, .16]).

When experiencing VR seated, head yaw positively affected learning, while hands' pitch and yaw hindered learning. The regressions predicting learning from the head and hand movements in seated conditions showed positive effects on learning of head yaw ($F(1,88) = 5.10$, $p = 0.026$, $\eta^2_p = 0.05$, 90% CI [0.00, 0.15]), and negative effects of hand's pitch and yaw (pitch: $F(1,88) = 5.06$, $p = 0.027$, $\eta^2_p = 0.05$, 90% CI [0.00, 0.15]; yaw: $F(1,88) = 4.40$, $p = 0.039$, $\eta^2_p = 0.05$, 90% CI [0.00, 0.14]). No effects were found in the standing conditions (head yaw: $F(1,202) = 1.19$, $p = 0.276$ $\eta^2_p < 0.01$, 90% CI [0.00, 0.04]; hand pitch: $F(1,197 = 0.03$, $p = 0.855$, $\eta^2_p < 0.01$, 90% CI [0.00, 0.00] ; hand yaw: $F(1,197 = 0.01$, $p = 0.908$, $\eta^2_p < 0.01$, 90% CI [0.00, 0.01]).

Head translation increased self-efficacy but hindered learning. Pearson's correlation between head-translation and self-efficacy was positive ($r = 0.20$, $t(302) = 3.54$, $p < .001$), while it was negative between head-translation and learning ($r = -0.24$, $t(303) = -4.36$, $p < .001$). Two causal mediation analyses were run, the first including self-efficacy as an outcome, movement conditions as a predictor, and head translation as a mediator. The second one included the same predictor and mediators but had learning as an outcome. In both models, head translation showed a significant and full mediation effect: in the model predicting self-efficacy, it was positive (*ACME* = .232, *p* = .036; *ADE* = .128, *p* = .440; *Total effect* = .361, p < .001) and in the model predicting learning it was negative (*ACME* = -.087, *p* < .001; *ADE* = .011, *p* = .800; *Total effect* = -0.076, *p* < .001). Scatter plots showing the relationship between head translation and self-efficacy and head translation and learning are shown in Figure 5.

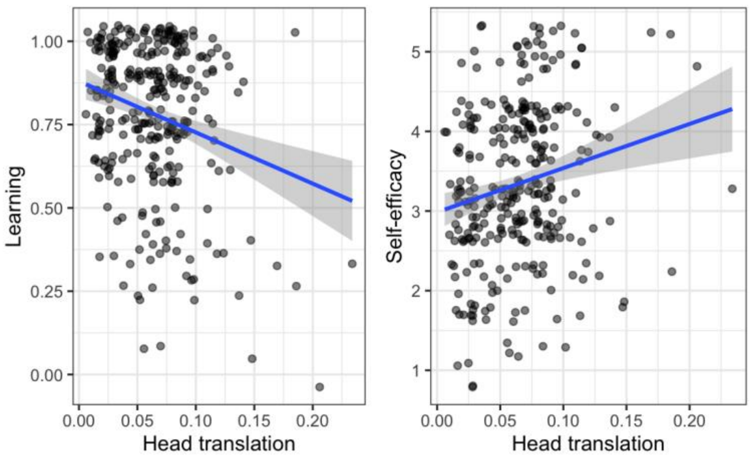

Figure 5. Visual representations of the relationships between head translation and learning and head translation and self-efficacy**.** The blue line shows a linear regression between the variables.

4. Discussion

This study investigated how VR design can influence learning and factors motivating climate change behavior. We pre-registered and tested hypotheses and research questions formulated based on the cognitive load theory of educational multimedia design, embodied cognition, human-computer interaction, climate change behavior, message framing and motivated reasoning when communicating climate change. Because using VR to investigate human behavior related to climate change is a relatively young area of research, we also ran several exploratory analyses to investigate the relationship between the factors motivating climate change behavior after a VR experience about OA, and the effects of body movement on those factors. Our main finding is that walking around during a VR experience caused a paradox, eliciting higher feelings of self-efficacy while hindering learning. Moreover, linking the experience narrative to climate change impaired learning compared to language that did not make the direct link. Exploring the relationship between knowledge and behavior, we found that learning alone was not enough to impact behavior, but this impact was mediated through risk perception. Likewise, trust in the information indirectly influenced behavior via risk perception, i.e., the more the participants trusted the message, the more they were willing to engage in climate-change behavior.

Because one of the unique features of VR is allowing users to walk around and interact with digital content, and movement and gesturing [48–50] have significant effects on learning, VR can benefit from embodied cognition compared to other media [21,28,47,54]. However, our study showed that experiencing VR seated was better for learning than walking around and that hand movement impaired learning when having a seated experience. Although the experience was designed to encourage meaningful movement, participants could have engaged in non-meaningful movements, such as walking around when not prompted to, impeding learning. This finding indicates that interactive simulations in VR may encourage interactions that are not meaningful, even if not intended to, leading to increased extraneous cognitive load and less learning [38,39]. The inconsistent findings between VR and computer monitors for conceptual learning found in the literature [45,94,95] may be driven by the influence of movements unrelated to the learning task in VR. Hence, future studies could experimentally test this hypothesis or meta-analyze previous studies, targeting the relationship between the body movements elicited by the experiences, the learning task, and learning outcomes.

Our data also showed that body movement in VR created a paradox: more walking during the experience led to less learning and higher self-efficacy. Previous studies have shown, through subjective measures, that sense of agency mediated the difference in self-efficacy in media comparison studies [22]. This study is the first to use actual movement data to investigate the relationship between movement in VR and self-efficacy. Our data confirmed previous speculations that movement in VR could be the mechanism for increasing self-efficacy [22,96]. As the human brain is constantly making predictions about the environment, a possible explanation is that as more the participants explored the VR environment, the more predictions they made, and more often the predictions were confirmed, which contributed to increasing the sense of agency and self-efficacy [55–57,97]. Moreover, our study indicates that movements in VR have a greater impact on learning and self-efficacy than adding pauses to the experience. We replicated Ahn and colleagues' findings [44], showing that adding pauses to reduce the possible cognitive load from the narrative did not influence presence or learning. We expanded this investigation by finding that content segmentation in VR had no effects on the factors motivating climate change behavior, suggesting that this could be a neutral strategy to reduce the amount of information at once in interventions heavy on content.

We also found that linking the VR narrative to "climate change", a phrase that has become politicized [80] negatively affected learning compared to a neutral framing. Connecting it to a politicized term could lead people to associate the experience to a political experience and reduce trust, which could have reduced learning. Or, perhaps, the connection of the concept of climate change to feelings of overwhelm and anxiety [98] could elicit defensive psychological processes that could impair learning [76,98,99]. Moreover, our learning questions focused on OA, not climate change. That could have facilitated recall for participants in the OA conditions. In light of Lakoff and Johnson's work [100] on metaphorical concepts and the human conceptual system, Dickinson and colleagues [76] suggest that when communicating about climate change, the message should form cognitive bridges to familiar concepts and prior experiences. In this sense, the OA framing could also have helped participants create bridges between the knowledge needed to understand the OA process. In contrast, the climate change framing may have facilitated connections to the broad concept of climate change instead of OA.

Our study also contributes to the research on political views and climate change [80,101,102], bringing empirical evidence of the relationship between political views and factors motivating behavior. Although our data show that political views did not directly influence behavior or knowledge, they influenced three factors motivating behavior indicated by van Valkengoed and Steg [14] as the most impactful ones: trust, risk perceptions, and beliefs. Participants with a liberal view reported higher trust, risk perception, and beliefs in climate change than more conservative participants, which is aligned with studies showing a positive correlation between liberal views and climate change acceptance [102–106]. Still, there was no significant difference between the degree to which conservatives and liberals engaged in climate-change behavior, which is counter to other studies indicating that Democrats (liberal) are significantly more likely to have pro-climate attitudes and behaviors [105]. Although we do not have data to test this, one possibility is that the VR experience could have positively influenced conservatives concerning climate change behavior, which would result in the observed similarities between the two groups in terms of behavior after the experience. Although this study did not investigate how political views moderate the effect of VR on climate change behaviors, a future study can explore this.

Finally, our data indicate empirical evidence to van Valkengoed and Steng's theoretical hypotheses that risk perception would mediate the relationship between knowledge and behavior and between trust and behavior [14]. Because VR can simulate future scenarios and trigger emotions, it can bring the often invisible but significant long-term climate change effects psychologically close, contributing to a better understanding of the risks of not acting on climate change. This way, VR could support climate change behavior by enhancing risk perception, and future studies should investigate this potential.

Limitations

Although this study was carefully crafted in consultation with experts in VR, psychology, climate change communication, marine biology, social sciences, and statistics, there are some limitations. First, this is a field study with multiple locations. Some locations were museums and aquariums with external noise and passersby around the VR experience. To reduce the influence of locations' variation on the results, we controlled our models for the random effects of location. Also, we used single-item measures to assess subjective measures other than learning. This decision was made after piloting the questionnaire on paper and the VR experience with the embedded questionnaire. During the pilots, participants often complained about the length of the questionnaire and the effort taken to answer them. To avoid having participants in VR for extended periods (that could cause discomfort) and increase the chance of participants answering all the questions, we followed [107] and Allen and colleagues [108] research on single-item assessment. The authors argue that single-item measures save respondents' time and can be as valid as multiple items, hence should be used when time is a constraint, for example when participants are volunteering in a museum.

5. Conclusions and Future Directions

The increase in climate change-related events and losses urges for effective and scalable interventions. Virtual reality has shown promising results in communicating climate change and enhancing pro-environmental behaviors. This study investigated how VR design can influence learning and factors motivating climate change behavior related to ocean acidification. We found that body movement and message framing affected learning and that risk perception mediated the relationship between learning and behavior. Our data showed that moving around during the VR experience increased participants' feelings of self-efficacy but hindered learning, compared to having a seated experience. Also, not connecting ocean acidification directly to climate change enhanced learning compared to a framing that explicitly made that connection. Finally, we found that learning and trust indirectly influenced climate change behavior via risk perception.

Given the complexity of learning about ocean acidification and climate change, more studies are needed to uncover the relationship between interaction in VR, learning, and climate change behavior. Future studies should explore multiple exposures and long-term effects of VR experiences on climate change learning and behaviors. They should also explore if having several VR experiences would influence unintended movement in VR, and how that would influence learning. Moreover, it is important to investigate how including segmentations that present an overview of what is being learned during the experience (as opposed to our silent segmentations) would influence learning. Finally, future studies should compare the effects of answering questions in VR with answering them on paper or on a computer on learning and subjective measures. With the fast advances in VR design and interactions, and the possibility to customize the experiences, future studies should also investigate how building personalized climate-related experiences can influence engagement and climate change behaviors.

Author Contributions: Conceptualization: A.C.M.Q., G.F., A.T.A., J.N.B. ; methodology: all authors; software: A.L.; validation: all authors; formal analysis: A.C.M.Q. and A.T.A.; investigation: all authors; resources: A.C.M.Q., G.F., J.N.B.; data curation: A.C.M.Q., A.T.A., A.L.; writing—original draft preparation: A.C.M.Q. and A.L.; writing—review and editing: all authors; visualization: A.C.M.Q.; supervision: J.N.B; project administration: A.C.M.Q., G.F., J.N.B.; funding acquisition: A.C.M.Q., G.F., J.N.B. All authors have read and agreed to the published version of the manuscript." Please turn to the CRediT taxonomy for the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

Funding: This research was funded by National Science Foundation (Award # 1907050) and Knut och Alice Wallenbergs Stiftelse (#20170440).

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board (or Ethics Committee) of Stanford University for studies involving humans.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data will be available after publication at https://osf.io/phxar.

Acknowledgments: We thank the Stanford Accelerator for Learning, Tobin J. Asher, Shawnee Baughman, Krain Chen, Aaleyah Lewis, Cairo Mo, Emily E. O'Neal, Andrew J. Pollack, Andrew L. Ying, the Museum at Prairiefire, Pacific Whale Foundation, St Joseph Academy, Boise School District (Idaho), VRKade, Marin's Community School, XR Libraries, Churchill County High School, Monterey County Free, Barberton High School, Kent Denver School, University of Southampton, Maritime Museum & Aquarium and Harvard University for their assistance in this study.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Pre-registered hypotheses, data analyses results, and conclusions.

Hypotheses	Sub hypotheses	Test statistic; significance level (uncorrected); effect size, and confidence intervals	Result	Conclusion
H1: Participants in segmented conditions will score higher for learning than participants in non-segmented conditions.		$F(1, 276) = 0.276$ $p = 0.599$ $\eta^2{}_p < 0.001$ [0.00, 0.02]	Not supported	There was no significant difference in learning between having pauses or not during the experience.
H2: Participants in non-segmented conditions will score higher for presence than participants in segmented conditions.		$F(1, 292) = 0.042$ $p = 0.837$ $\eta^2{}_p < 0.001$ [0.00, 0.01]	Not supported	Adding pauses to the experience did not significantly influence

				participants' feelings of presence.
H3: Participants in standing conditions will score higher for learning, behavior, concern, risk perception, causes, beliefs about increased carbon dioxide emissions, presence, self-efficacy and trust than participants in seated conditions.	a) learning	$F(1, 289) = 0.210$ $p = 0.647$ $\eta^2_p < 0.001$ [0.00, 0.01]	Not supported	Having a standing VR experience elicited higher feelings of presence and self-efficacy than having a seated VR experience.
	b) behavior	$\chi^2(1) = 0.857$ $p = 0.354$ Std. coef = -0.46 [-1.44, 0.51]	Not supported	
	c) concern	$F(1, 223) = 0.065$ $p = 0.798$ $\eta^2_p < 0.001$ [0.00, 0.01]	Not supported	
	d)risk perception	$F(1, 292) = 0.485$ $p = 0.487$ $\eta^2_p < 0.01$ [0.00, 0.02]	Not supported	
	e) causes	Estimate = 0.455 p = 0.347 Std. coef = 0.46 [-0.50, 1.41]	Not supported	
	f)beliefs about increased carbon dioxide emissions	$F(1, 292) = 0.003$ $p = 0.986$ $\eta^2_p < 0.001$ [0.00, 0.00]	Not supported	
	g) presence	$F(1, 292) = 4.541$ $p = 0.034$ $\eta^2_p = 0.02$ [0.00, 0.05]	Supported	
	h) self-efficacy	$F(1, 292) = 12.540$ $p < 0.001$ $\eta^2_p = 0.04$ [0.01, 0.08]	Supported	
	i) trust	$F(1, 143) = 1.632$ $p <= 0.203$ $\eta^2_p = 0.01$ [0.00, 0.06]	Not supported	
H4: Participants in female-voiced conditions will score higher for learning than participants in male-voiced conditions.		$F(1, 275) = 0.004$ $p = 0.952$ $\eta^2_p < 0.001$ [0.00, 0.00]	Not supported	The sex of the voice-over did not influence learning.
H5: Results for self-efficacy comparing female-voiced and male-voiced conditions will be gender dependent, with females scoring higher than males in female-voiced conditions and vice versa.	a) women will score higher than men for self-efficacy in female-voiced narration conditions	$F(1, 147) = 10.45$ $p = 0.001$ $\eta^2_p = 0.07$ [0.02, 0.14]	Not supported	Men scored higher for self-efficacy toward science than women, regardless of the sex of the voice-over.
	b) men will score higher than women for self-efficacy in male-voiced narration conditions	$F(1, 143) = 9.261$ $p = 0.002$ $\eta^2_p = 0.06$ [0.01, 0.13]	Supported	
H6: Participants in male-voiced conditions will score higher for trust than participants in the female-voiced conditions.		$F(1, 289) = 0.526$ $p = 0.469$ $\eta^2_p < 0.001$ [0.00, 0.02]	Not supported	The gender of the voice-over had no significant effect on how much participants trusted the information received.
H7: Participants in Climate Change framing conditions who score higher in the political spectrum (i.e., left/liberal) will score higher for learning, behavior, concern, risk perception, causes, beliefs about	a) behavior	$\chi^2(1) = 0.270$ $p = 0.869$ Std. coef = 0.04 [-0.41, 0.50]	Not supported	Participants with a tendency for a left/liberal political view scored higher for their risk perception, concern, and beliefs about OA and how much they trusted the

increased carbon dioxide emissions, and trust than participants that score lower in the political spectrum (i.e., right/conservative).				information received than participants with a right/conservative political view.
	b) concern	$F(1, 149) = 5.044$ $p = 0.026$ $\eta^2_p = 0.03$ [0.00, 0.09]	Supported	
	c)risk perception	$F(1, 150) = 22.533$ $p < 0.001$ $\eta^2_p = 0.13$ [0.06, 0.22]	Supported	
	d) causes	Estimate = 0.576 $p = 0.007$ Std. coef = 0.76 [0.21, 1.32]	Supported	
	e) beliefs	$F(1, 150) = 4.756$ $p = 0.031$ $\eta^2_p = 0.03$ [0.00, 0.09]	Supported	
	f) learning	$F(1, 146) = 0.103$ $p = 0.749$ $\eta^2_p < 0.001$ [0.00, 0.02]	Not supported	
	g) trust	$F(1, 148) = 5.453$ $p = 0.021$ $\eta^2_p = 0.04$ [0.00, 0.10]	Supported	

* We ran linear mixed-effects models to predict learning, concern, risk perception, beliefs about increased carbon dioxide emissions, presence, self-efficacy and trust. For those models, partial eta squared (η^2_p) with a 90% confidence interval (CI) was computed using Sums-of-Squares. For generalized mixed-effects models (models predicting climate change behavior) and ordinal logistic regressions (models predicting causes attributed to OA), standard coefficients were reported along with 95% CI.

References

1. Heating up Heating Up. *Nat. Clim. Chang.* **2022**, *12*, 693, doi:10.1038/s41558-022-01462-x.
2. IPCC Summary for Policymakers. In *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M.I., Huang, M., Eds.; Cambridge University Press., 2021; pp. 3–32.
3. Burger, F.A.; Terhaar, J.; Frölicher, T.L. Compound Marine Heatwaves and Ocean Acidity Extremes. *Nat. Commun.* **2022**, *13*, 4722, doi:10.1038/s41467-022-32120-7.
4. King, A.D.; Peel, J.; Ziehn, T.; Bowen, K.J.; McClelland, H.L.O.; McMichael, C.; Nicholls, Z.R.J.; Sniderman, J.M.K. Preparing for a Post-Net-Zero World. *Nat. Clim. Chang.* **2022**, doi:10.1038/s41558-022-01446-x.
5. McKinley, G.A.; Fay, A.R.; Eddebbar, Y.A.; Gloege, L.; Lovenduski, N.S. External Forcing Explains Recent Decadal Variability of the Ocean Carbon Sink. *AGU Adv.* **2020**, *1*, e2019AV000149, doi:https://doi.org/10.1029/2019AV000149.
6. Doney, S.C.; Fabry, V.J.; Feely, R.A.; Kleypas, J.A. Ocean Acidification: The Other CO2 Problem. *Ann. Rev. Mar. Sci.* **2009**, *1*, 169–192, doi:10.1146/annurev.marine.010908.163834.
7. Doney, S.C.; Busch, D.S.; Cooley, S.R.; Kroeker, K.J. The Impacts of Ocean Acidification on Marine Ecosystems and Reliant Human Communities. *Annu. Rev. Environ. Resour.* **2020**, *45*, 83–112, doi:10.1146/annurev-environ-012320-083019.
8. Goldenberg, S.U.; Nagelkerken, I.; Ferreira, C.M.; Ullah, H.; Connell, S.D. Boosted Food Web Productivity through Ocean Acidification Collapses under Warming. *Glob. Chang. Biol.* **2017**, *23*, 4177–4184, doi:https://doi.org/10.1111/gcb.13699.

9. Guest, H.; Lotze, H.K.; Wallace, D. Youth and the Sea: Ocean Literacy in Nova Scotia, Canada. *Mar. Policy* **2015**, *58*, 98–107, doi:https://doi.org/10.1016/j.marpol.2015.04.007.
10. Grothmann, T.; Patt, A. Adaptive Capacity and Human Cognition: The Process of Individual Adaptation to Climate Change. *Glob. Environ. Chang.* **2005**, *15*, 199–213, doi:https://doi.org/10.1016/j.gloenvcha.2005.01.002.
11. Kasperson, R.E.; Renn, O.; Slovic, P.; Brown, H.S.; Emel, J.; Goble, R.; Kasperson, J.X.; Ratick, S. The Social Amplification of Risk: A Conceptual Framework. *Risk Anal.* **1988**, *8*, 177–187, doi:https://doi.org/10.1111/j.1539-6924.1988.tb01168.x.
12. Lindell, M.K.; Perry, R.W. The Protective Action Decision Model: Theoretical Modifications and Additional Evidence. *Risk Anal.* **2012**, *32*, 616–632, doi:https://doi.org/10.1111/j.1539-6924.2011.01647.x.
13. Renn, O. The Social Amplification/Attenuation of Risk Framework: Application to Climate Change. *WIREs Clim. Chang.* **2011**, *2*, 154–169, doi:https://doi.org/10.1002/wcc.99.
14. van Valkengoed, A.M.; Steg, L. Meta-Analyses of Factors Motivating Climate Change Adaptation Behaviour. *Nat. Clim. Chang.* **2019**, *9*, 158–163, doi:10.1038/s41558-018-0371-y.
15. Nisa, C.F.; Bélanger, J.J.; Schumpe, B.M.; Faller, D.G. Meta-Analysis of Randomised Controlled Trials Testing Behavioural Interventions to Promote Household Action on Climate Change. *Nat. Commun.* **2019**, *10*, 4545, doi:10.1038/s41467-019-12457-2.
16. Nielsen, K.S.; Marteau, T.M.; Bauer, J.M.; Bradbury, R.B.; Broad, S.; Burgess, G.; Burgman, M.; Byerly, H.; Clayton, S.; Espelosin, D.; et al. Biodiversity Conservation as a Promising Frontier for Behavioural Science. *Nat. Hum. Behav.* **2021**, *5*, 550–556, doi:10.1038/s41562-021-01109-5.
17. Mickle, T.; Chen, B.X. Apple Starts Connecting the Dots for Its next Big Thing. *New York Times* 2022.
18. Bailenson, J.N. *Experience on Demand: What Virtual Reality Is, How It Works, and What It Can Do.*; 1st ed.; W.W. Norton & Company: New York, NY, USA, 2018; ISBN 0393253694.
19. Fauville, G.; Queiroz, A.C.M.; Bailenson, J.N. Virtual Reality as a Promising Tool to Promote Climate Change Awareness. *Technol. Heal.* **2020**, 91–108.
20. Box-Steffensmeier, J.M.; Burgess, J.; Corbetta, M.; Crawford, K.; Duflo, E.; Fogarty, L.; Gopnik, A.; Hanafi, S.; Herrero, M.; Hong, Y.; et al. The Future of Human Behaviour Research. *Nat. Hum. Behav.* **2022**, *6*, 15–24, doi:10.1038/s41562-021-01275-6.
21. Markowitz, D.M.; Laha, R.; Perone, B.P.; Pea, R.D.; Bailenson, J.N. Immersive Virtual Reality Field Trips Facilitate Learning about Climate Change. *Front. Psychol.* **2018**, *9*, 2364.
22. Queiroz, A.C.M.; Fauville, G.; Herrera, F.; Leme, M.I. da S.; Bailenson, J.N. Do Students Learn Better With Immersive Virtual Reality Videos Than Conventional Videos? A Comparison of Media Effects With Middle School Girls. *Technol. Mind, Behav.* **2022**, *3*, doi:10.1037/tmb0000082.
23. Mirauda, D.; Capece, N.; Erra, U. Sustainable Water Management: Virtual Reality Training for Open-Channel Flow Monitoring. *Sustainability* **2020**, *12*, doi:10.3390/su12030757.
24. Makransky, G.; Mayer, R.E. Benefits of Taking a Virtual Field Trip in Immersive Virtual Reality: Evidence for the Immersion Principle in Multimedia Learning. *Educ. Psychol. Rev.* **2022**, *34*, 1771–1798, doi:10.1007/s10648-022-09675-4.
25. Queiroz, A.; McGivney, E.; Liu, S.X.; Anderson, C.; Beams, B.; DeVeaux, C.; Han, E.; Miller, M.R.; Hancock, J.T.; Bailenson, J.N. Collaborative Tasks in Immersive Virtual Reality Increase Learning. In Proceedings of the Proceedings of the 16th International Conference on Computer-Supported Collaborative Learning; 2023.
26. Ahn, S.J. (Grace); Bostick, J.; Ogle, E.; Nowak, K.L.; McGillicuddy, K.T.; Bailenson, J.N. Experiencing Nature: Embodying Animals in Immersive Virtual Environments Increases Inclusion of Nature in Self and Involvement with Nature. *J. Comput. Commun.* **2016**, *21*, 399–419, doi:10.1111/jcc4.12173.
27. Nelson, K.M.; Anggraini, E.; Schlüter, A. Virtual Reality as a Tool for Environmental Conservation and Fundraising. *PLoS One* **2020**, *15*, 1–21, doi:10.1371/journal.pone.0223631.

28. Ahn, S.J. (Grace); Bailenson, J.N.; Park, D. Short- and Long-Term Effects of Embodied Experiences in Immersive Virtual Environments on Environmental Locus of Control and Behavior. *Comput. Human Behav.* **2014**, *39*, 235–245, doi:https://doi.org/10.1016/j.chb.2014.07.025.
29. Fonseca, D.; Kraus, M. A Comparison of Head-Mounted and Hand-Held Displays for 360° Videos with Focus on Attitude and Behavior Change. In Proceedings of the AcademicMindtrek 2016 - Proceedings of the 20th International Academic Mindtrek Conference; 2016; pp. 287–296.
30. Plechatá, A.; Morton, T.; Perez-Cueto, F.J.A.; Makransky, G. A Randomized Trial Testing the Effectiveness of Virtual Reality as a Tool for Pro-Environmental Dietary Change. *Sci. Rep.* **2022**, *12*, 14315, doi:10.1038/s41598-022-18241-5.
31. Sundar, S.S.; Kang, J.; Oprean, D. Being There in the Midst of the Story: How Immersive Journalism Affects Our Perceptions and Cognitions. *Cyberpsychology, Behav. Soc. Netw.* **2017**, *20*, 672–682, doi:10.1089/cyber.2017.0271.
32. Lo, S.-C.; Tsai, H.-H. Design of 3D Virtual Reality in the Metaverse for Environmental Conservation Education Based on Cognitive Theory. *Sensors* **2022**, *22*, doi:10.3390/s22218329.
33. Plechatá, A.; Morton, T.; Perez-Cueto, F.J.A.; Makransky, G. Why Just Experience the Future When You Can Change It: Virtual Reality Can Increase Pro-Environmental Food Choices Through Self-Efficacy. *Technol. Mind, Behav.* **2022**, *3*.
34. Monroe, M.C.; Plate, R.R.; Oxarart, A.; Bowers, A.; Chaves, W.A. Identifying Effective Climate Change Education Strategies: A Systematic Review of the Research. *Environ. Educ. Res.* **2019**, *25*, 791–812, doi:10.1080/13504622.2017.1360842.
35. Landrum, A.R.; Eaves, B.S.; Shafto, P. Learning to Trust and Trusting to Learn: A Theoretical Framework. *Trends Cogn. Sci.* **2015**, *19*, 109–111, doi:https://doi.org/10.1016/j.tics.2014.12.007.
36. Sweller, J. Implications of Cognitive Load Theory for Multimedia Learning. *Cambridge Handb. Multimed. Learn.* **2005**, *3*, 19–30, doi:10.1017/CBO9780511816819.003.
37. Mayer, R.E.; Colvin Clark, R. Instructional Strategies for Receptive Learning Environments. *Handb. Improv. Perform. Work. Vol. 1-3* **2009**, 298–328.
38. Clark, R.C.; Mayer, R.E. Learning by Viewing versus Learning by Doing: Evidence-Based Guidelines for Principled Learning Environments. *Perform. Improv.* **2008**, *47*, 5–13, doi:https://doi.org/10.1002/pfi.20028.
39. Mayer, R.E.; Moreno, R. Nine Ways to Reduce Cognitive Load in Multimedia Learning. *Educ. Psychol.* **2003**, *38*, 43–52, doi:10.1207/S15326985EP3801_6.
40. Nelson, B.C.; Erlandson, B.E. Managing Cognitive Load in Educational Multi-User Virtual Environments: Reflection on Design Practice. *Educ. Technol. Res. Dev.* **2008**, *56*, 619–641.
41. Parong, J.; Mayer, R.E. Learning Science in Immersive Virtual Reality. *J. Educ. Psychol.* **2018**, *110*, 785–797, doi:https://doi.org/10.1037/edu0000241.
42. Wang, Y.; Wang, F.; Mayer, R.E.; Hu, X.; Gong, S. Benefits of Prompting Students to Generate Summaries during Pauses in Segmented Multimedia Lessons. *J. Comput. Assist. Learn. n/a*, doi:https://doi.org/10.1111/jcal.12797.
43. Sanchez-Vives, M. V; Slater, M. From Presence to Consciousness through Virtual Reality. *Nat. Rev. Neurosci.* **2005**, *6*, 332.
44. Ahn, S.J. (Grace); Nowak, K.L.; Bailenson, J.N. Unintended Consequences of Spatial Presence on Learning in Virtual Reality. *Comput. Educ.* **2022**, *186*, 104532, doi:https://doi.org/10.1016/j.compedu.2022.104532.
45. Mayer, R.E.; Makransky, G.; Parong, J. The Promise and Pitfalls of Learning in Immersive Virtual Reality. *Int. J. Human–Computer Interact.* **2022**, *0*, 1–10, doi:10.1080/10447318.2022.2108563.
46. Barsalou, L.W. Grounded Cognition. *Annu. Rev. Psychol.* **2008**, *59*, 617–645, doi:10.1146/annurev.psych.59.103006.093639.
47. Glenberg, A.M. Embodiment as a Unifying Perspective for Psychology. *WIREs Cogn. Sci.* **2010**, *1*, 586–596, doi:https://doi.org/10.1002/wcs.55.
48. Goldin-Meadow, S. *Hearing Gesture*; Harvard University Press, 2003; ISBN 9780674010727.
49. Goldin-Meadow, S.; Cook, S.W.; Mitchell, Z.A. Gesturing Gives Children New Ideas About Math. *Psychol. Sci.* **2009**, *20*, 267–

272, doi:10.1111/j.1467-9280.2009.02297.x.

50. Hostetter, A.B.; Alibali, M.W. Visible Embodiment: Gestures as Simulated Action. *Psychon. Bull. Rev.* **2008**, *15*, 495–514, doi:10.3758/PBR.15.3.495.
51. Niedenthal, P.M.; Barsalou, L.W.; Winkielman, P.; Krauth-Gruber, S.; Ric, F. Embodiment in Attitudes, Social Perception, and Emotion. *Personal. Soc. Psychol. Rev.* **2005**, *9*, 184–211, doi:10.1207/s15327957pspr0903_1.
52. Stern, E. Embodied Cognition: A Grasp on Human Thinking. *Nature* **2015**, *524*, 158–159, doi:10.1038/524158a.
53. Clark, A. An Embodied Cognitive Science? *Trends Cogn. Sci.* **1999**, *3*, 345–351, doi:10.1016/S1364-6613(99)01361-3.
54. Kilteni, K.; Groten, R.; Slater, M. The Sense of Embodiment in Virtual Reality. *Presence Teleoperators Virtual Environ.* **2012**, *21*, 373–387, doi:10.1162/PRES_a_00124.
55. David, N.; Newen, A.; Vogeley, K. The "Sense of Agency" and Its Underlying Cognitive and Neural Mechanisms. *Conscious. Cogn.* **2008**, *17*, 523–534.
56. Wahlheim, C.N.; Eisenberg, M.L.; Stawarczyk, D.; Zacks, J.M. Understanding Everyday Events: Predictive-Looking Errors Drive Memory Updating. *Psychol. Sci.* **2022**, *33*, 765–781, doi:10.1177/09567976211053596.
57. Roselli, C.; Ciardo, F.; De Tommaso, D.; Wykowska, A. Human-Likeness and Attribution of Intentionality Predict Vicarious Sense of Agency over Humanoid Robot Actions. *Sci. Rep.* **2022**, *12*, 13845, doi:10.1038/s41598-022-18151-6.
58. Bandura, A. *Self-Efficacy in Changing Societies*; Cambridge university press, 1995;
59. Moser, S.C. Communicating Climate Change: History, Challenges, Process and Future Directions. *Wiley Interdiscip. Rev. Clim. Chang.* **2010**, *1*, 31–53.
60. Crowelly, C.R.; Villanoy, M.; Scheutzz, M.; Schermerhornz, P. Gendered Voice and Robot Entities: Perceptions and Reactions of Male and Female Subjects. In Proceedings of the 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems; 2009; pp. 3735–3741.
61. Ghazali, A.S.; Ham, J.; Barakova, E.I.; Markopoulos, P. Effects of Robot Facial Characteristics and Gender in Persuasive Human-Robot Interaction. *Front. Robot. AI* **2018**, *5*, 73.
62. Sandygulova, A.; O'Hare, G.M.P. Age- and Gender-Based Differences in Children's Interactions with a Gender-Matching Robot. *Int. J. Soc. Robot.* **2018**, *10*, 687–700, doi:10.1007/s12369-018-0472-9.
63. Nass, C.; Moon, Y.; Green, N. Are Machines Gender Neutral? Gender-Stereotypic Responses to Computers With Voices. *J. Appl. Soc. Psychol.* **1997**, *27*, 864–876, doi:https://doi.org/10.1111/j.1559-1816.1997.tb00275.x.
64. Lee, E.J.; Nass, C.; Brave, S. Can Computer-Generated Speech Have Gender? An Experimental Test of Gender Stereotype. In Proceedings of the CHI '00 Extended Abstracts on Human Factors in Computing Systems; Association for Computing Machinery: New York, NY, USA, 2000; pp. 289–290.
65. Nass, C.; Moon, Y. Machines and Mindlessness: Social Responses to Computers. *J. Soc. Issues* **2000**, *56*, 81–103, doi:https://doi.org/10.1111/0022-4537.00153.
66. Khashe, S.; Lucas, G.; Becerik-Gerber, B.; Gratch, J. Buildings with Persona: Towards Effective Building-Occupant Communication. *Comput. Human Behav.* **2017**, *75*, 607–618.
67. Liu, S.R. Gendered Science Communication: The Role of Speaker Gender & Pitch in Perceived Credibility and Persuasion of Climate Science, University of Pennsylvania, 2022.
68. Entman, R.M. Framing: Toward Clarification of a Fractured Paradigm. *J. Commun.* **1993**, *43*, 51–58, doi:https://doi.org/10.1111/j.1460-2466.1993.tb01304.x.
69. Nisbet, M.C. Communicating Climate Change: Why Frames Matter for Public Engagement. *Environ. Sci. Policy Sustain. Dev.* **2009**, *51*, 12–23, doi:10.3200/ENVT.51.2.12-23.
70. Boykoff, M.T. *Who Speaks for the Climate?: Making Sense of Media Reporting on Climate Change*; Cambridge University Press, 2011;

71. Morton, T.A.; Rabinovich, A.; Marshall, D.; Bretschneider, P. The Future That May (or May Not) Come: How Framing Changes Responses to Uncertainty in Climate Change Communications. *Glob. Environ. Chang.* **2011**, *21*, 103–109, doi:https://doi.org/10.1016/j.gloenvcha.2010.09.013.
72. Whitmarsh, L.; Xenias, D.; Jones, C.R. Framing Effects on Public Support for Carbon Capture and Storage. *Palgrave Commun.* **2019**, *5*, 17, doi:10.1057/s41599-019-0217-x.
73. Eslen-Ziya, H. Humour and Sarcasm: Expressions of Global Warming on Twitter. *Humanit. Soc. Sci. Commun.* **2022**, *9*, 240, doi:10.1057/s41599-022-01236-y.
74. Davis, J.J. The Effects of Message Framing on Response to Environmental Communications. *Journal. \& Mass Commun. Q.* **1995**, *72*, 285–299, doi:10.1177/107769909507200203.
75. Ahn, S.J. (Grace); Fox, J.; Dale, K.R.; Avant, J.A. Framing Virtual Experiences: Effects on Environmental Efficacy and Behavior Over Time. *Communic. Res.* **2015**, *42*, 839–863, doi:10.1177/0093650214534973.
76. Dickinson, J.L.; Crain, R.; Yalowitz, S.; Cherry, T.M. How Framing Climate Change Influences Citizen Scientists' Intentions to Do Something About It. *J. Environ. Educ.* **2013**, *44*, 145–158, doi:10.1080/00958964.2012.742032.
77. Diamond, E.; Urbanski, K. The Impact of Message Valence on Climate Change Attitudes: A Longitudinal Experiment. *Environ. Commun.* **2022**, *16*, 1046–1058, doi:10.1080/17524032.2022.2151486.
78. Bain, P.G.; Hornsey, M.J.; Bongiorno, R.; Jeffries, C. Promoting Pro-Environmental Action in Climate Change Deniers. *Nat. Clim. Chang.* **2012**, *2*, 600–603, doi:10.1038/nclimate1532.
79. Audretsch, D.B.; Feldman, M.P. R&D Spillovers and the Geography of Innovation and Production. *Am. Econ. Rev.* **1996**, *86*, 630–640.
80. Cooke, S.L.; Kim, S.C. Exploring the "Evil Twin of Global Warming": Public Understanding of Ocean Acidification in the United States. *Sci. Commun.* **2019**, *41*, 66–89, doi:10.1177/1075547018821434.
81. Kahan, D.M. Ideology, Motivated Reasoning, and Cognitive Reflection: An Experimental Study. *Judgm. Decis. Mak.* **2012**, *8*, 407–424.
82. Guilbeault, D.; Becker, J.; Centola, D. Social Learning and Partisan Bias in the Interpretation of Climate Trends. *Proc. Natl. Acad. Sci.* **2018**, *115*, 9714–9719, doi:10.1073/pnas.1722664115.
83. Google Google Sheets API Overview. Available online: https://developers.google.com/sheets/api (accessed on 10 March 2023).
84. Fauville, G.; Strang, C.; Cannady, M.A.; Chen, Y.-F. Development of the International Ocean Literacy Survey: Measuring Knowledge across the World. *Environ. Educ. Res.* **2019**, *25*, 238–263.
85. Won, A.S.; Perone, B.; Friend, M.; Bailenson, J.N. Identifying Anxiety Through Tracked Head Movements in a Virtual Classroom. *Cyberpsychology, Behav. Soc. Netw.* **2016**, *19*, 380–387, doi:10.1089/cyber.2015.0326.
86. Li, B.J.; Bailenson, J.N.; Pines, A.; Greenleaf, W.J.; Williams, L.M. A Public Database of Immersive VR Videos with Corresponding Ratings of Arousal, Valence, and Correlations between Head Movements and Self Report Measures. *Front. Psychol.* **2017**, *8*.
87. Kuznetsova, A.; Brockhoff, P.B.; Christensen, R.H.B.; others Package 'Lmertest.' *R Packag. version* **2015**, *2*, 734.
88. Lüdecke, D.; Lüdecke, M.D. Package 'SjPlot.' *R Packag. version* **2015**, *1*.
89. Fox, J.; Weisberg, S.; Adler, D.; Bates, D.; Baud-Bovy, G.; Ellison, S.; Firth, D.; Friendly, M.; Gorjanc, G.; Graves, S.; et al. Package 'Car.' *Vienna R Found. Stat. Comput.* **2012**, *16*.
90. Vatcheva, K.P.; Lee, M.; McCormick, J.B.; Rahbar, M.H. Multicollinearity in Regression Analyses Conducted in Epidemiologic Studies. *Epidemiol. (Sunnyvale, Calif.)* **2016**, *6*.
91. Ben-Shachar, M.S.; Lüdecke, D.; Makowski, D. Effectsize: Estimation of Effect Size Indices and Standardized Parameters. *J. Open Source Softw.* **2020**, *5*, 2815, doi:10.21105/joss.02815.

92. Lakens, D. Calculating and Reporting Effect Sizes to Facilitate Cumulative Science: A Practical Primer for t-Tests and ANOVAs. *Front. Psychol.* **2013**, *4*, doi:https://doi.org/10.3389/fpsyg.2013.00863.
93. Villena-Taranilla, R.; Tirado-Olivares, S.; Cózar-Gutiérrez, R.; González-Calero, J.A. Effects of Virtual Reality on Learning Outcomes in K-6 Education: A Meta-Analysis. *Educ. Res. Rev.* **2022**, *35*, 100434, doi:https://doi.org/10.1016/j.edurev.2022.100434.
94. Jensen, L.; Konradsen, F. A Review of the Use of Virtual Reality Head-Mounted Displays in Education and Training. *Educ. Inf. Technol.* **2018**, *23*, 1515–1529.
95. Queiroz, A.C.M.; Tori, R.; Moreira, N.A.; Silva Leme, M.I. da Using HMD-Based Immersive Virtual Environments in Primary/K-12 Education. *Commun. Comput. Inf. Syst.* **2018**, *840*, 1–14.
96. Makransky, G.; Petersen, G.B. The Cognitive Affective Model of Immersive Learning (CAMIL): A Theoretical Research-Based Model of Learning in Immersive Virtual Reality. *Educ. Psychol. Rev.* **2021**, *33*, 937–958, doi:10.1007/s10648-020-09586-2.
97. Heilbron, M.; Armeni, K.; Schoffelen, J.-M.; Hagoort, P.; de Lange, F.P. A Hierarchy of Linguistic Predictions during Natural Language Comprehension. *Proc. Natl. Acad. Sci.* **2022**, *119*, e2201968119, doi:10.1073/pnas.2201968119.
98. Dickinson, J.L. The People Paradox: Self-Esteem Striving, Immortality Ideologies, and Human Response to Climate Change. *Ecol. Soc.* **2009**, *14*, 34.
99. Pyszczynski, T.; Greenberg, J.; Solomon, S. A Dual-Process Model of Defense against Conscious and Unconscious Death-Related Thoughts: An Extension of Terror Management Theory. *Psychol. Rev.* 1999, *106*, 835–845.
100. Lakoff, G.; Johnson, M. The Metaphorical Structure of the Human Conceptual System. *Cogn. Sci.* **1980**, *4*, 195–208.
101. Krange, O.; Kaltenborn, B.P.; Hultman, M. "Don't Confuse Me with Facts"—How Right Wing Populism Affects Trust in Agencies Advocating Anthropogenic Climate Change as a Reality. *Humanit. Soc. Sci. Commun.* **2021**, *8*, 255, doi:10.1057/s41599-021-00930-7.
102. Sparkman, G.; Geiger, N.; Weber, E.U. Americans Experience a False Social Reality by Underestimating Popular Climate Policy Support by Nearly Half. *Nat. Commun.* **2022**, *13*, 4779, doi:10.1038/s41467-022-32412-y.
103. Abeles, A.T.; Howe, L.C.; Krosnick, J.A.; MacInnis, B. Perception of Public Opinion on Global Warming and the Role of Opinion Deviance. *J. Environ. Psychol.* **2019**, *63*, 118–129, doi:https://doi.org/10.1016/j.jenvp.2019.04.001.
104. Ehret, P.J.; Boven, L. Van; Sherman, D.K. Partisan Barriers to Bipartisanship: Understanding Climate Policy Polarization. *Soc. Psychol. Personal. Sci.* **2018**, *9*, 308–318, doi:10.1177/1948550618758709.
105. McCright, A.M. Political Orientation Moderates Americans' Beliefs and Concern about Climate Change. *Clim. Change* **2011**, *104*, 243–253.
106. McCright, A.M.; Dunlap, R.E. The Politicization of Climate Change and Polarization in the American Public's Views of Global Warming, 2001–2010. *Sociol. Q.* **2011**, *52*, 155–194, doi:10.1111/j.1533-8525.2011.01198.x.
107. Bergkvist, L. Appropriate Use of Single-Item Measures Is Here to Stay. *Mark. Lett.* **2015**, *26*, 245–255.
108. Allen, M.S.; Iliescu, D.; Greiff, S. Single Item Measures in Psychological Science: A Call to Action. **2022**.