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Contextualizing cross-national patterns in household climate change adaptation

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Understanding social and behavioural drivers and constraints of household adaptation is essential to effectively address increasing climate-induced risks. Factors shaping household adaptation are commonly treated as universal, despite an emerging understanding that adaptations are shaped by social, institutional and cultural contexts. Using original surveys in the United States, China, Indonesia and the Netherlands ($N = 3{,}789$), we explore variations in factors shaping households' adaptations to flooding, the costliest hazard worldwide. We find that social influence, worry, climate change beliefs, self-efficacy and perceived costs exhibit universal effects on household adaptations, despite countries' differences. Disparities occur in the effects of response efficacy, flood experience, beliefs in governmental actions, demographics and media, which we attribute to specific cultural or institutional characteristics. Climate adaptation policies can leverage the revealed similarities when extrapolating best practices across countries yet should exercise caution, as context-specific socio-behavioural drivers may discourage or even reverse household adaptation motivation.

Worldwide, escalating climate-induced hazards inflate economic damages[1], undermine livelihoods[2] and force migration[3]. The approaching new climate reality calls for urgent and ambitious adaptation at all levels—from government-led actions to household climate change adaptation behaviour[4,5]. Understanding how and why households adapt is critical for diminishing adaptation deficits and overcoming socially constructed adaptation limits[6], for fostering societal resilience[7] and for risk communication[8]. Recent research on households' adaptation behaviour in response to climate-induced hazards provides valuable insights into factors shaping individual motivations to adapt[9,10]. Growing empirical evidence indicates that perceptions, experience and self-efficacy could facilitate or inhibit households' adaptation to hazards[11,12].

Flooding is the most widespread and costliest climate-induced hazard worldwide[13]. Previous work has advanced our understanding of the empirical drivers of household flood adaptation but has primarily focused on single countries, with rare exceptions that utilize non-synchronous and non-identical surveys[14,15]. Furthermore, while climate change disproportionately impacts Global South countries, most surveys on households' flood adaptation are conducted on the Global North[16]. Yet, adaptation is locally shaped, and social, institutional and cultural factors probably affect individual adaptation behaviour[6,11,17,18]. In exploring these influences, past work has faced data limitations[11,16], with the result that household adaptation and its drivers and constraints are often discussed uniformly across diverse contexts.

Household adaptation involves different actions, ranging from seeking information to hazard-proofing one's property. Previous studies suggest that households' adaptation behaviours that vary in effort and costs could trigger different decision pathways[12,19]. Yet, research that specifically tests to what extent the drivers of different adaptations vary is notably missing. Extrapolating a universal theoretical and empirical understanding of household adaptation behaviour in diverse and understudied contexts therefore remains a key challenge in the field of climate adaptation[11,20].

To address this gap, we question to what extent commonly theorized factors of household adaptation have analogous effects across different contexts and across adaptation types that require varying degrees of implementation efforts. To gather sufficient data to answer these research questions, in March–April 2020 we conducted identical household surveys ($N = 3{,}789$) in four countries: the United States, China, Indonesia and the Netherlands. We focus on coastal urban areas, which are vulnerable to flash, river and coastal floods and to sea level rise (see Supplementary Table 2 for the specific survey location details)[21]. The four countries represent unique social, institutional, cultural and geographic contexts. The United States and the Netherlands are two Global North nations where theories of behaviour under risk were developed and advanced[10,22], and flood surveys are repeatedly administered[16]. China and Indonesia are two Global South nations where prior surveys on factors motivating households' flood adaptation behaviour are limited. All four, however, are front-runners in escalating flooding risk[21] yet vary in the frequency of flood experiences, from nearly annual (Indonesia) to once in a lifetime (the Netherlands). The four cases differ culturally and in the role governments take in adapting to climate-induced floods (stronger centralized protection in the Netherlands and China versus more individual responsibility in Indonesia and the United States).

To measure adaptation intention, we examine 18 household-level actions (the details are provided in the Methods). Drawing on prior findings on the differences in adaptation motivation towards flooding based on the type of measures and potential synergies[12,19], we classify our 18 measures into two groups (supported by confirmatory factor analysis; Supplementary Table 6). High-effort measures (8) involve structural, usually irreversible modifications to one's home, and low-effort measures (10) comprise less intensive non-permanent protection and communication actions. For both groups, we estimate the proportion of intended actions from the remaining actions (actions not yet undertaken) per case study. Adaptation intention for these two groups is the focus of our analysis ('Dependent variables' in Methods).

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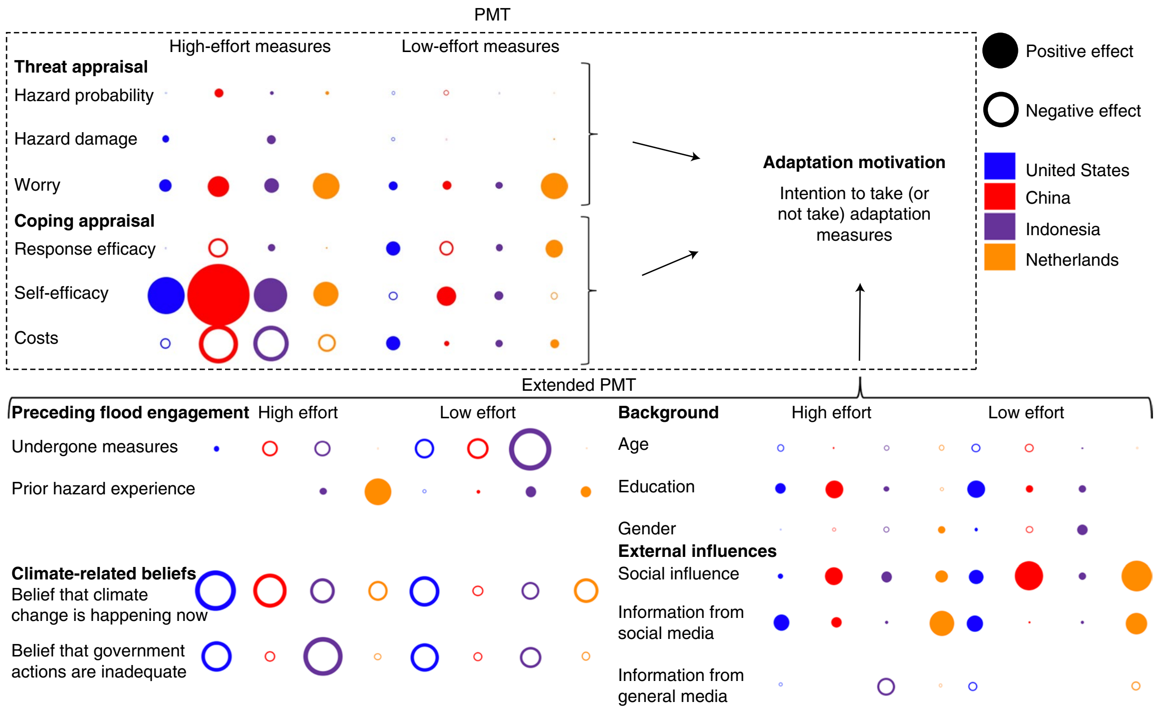

Fig. 1 | Social and behavioural factors motivating household climate change adaptation in four countries. Results are shown for the United States ($N=1{,}139$ survey respondents), China ($N=842$), Indonesia ($N=1{,}080$) and the Netherlands ($N=728$). All 16 variables under the categorical groupings (bold text) are included in the Bayesian beta regression models. The circles demonstrate the effects of these variables on households' adaptation intentions for high-effort and low-effort measures. The size of the circle is proportional to the size of the effect, which if negative, is presented by a hollow circle; the colours distinguish the four countries.

To determine what drives and hinders households' adaptation decisions, we build on protection motivation theory (PMT)[10,22,23]. Following previous work[9,10,24], our survey examines perceived hazard probability, perceived damage and worry about flooding driving threat appraisal, and self-efficacy, response efficacy and perceived cost shaping coping appraisal (Fig. 1). We expand the original PMT model to account for preceding engagement with hazards (prior actions and experiences)[25,26], external influences (media and peers)[27], climate-related beliefs[28] and demographic background[29]. Our 16 explanatory variables (Fig. 1; see the details in the Methods) thus go beyond interpersonal factors to account for some intrapersonal cues considered essential for behavioural adaptation[11]. To quantify the effects of these 16 socio-psychological factors on household adaptation intentions, we estimate and analyse the effects from Bayesian beta regression models (Methods), separately by country and measure group.

We find that while a few drivers (such as social expectations and worry) have universally consistent effects across countries and measure groups, others exhibit salient differences across countries (response efficacy) or measures (self-efficacy and cost) (Figs. 1 and 2). Key similarities and differences in the drivers across countries, when properly contextualized, could help strategies aimed at extrapolating household adaptations to data-scarce regions.

Patterns in primary drivers of household adaptation

The perception of a greater threat is generally associated with an increased likelihood of taking adaptive action[23]. In line with past empirical work[12,19,24], our analysis affirms that emotional, rather than analytical, reasoning drives household decisions. The former is intuitive and fast[30], while probabilities requiring cognitive efforts are abstruse to the public[31]. Perceived probability and damage offer little power in explaining households' intentions to adapt across all four countries ('Fl. Prob.' and 'Fl. Damage' in Fig. 2). The effect of perceived damage in Indonesia presents an exception when estimating high-effort measures, possibly due in part to the vulnerable position and high exposure to flood damage that many households face in Jakarta annually[32]. Yet, even in Indonesia, 'Worry' offers more explanatory power than the calculated risk variables ('Fl. Prob.' and 'Fl. Damage'). 'Worry' has a consistently positive relationship with adaptation intention for both high- and low-effort measures across all countries (Fig. 2).

Coping appraisal is generally a strong predictor of action[10,19]. Among the three coping appraisal variables, the effects of two—self-efficacy and perceived costs—on household intention to take high-effort measures are universally consistent across the four countries (Fig. 2a). In line with PMT and with past research[10], households who report greater capability and view the measures as generally less expensive ('Self Eff.' and 'Cost', Fig. 2a) are more likely to intend adaptation for high-effort measures. Notably, in the two economically wealthier Global North countries (the United States and the Netherlands), perceived cost is two to four times less of a deterrent in household adaptation compared with the two Global South countries (China and Indonesia) (Supplementary Section 4), calling for innovative climate finance solutions that support adaptive capacity in the Global South.

The effect of response efficacy on intending to undertake high-effort measures differs among countries (Fig. 2). In the United States and the Netherlands, it probably has no effect on adaptation intentions; in Indonesia, the effect is marginally positive. In China, however, we observe a negative effect, meaning that households that generally view these household adaptation measures as less effective overall paradoxically are more likely to adapt. While a null or negative response efficacy is not unheard of when estimating a grouped adaptation variable[27,29], past empirical work usually demonstrates positive effects of 'Resp. Eff.' on adaptation intentions[9]. Chinese culture, in comparison with the other three case studies,

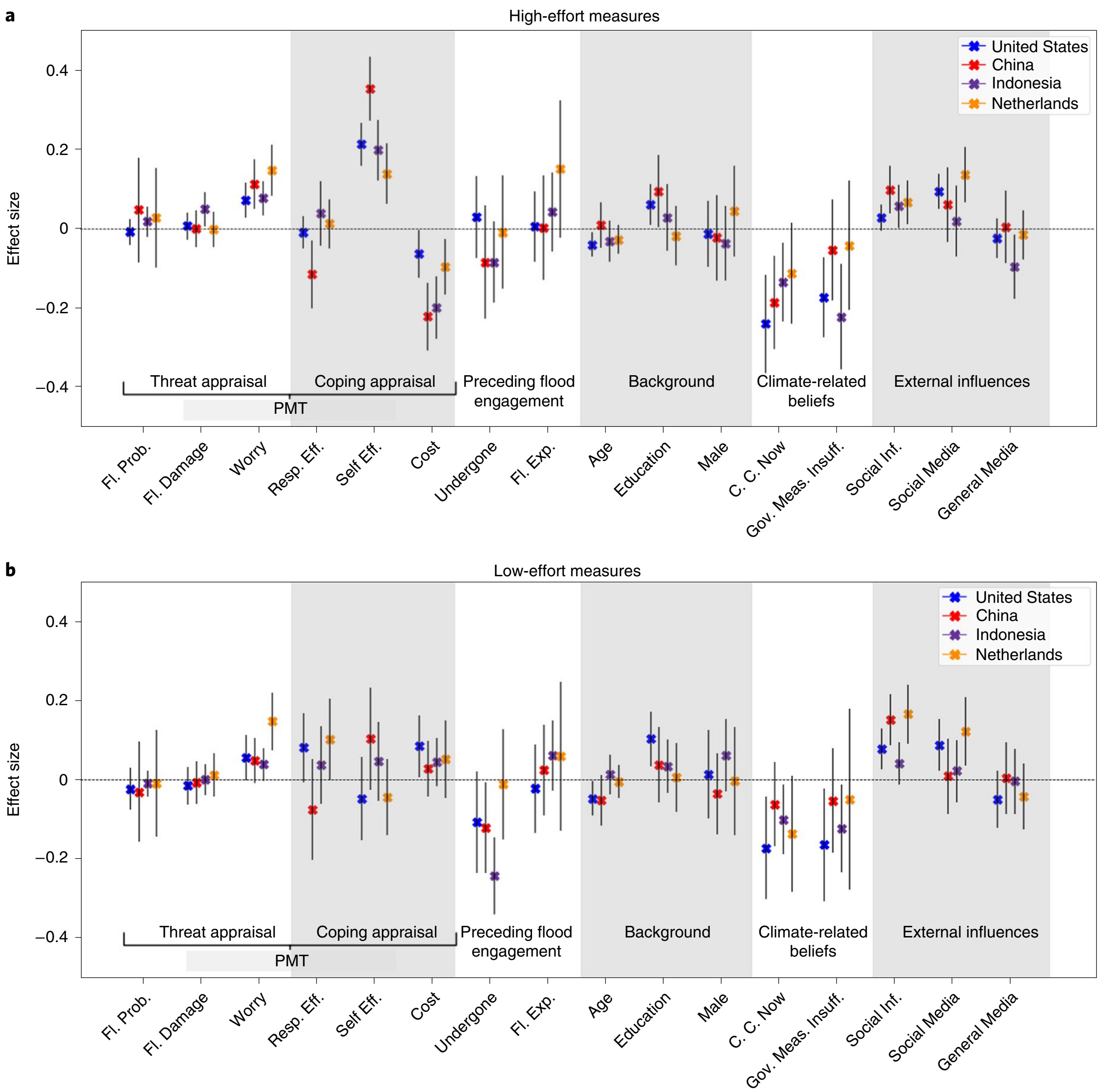

Fig. 2 | Effect distributions for factors influencing households' intentions to adapt to flooding. a,b, Mean effects and 95% credible intervals calculated from Bayesian beta regression models are shown. The models are run separately by adaptation type—low effort (**a**) or high effort (**b**)—in four countries (United States (N=1,139), China (N=842), Indonesia (N=1,080) and the Netherlands (N=728)).

is more long-term oriented[33]. Longer-term-oriented cultures situate their beliefs in a broader temporal context, potentially situating the way people assess efficacy in the longer term. Possibly, flood-aware respondents in China who see property-level adaptions as less effective in the long term may yet recognize the short-term utility of some measures—and hence are driven to adapt to remedy the more imminent adversities.

For low-effort measures, in contrast to PMT, perceived costs have a reverse effect on households' intentions to adapt in all four countries (Fig. 2b and Supplementary Section 4). Likewise, compared with high-effort measures, we see a universal substantial decrease in the effect of self-efficacy on intentions for low-effort adaptations. The change in effects is probably due to the fact that several of the measures in this group are free and require minimal effort (that is, coordinating with neighbours or moving expensive furniture to a higher floor). Hence, measures that require less time and resource investments probably have different psychological drivers and/or are made using varying heuristic shortcuts[30,34]. Furthermore, we find larger standard errors and slightly greater variance in the effects of 'Resp. Eff.' among countries for low-effort measures than for high effort—possibly due to more accurate reporting on intentions to undertake high-effort measures[35]. Intentions to pursue low-effort adaptations by households in the United States, the Netherlands and, to a lesser degree, Indonesia are positively affected by 'Resp. Eff.', while the negative effect in China remains, though lessened.

Role of experience, background, beliefs and social influence

In Indonesia and the United States, 46% and 48%, respectively, of the households included in this analysis reported having experienced a flood, in stark contrast with China (19%) and the Netherlands (15%) (Supplementary Table 1). Yet, prior flood experience is a weak predictor of high-effort adaptations among our respondents everywhere except the Netherlands ('Fl. Exp.', Fig. 2a). In China, Indonesia and the United States, floods occur annually throughout the country. Dutch residents, by contrast, rarely experience them, except occasionally with heavy rainfall or in unembanked areas.

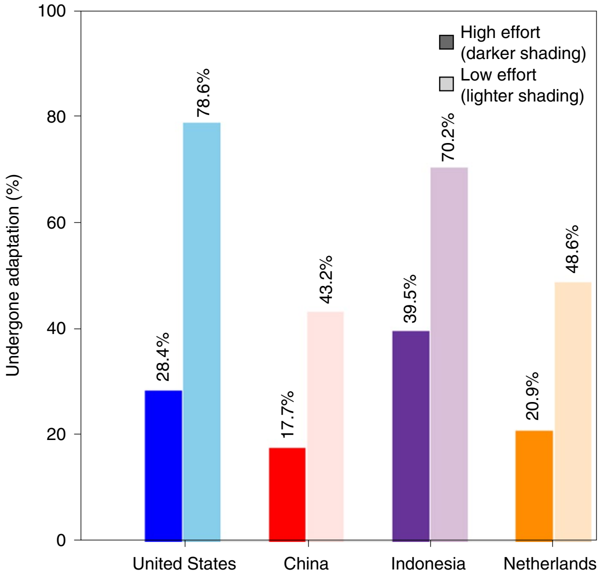

Fig. 3 | Percentage of households that have undertaken adaptation measures. The percentage of households that have previously undertaken at least one adaptation in each category. Darker shades represent high-effort measures, lighter shades represent low-effort measures.

Since beliefs and personal baselines are formed in the context of personal experiences[36], for a Dutch household, a flood is a unique experience, creating a memorable availability heuristic[34] that positively influences (95% likely) adaptation intentions.

Our data demonstrate that 17.7–39.5% of households in the four countries have already undertaken high-effort adaptation measures, and almost twice as many (43.2–78.6%) have adopted low-effort measures (Fig. 3). The effect of prior adaptation on intending additional low-effort measures is strongly negative everywhere except the Netherlands (a null effect for 'Undergone', Fig. 2b), whereas for high-effort measures, the likely negative effect is lessened and is present only in China and Indonesia (Fig. 2a). Both countries suffered major floods in the nine months before our survey: 2019 Typhoon Lekima in China and the 2019 Jakarta floods in Indonesia. Possibly, households in these countries have more recently undertaken high-effort flood adaptation measures, lessening the likelihood that they would need to intend others in the immediate future.

While the effect is not included in the models (to maintain model independence for comparative purposes), it is worth noting that households that have not undertaken low-effort measures are more likely to intend high-effort measures (Wilcoxon rank-sum: for each individual country, $P<0.001$). Still, households that have not undertaken high-effort measures—in the United States (Wilcoxon rank-sum: $P<0.001$), China (Wilcoxon rank-sum: $P<0.01$) and the Netherlands (Wilcoxon rank-sum: $P<0.01$)—are more likely to intend low-effort measures. This is not the case in Indonesia ($P=$ not significant), where due to the relatively high flood exposure, households that feel at risk have probably already taken at least some low-effort measures.

The effects we observe from the demographic variables are mixed and generally weak (Fig. 2). In the United States, Indonesia and the Netherlands, 'Age' has a small negative effect on intentions to pursue high-effort measures, perhaps due to the discounting of implementation efforts over the remaining lifetime in the respondents' own property. Age also discourages low-effort measures in the United States and China. That elder respondents are less likely to intend adaptation than younger respondents is concerning: they are more vulnerable and require specific attention during and after disasters[37]. 'Education' has a positive effect on adaptation intentions only for households in the United States (>99% likely for both high- and low-effort measures) and China (98% likely for high-effort measures), while in other countries it matters less. Gender has a likely null effect everywhere except Indonesia, where men seem more likely than women (92% certainty) to intend low-effort measures. Our sample respondents are slightly more educated than the general population and in China and Indonesia somewhat younger, possibly influencing the effects (Supplementary Tables 3 and 4). However, since other work has likewise found inconsistent effects for demographics[15], we do not foresee any substantial bias in the effects of measured variables.

Across the four countries, between 62% and 79% of respondents believe that climate change is happening now (Supplementary Table 1). Past work, however, has shown that belief in climate change often does not translate into action[38], can deter action[39] and does not necessarily have a strong cognitive link with extreme weather events[40,41]. Here the belief that climate change is happening now ('C. C. Now', Fig. 2) consistently has a negative direct effect in all four countries. The reason could be that households that believe in the urgency of climate change have already taken some actions—as many in our dataset have (Fig. 3). Notably, the belief in climate change is associated with having previously undertaken low-effort measures ($\chi^2=123$, $P=0.0$). While there is no discernible relationship between belief in climate change and previously undertaken high-effort measures, as noted with past action, having undertaken low-effort measures is associated with less intention for both high and low effort. Hence, it probably quells protection motivation[24] and possibly explains the negative relationships.

Government adaptation many influence households' intentions. Previous research has often found negative effects on households' adaptation intentions of trust in governmental protection or of belief that it is the government's responsibility[29]. We go beyond measuring general beliefs and asked specifically whether households think actions already taken by their respective governments were sufficient (Supplementary Table 1). In Indonesia and the United States, the belief that the current government measures are inadequate discourages household adaptation intentions for both types of measure (>98.5% likely), whereas in China and the Netherlands, the effect is small and uncertain, hence probably null ('Gov. Meas. Insuff.', Fig. 2). Two institutional and experiential differences between countries could explain the observed disparity in effects. First, the negative relationship in the United States and Indonesia between the belief that governmental measures are inadequate and personal adaptation intention aligns with other work that finds public and private adaptation can go hand in hand, especially for adaptations that entail structural property modifications[9,27,29]. This relationship has been previously rationalized by the logic that past flood events or close calls can trigger both public action and private household adaptation[29]. Indeed, if our respondents in any country have experienced a flood, they are more likely to have already undertaken measures (high effort: $\chi^2=123$, $P=0.0$; low effort: $\chi^2=61$, $P=0.0$), possibly lessening the intention for further action. In Indonesia and the United States, more people have experienced floods than in the Netherlands and China (Supplementary Table 1). If a household has experienced a flood, they are also more likely to view the government measures as insufficient ($\chi^2=30$, $P<0.001$). Second, China and the Netherlands have a similar, collectivist approach to flood management that is, in general, trusted by the populaces[42–44]. In Indonesia and the United States, many disaster management programmes are viewed generally more unfavourably and as insufficient[43,45–48]. Our own data reflect these sentiments: 11% of Dutch and 22% of Chinese view flood protection measures already taken by the government as insufficient compared with 30% in Indonesia and 43% in the United States.

Norms play a strong role in influencing behaviour[11,18,27]. Our analysis supports this notion: the perceived expectations of one's friends, family and neighbours, as prescriptive norms, positively influence the intention to implement both high- and low-effort measures across all four countries ('Social Inf.', Fig. 2 and Supplementary Information). The four countries differ in the extent of social influence on households' adaptation, with the United States exhibiting the lowest positive effect of social influence on high-effort adaptations, perhaps due to the nation's individualistic culture[33]. With low-effort measures, we find that social expectations play a higher role in China and the Netherlands than in the United States and Indonesia, in spite of the mean of 'Social Inf.' being lower in China (2.9) and the Netherlands (2.3) than in the United States (3.3) and Indonesia (3.3) (t-tests: China < Indonesia and the United States, $P < 0.001$; Netherlands < Indonesia and the United States, $P < 0.001$). This phenomenon could be due to the influence of social norms that often go undetected by the influenced party[49]. Alternatively, the higher effects of social expectations in China and the Netherlands could be due to the confirmation bias[50], when respondents are more likely to report higher social expectations if they have already undertaken a low-effort measure ($t = 3.7$, $P = 0.0$). In the United States and Indonesia, households report higher social expectations but also are much more likely to have already undertaken both high- and low-effort adaptations (Fig. 3). As such, while they report a higher prescriptive norm, it is less likely to inspire action, as many households already conform to the norm.

The traditional general media has a likely null or slightly negative effect on household adaptation intentions across all countries except Indonesia. There it distinctly discourages households from intending high-effort measures ('General Media', Fig. 2a), possibly signalling distrust in information from the media[51]. Conversely, social media has, in general, a positive effect on adaptation intentions for high- and low-effort measures for the Netherlands and the United States and a lower or probably null effect in China and Indonesia. The Internet in the United States and the Netherlands is among the most 'free' and hosts generally unrestricted content. In Indonesia, the Internet falls on the lower end of the scale of 'partly free' in terms of content restrictions, and China's is one of most censored in the world[52]. Differences in content restrictions could influence what people can post and read on social media, how much they trust the information and the effect it has on adaptation intention.

Discussion and conclusions

Using unique surveys from four socially, institutionally and culturally diverse countries, we statistically study similarities in the drivers of household adaptations. Universally, affect (worry) and social influence drive adaptation intentions, while perceived probability and damage have nearly no effect on motivating households' actions (except in Indonesia for high-effort measures). Self-efficacy and perceived costs are the strongest driver and barrier, respectively, for households' intentions to adopt high-effort measures. Beliefs in ongoing climate change have negative effects on adaptation intentions, perhaps because households with a sense of urgency have already adapted.

Disparities in the effects indicate that the social, institutional and cultural contexts manifest meaningful differences in what motivates household adaptation intentions. Prior flood experience has little effect on household adaptation except in the Netherlands, where it is a rare experience. Negative effects of beliefs in the insufficiency of governmental measures on households' adaptation intentions are two to six times stronger in the United States and Indonesia than in the Netherlands and China. Notably, education encourages adaptation only in China (high-effort measures) and the United States; and social media facilitates household adaptation in the Netherlands and the United States, but hardly in Indonesia and China. Several socio-psychological factors exhibit differences in effects between high- and low-effort measures, indicating that households may utilize various heuristics depending on the measures under consideration. Finally, while perceived costs universally discourage households' adaptation, their effect is two to four times stronger in the two Global South countries than the two in the more affluent Global North.

Our unique dataset and analysis across countries extend past research by refining assumptions about what commonly theorized factors of household adaptation are universal versus context dependent, distinguishing between high- and low-effort measures. The coverage of four countries impedes a statistical attribution of cross-country variations in effects, limiting us to qualitative arguments on observed differences. Future work could consolidate existing fragmented survey data in globally shared databases to permit numerical cross-country analysis, including structural models, to help unravel contextual, complex intravariable relationships. Such datasets will permit a systematic analysis of contextually shaped patterns in household adaptation behaviour, and enable researchers to meaningfully extrapolate to data-scarce regions when projecting households' adaptation progress or designing adaptation policies. Furthermore, future surveys should prioritize longitudinal designs to elicit whether and how intentions lead to actions to assist in closing the intention–behaviour gap. Panel data will permit monitoring the speed and effectiveness of household adaptation progress—an important supplement to the tracking of government-led measures[6,53].

A recent review[11] stresses the importance of complementing interpersonal factors with intrapersonal ones when studying households' responses to climate-induced hazards. Our study partially responds to this call by capturing prescriptive social norms and consistently finds a positive effect in four countries. Future work could expand to study network and cohesion effects, and deepen to explore related social processes, such as social amplification of risk[54,55] or information cascades in networks[56,57]. Computational social science methods, such as network analysis and agent-based modelling, are especially well suited to studying dynamic feedbacks between intra- and interpersonal factors. Finally, the revealed uniform strong effects of self-efficacy and perceived costs underscore the need to further investigate adaptive capacity. Other elements theorized to constitute households' adaptive capacity—diversity, access to capital, institutional capacity and learning[58]—should be systematically captured in future climate adaptation surveys.

Our findings have implications for climate change adaptation policies as well. To prompt household adaptation behaviour, personalized narratives appealing to affect should complement the communication of climate-driven risks. Since social expectations consistently facilitate adaptation, associating desired behaviour with a positive group identity could aid household adaptation diffusion and soften socially constructed adaptation limits. Policies aimed at closing the adaptation gap by promoting the diffusion of household-level action should target high- and low-effort actions differently. Importantly, knowledge on drivers and constraints of household adaptation should be transferred to new areas with caution, as a driver in one context may be a constraint in another.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41558-021-01222-3.

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Methods

All research and data collection complies with the European Research Council Horizon 2020's data requirements and Research Ethics and Integrity policy. This research was approved by the Behavioral Management and Sciences Ethics Committee at the University of Twente, request number 191249.

Data collection. In March–April 2020, we ran household surveys in flood-prone coastal cities in the United States, China, Indonesia and the Netherlands. The surveys were conducted online by YouGov, and the data analysed and presented in this paper are from identical, translated questions in the respective languages of each country[59]. The survey was written in English by the authors, one of whom is a native speaker from the United States. For the non-US respondents, the survey was professionally translated by YouGov field experts in each country, and the translation was reviewed by a climate adaptation scientist from each of the four countries to help ensure cross-national relevance of the measures and aid in avoiding cultural bias. Furthermore, YouGov field experts provided relevant information on national context, culture-specific ethical considerations and legislation that aided in the design of the survey.

YouGov forms representative panels on the basis of national statistics. In China, the Netherlands and Indonesia, we specifically controlled for gender representation, and we controlled for age and gender in the United States (Supplementary Section 2). YouGov has a number of quality assurance measures in place, such as excluding speeding respondents (those who click through too rapidly to allow reading), inviting future panelists to participate before announcing the topic (helping avoid self-selection bias) and verifying personal details given when respondents are registered for the panel. Furthermore, respondents who consistently click the same (that is, the first) answer are filtered out. Finally, YouGov limits the number of surveys that respondents can participate in monthly to reduce survey fatigue and conditioning[60]. The YouGov platform for online surveys is accessible via mobile phones; as such, according to the field teams, a lack of Internet at home is not a barrier to reaching a representative sample. As our research was focused on major urban centres, Internet access was not a limiting factor[61,62]. Employing an external company is necessary when running such a large-scale, cross-national survey in a reproducible way. However, it is expensive and mandates outsourcing sampling and quality assurance. With YouGov's extensive history of conducting high-quality surveys for academic, government and corporate entities, we are confident that the sample and data quality are properly upheld.

Dependent variables. We studied 18 household-level flood adaptation measures (Supplementary Table 5). We selected the relevant measures by reviewing prior empirical work guided by several meta-analyses[9,10,16,24], as well as case studies that looked in depth at adaptation in each country[44,63–65]. Here we analyse adaptation intentions instead of already undertaken actions to avoid issues with feedback effects of undertaken measures on risk perception[24]. Prompted by recent research[12,19], we separate the adaptation measures into a high-effort group (measures involving structural modification to one's home and necessitating considerable time and financial investments) and a low-effort group (non-permanent flood mitigation actions as well as communication and information-seeking behaviour). The two groups vary in the effectiveness of reducing hazard impacts and the extent of improving households' resilience (compare raising the ground-floor level with seeking hazard-related information). During the survey, within each group, we randomized the order in which the respondents saw the adaptation actions. The grouping on the survey probably contributes to some within-group consistency. See Supplementary Section 3 for factor loadings and alphas on both groups.

For all adaptation measures, respondents could select the following options:

1. I have already implemented this measure
2. I intend to implement this measure in the next 6 months
3. I intend to implement this measure in the next 12 months
4. I intend to implement this measure in the next 2 years
5. I intend to implement this measure in future, after 2 years
6. I do not intend to implement this measure

Options 2–5 were grouped together, by measure type, to indicate future intention. The questionnaire design allows us to construct a dependent variable on the basis of the proportion of remaining measures a respondent can still pursue (the number not undertaken) per measure group (equation (1)). This proportional formulation of the dependent variable helps maintain consistency across respondents and accounts for the fact that different respondents probably have already undertaken a number of different measures. Already reflected in the reported sample size, our analysis of adaptation intentions excludes all households that had already undertaken all measures in a given group, as they have nothing left to intend:

$$\mathrm{DV}_i = \frac{\text{Intended measures}_i}{\text{Total measures} - \text{Undergone measures}_i} \tag{1}$$

This specification of the dependent variable has several advantages over other approaches of modelling intention to take multiple actions. Ordinal logit models and count models do not explicitly incorporate the fact that many respondents may have already undertaken some of the measures asked and therefore cannot 'intend' to do something they have already done. Furthermore, count models such as binomial regression assume Bernoulli trials, which we deemed potentially inappropriate in light of recent research that notes the connectivity between related measures[12,19]. Binary logistic/probit regression (which groups any intention as a 1 and no intention as a 0) overcomes this issue; but in grouping all intended measures together, even if the intended adaptation measures are in subgroups, information about quantity is lost. We therefore chose a ratio of the intention to pursue adaptations proportional to the remaining measures in the corresponding group as the dependent variable (equation (1)). While acknowledging that the likelihood of observing differences in effects is subdued[66] and the fact that for measure-specific variables (that is, self-efficacy), averages must be used[67], we argue that this dependent variable is a good representation of household intention to pursue adaptation measures accounting for the ones already taken in the same group.

Explanatory variables. The presented analysis focuses on flood adaptation measures and factors driving household intentions to pursue them. The survey design relies on an extensive review of the empirical adaptation literature aided by several meta-analyses[9,10,16,24]. Six of the variables used in our analysis make up the base PMT variables that often explain household adaptation intentions, and the remaining ten are variables frequently used to explain households' protective actions against flooding. While not exhaustive of all tested constructs, we identified these 16 variables as drivers of household adaptation motivation that were regularly found to be influential in past work[24–29]. The list of constructs, the questions used to solicit the variables and their descriptive statistics are available in Supplementary Table 1. Survey length limitations in the present study compelled mainly single-item previously validated questions[14,25,27]. While this is a tested, reliable method that produces comparable and quality data[68], future research could benefit from multi-item measurements. As all of these variables have been previously studied, we were able to compare effects with past work to help ensure that the constructs were understood. We checked the variance inflation factors of all variables in the model to ensure that multi-collinearity was not problematic (all variance inflation factors <2).

Data analysis. To model the proportions of measures that households intend to take from those remaining, we estimate a Bayesian beta regression model. It performs substantially better, on the basis of WAIC scores (see Supplementary Table 5 for more information), than other models we tested that can accommodate a proportion as a dependent variable (linear and logistic regression). Previous work has found that adaptation intention can occur 'in concert'[12], which can lead to bimodal distributions. Our data confirm this finding and further support the beta regression model choice, as the beta family is very flexible with regard to the array of density forms it can accommodate[69]. Beta regression models cannot contain values exactly equal to one or zero; thus, before estimating the model, we scale the dependent variable, the intention proportion values by group (Y), to fit between 0 and 1 (ref. [70]):

$$Y_i = \frac{Y'(N-1)+0.5}{N} \tag{2}$$

The probability density function of the beta distribution is:

$$p(y|a,b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} y^{a-1}(1-y)^{b-1} \tag{3}$$

where $a,b>0$, and Γ is the gamma function. We run all of our models in Python with the PYMC3 package[71]. We parameterize the beta distribution in terms of its means (m) and standard deviation (σ). All coefficient priors in all models are broadly set as $\beta_i \sim \mathrm{N}(0, 5)$ and all intercepts as $\beta_0 \sim \mathrm{N}(0, 10)$. We set the prior variance as $\sigma \sim \mathrm{halfN}(0.5)$, bounded at the upper end with $\sqrt{\delta(1-\delta)}$, where δ is the minimum value of y, transformed by the inverse logit function for each country that, when input into the above function, determines the upper limit on the value of σ (ref. [71]). Next, we transform the values to the beta distribution shape parameters (a and b) using:

$$a = mk \qquad b = (1-m)k \qquad k = \frac{m(1-m)}{\sigma^2} - 1 \tag{4}$$

Constructed from the a and b parameters shown above, Bayesian beta regression models are typically reparameterized and represented with $\mu = \frac{a}{a+b}$ and $\gamma = a+b$ (refs. [69,72,73]). Thus, where $\boldsymbol{\beta}$ is a vector of regression coefficients and intercept, $\boldsymbol{\beta} = (\beta_0, \beta_1 \ldots \beta_i)$ and $\mathbf{y} = (y_1, y_2 \ldots y_n)$, the Bayesian beta regression model we consider is:

$$y_i|\mu_i,\ \gamma_i,\ \sim \mathrm{Beta}(\mu_i\gamma_i), \gamma_i(1-\mu_i) \tag{5}$$

$$\mu_i = F(\beta^\top x_i) \tag{6}$$

where $\mathrm{F}(\cdot)$ is the inverse logit function that transforms our linear combination of explanatory variables (x_i).

In various places throughout the paper, we compare the relationship of a specific variable between countries via means testing with *t*-tests or note the relationship between two variables with a *t*-test, a Wilcox-rank sum test or a chi-squared test. For both epistemological reasons (this type of survey is repeatable) and ease of understanding, we use frequency statistics in these instances. Test scores and *P* values are reported in the text.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability
The data that support the findings of this study are available from the corresponding authors upon reasonable request. The authors are working to deposit the data used in this analysis in an online repository by 2023. When this occurs, an announcement will be made on http://www.sc3.center/.

Code availability
The code used to analyse the data will be made available at http://www.sc3.center/.

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Author contributions
T.F. designed and directs the research project. B.N. and T.F. conceived of the empirical research design and wrote the survey with input from A.N. and A.T. B.N. analysed the data with guidance from T.F. and A.N. All authors discussed the results and contributed to writing the manuscript.

Competing interests
The authors declare no competing interests.

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Software and code

Policy information about availability of computer code

Data collection	The data was collected through YouGov's online survey platoform.
Data analysis	Data was analyzed in Python Version 3.8.1. Principle packages used for analysis were: Pandas (1.1.3), Numpy (1.19), and PYMC3 (3.10.0). For visualization: Matplotlib (3.2.2)

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Study description	The data used in this analysis comes from the first wave of our longitudinal survey. The collected data is quantitative and the primary method of analysis is statistical.
Research sample	Research sample is a representative sample (gender) of residents living in the cities and outlying areas of: Miami, FL, USA; Houston, TX, USA, New Orleans, LA, USA (Total N=1993) Rotterdam, Netherlands (N=1251); Jakarta, Indonesia (N=2061); Shanghai, China(N=1174). Whole sample - Genders: 3295 Females, 3184 Males; Whole sample - Ages: (18-24): 1178, (25-34): 2071, (35-44): 1357, (45-54):738, (55-64): 538, (65+): 597
Sampling strategy	The sampling was done by YouGov. The company maintains a representative panel in each of the locations listed above. From this panel, we sampled randomly.
Data collection	The data was collected via a respondent filling out an online survey on the YouGov's platform accessible via personal computers and mobile phones. The research objective was explained to the respondent in an introduction.
Timing	March - April 2020.
Data exclusions	No received data was excluded. YouGov filters and excludes for respondents who repeatedly select the same answer (i.e. marking "2's" for all questions).
Non-participation	The panel was kept open until a defined number of respondents fully completed the questionnaires.
Randomization	There was no randomization necessary for this analysis.

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Policy information about studies involving human research participants

Population characteristics	Representative samples in each case study, see above
Recruitment	The survey respondents were recruited through YouGov's on-line panel. As our research sites are urban areas, Internet access is common in these areas. Also the YouGov platform assures also a mobile-phone friendly interface, permitting potential respondents to participate from their phones (which have almost 100% penetration in our case study areas). Hence, a limiting (Internet) access based bias is not a concern here.
Ethics oversight	Research was approved by the Behavioral Management and Sciences Ethics Committee at University of Twente. Request Number: 191249. All respondents give a clear consent in participating in this research.

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