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RESEARCH ARTICLE

Using virtual simulations of future extreme weather events to communicate climate change risk

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Abstract

Virtual simulations of future extreme weather events may prove an effective vehicle for climate change risk communication. To test this, we created a 3D virtual simulation of a future tropical cyclone amplified by climate change. Using an experimental framework, we isolated the effect of our simulation on risk perceptions and individual mitigation behaviour for a representative sample ($n = 1507$) of the general public in Hong Kong. We find that exposure to our simulation is systematically associated with a relatively small decrease in risk perceptions and individual mitigation behaviour. We suggest that this is likely due to climate change scepticism, motivation crowding, geographical and temporal distance, high-risk thresholds, feelings of hopelessness, and concerns surrounding the immersiveness of the virtual simulation.

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Introduction

A number of studies hypothesise a process where experiencing an extreme weather event can reduce the psychological distance of climate change and increase risk perceptions of climate change, which in turn drives individual behavioural change through a negative feedback loop [1–6]. Evidence in the literature is mixed, with some studies suggesting a positive association between experiencing an extreme weather event and increased risk perceptions of climate change [5,7–13] and other studies finding no systematic evidence of an association [14–20]. Isolating the effect of experiencing an extreme weather event on climate change risk perceptions and behavioural change is challenging as individuals are unable to be randomly assigned to experience extreme weather events. This means that studies are largely dependent on methodological approaches that examine how risk perceptions and behaviour differ between

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individuals exposed to a given extreme weather event and individuals who were not exposed to the event. As extreme weather events tend to be concentrated geographically, this approach is subject to systematic bias [4,21,22].

At the same time, an emerging body of literature examines the potential for visualisation as a risk communication tool that can reduce the psychological distance between individuals and the impacts of climate change [23,24]. For example, studies have visualised the impacts of climate change using 2D interactive hazard maps [25–27], 3D maps and simulations [28,29], serious games [30–32], and augmented reality and virtual reality experiences [33–37].

We combined advancements in the use of visualisation to communicate climate change risks with an experimental framework that obviates the methodological issue of randomisation to test whether virtual simulations of future extreme weather events can communicate climate change risk to the general public in Hong Kong. Specifically, we randomly assigned individuals to a treatment consisting of a virtual simulation of a future extreme weather event that is amplified by climate change. We measured climate change risk perceptions using verified index measures [38,39] and generated observable individual mitigation behaviour using a modified dictator game [40–42]. We analysed the data generated by our experiment using censored regression analysis and generalised structural equation modelling to identify the mediated treatment effect.

Methods

Study site

We selected Hong Kong as our study site for two reasons. First, like many coastal cities in Asia, Hong Kong is at risk from the impacts of anthropogenic climate change. These include, among others, a rising sea-level, more intense tropical cyclones (known regionally as 'typhoons'), torrential rainfall, and prolonged heatwaves [43]. While the risks facing Hong Kong are very real, the public tends to possess relatively low risk perceptions of climate change [44,45]. Second, Hong Kong braces for typhoon season every year, especially between June and September. While Hong Kong's advanced early-warning systems and typhoon defences are presently robust, we can expect future typhoons to pose a far greater risk to Hong Kong due to climate change through three primary channels. First, the sea-level is expected to rise significantly before the turn of the century [46] making Hong Kong significantly more exposed to storm surges associated with typhoons [47]. Second, rising ocean temperatures mean that we expect the rainfall rate associated with a typhoon to increase by around 14% thereby increasing the risk of flooding [48]. Third, it is likely that due to rising ocean temperatures, the intensity of typhoons will increase [48,49].

Virtual simulation of a future extreme weather event

To create our virtual simulation, we modelled a synthetic typhoon that approximates a near worst-case scenario for Hong Kong while increasing the sea-level by 1.5 metres to represent the future effects of climate change [50]. Our synthetic typhoon is based on Super Typhoon Mangkhut, which impacted the Pearl River Delta (PRD) region in 2018. Typhoon track, intensity and tidal timing have a strong correlation with surge heights and taken together, create unfavourable conditions. Typhoon Mangkhut moved towards the PRD coasts following a north-westerly track direction–one of the most common tracks in the western North Pacific. It made landfall around 160km west of Hong Kong. We shifted the track for our synthetic typhoon 100km northward from that of Mangkhut placing Hong Kong within the most dangerous quadrant of the typhoon (S1 Fig). Super Typhoon Mangkhut maintained its peak intensity of around 250km/h until it battered Cagayan, Philippines at 2:00 UTC+8 on 15 September

2018 and its intensity was maintained at around 175km/h until it made landfall in Guangdong province, China. To consider a near worst-case scenario, we maintained the intensity of our synthetic typhoon at around 250km/h for both its pre-landfall and landfall hours (S2 Fig). The destructiveness of Super Typhoon Mangkhut in Hong Kong was mitigated largely due to neap tide. For our synthetic typhoon, we selected an extreme high tide level using the OSU TPXO-atlas8 tide model [51] and assumed its consistence with the approaching synthetic typhoon (S3 Fig) [52].

We used the tide-surge numerical model SCHISM [53] for the South China Sea region to resolve surge and inundation processes with unstructured meshes. We used the 30 arc-second General Bathymetric Chart of the Oceans (GEBCO) to interpolate mesh nodes, as well as a range of high-resolution datasets, including: 1 arc-second Shuttle Radar Topography Mission (STRM) [54] data for the Pearl River Estuary, 5m-grid Digital Terrain Model (DTM) data from the Hong Kong Lands Department, 500m resolution digital bathymetry data from the Hong Kong Hydrographic Office, and nautical charts with scales ranging from 1:5000 to 1:250,000 from the Navigation Guarantee Department of the Chinese Navy. We simulated sea surface levels and the velocity fields associated with storm surges and tidal currents using Yang et al.'s [55] wind-tide-surge numerical modelling package, which resolves the meteorological fields associated with typhoons through parametric vortex models [56,57] and through hydrodynamics using SCHISM. To do so, we updated the model grid to include potential inundation areas in Hong Kong. These potential inundation areas were calculated using 50-m isolines (referring to mean sea-level) from 5m resolution Digital Terrain Model data (S4 Fig). Our computational domain is illustrated in S5 Fig. The computation of inundation processes considered tide-surge interaction but the effect of waves was not accounted for in the modelling simulation. The maximum inundation depths under the 1.5m SLR scenario are shown in S6 Fig. We validated our model by simulating both Super Typhoon Hato (2017) and Super Typhoon Mangkhut (2018) (see S7 and S8 Figs) and comparing our modelled wind and pressure fields with Yang et al. [55].

We used the data generated from our modelling to create a virtual simulation that uses the inundation data to hydrodynamically model and visualise the storm surge flowing into urban Hong Kong. To do so, we used Autodesk 3ds Max 2021 and Chaos Group's Vray and Phoenix systems to render and simulate our model. Rendering was completed using the render farm system AWS Thinkbox Deadline. Due to its widespread recognisability, we selected arguably the most iconic area in Hong Kong as the focus of our simulation: Central. Central is Hong Kong's central business district and is a major retail and entertainment hub. The area is home to the iconic Star Ferry Terminal, the General Post Office (a colonial-era landmark building) and the Hong Kong Observation Wheel, among other landmarks. Our simulation took the form of a 3D cinematic animation that lasted for one minute and nineteen seconds and was optimised for viewing on mobile phones, tablets, and personal computers. We populated our simulation with vehicles to lend a sense of scale, and we selected a number of cinematic angles to engage participants from relatable perspectives (see S9 Fig).

Experimental design and protocol

We considered an online experiment to be an efficient research design to test whether visualisations of future extreme weather events can be an effective vehicle for climate change risk communication [58,59]. We worked with YouGov Hong Kong to enumerate a sample that can be considered broadly representative of Hong Kong's adult population. YouGov Hong Kong adopt a random stratified sampling strategy weighted on age and sex to approximate the population of Hong Kong. YouGov Hong Kong are the leading survey operators in the territory and their panel consists of around 50,000 individuals. We enumerated our experiment in both English and Traditional Chinese. Our usable sample consisted of 1,507 individuals (see S1 Table for summary statistics). We randomly assigned all individuals into treatment ($n = 753$) and control groups ($n = 754$). For both our treatment and control groups, we measured risk perceptions of climate change [38] and used a modified dictator game to generate observable data on individual mitigation behaviour [40–42,60] (see S1 Text for the experimental protocol).

Our experiment consisted of the following stages. First, to ensure that participants had a baseline knowledge of climate change and to control for experimenter demand effects, all participants read an introductory text of one short paragraph explaining the basics of climate change in Hong Kong and its expected impacts with a focus on typhoons. Participants further read a second short paragraph that outlined potential ways of mitigating climate change and its impact in Hong Kong. This paragraph was included to reduce the feeling of anxiety or hopelessness that participants may have felt after being presented with the potential impacts of climate change, which may have led to participants disengaging with the experiment [42,61–64].

In the second stage of the experiment, all participants were presented with a set of questions to be answered on a 1–10 scalesee S2 Table. The survey questions were based on van der Linden's [38] Climate Change Risk Perception Model (CCRPM) and included questions on climate change knowledge, personal experience with typhoons, social norms and value orientations, and social demographics [40,42,65]. Next, participants in the treatment group were instructed that they were to experience a virtual simulation of the impacts of a future typhoon projected to hit Hong Kong sometime between 2050 to 2100. We selected this time-period in-line with sea-level rise projections for Hong Kong [50]. Participants in the treatment group were presented with our virtual simulation treatment. To ensure that all participants watched the simulation in its entirety, the option to continue with the experiment was only made available once the simulation had finished. Participants in the control group did not engage with the simulation.

Next, participants in both the control and treatment groups were presented with eight questions (on a 1–10 scale) designed to capture risk perceptions of climate change that were used to create a holistic risk-index [38]. Participants proceeded to play a modified dictator game to generate observable behavioural data on climate change mitigation [40,42,60]. Dictator games are two-player games where one-player ('the dictator') is given an endowment and must decide how much of that endowment to keep for themselves, and how much to give to the second player. Following Ibanez et al. [41] and Shrum [42], we modified the dictator game so that the second player was a real-world Hong Kong-based organisation that supports climate change mitigation activities through offsetting carbon emissions. The organisation we selected was CLP Power Hong Kong Limited, who run arguably the most developed carbon credit scheme in Hong Kong.

Before playing the dictator game, participants were given a text instruction detailing that the average Hong Kong resident generates around six tonnes of carbon emissions per year. Participants were told that one way to reduce the impact of climate change is to decarbonise and achieve net zero emissions and that this can be done by purchasing carbon credits to offset their own individual carbon emissions. Individuals were then given a stylised, worked example, where they were told that by purchasing HK$500 (US$65) of carbon offsets per year, they could offset their carbon emissions for a year (six tonnes). Pilot testing of our protocol found that most individuals were unfamiliar with the concept of offsetting carbon emissions. We therefore considered the information provided and the personalisation of the offsetting exercise necessary to familiarise individuals with the concept of carbon offsetting, and to give a sense of monetary scale. We note that this introduced additional complexity into individual motivations and that there is a possibility that individual mitigation behaviour is affected by current environmental behaviour (e.g. a low or high carbon footprint).

Following Shrum [42], we informed participants that as a further token of appreciation for participating in our study, they were to have the chance to win a cash voucher worth HK$500 (US$65). We made clear that this was in addition to the remuneration participants received for participating in the experiment as set by YouGov Hong Kong. Participants were told that if they were successful in winning the cash voucher they were free to keep the entire amount or to contribute some or all of it to offset their carbon emissions. They were told that any amount that they chose to contribute to offsetting carbon emissions would be used to purchase carbon credits through a verifiable scheme run by CLP Power Hong Kong Limited. Participants chose among 51 options (in increments of HK$10) that divided the HK$500 between what the participant chose to keep and what they chose to donate to offset emissions. After completing the modified dictator game, participants in the treatment group were asked two questions concerning their motivations and sentiments underlying the experiment to verify the internal validity of our experiment [66]. Specifically, participants were asked whether the virtual simulation had increased their risk perceptions of climate change and to explain how.

Ethics statement

Formal written consent was obtained from all participants who participated in the experiment and ethical approval for our experiment was obtained from the Human Research Ethics Committee at the University of Hong Kong (Ref: EA200187).

Estimation strategy

We are interested in isolating the treatment effect of experiencing a virtual simulation of a future extreme weather event on risk perceptions of climate change. To do so, we constructed a 0–10 scaled index measure of climate change risk perceptions [38]. We estimated the treatment effect of our virtual simulation on risk perceptions in two ways. First, we ran a two-sample Wilcoxon (Mann-Whitney) rank sum test. Second, we estimated the treatment effect of our virtual simulation on risk perceptions using a censored regression model of the following form:

$$\rho_i = \alpha_0 + \zeta d_i^{treat} + \beta \Phi_i + \varepsilon_{i,d} \tag{1}$$

where ρ_i represents individual $i's$ risk perceptions of climate change, α_0 is the model intercept, d_i^{treat} is a dummy variable that is set to 1 if individual i is in the treatment group, $\Phi_{i,t}$ represents a vector of control variables for individual i and β denotes their respective coefficients. Our vector of control variables includes demographic, cognitive, experiential, and socio-cultural variables (see S2 Table). The coefficient ζ captures the treatment effect. $\varepsilon_{i,d}$ is our error term and is clustered at the regional level. We selected a censored regression model to account for ceiling effects due to upper-censoring at 10 in our risk index measure (see S10 Fig).

Theoretically, we expect experiences with extreme weather events to affect mitigation behaviour through changes in risk perceptions [1–6]. To test for evidence of this process, we estimated the following generalised structural equation model:

$$\rho_i = \alpha_0 + \beta_1 \tau_i + X_i' \Phi + \varepsilon_{\rho_i} \tag{2}$$

$$\gamma_i = \alpha_1 + \lambda_1 \rho_i + \lambda_2 \tau_i + \lambda_3 \tau_i \rho_i + \varepsilon_{\gamma_i} \tag{3}$$

where ρ_i represents risk perceptions of climate change for individual i and β_1 represents the effect of individual i being exposed to the treatment, τ_i, and $X_i'\Phi$ represents our vector of control variables. γ_i represents observed individual mitigation behaviour for individual i, and λ_1 captures the mediating effect of ρ_i on γ_i. λ_2 captures the direct effect of τ_i on γ_i, λ_3 captures the interaction between τ_i and ρ_i, and ε_{ρ_i} and ε_{γ_i} represent regionally clustered error terms for Eqs (2) and (3), respectively. To account for ceiling effects of our mediating variable, we estimated a Tobit model with censored Gaussian outcomes.

Results

We estimated the treatment effect of our virtual simulation on risk perception using a two-sample Wilcoxon (Mann-Whitney) rank sum test and found a statistically significant difference between our treatment and control groups at the 5% significance level ($p = 0.047$). We continued our analysis by estimating a censored regression model. Table 1 presents our estimations of the treatment effect of our virtual simulation on risk perceptions (S3 Table presents estimations for our full list of covariates). In column 1, we include only our treatment and find that experiencing the virtual simulation is associated with lower risk perceptions at the 5% significance level ($p = 0.024$). In column 2, we include socio-demographic controls and now find our results to be statistically significant at the 1% significance level ($p = 0.005$) with a coefficient of -0.135. In column 3, we include our experiential controls and continue to find our results to be highly statistically significant ($p = 0.009$). We include our cognitive controls in column 4 and find our results to be statistically significant at the 5% level ($p = 0.032$). In column 5, our preferred specification, we further include our socio-cultural controls and find that treated individuals are associated with a 0.115 expected decrease in climate change risk perceptions at the 5% significance level ($p = 0.032$).

Next, we tested for the presence of a mediated treatment effect where exposure to our virtual simulation affects individual mitigation behaviour through changes in risk perceptions. Table 2 presents our generalised structural equation estimations. In column 1, we find a negative mediated effect that is statistically significant at the 1% level with a coefficient of -1.795 ($p = 0.003$). In columns 2–5, we systematically include our socio-demographic, experiential, cognitive and socio-cultural controls and continue to find a negative mediated effect, albeit at the 10% significance level ($p = 0.072$; $p = 0.065$; $p = 0.060$; $p = 0.059$).

To better contextualise our findings, we asked individuals (see S1 Text) in the treatment group two questions concerning their motivations and sentiments underlying the experiment. Specifically, participants were asked whether the virtual simulation affected their risk

Table 1. Risk perceptions of climate change.

	(1)	(2)	(3)	(4)	(5)
Treatment effect	-0.124**	-0.135***	-0.136***	-0.133**	-0.115**
	(0.055)	(0.049)	(0.052)	(0.062)	(0.054)
Socio-demographic controls	No	Yes	Yes	Yes	Yes
Experiential controls	No	No	Yes	Yes	Yes
Cognitive controls	No	No	No	Yes	Yes
Socio-cultural controls	No	No	No	No	Yes
Log pseudolikelihood	-2649.238	-2640.702	-2629.454	-2610.539	-2397.096
N	1507	1507	1507	1507	1507

Note: Standard errors are in parentheses and are clustered at the regional level.

$^{*}p<0.10$

$^{**}p<0.05$,$^{***}p<0.01$.

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Table 2. Mediated treatment effects.

	(1)	(2)	(3)	(4)	(5)
Mediated treatment effect	-1.707***	-1.822*	-1.781*	-2.072*	-1.745*
	(0.658)	(1.105)	(1.057)	(1.207)	(1.011)
Socio-demographic controls	No	Yes	No	Yes	No
Experiential controls	No	Yes	No	Yes	No
Cognitive controls	No	Yes	No	Yes	No
Socio-cultural controls	No	Yes	No	Yes	No
Log pseudolikelihood	-12553.998	-12549.478	-12549.143	-12539.203	-12533.625
N	1507	1507	1507	1507	1507

Note: We follow the suggestion made by Rucker et al. [67] that for studies focused on understanding mediated effects proposed by theory, the focus should be on testing for the mediation effect rather than placing undue emphasis on the direct effect. For all specifications of our estimated model, we do not find a statistically significant direct effect between our treatment and our measure of mitigation behaviour. Standard errors are in parentheses and are clustered at the regional level.

*$p<0.10$

$p<0.05$,*$p<0.01$.

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perceptions of climate change (yes/no) and to explain how (open-ended question). One hundred and eighty-seven individuals elected to provide an open-ended explanation as to why the virtual simulation had decreased their risk perceptions of climate change.

One hundred and ten of the explanations given referred to one of the four dimensions of psychological distance to climate change: hypothetical, spatial, temporal, and social [68,69]. Starting with hypothetical distance, thirty-nine individuals referenced reasons to do with climate sceptical viewpoints, such as the belief that anthropogenic climate change is not happening and that the simulated storm surges are not going to occur. A further twenty-four individuals referred to temporal distance by stating that they found the impacts of climate change to be too far in the future relative to here-and-now issues. Spatial distance was cited by three individuals who stated that the visualisation had no effect as it only depicted one area of Hong Kong, and that they lived in more mountainous areas of the territory. Forty-seven individuals mentioned reasons to do with the social distance of climate change. These include twenty individuals who stated that they were helpless to do anything, eleven individuals who said that climate change is not their problem, thirteen individuals who stated that the storm surge visualised in the simulation was not sufficiently destructive as to worry them, and three individuals who said that they were aware of the effects of climate change and had already been making conscious pro-environmental decisions in their lives. This is consistent with motivation crowding theory and suggests that our simulation (an external intervention) may have potentially crowded out the intrinsic motivation of individuals who already made pro-environmental decisions [70]. Notably, seventy-four individuals had issues with the virtual simulation itself. These centred around the level of realism of the simulation, particularly the lack of a first-person perspective, the absence of wind-related damage, and the fact that the simulation was not populated by people.

Discussion

Our findings contribute to the literature and to climate change risk communication policy in two ways. First, we provide systematic evidence on the use of virtual simulations of future extreme weather events as an availability heuristic to communicate climate change risks to the public. We find that experiencing a 3D virtual simulation of a future extreme weather event amplified by climate change was systematically associated with a decrease in risk perceptions of climate change for our representative sample of Hong Kong's population. Self-reported explanations suggest that this is likely due to climate change scepticism, motivation crowding, geographical and temporal distance, high-risk thresholds, feelings of hopelessness, and concerns surrounding the immersiveness of the virtual simulation. These explanations suggest that exposure to our virtual simulation did not decrease the psychological distance of climate change for a substantial number of individuals in our treatment group.

While many of these reasons are deep-seated and will likely require a multi-pronged and comprehensive engagement strategy, we can engage with concerns surrounding the immersiveness of the simulation. In our present study, we used a 3D visualisation of a future extreme weather event amplified by the impacts of climate change. We consider examining the potential of such 3D visualisations as a climate change risk communication vehicle to be important given its relatively low-cost of production and high scalability. This is as 3D visualisations can be optimised across a range of individual and public platforms (e.g. mobile phones, tablets, computers, televisions, digital billboards) to reach a broad segment of the general population. At the same time, such 3D visualisations are inherently limited in their ability to provide individuals with an interactive and/or immersive experience. It is plausible that more interactive and immersive approaches may be more effective in reducing the psychological distance of climate change. These include, for example, the co-production and co-development of interactive 3D visualisations [23,71] and virtual reality experiences [72]. Interactive and/or more immersive approaches to visualisation are, however, likely to be both more costly and difficult to scale-up due to the need for contextualisation and specialist equipment.

Second, our experimental framework allowed us to obviate some of the issues of randomisation and attribution and to test for the existence of a negative feedback loop where changes in risk perceptions may drive individual behavioural change [1–6]. We find only relatively weak statistical evidence for a mediating effect on individual climate change mitigation behaviour suggesting that experiential processing may not translate into effective behavioural change. Our findings are broadly consistent with Ma et al. [45], who find some evidence of maladaptation practices among individuals in Hong Kong with relatively higher risk perceptions of climate change, and with Bradley et al. [39] and Lieske [73], who suggest that behavioural change is dependent on perceptions of response efficacy, among other factors. Notwithstanding the strengths of our experimental research design, we are cognisant that our findings present a snapshot of a measure of behavioural change determined in a controlled environment [66].

Conclusions

We used an experimental framework to test whether a 3D virtual simulation of a future extreme weather event amplified by climate change affects individual measures of risk perception and mitigation behaviour in Hong Kong, a major coastal city in Asia. Our findings suggest that, on average, exposure to our simulation led to a decrease in risk perceptions of climate change and had a negative mediated effect on our measure of individual mitigation behaviour. While our findings raise a fundamental cautionary issue on the use of 3D visualisations to communicate risk to the general public, we suggest that interactive and/or immersive experiences may prove a more effective vehicle for climate change risk communication albeit to a more limited audience.

Supporting information

S1 Fig. Tracks for Typhoon Mangkhut and synthetic typhoon.
(PNG)

S2 Fig. Comparison of maximum wind speeds calculated from parametric vortex models: (a) Typhoon Mangkhut and (b) Synthetic typhoon.
(PNG)

S3 Fig. Comparison of time series of simulated astronomical tidal levels (in present sea level) for Typhoon Mankghut and the synthetic typhoon (panel a) (extracted from OSU TPXO-atlas8 tide model) at Quarry Bay station (panel b).
(PNG)

S4 Fig. Planar view of model grids for (a) Hong Kong and (b) Victoria Harbour.
(PNG)

S5 Fig. Computational domain.
(PNG)

S6 Fig. Maximum inundation depths (limited to focused areas) associated with the synthetic typhoon under 1.5m SLR scenario.
(PNG)

S7 Fig. Comparison between simulated storm tide and observational data during Typhoon Hato (2017).
(PNG)

S8 Fig. Comparison between simulated storm tide and observational data during Typhoon Mangkhut (2018).
(PNG)

S9 Fig. Aerial still images from the virtual simulation of storm surges inducted by a future typhoon in Hong Kong.
(PNG)

S10 Fig. Frequency histogram S1 Table. Summary statistics by group.
(PNG)

S1 Table. Summary statistics by group.
(DOCX)

S2 Table. Data glossary.
(DOCX)

S3 Table. Risk perceptions of climate change (full table).
(DOCX)

S1 Text. Experimental protocol.
(DOCX)

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