Article:
Berghäuser, Lisa, Bubeck, Philip, Hudson, Paul et al. (2023) Identifying and characterising individual flood precautionary behaviour dynamics from panel data. International Journal of Disaster Risk Reduction. 103835. ISSN: 2212-4209

https://doi.org/10.1016/j.ijdrr.2023.103835

Journal Pre-proof

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PII: S2212-4209(23)00315-1

DOI: https://doi.org/10.1016/j.ijdrr.2023.103835

Reference: IJDRR 103835

To appear in: *International Journal of Disaster Risk Reduction*

Received Date: 18 October 2022

Revised Date: 20 June 2023

Accepted Date: 29 June 2023

Please cite this article as: L. Berghäuser, P. Bubeck, P. Hudson, A.H. Thieken, Identifying and characterising individual flood precautionary behaviour dynamics from panel data, *International Journal of Disaster Risk Reduction* (2023), doi: https://doi.org/10.1016/j.ijdrr.2023.103835.

Identifying and characterising individual flood precautionary behaviour dynamics from panel data

Lisa Berghäuser[1]*, Philip Bubeck[1], Paul Hudson[1,2], Annegret H. Thieken[1]

[1]Institute of Environmental Science and Geography, University of Potsdam, Karl-Liebknecht-Str. 24-25, 14476 Potsdam, Germany

2 Department of Environment and Geography, University of York, York, United Kingdom

* Corresponding author: Lisa Berghäuser

E-Mail: lisa.berghaeuser@uni-potsdam.de

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Lisa Berghäuser[1]*, Philip Bubeck[1], Paul Hudson[1,2], Annegret H. Thieken[1]

[1]Institute of Environmental Science and Geography, University of Potsdam, Karl-Liebknecht-Str. 24-25, 14476 Potsdam, Germany

2 Department of Environment and Geography, University of York, York, United Kingdom

* Corresponding author: Lisa Berghäuser

E-Mail: lisa.berghaeuser@uni-potsdam.de

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Abstract Individual precautionary behaviour in response to flooding can considerably reduce flood impacts. Therefore, understanding its drivers and temporal dynamics is of high interest for risk management and communication. Previous studies are mostly based on temporally limited data by using cross-sectional surveys. Here we identified and characterised different types of trajectories of adaptive behaviour after a flood event. We used panel data, where 227 households were repeatedly surveyed within 45 months after the flood of June 2013 in Germany about their precautions. To identify robust groups, we applied and compared two clustering methods: latent class growth analysis (*LCGA*) and k-means based cluster analysis for panel data (*kmlShape*). Three different groups were consistent across the two methods and showed different dynamic adaptive behaviour over the survey period: a 'high standard' (35 % of the sample), a 'high performer' (37 %) and a 'low adaptive' (28 %) group. The high standard group was characterised by a significantly higher protection motivation and flood experience in comparison to the other groups. The high performer group showed the largest increase in implemented precautionary measures after the flood, but also expressed a general fatalistic attitude towards floods. The low adaptive group trusted their community significantly more in managing floods and reported little access to information and support. The results indicate that tailored risk communication and funding schemes might be needed to support low adaptive types of flood-prone residents. They also present a starting point for the implementation of empirically based, heterogeneous adaptation behaviour in socio-hydrological models.

Keywords: Precautionary Behaviour; Panel; temporal dynamics; flooding; property-level flood adaptation

1 Introduction

Of the potential natural hazard events, flooding is among the most common and challenging (CRED, 2019). According to the European Environment Agency (EEA, 2019), floods accounted for a total loss of € 162 billion across the EEA's members in the past 40 years. Therefore, understanding the process of generating and limiting potential flood impacts is integral to integrated flood risk management. This management concept requires that all stakeholders threatened by flooding undertake action to limit the adverse impacts. This includes precautionary behaviour of private households (Aerts et al. 2018; Kuhlicke et al. 2020; Merz et al. 2010). The German federal act on improving precautionary flood protection from 2005 (and later revisions) for instance asks people in flood-prone areas to protect themselves to the best of their ability (Thieken, et al. 2016a).

The residents of flood-prone areas can considerably reduce flood impacts by the implementation of precautionary, i.e., adaptive, measures (Clay et al. 2020; Hudson et al. 2014; Kreibich et al. 2015; May et al. 2014). These are implemented before a flood event and can significantly reduce flood vulnerability (Sairam et al. 2019). In principle, we can distinguish three approaches for precautionary measures to limit vulnerability: dry flood-proofing (measures that prevent the flood water from entering the building), wet flood-proofing (structural measures that limit impacts when the building is flooded), and risk transfer, i.e., purchasing flood insurance (Kreibich et al. 2015; Thieken et al. 2016b).

Our current scientific knowledge about precautionary behaviour has mostly been drawn from cross-sectional studies where the information is limited to the narrow temporal window of the survey (Bubeck et al. 2012; Hudson et al. 2020; Kellens et al. 2013; Kuhlicke et al. 2020). Since precautionary behaviour and its underlying drivers might change over time, panel or longitudinal surveys offer the opportunity to uncover these changes. These survey designs repeatedly survey the same individuals over multiple time steps to record the evolution of their actions, perceptions, and attitudes. In the natural hazard domain panel studies are rare, especially concerning precautionary behaviour (Bubeck et al. 2012; Hudson et al. 2020; Kellens et al. 2013). Only recently we observe a change towards more longitudinal research designs in the literature (Botzen et al. 2020; Bubeck et al. 2020; Franceschinis et al. 2021; Mondino et al. 2020, 2021). Existing panel studies support the notion that flood-affected residents show heterogeneous adaptive behaviour over time (Botzen et al. 2020; Bubeck et al. 2020; Franceschinis et al. 2021). Given the importance of learning more about flood risk adaption dynamics, the scarcity of panel survey data is a profound limitation. In overcoming this limitation, we will be more able to characterise the adaptation dynamics of residents of flood-prone areas suitably. This has been called for in coupled socio-hydrological modeling, where empirically derived adaptation dynamics should be integrated into risk assessments (Aerts 2020). This is because proactive adaptation alters vulnerability and alterations in vulnerability are a major driver of flood risk (Kreibich et al. 2017). Use of empirically defined adaptive behaviour dynamics in dynamic flood risk models can produce more useful results and scenarios for decision makers because it acknowledges the underlying complexity in more detail.

This paper thus seeks to contribute to the emerging literature on understanding the dynamics of household adaptation, i.e., precautionary behaviour. This is through the identification of different adaptation dynamics or trajectories, followed by a comparison of their characterization. For that, we used one of the few suitably focused panel datasets that was conducted after a severe, large-scale river flood in May/June 2013. The flood affected many European countries, including Germany, where record breaking high water levels occurred (Thieken et al. 2016b). In the month before the event, exceptionally high amounts of precipitation fell, leading to already saturated soils in the catchments, which in combination with renewed heavy rainfall triggered the flood (Merz et al. 2014). All major river catchments in Germany were affected, but the flood was particularly severe in the catchments of the Danube and Elbe. From a hydrological perspective, the event was classified as the most severe in Germany since 1950 and caused extensive financial damage with approximately six to eight billion € in total damage in Germany, with the federal states of Saxony-Anhalt and Saxony being the hardest hit (Thieken et al., 2016b). The flooding further caused substantial damage to infrastructure and environment. The panel targeted affected people who had suffered financial losses. The 227 respondents were interviewed three times over a four-year period, i.e. 9, 18 and 45 months post-flood using computer-aided telephone interviews. The standardized questionnaire included, amongst others, questions regarding what and when precautionary measures were implemented. Previous analyses showed temporal changes in protection motivation, precautionary behaviour and self-reported recovery (Bubeck et al. 2020), which serves as a starting point for the current analysis.

We use this unique data to model the precautionary behaviour trajectories of the combined implementation of 16 different precautionary measures. We investigate the potential for heterogeneous behavioural dynamics by applying and comparing two different clustering techniques: Latent Class Growth Analysis (*LCGA)* and a k-means based cluster analysis for longitudinal data, *kmlShape*. Since analysing panel data is rather new in this field, new insights and experiences with suitable methods are needed. The implementation of two clustering techniques therefore provides two advantages. First, we provide a dedicated methodological contribution to the analysis of panel data with three survey waves. Second, comparing and assessing to what extent the methods produce similar results additionally allows the identification of robust groups of adaptive behaviour.

Once robust trajectories of adaptive behavioural dynamics have been established, we investigate if explanatory factors drawn from commonly employed socio-psychological models can be used to explain why different adaptive behaviour trajectories occur using post-hoc comparison tests. For example, the Protection Motivation Theory (PMT, Rogers [1975, 1983]) or the Protective Action Decision Model (PADM, Lindell and Perry 2012) are prominent examples in the existing literature of such guiding theories (Bamberg et al. 2017; Bubeck et al. 2012; Kuhlicke et al. 2020; Poussin et al. 2014). Learning which variables are associated with different adaptive pathways, could further enhance coupled socio-hydrological models and improve risk management.

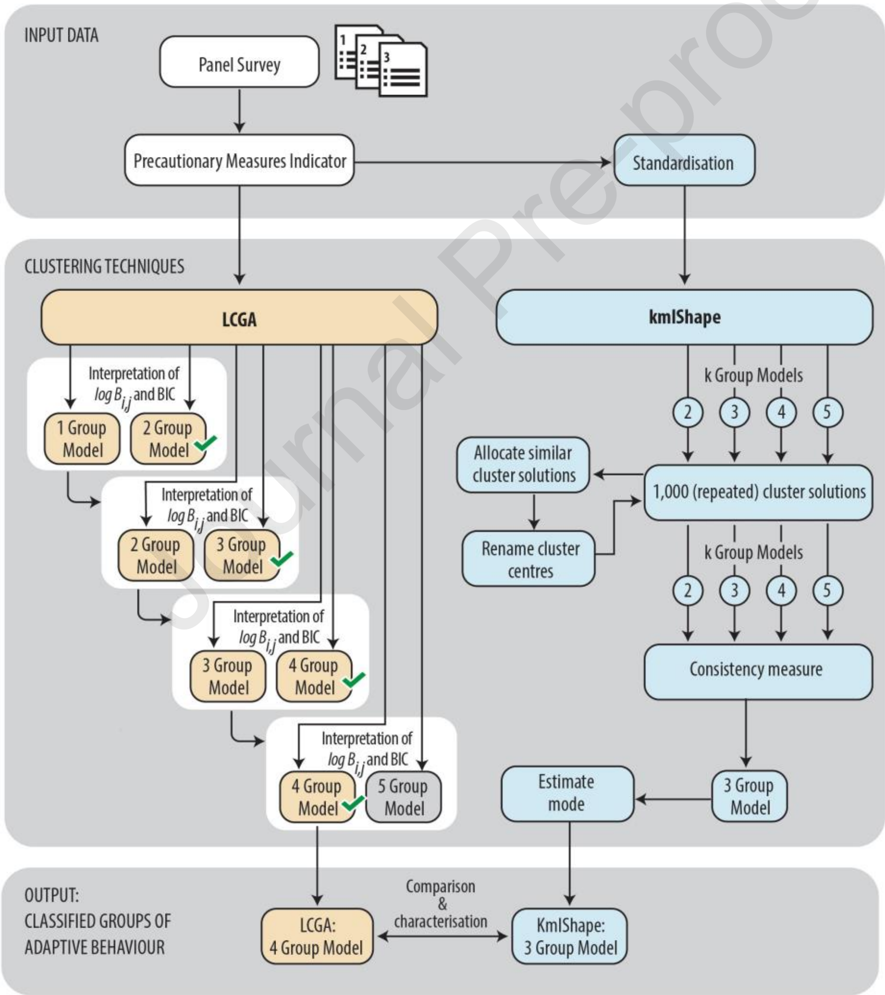


Fig. 1: Overall Clustering Workflow.

2 Data and Methods

Our workflow is depicted in Fig. 1. First, a dynamic precautionary measures indicator was derived as the dependent variable for the clustering techniques. Both clustering techniques followed different procedures and quality criteria to identify the number of behavioural trajectories and their respective geometry. The results are compared across the methods as a cross-validation inspired proceeding. Second, we use variables drawn from commonly employed behavioural theories to investigate if and how the identified groups are different to each other via a series of post-hoc comparison tests.

2.1 Quantifying adaptive behaviour

The panel used for this study has been introduced and described in more detail by Bubeck et al. 2020 and Hudson et al. 2020. From the panel, data on adaptive behaviour as well as on several related characteristics like attitudes, perceptions, and socioeconomic properties of the respondents were used to identify and characterise different types of dynamic, precautionary behaviour. We use the number of implemented precautionary measures as a metric for the adaptive level of flood-impacted respondents. During the interview, respondents were asked to state if and when they implemented different precautionary measures. The choice of elicited measures was based on previous works by Kienzler et al. (2015), Kreibich et al. (2011), and Thieken et al. (2016a), among others. Hudson et al. (2014) and Thieken et al. (2005) showed that the studied precautionary measures show different levels of effectiveness in reducing flood damage. We use this information to estimate a weighted precautionary measures indicator *pi*, which is described by Laudan et al. (2020) and further presented in the appendix. The final indicator ranges from zero, signifying no preparedness, to 48, signifying the employment of all measures asked about in the panel.

We evaluate *pi* for each respondent over four time periods: before the 2013 flood event, within 9 months post-flood, between 9-18 months post-flood, and between 18 - 45 months post-flood. Due to the survey design, the data does not include information about measures that were removed or had deteriorated. If a respondent reported a measure as implemented at one of the four time steps, it was counted as implemented in the following periods as well. Consequently, *pi* can only remain constant or increase in value across survey waves.

2.2 *Clustering techniques for panel data*

A common method family to identify different homogeneous groups among a sample is cluster analysis (Everitt et al. 2011, p. 67). Longitudinal data requires distinct clustering techniques (Everitt et al. 2011; Frees 2004). An example is Latent Class Growth Analysis (*LCGA*), a type of growth mixture modelling developed by Nagin (1999). Bubeck et al. (2020) used *LCGA* on a sum of precautionary measures that were classified as high or medium cost by Rözer et al. (2016). Another method is k-means Cluster Analysis, such as *kmlShape*, that identifies distinct subgroups in longitudinal data through the shapes of trajectories as introduced by Genolini and Guichard (2016). Each of the methods works fundamentally different. *kmlShape* is an exploratory approach that provides evidence only in context with further information (Schnell et al. 2018) and focuses on the geometry of the trajectories, whereas *LCGA* fits a set of polynomial functions as trajectories to describe the subgroups. We apply both clustering approaches to the precautionary measure indicator *pi* (appendix A.1). By comparing both methods, we aim to identify robust groups that are identified consistently across the two methods.

The clustering process was repeated twice. First, with the full panel (N = 227) and second, with a panel only including homeowners (N = 194), because residents of flood-prone areas that are homeowners often have more abilities to implement, especially structural, measures. Through the combination of this sensitivity analysis and the comparison of two different clustering techniques, we test the robustness of different behavioural groups.

2.2.1 *LCGA*

LCGA is a group-based modelling strategy that uses finite mixtures of probability distributions for distinguishing representative trajectories of subgroups in the overall sample (Jones and Nagin 2013; Nagin 1999). Heterogeneous response trajectories are summarized by a fixed set of polynomial functions that each represent a distinct subgroup in the sample. This means that all individuals clustered in this subgroup are represented by the same polynomial function. The optimal number of subgroups was selected by an iterative process based on model fit indices (see Fig. 1), namely the sample size adjusted Bayesian Information Criterion and the log Bayes factor (Jones et al. 2001). The suitability of the detected subgroups was examined further by checking their average posterior probabilities. Following Nagin and Odgers (2010), average posterior probabilities within a trajectory group should exceed a minimum threshold of 0.7 to conclude that the group displays a similar trajectory.

A comprehensive introduction to the method and tutorial can be found in Andruff et al. (2009). Jones and Nagin (2013) introduced the Stata extension Traj that we employed.

2.2.2 *kmlShape*

Genolini and Guichard (2016) introduced *kmlShape* as a k-means based clustering algorithm for the analysis of longitudinal data based on the geometric shapes of the trajectories. Genolini and Guichard (2016) showed its key advantage in that by considering the shapes of the trajectories it resulted in clusters that fit closer to the true mean of the cluster centers. We employed this approach using the R package *kmlShape* (Genolini et al. 2016; R Core Team 2018).

Following Genolini and Guichard (2016), the data was standardised by dividing the *pi* by the range of the time (in months) and multiplying it by the range of the *pi*, before performing the classification with *kmlShape* (Fig. 1). We further follow the standard procedure for k-means clustering, to start with a predefined number of subgroups to be separated. Therefore, we started with $k \in \{2,3,4,5\}$ expected subgroups. The choice of potential subgroups was influenced by the results of Bubeck et al. (2020). Additionally, as k-means clustering is sensitive to the initial configuration, that is usually randomly allocated, the algorithm was run with 1,000 iterations. To validate the cluster solutions, we followed the suggestion of Janssen et al. (2012) to estimate the Euclidean distance and allocated the clusters by the smallest distance to compare solutions across iterations.

Since *kmlShape* is not based on classical distance measures, no classical quality criteria can be applied to estimate the quality of the results (Genolini and Guichard, 2016). Previous works that applied k-means clustering used and described a consistency measure $\bar{S}$ to identify the optimal number of clusters (Kok et al. 2010; Sietz et al. 2011). Following this approach, the number of respondents that were allocated to the same group were counted and divided by the total amount of respondents. A high consistency reaches a maximum value of one and signifies that all respondents are allocated to similar trajectories. The interpretation of $\bar{S}$, i.e. the result with the highest $\bar{S}$ of $k \in \{2,3,4,5\}$, lead to the optimal number of k subgroups for validation.

2.3 *Characterisation of precautionary behaviour trajectories*

After identification of the robust trajectories across the two clustering methods, we attempt to characterise the differences across the respondents within each identified behaviour trajectory. We used post-hoc tests to compare the identified groups from the clustering techniques to an extended set of variables drawn from the panel. For numerical variables (including ordinal variables) we applied post-hoc Dunn's test (Dunn 1964) with the use of the PMCMR package by Pohlert (2014). For categorical and binary variables, a post-hoc pairwise chi-squared test was applied. Following the suggestion of Field et al. (2012), a p-value correction with the Holm–Bonferroni method (Holm 1979) was applied considering the error of incorrectly rejecting the null hypothesis after multiple comparisons. Post-hoc tests were applied on a variable-by-variable basis.

Tab. 1 presents the independent variables, showing selected items from the questionnaire, their operationalisation in the socio-psychological models and the type of measurement. According to Rogers (1975, 1983), protection motivation is a leading factor to trigger adaptive responses. Therefore, we included a question regarding the individual protection motivation (defined in Tab. 1). Mainly two perceptual processes further determine individual protection motivation: threat appraisal and coping appraisal (Rogers [1975, 1983]).

Table 1: List of selected variables with definitions, grouped by their operationalisations in socio-psychological theories, type of measurement (O - ordinal scale, C - continuous variables, N - nominal variables) and sample size (n).

Operationalisation in socio-psychological theories	Item from the questionnaire with unit	Type	n
Protection motivation			
Protection motivation	Personally, I will do everything possible to protect the house I live in from flooding (from [1] fully agree, to [6] fully disagree).	O	223
Threat appraisal			
Perceived (future) probability	How likely do you think it is that your apartment or house will be affected by flooding again (from [1] very likely, to [6] very unlikely)?	O	210
Perceived (future potential) damage	How do you assess the negative effects of a possible future flood for you personally (from [1] very bad, to [6] not bad)?	O	215
Coping appraisal			
Perceived response efficacy	Private precautionary measures can significantly reduce flood damage (from [1] I fully agree to [6] I fully disagree).	O	227
Perceived response cost	Private preventive measures are far too expensive (from [1] I fully disagree to [6] I fully agree).	O	225
Perceived self efficacy	Personally, I do not feel able to implement even ONE of the measures mentioned earlier (from [1] I fully disagree to [6] I fully agree).	O	219
Non-protective responses: maladaptive thinking			
Fatalism	There is generally nothing that can be done about floods and flood damage (from [1] fully agree, to [6] fully disagree).	O	227
Wishful thinking	It won't be as bad as 2013 again (from [1] fully agree, to [6] fully disagree)!	O	218
Denial & avoidance	I don't like to think about future flood damage at all! -and- I try to think as little as possible about the possibility of being affected by a flood again (from [1] fully agree, to [6] fully disagree).	O	227
Threat experience			
Flood experience 1	How many times have you personally - before May/ June 2013 - been damaged by floods ([0] never before, [1] once, [2] twice, [3] thrice, [4] four times, [5] more than four times)?	O	224
Flood experience 2	Estimated flood experience indicator from Thieken et al. (2005) including i.a. flood impact and time that has passed (from 0 - no experience to 10 - very experienced).	O	217
Flood impacts on buildings (2013)	Loss ratio of buildings (from 0 - 1).	C	119
Flood impacts on household contents (2013)	Loss ratio of (household) contents (from 0-1).	C	145
Dominating flood type (2013)	Type of flood that caused the damage ([1] dam failure, [2] fluvial flood, [3] pluvial flood, [4] groundwater flooding, [97] other).	N	227
Perceived responsibility			

Perceived self-responsibility	Every individual has a responsibility to reduce flood damage as much as possible (from [1] I fully agree, to [6] I fully disagree).	O	215
Perceived individual responsibility	Those who live by the river must expect floods and make their own provisions (from [1] I fully agree, to [6] I fully disagree).	O	227
Perceived responsibility of the government	Flood preparedness is the responsibility of public agencies, not private individuals (from [1] I fully agree, to [6] I fully disagree).	O	226
Trust in federal government	How much do you trust the federal government to manage floods, i.e., preparedness, response, and damage repair (from [1] I trust very much, to [6] I don't trust at all)?	O	225
Trust in community	How much do you trust the community to manage floods, i.e., preparedness, response, and damage repair (from [1] I trust very much, to [6] I don't trust at all)?	O	226
Framing factor: available information & support			
Information & support	There is far too little information and advice available on private flood preparedness (transformed scale) - and - There are enough tax deductions and incentive programs to fund private flood preparedness. – and - Our community provides very good information about flood hazards and possible precautionary measures (from [1] I fully agree, to [6] I fully disagree).	O	214
Framing factor: social context			
Household size	How many people live permanently in your household, including yourself and all children (No. of people)?	C	226
No. of children, age< 14	How many children under the age of 14 live in your household (No. of children)?	C	221
Observational learning/social norm	Have your neighbors and/or friends taken precautions against potential flood damage or purchased insurance ([1] yes, most of them, [2] yes, some, [3] yes, a few, [4] no, none).	N	162
Perceived social capital	The flood significantly strengthened the social cohesion in my immediate environment (family, friends, neighbors - from [1] I fully agree to [6] I strongly disagree).	O	226
Framing factor: socio-demographics			
Ownership	Are you a tenant or owner of the building you live in ([1] tenant, [2] owner)?	N	227
Income	Monthly net income of household Inet ([11] Inet ≤ 500 €, [12] 500 €< Inet ≤ 1000 €, [13] 1000 €< Inet ≤ 1500 €, [14] 1500 € < Inet ≤ 2000 €, [15] 2000 € < Inet ≤ 3000 €, [16] Inet ≥ 3000 €).	C	168
Age	May I ask how old you are (Age)?	C	212
Sex	Assessed gender of respondent by interviewer without questioning (Gender).	N	227
Education	What is your highest general education degree ([11] no school-leaving qualification, [12] Hauptschul diploma (lower secondary education) or Volksschule (school-type before 1960, 8 years of education), [13] Realschule diploma or Mittlere Reife (types of secondary school graduation), [14] Polytechnic Secondary School (diploma in Eastern Germany, 10 years of education), [15] Specialised Abitur, [16] Abitur, [17] University degree)?	N	225

1

Threat appraisal describes each person's perception of the probability and severity of future flood losses. Coping appraisal is conceptualised by three sub-components: the perceived response efficacy, self-efficacy and response costs (Rogers [1975, 1983]). All five items were included in the post-hoc comparison test.

Following the protection motivation theory, non-protective attitudes like fatalism, denial and wishful thinking can have a diminishing effect on the protection motivation. We included four non-protective responses as potentially explanatory variables: fatalism, wishful thinking, denial and avoidance.

Threat experience appraisal, introduced by Grothmann and Reusswig (2006) describes the extent of individual flood experience. We consider this as the number of previous experienced flood events, an estimated experience indicator, financial damage from the 2013 flood on building and household contents, and the dominating flood type that caused the damage.

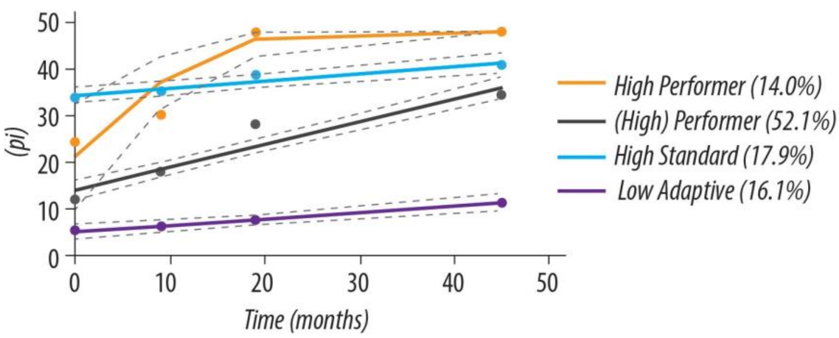
Perceived responsibility is also assumed to trigger adaptive responses (Lindell and Perry, 2012). Several questions in the questionnaire assessed the perceived self, individual, and governmental responsibility, as well as trust in the federal government and in the community.

Several contextual factors were selected in addition to socio-demographic factors ownership, income, age, sex, and education of the respondent: perceived available information and advice on private flood preparedness as well as perceived potential financial support. The respondent's social context was assessed as another framing factor. For that, the household size and the number of children under the age of 14 living in the same household, as well as precautionary behaviour of neighbours, families and friends of the respondent and the perceived strengthened social cohesion due to the flood was assessed.

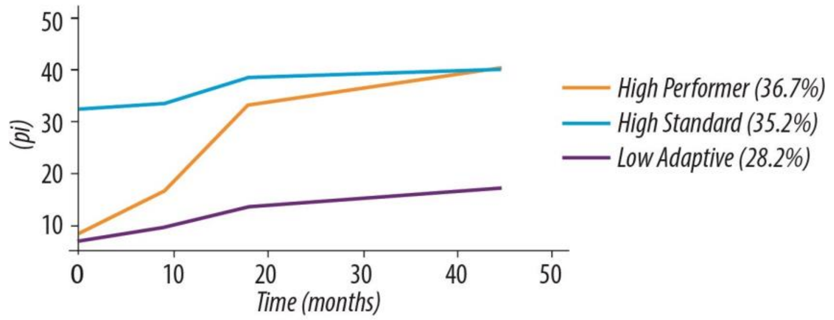
We selected the above-mentioned variable values (Tab. 1) from the first survey wave of the panel to explain the impulse that leads to a specific direction of adaptation. This is because Bubeck et al. (2020) showed the largest changes in their shape and directory after the first survey wave.

Given the relatively small sample, missing data can be problematic. We made use of the structure of the panel to impute missing values. This was achieved by using the response from the identical question from the second survey wave to replace missing values in the first wave. To limit potential measurement error, we only impute data if the variable in question showed no significant change between the first and second survey waves when tested with Friedman's ANOVA on the whole sample. We reduced the proportion of missing observations from 9.8 % to 6.2 % of the overall sample size. The individual questions where this is applicable are noted in the appendix including the variable's F-statistics.

Additionally, to reduce the number of items used in the analysis, when several questions referred to similar concepts, we used Cronbach's α (Cronbach 1951) to test the reliability of the questions. A Cronbach's α > 0.7 for a set of questions allowed us to assume that they measured the same central concept. In this case the mean value of the questions was included instead of separate variables. This was applied to the variables of denial and avoidance and information and support (Tab. 1).



(a) LCGA



(b) kmlShape.

Fig. 2: (a) Classified subgroups of *pi* with *LCGA* with 95% confidence intervals and (b) *kmlShape*.

3 Results and Discussion

3.1 *Classifying dynamic precautionary behaviour*

Based on the model fit indices (see appendix A.3), the four group trajectory model was the best result for the *LCGA*. Details on the estimates and standard errors of the linear terms are attached in the supplementary files (A.3).

Fig. 2a shows the development of the *pi* for the four identified adaptive trajectories as identified by the *LCGA*. We observed that 17.9 % of the sample was allocated to a group that was well prepared before the flood hit, and implemented further (but limited) precautionary measures over time (High Standard group (HS) in light blue, Fig. 2a). The Low Adaptive group (LA in violet, 16.1 % of the sample) was not well prepared before the flood hit and, after four years, showed little change in the number of precautionary measures they reported. The other two groups showed a learning effect from the flood event and, while with different trajectories, implemented considerable number of additional measures over the survey period. Hence, both are labelled as high performer groups HP and (H)P. The (H)P group in grey is the largest group within our sample (52.1 %). This trajectory starts at a low-medium level of precautionary behaviour, but after four years reached the level of the HS group. The HP group in orange (14 % of the sample) showed a large variability in the early time steps, but this reduced in later survey waves. The trajectory in Fig. 2a shows a medium level of precautionary behaviour before the 2013 flood, but after four years implemented nearly all measures that were asked in the panel and overshot the HS group. In these results, we find that the trajectory groups identified by Bubeck et al. (2020) are robust to the inclusion of new indicators of adaptive behaviour. The current study included a wider range of measures, e.g. buying an insurance policy or attending a seminar on how to prevent flood damage, weighted in accordance with their perceived effectiveness.

Fig. 2b presents the results of the *kmlShape* clustering approach. Based on average consistency, presented in the appendix (A.3), the approach indicated three representative trajectories of adaptive behaviour. Like the *LCGA*, we observed a group that already implemented a good number of precautionary measures before the flood event and adapted further (HS group in light blue, 35.2 % of the sample). The second and third group (HP in orange with 36.7 %, LA in violet with 28 % of the sample) were not well prepared before the flood hit. However, the HP group learned from the flood event and adapted well during the survey period. On the other hand, the LA group barely changed their level of precaution over the survey period by comparison. Fig.s 2a and 2b illustrate, based on similar colouring, where we observe similar trajectories across the two methods. The HS and the LA groups especially showed similar behaviour over time and were classified by both methods alike. Moreover, from comparing the trajectories, we infer that the HP group in *kmlShape* was split into two further groups by the *LCGA* method, even though the pattern of adaptation is slightly different.

The contingency table (Tab. 2) compares the groups directly with each other and shows whether individual respondents were allocated to the same or a different group by the two classification methods. We observed that 31 respondents that were allocated to the HP group by the *LCGA* were also allocated as the HP group and the HS group by *kmlShape*. This is plausible, as the uncertainty ranges of the *LCGA*- HP-group included a high prior-to-the-flood-precaution that would be comparable to the HS group (Fig. 2a). Most of the respondents (N = 118) were allocated to the (H)P group by the *LCGA*. Of those, 58 % were also allocated to the HP group by the *kmlShape*. However, we also find some respondents that were allocated to the HS and even the LA group by *kmlShape*. Therefore, we consider this group as the one where results differ the most. Respondents allocated to the HS group and the LA group by the *LCGA* however match the identification with *kmlShape* by 100 %. Therefore, we consider the LA group as especially robust, as it was found consistently across both methods.

Table 2: Contingency table to compare the different classification methods *LCGA* and *kmlShape* (HP - High Performer, HS - High Standard, LA - Low Adaptive)

	HP (*kmlShape*, N = 83)	**HS** (*kmlShape*, N = 80)	**LA** (*kmlShape*, N = 64)
HP (*LCGA*, N = 31)	15	16	0
(H)P (*LCGA*, N = 118)	68	23	27
HS (*LCGA*, N = 41)	0	41	0
LA (*LCGA*, N = 37)	0	0	37

A direct comparison of both methods is difficult (as noted in Section 2.2). Nevertheless, both methods resulted in a similar shape of the trajectories and thus a similar dynamic behaviour. Therefore, we argue that we can learn from both methods that we can, overall, distinguish three different groups of adaptive behaviour: the HP, HS, and LA groups. The HP group was split into two further subgroups by the *LCGA*, the difference being the final level of adaptation after four years. We argue that the fundamental dynamic behind this group is the same and that both groups are comparable with the *kmlShape*'s HP group. Therefore, for the characterisation of these behaviour groups we focused on the results from kmlShape to simplify and generalize our results. Separating the sample into three rather than four groups is an additional benefit for the post-hoc tests, as it keeps sample size reasonably high. The detailed results of the characterisation for the LCGA groups are reported in Appendix A.4.

Our results indicate that a significant share of precautionary measures is implemented considerably later post-flood. This dynamic cannot be accurately captured by cross-sectional survey designs. Previous cross-sectional surveys in the area showed that when respondents were asked about their adaptive behaviour, they tended to employ 50-70 % of the precautionary measures that were asked in the questionnaire (see e.g. Kienzler et al. 2015; Thieken et al. 2016b).

The HP group, for instance, showed the highest implementation of precautionary measures between the first and second survey wave. Before that, this group showed little to medium implemented precautionary measures (across both methods). According to our results, this applies to 37- 66 % of residents of flood-prone areas. Others, however, might be of a low adaptive type and might not adapt much after a flood event. (16-28 % of flood-affected residents according to our results).

The composition of *pi* leads to some limitations. First, it is important to note that our approach does not allow a trajectory where the precautionary indicator is decreasing, i.e. precautionary measures are, once implemented, assumed to be permanent, i.e. remain constant over time. However, the precautionary level might decrease. Structural measures might age and deteriorate or knowledge from seminars might be forgotten. Data from a repeated cross-sectional study in northern Italy showed that, in fact, the perceived preparedness decreased over a period of 13 years (Mondino et al. 2020).

Another limitation might originate from the use of the precautionary indicator that was built by weighting precautionary measures by their effectiveness that served as a representative value for the adaptive behaviour of flood-affected residents. Achieving a value of 48 indicated the highest achievable value. This, however, should not reflect a ‘perfect precaution’. Households might be limited in what kind of measures are feasible or applicable. That means that a household with a lower *pi* value could however reflect the individual optimal precaution. The weighting that went into the *pi* was based on the findings of effectiveness of precautionary measures by Kreibich et al. (2015). This must be seen as an approximation, as the effectiveness of measures may differ in individual cases. For example, buying insurance was not weighted in this study, as this factor is not effective in directly preventing flood impacts. In repairing flood losses, insurance play a considerable, however indirect, role by refunding flood losses.

3.2 Characterisation of different types of adaptive behaviour

To assess potential differences in the identified behaviour groups, we used post-hoc test statistics on a number of variables. Tab. 3 reports the central values of the three groups resulting from *kmlShape* (HP, HS and LA) together with the adjusted p-values of post-hoc test statistics. Overall, the three types of groups were surprisingly similar regarding most of the assessed socio-psychological variables. The groups differ significantly in seven out of 28 factors.

Interpretation of post-hoc Dunn’s Test showed that the protection motivation of the HS group was significantly higher than the LA group. This seems plausible, as the HS group was already well prepared before the flood, whereas the low adaptive group was not well prepared. The HP group had a relatively low motivation in the first survey wave in comparison to the HS group. Still, the HP group implemented many measures after the first survey wave despite the relatively lower initial level of starting motivation. However, the post-hoc Dunn’s test showed no significant difference in the protection motivation of the HP group in comparison to the LA or the HS group. This indicates that protection motivation is an important driving factor to implement precautionary measures for the HS type, but not a central driver.

High threat appraisal and high coping appraisal is positively correlated with adaptive behaviour (Rogers [1975, 1983]). This did not match our findings. The central values showed rather similar values for the three groups. Regarding threat appraisal, the HS group expressed

Table 3: Central values of the first survey wave and adjusted p-values of Dunn's Test or chi squared for the *kmlShape* groups (HP - High Performer, HS - High Standard, LA - Low Adaptive). Significance stars refer to probability levels as: * for levels below 0.1, ** for levels below 0.05, *** for levels below 0.01.

Variable	HP Mean (SD)/Mode	HS Mean (SD)/Mode	LA Mean (SD)/Mode	HP vs HS	HP vs LA	HS vs LA
Protection motivation						
Protection motivation	1.46 (1.16)	1.18 (0.50)	1.66 (1.23)	0.175	0.175	0.009***
Threat appraisal						
Perceived (future) probability	4.49 (1.61)	4.63 (1.59)	4.20 (1.65)	0.585	0.585	0.281
Perceived (future potential) damage	2.22 (1.41)	1.96 (1.21)	2.43 (1.71)	0.610	0.753	0.610
Coping appraisal						
Perceived response efficacy	2.78 (1.91)	2.44 (1.76)	3.12 (2.00)	0.501	0.501	0.102
Perceived response cost	4.08 (1.75)	3.85 (1.64)	4.03 (1.70)	0.908	0.964	0.964
Perceived self efficacy	2.44 (1.72)	2.70 (1.91)	2.88 (1.66)	0.779	0.393	0.779
Non-protective responses: maladaptive thinking						
Fatalism	2.71 (1.68)	3.29 (1.69)	2.92 (1.85)	0.071*	0.519	0.280
Wishful thinking	4.13 (1.95)	4.53 (1.94)	3.95 (1.91)	0.276	0.546	0.143
Denial & avoidance	2.27 (1.15)	2.08 (1.10)	2.33 (1.22)	0.735	0.856	0.735
Threat experience						
No. of previous flood experience	0.96 (1.37)	1.36 (1.46)	0.87 (1.22)	0.055*	0.901	0.055*
Flood experience indicator	1.79 (2.29)	2.76 (2.45)	1.74 (2.13)	0.024**	0.988	0.027**
Loss ratio of buildings (2013)	0.17 (0.19)	0.13 (0.19)	0.13 (0.15)	0.403	0.455	0.926
Loss ratio of (household) contents (2013)	0.28 (0.28)	0.20 (0.24)	0.23 (0.27)	0.289	0.504	0.685
Damaging flood type (2013)	Fluvial flood (59.0 %)	Fluvial flood (65.5 %)	Fluvial flood (54.7 %)	0.258	0.596	0.502

Perceived responsibility						
Perceived self-responsibility	1.94 (1.45)	1.56 (0.98)	1.68 (1.24)	0.848	0.848	0.936
Perceived individual responsibility	2.57 (1.59)	2.40 (1.48)	2.62 (1.69)	1.000	1.000	1.000
Perceived responsibility of the government	3.25 (1.77)	3.04 (1.58)	3.00 (1.63)	1.000	1.000	1.000
Trust in federal government	3.61 (1.47)	3.67 (1.56)	3.59 (1.38)	1.000	1.000	1.000
Trust in community	3.00 (1.67)	2.83 (1.58)	2.30 (1.33)	0.537	0.033**	0.103
Framing factor: available information & support						
Information & support	4.03 (1.29)	3.97 (1.40)	3.45 (1.36)	0.659	0.020**	0.041**
Framing factor: social context						
Household size	2.40 (1.24)	2.20 (0.91)	2.19 (1.05)	0.972	0.894	0.972
No. of children (age < 14)	0.21 (0.61)	0.06 (0.25)	0.22 (0.63)	0.556	0.993	0.556
Observational learning/social norm	High (30.1 %)	High (43.8 %)	High (28.1 %)	0.654	0.654	0.351
Perceived social capital	2.23 (1.47)	2.03 (1.62)	2.17 (1.58)	0.302	0.829	0.829
Framing factor: socio-demographics						
Ownership	Owner (86.8 %)	Owner (93.8 %)	Owner (73.4 %)	0.215	0.136	0.005***
Income	1000-1500 € (20.5 %)	2000-3000 € (18.8 %)	1000-1500 € (32.8 %)	0.278	0.278	0.278
Age of respondent	61.84 (9.59)	62.16 (10.29)	62.15 (12.99)	1.000	1.000	1.000
Education	Realschule (32.5 %)	Academic (20.0 %)	Realschule (26.6 %)	0.360	1.000	1.000
Gender	Women (69.9 %)	Women (62.5 %)	Women (62.5 %)	1.000	1.000	1.000

the highest perceived probability and the highest perceived potential future damage in contrast to the LA group, who showed small central values. However, Dunn's Test showed no statistically significant difference between the three groups for all five items.

A high coping appraisal and particularly, a high self-efficacy can be a beneficial factor of adaptive behaviour (van Valkengoed and Steg 2019). However, the results of the post-hoc Dunn's test showed no statistically significant difference between the types of adaptive behaviour. In future works it has to be checked whether these items might influence protection motivation and hence adaptive behaviour indirectly.

Factors that would be classified as non-adaptive responses (Rogers [1975, 1983]), i.e., attitudes of denial, avoidance and wishful thinking, did not show a significant difference in comparison between the different subgroups either. This indicates that regarding these factors respondents are characterised by similar attitudes. Fatalistic attitudes however showed a significant difference between the HP and the HS group. In comparison to the HS group, the HP group agreed significantly more with the statement that 'there is generally nothing that can be done about floods and flood damage'. This is interesting as the HP group showed adaptive behaviour after the first survey wave. It is important to note that due to the length of the survey most concepts were only reflected by one item in the questionnaire. To further investigate the influence of threat and coping appraisal and maladaptive thinking this should be changed in future studies.

We compared the different behavioural types according to their threat experience by including an indicator for flood experience that takes into account previous damage, flood impacts and the time that has passed since the last flood (Thieken et al. 2005) as well as the number of previously experienced floods. Results showed significant differences between the HS group when compared with the HP and the LA group. The HP group in comparison to the LA group showed no significant difference. This indicated that the HS group was significantly more experienced with floods in comparison to the others. Therefore, we found that the personal experience of a flood could trigger an adaptive response. The effect that personal experience can influence the willingness to take precautions has been previously found in the literature (e.g. Bubeck et al. (2012); Poussin et al. (2014)). Others however, e.g. van Valkengoed and Steg (2019), found flood experience to be weakly related to adaptation. We observed that the LA type did not adapt much after the experience of a flood. If the flood experience was milder in comparison to the other groups, this effect would be plausible: according to the review of Wachinger et al. (2013), experiencing a flooding without being impacted can lower the risk perception and therefore, adaptation response. However, we do not find indications that the LA type experienced lesser impact than the other groups. The loss ratios of the building and the household contents from 2013 showed no significant difference in comparison to the other groups (Tab. 3). Based on these findings, we conclude that the experience of the threat has an adaptive effect on a proportion of households affected by a flood, but does not trigger an adaptive response in all respondents. Differing results on the influence of flood experience on adaptation could originate from hidden heterogeneity within the underlying population. Depending on how the study sample is distributed among the identified groups, the overall effects would move in different directions. For example, a high proportion of respondents of LA type in a study sample could result in low adaptation despite flood experience.

We further compared the loss ratios of buildings and household contents to draw conclusions about flood impacts. When comparing the central values, the HP group reported the highest losses in comparison to the other groups, but differences were not significant. The same applies to the flood type, where most of all groups reported a fluvial flood type. This indicated that damage or the experienced flood type were not primary driving factors for adaptive behaviour. However, the sample size of the loss ratios was relatively small and effects might have been missed.

The three groups reported similar perceptions about who is responsible for flood preparedness or reducing potential flood damage. All rather agreed that every individual has a responsibility to reduce potential flood damage as much as possible and slightly disagreed that flood preparedness should be the full responsibility of the government. All similarly rather did not trust the federal government to manage floods. The trust in the community to manage floods, however, was significantly higher in the LA group in comparison to the HP group that reported a rather neutral opinion. This might indicate that a high trust in the community for the preparedness and damage repair of floods might trigger non-adaptive responses. However, the HS group also reported that they rather trust in the community regarding flood preparedness and showed no significant difference in comparison to the LA or the HP group. Therefore, for the HS group other factors might have been important as well that motivated people to act.

The perceived availability of information and support regarding flood preparedness was significantly less distinct in the LA group when compared with the HS and the HP group who perceived a similarly sufficient number of available initiatives. This indicates that information and support was an important driving factor for adaptive responses.

Regarding their social context, the three groups showed similar characteristics. They lived in a household size of 2-3 people with 0-1 child. Most of their neighbours and friends took precautionary measures and they agreed that the flood event had rather strengthened the social cohesion in their immediate environment. The average age of the respondents from all three groups was approximately 62 years and approximately 65 % were women. The HP and LA group had a mean monthly net household income of 1000-1500 €, while the HS group reported a mean monthly net income of 2000-3000 €. Most of the respondents from the HP and the LA group went to *Realschule* (comparable to secondary school or high school) while most of the HS group reported an academic education. However, regarding their income or education the three groups showed no significant difference. Here it is to note that the sample size for income was relatively small and effects might have been missed.

Most of the respondents from the HS group were homeowners (93 %). They significantly differ in that regard in comparison to the LA group, where just 73 % of the respondents were homeowners. Consequently, the group that did not adapt well also showed the lowest share of homeownership. This is likely correlated to the low adaptive behaviour, as tenants are limited in the structural modifications in their apartments. However, the sensitivity analysis, where tenants were omitted from the sample, resulted in identical types of behaviour for both clustering methods. Therefore, homeowners can also be of a low adaptive behaviour type but that they have a higher likelihood to be allocated to a type that adapts over time or already is well prepared. That is supported by the similarity of the HP and the HS group, where respondents reported mostly to own their property. Therefore, the analysis seems to be robust against ownership and indicates that tenantry is not a driving factor for non-adaptive responses.

4 Conclusion

Research on property-level adaptation is mostly drawn from cross-sectional studies where temporal dynamics remain unexplored due to the survey design. Residents of flood-prone areas however play an important role in integrated flood risk management, in which the dynamics of precautionary behaviour need to be explored to improve flood risk management (Aerts et al. 2018). This argument is further strengthened by recent studies that showed that flood-affected residents show heterogeneous response trajectories (Franceschinis et al. 2021, Bubeck et al. 2020, Botzen et al. 2020).

We contribute to the wider literature, in this vein, by investigating different trajectories of precautionary behaviour and the respondents within each group through the use of a panel following individuals impacted by the 2013 flood event. The analysis is based on an indicator that includes precautionary measures that account for dry and wet flood proofing, but not risk transfer. Based on two different clustering techniques, we identified three different types of adaptive behaviour: first, a high standard type that was already well prepared for the 2013 flood and optimized their adaptation in the aftermath (35 % of the sample); second, a low adaptive type that was not well prepared in 2013 and has barely adapted after the flood (28 % of the sample); and third, a high performer type that was not well prepared in 2013, but learned from the experience and implemented a large number of precautionary measures over the survey period of 45 months (37 %). While the comparison between *LCGA* and *kmlShape* showed that some individuals are not equally categorised into specific groups, the LA group seems to be most robust.

The three different types of adaptive behaviour show, overall, quite similar respondent characteristics. They were characterised by similar threat appraisal, coping appraisal, attitudes of denial, avoidance and wishful thinking, impacts of the 2013 flood and social context. They also had similar perceptions about who should be responsible for flood preparedness or flood damage control and were characterised by similar socio-economic demographics like income, age, education or gender divides. Few factors showed statistically significant differences. This indicates that further factors from outside of the two core theories, i.e. protection motivation theory (PMT) and protective action decision model (PADM), are driving the dynamic behavioural process. Already well-prepared respondents (High standard) were highly flood experienced with protection motivation remaining high. Respondents that were not well prepared for the 2013 flood event had little to no prior flood experience. Among them, the high performing group showed a significantly higher fatalistic attitude in the first wave in comparison to the already well-prepared group. However, this group implemented a considerable number of measures in the aftermath. A considerable share of flood-prone residents did not adapt well before or after the flood (the low adaptive). To trigger adaptation in this group, specific risk communications and tailored financing programs might be needed. The characterisation of this behavioural type revealed that respondents in this group tended to have a higher trust in community flood management and had the lowest proportion of property ownership. They further reported that they receive far too little information and advice on flood preparedness and possible precautionary measures, and that they feel there are not enough tax deductions and further financial incentives for flood preparedness. Policy interventions could address these points by providing more targeted support to this group. If necessary, it would have to be evaluated whether financial aid after flood events could better ensure flood adaptations in damaged households and whether information campaigns could be better planned so that they reach everyone. Furthermore, stakeholders like housing associations or cooperatives might have to be addressed, too. If such policies are successfully implemented and effective, the statistically significantly lower protection motivation of this group could also increase, which could lead to a generally increased adaptive response.

These results contribute to the fundamental understanding of individual precaution dynamics. Still, we know little about the decrease of precaution over time, as, due to the survey design, the precautionary indicator does not include information about removed or damaged measures. Future studies should address this issue.

The results are important for coupled socio-hydrological or agent-based models, as they allow an empirical deduction of dynamic vulnerability. Thus, socio-hydrological models cannot usefully or accurately model adaptation trajectories without input such as that presented in this study.

Acknowledgements: This work was supported by the University of Potsdam and the Deutsche Forschungsgemeinschaft (DFG) under Grant GRK2043/1 and GRK2043/2; and the German Ministry of Education and Research (BMBF) under Grant 13N13017.

Declaration of interest:

The authors declare that they have no conflict of interest.

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Data Availability Statement

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials. The raw data are available on request from the corresponding author, Lisa Berghäuser. The data are not publicly available due to restrictions e.g. their containing information that could compromise the privacy of research participants.

Word Count: 6537

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: