ORIGINAL PAPER

Developing strategic targeted interaction design to enhance disaster resilience of vulnerable communities

Eefje Hendriks[1] · **Mia Stokmans**[2]

Abstract

Still too often, technical reconstruction assistance does not lead to adoption of hazard-resistant construction techniques by disaster-affected households. Ideally, effective interactions should be framed and communicated in such a way that it appeals to different intentions of individual households to build back safer. Currently, there is no model for humanitarian interactions that indicates what household characteristics reveal intention differences. To develop audience-specific interactions, this study adapted the three stages used in marketing: segmentation, targeting, and positioning, and the established social scientific model motivation, ability, and opportunity. Our strategic targeted interaction design (STID) method segments the affected population based on intentions to build back safer and provides tailored interactions. Based on similarities, 27 target groups are identified, requiring different interaction approaches. To test viability of the STID method, data were collected through 865 open-ended household interviews in earthquake affected communities in Nepal. Cluster analysis shows the presence of different target groups within the same communities. Descriptive statistics of the target groups led to a proposal of audience-specific interaction strategies to enhance safer construction practices and reduce disaster risk. Our analysis indicates a combination of multiple interaction strategies, prioritizing the learning process and interactions within communities over interactions with external actors. This study presents a highly promising method toward personalization of aid, tailored to perceptions of target groups over general community characteristics.

Keywords Humanitarian assistance · Post-disaster reconstruction · Cluster analysis · Knowledge adoption · Motivation ability opportunity · Nepal

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1 Introduction

Natural hazards are increasingly common threats for vulnerable houses and citizens of countries from the global south. Over 1 billion people in the global south live are vulnerable to hazards due lacking coping mechanisms of poorly built houses in highly exposed areas (United Nations Office for Disaster Risk Reduction 2022). Annually, 185 million individuals are affected by natural hazards resulting in an economic loss of 223.8 billion USD (CRED 2023) and leaving over 306 thousand people homeless (Ritchie et al. 2022). Governments and humanitarian organizations are increasingly concerned by the disproportionate impact of disasters on housing in poor areas (UNISDR 2015; World Bank Group and GFDRR 2016; Hallegatte et al. 2017) and seek effective assistance strategies that support communities to retrofit existing houses and construct new houses complying with hazard-resistant standards (World Bank 2022). Yet, despite good intentions of humanitarian agencies and governments, technical reconstruction assistance aimed at enhancing resilience, only reaches a fraction of affected populations (Opdyke and Wang 2021), and does not always enhance housing safety (Hendriks and Opdyke 2021).

The call for more effective assistance is growing, requiring analysis of the wider impact of assistance on people's lives through robust humanitarian evaluations (Kelling 2019; Global Shelter Cluster 2022a). Every year 2.5 billion USD is needed for shelter and settlement assistance after disaster and conflict, to assist approximately 75 million affected persons primarily in countries in the global south, from which 54% is covered (Global Shelter Cluster 2023a). Most available humanitarian funding is used for emergency needs (Global Shelter Cluster 2023a), leaving approximately 80–90% of the people whose house is damaged, lost, or destroyed to reconstruct and repair with little to no formal assistance (Parrack et al. 2014; Flinn et al. 2017; Morel and Global Shelter Cluster 2018). Targeted approaches focusing on hazard-resistant principles could reach a larger percentage of affected populations (Richardson 2023), by exploring in depth factors affecting households' intentions and ability to build back safer (Turnbull et al. 2015; Global Shelter Cluster 2022b).

Despite a wide range of studies into failing interactions aimed at innovation and risk prevention (Rogers 2002; Ramseyer Winter and MSW 2013; Dhimal et al. 2014), practitioners struggle to address root causes of behavior leading to unsafe building (Jimenez et al. 2014; Interaction and USAID 2019; Albris et al. 2020). Technical knowledge gained on resilient sheltering and housing in the last several decades has not solved the limited transfer of skills and knowledge (InterAction 2020; Hendriks and Opdyke 2021). Humanitarian organizations repeatedly stress the importance of context and call for localization of aid (ALNAP 2021, 2022; Metcalfe-Hough et al. 2021) and have developed country specific assistance profiles for shelter assistance (Global Shelter Cluster 2023b). More impact evaluations of individual case studies, to build a knowledge base and enhance generalizability (Global Shelter Cluster 2017; Interaction and USAID 2019). The type of shelter assistance provided rarely serves everyone's needs (Zerio et al. 2016; Maly 2018), and there could be stronger alignment of support to individual households intentions to build back safer. Examining factors affecting household decision-making could help to define more appropriate assistance for individual households or (parts of) communities, such has been explored in health care (Straus et al. 2011; Webb and Weinstein Sheffield 2021). Evidence can make aid more effective, more ethical, and more accountable (Global Shelter Cluster 2022a; ALNAP 2023).

Communication is often identified as a key barrier to applying technical knowledge (Spiekermann et al. 2015). Current communication used in technical assistance is often primarily unidirectional from organizations to households and involves sharing technical

guidelines, for example, through construction manuals, vocational carpenter training, or construction of demonstration houses (UN-Habitat and AXA 2019). Efforts by some organizations are made to create a dialogue to create more locally feasible and acceptable technical recommendations (Craterre 2015). However, rarely is the type of assistance provided based on household-level characteristics, circumstances, and intentions and abilities. Earlier research has found that an understanding of hazard-resistant construction techniques alone does not necessarily lead to reduction of disaster risk (Eiser et al. 2012). Most assistance concentrates on developing knowledge and skills, overlooking the importance of personal motivations, knowledge, and opportunities to construct safer housing (Hendriks and Stokmans 2020). Consequently, there are opportunities to enhance for both the immediate and lasting effects of support for housing resilience (Spiekermann et al. 2015; UNISDR 2015).

Institutionalized barriers such as poverty, power, and marginalization significantly impact the agency of households to make reconstruction decisions that enhance their safety. Key questions driving reconstruction decisions—such as why households do not sufficiently protect themselves and how they may be incentivized to rebuild safely—are still insufficiently understood in disaster science. Moreover, opportunities to reconstruct abilities, beliefs and intentions can differ widely between households. This study aims to explore factors that drive reconstruction decisions, and link individual differences to the type of assistance needed. This study proposes and validates a method with data from the reconstruction in Nepal to inform (re)design of assistance to build back seismic resistant houses. Specifically, this study presents a new method to cluster individuals into target groups based on their intentions to build back safer as a base for audience-specific interactions. This study questions:

How can reconstruction assistance be tailored to intentions of disaster-affected households to build back safer housing?

2 Points of departure to develop targeted interactions

2.1 Importance of a target group approach

Post-disaster housing construction aims to improve pre-disaster fragile conditions, including physical, social, and economic dimensions related to disaster vulnerability (Tran 2015). There is a clear agreement that shelter and settlement assistance should address the whole recovery "process," enhancing resilience rather than the shelter as a "product" (Davis and Alexander 2016; George et al. 2023). However, assistance has addressed predominantly the visible physical safety of shelters, building back safer housing but potentially overlooking problematic long term social and cultural impacts (Tran 2015). To step away from evaluating safety improvements in homes as products, there is a call to evaluate the wider impact of shelter and settlement assistance on the individual or communal decision-making process (Interaction and USAID 2019).

Prior research has shown that circumstantial conditions, including social community structures, are often important for reconstruction decisions (Turnbull et al. 2015). Understanding the importance of context, humanitarian organizations stress that there is no one-size-fits-all for appropriate housing designs that can be just plugged and played (Global Shelter Cluster 2018; Crété et al. 2021; Metcalfe-Hough et al. 2021). They call for localization of aid, aiming to adapt safe construction practices to the community's way of living, balancing what is safe, feasible, and acceptable (Flinn 2020).

In line with the current conversations within the shelter and settlement sector, we argue that designing and constructing a different type of house after a disaster requires a *social innovation* instead of just a *product innovation,* profoundly linked to tradition and culture (Cresson et al. 1995). Technical knowledge awareness and understanding alone are insufficient to stimulate social change (Hoppe and de Vries 2018). The introduction of a new way of building a house requires a change in social processes, such as other ways of living, and changing norms and values within the community and time. It therefore also requires a study of social dynamics, social norms, and social processes. The most important behavioral theories, overlook the importance of social dynamics, such as the Theory of Planned Behavior (Ajzen 1985), Theory of Reasoned Action (Ajzen 1991), and Technology Acceptance Model (Davis 1989). Therefore, there is a need to rethink how assistance should be organized addressing the varying processes, opportunities, abilities, and beliefs of community members. New approaches are required that respect individual differences as part of a heterogeneous group.

2.2 Importance of an interactive intervention

Non-governmental and governmental agencies struggle with the accountability of household decisions that do not timely comply with their perspectives on state-of-the-art guidelines (Bandura 1977, 1994). People commonly tend to settle for solutions that are "good enough" to solve their problem (Simon 1993; Kahneman and Thaler 2006), despite their intentions to strive for the best solution. What people regard as "safe enough" is not always the same as compliance with building codes or recommended construction measures, and these perspectives should not be overlooked (Ackrill et al. 2013). Since the majority self-constructs their house after a disaster, it is both more realistic and ethical to target informed choice on the safety of the house. Twigg et al. (2021) stresses the importance of allowing people to make informed decisions; "*When putting people's choice and control at the center of support to self-recovery, shelter agencies will need to come to terms with the fact that Building Back Safer may not be a priority for everybody. Instead, they will have to focus on ensuring that people are making informed decisions equipped with the best knowledge and resources that they can obtain. A choice-based approach also implies a transference of the ownership of risk to the affected people. This shift puts a different emphasis on an aid agency's duty of care: where before there was a duty to supply high*
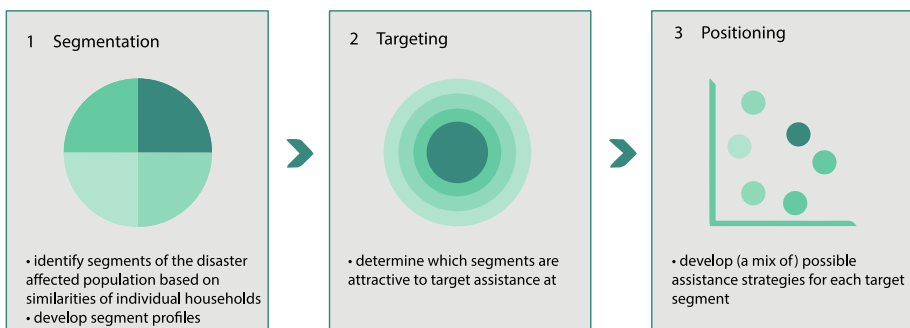
Fig. 1 Steps in market segmentation, targeting, and positioning Adapted from (Kotler and Armstrong 2010)

quality goods and services, now there is a need to enable informed choice through the provision of appropriate technical support and information."

In earlier work, this study's authors found indications that technical guidelines are not fully aligned with the household wishes, creating desires for modifications (Hendriks and Opdyke 2022). Co-creation, to safeguard the acceptance of the suggested techniques and materials, is an essential step in community engagement (Bowen et al. 2010) and boosts self-efficacy, the lack of which raises doubts about the longer-term resilience of the built environment. For the self-efficacy and resilience of communities on the long-term, people should be granted with the opportunity to learn from their own decisions (Bandura 1977, 1994). Ownership over decisions is also essential for knowledge retention within communities and should even be prioritized for successful recovery (Babister 2020), as this simulates the learning process of disaster-affected communities. This requires a multi-stakeholder collaborative approach between NGOs, policy makers and communities to co-design recovery assistance and interactions, and openness of community outsiders to adapt technical knowledge to the local environment, and traditions (Bowen et al. 2010).

3 Methods

3.1 Development approach for audience-specific interaction

We argue that community buy-in is crucial for acceptance of a new way of building. Therefore, in this study, we aim to develop social interactions which extend existing capacity for hazard-resistant housing construction. Our approach is based on the understanding that households normally intend to reconstruct safer houses, but in line with resources and acceptance of change by the community. We use the theory of market segmentation, to select tailored interaction, adapting "*what*" is offered and "*how*" it is offered to characteristics of households. This study uses the three-step target marketing research framework: (1) segmentation, (2) targeting, and (3) positioning (Kotler and Armstrong 2010) or STP, illustrated in Fig. 1. This framework is widely applied to develop effective targeted marketing and can also be used to develop interactions in the field of social innovations (Tournois 2016).

First, segmentation aims to identify meaningfully different groups within a population, with their own set of perceptions. Segmentation separate groups based on similarities and differences. Criteria for the creation of groups need to be chosen carefully to develop meaningful segment profiles for the purpose of the interactions. In this study, we aim to segment disaster-affected populations based on criteria that are likely to influence the way people respond to interactions. Second, through targeting, specific segments can be selected for specific interactions based on their "*perceived vulnerability*." In this study, *perceived vulnerability* can be defined by the barriers experiences to build back safer. The types of barriers and the demographic group that are selected for the interaction are a political and/or practical choice made within the philosophy of the interaction organizer. In the final step, positioning, interaction strategies are designed for selected target audiences by interpreting and addressing their main barriers.

3.2 Criteria for audience segmentation

Decisions made in the first step, segmentation of audiences, are crucial for effectiveness of interaction strategies. Segmentation strategies often make use of social demographic

Intentions to adopt hazard-resistant
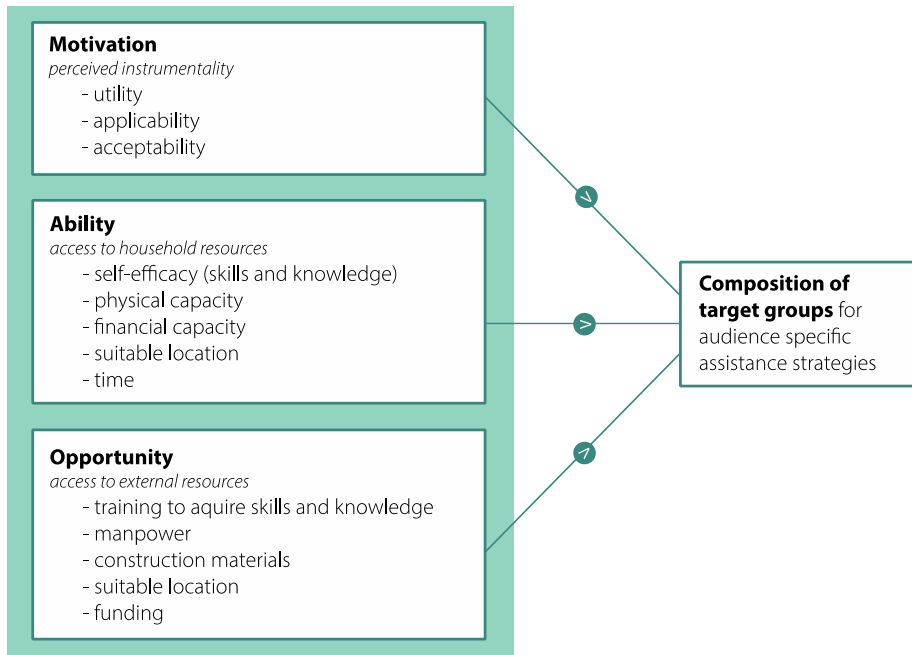construction techniques by households:

Fig. 2 Composing target groups based on motivation, ability, and opportunity

characteristics such as education, occupation, and income (Kotler and Armstrong 2010). Such characteristics are often poorly suited to distinguish households in the Global South, as households often share the same education level, have roughly the same income and often even occupation, see our Sect. 3.4 describing our sample. Income is often not a suitable discriminator as people routinely informally exchange goods and services instead of paying for them. Demographic characteristics insufficiently discriminate between groups of people with different intentions to build back safer. General objective characteristics, such as occupation, educational level, from before the disaster are not necessarily indicative for future behavior, as they are disrupted by the disaster, see our example in Sect. 3.4. Other more specific characteristics, such as subjective psychographic characteristics, are needed to clarify how groups will respond to type of interaction strategies (Verplanken 2018).

In this study, we use the psychographic characteristics: motivation, ability, and opportunity (MAO) to describe the likelihood that a household will build back safer. The model has been used in numerous social scientific studies (Gruen et al. 2005; Jepson et al. 2013; Le et al. 2014; Hung and Petrick 2016), but this study seeks to break new ground by applying it in disaster risk reduction. Our earlier work (Hendriks and Stokmans 2020) shows how this social scientific behavioral MAO model was useful to explore and explain differences in post-disaster reconstruction processes. For example, households having low motivation and low perception of their abilities or opportunities will be less likely to reconstruct hazard-resistant housing. We hypothesized that this model could assess different intentions to adopt hazard-resistant construction knowledge. This can potentially lead to effective

interaction design guidelines which appeal to specific audiences, enhancing the safety of the built environment. The potential of this idea has been recognized by various researchers (Crété et al. 2021; Twigg 2021).

In this study, we use the MAO model as a framework to unravel intentions of decision-makers to adopt novel technologies (Wiggins 2004; Stokmans 2005). Based on the MAO model, persons can be assigned to a specific segment based on a qualitative and quantitative analysis of their answers regarding their motivation, ability, and opportunity as was illustrated in (Hendriks and Stokmans 2020), see Fig. 2.

3.3 Systematic targeted interaction design method

For this targeted approach we have developed the systematic targeted interaction design (STID) method, presented in Fig. 3. The method uses the criteria of motivation, ability, and opportunity in the concept of segmentation, targeting, and positioning using a cluster analysis. The STID method contains several data coding steps, a cluster analysis procedure, and the selection of target groups and the design of the interaction. In the results sections, we elaborate further on how the method is applied.

3.4 Data sample

Data are needed to test if the STID method is valuable to segment audiences and if these segments can be linked to audience-specific interaction strategies. This study uses data collected three years after the earthquakes in April 2015 in Nepal that severely impacted the built environment and reflects upon this specific moment in time. The initial 7.8 magnitude earthquake struck in center of Nepal and affected the capital, Kathmandu, and the surrounding mountainous districts followed by multiple large aftershocks, destroying a significant portion of the housing stock and infrastructure. Data was selected from 17 communities in Okhaldhunga, one of the 14 most affected districts, see Fig. 4. Communities were identified using a combination of geographical boundaries and the smallest identifiable administrative order, the ward level. We acknowledge that social boundaries are not solely geographical or administrative, as people identify themselves as part of different groups on grounds of caste, religion, gender, or occupation. Selected communities are positioned in mountainous areas and primarily dependent on agriculture as a source of income (79%). Since the earthquakes had an impact on most of the housing stock, construction activities also became a primary source of income for many (19%). Although officially forbidden in Nepal, people still relate to castes, ethnic profiles with a different socioeconomic status, culture, and endogamy. From high to low we identified the following castes: Brahmin, Janjati, Dalit.

3.5 Data collection instrument

In this study, intentions to build back safer houses were assessed through 865 qualitative household interviews over the course of three months. Interviews included a list of open-ended structured questions (see Supplement Material) to assess motivation, ability, and opportunity (Hendriks and Stokmans 2020). Motivation is described as perceived instrumentality to build back safer and consists of perceived applicability, utility, and acceptability of the knowledge. Ability is conceptualized as readily available (with no additional costs or effort) household resources during reconstruction, consisting of the following
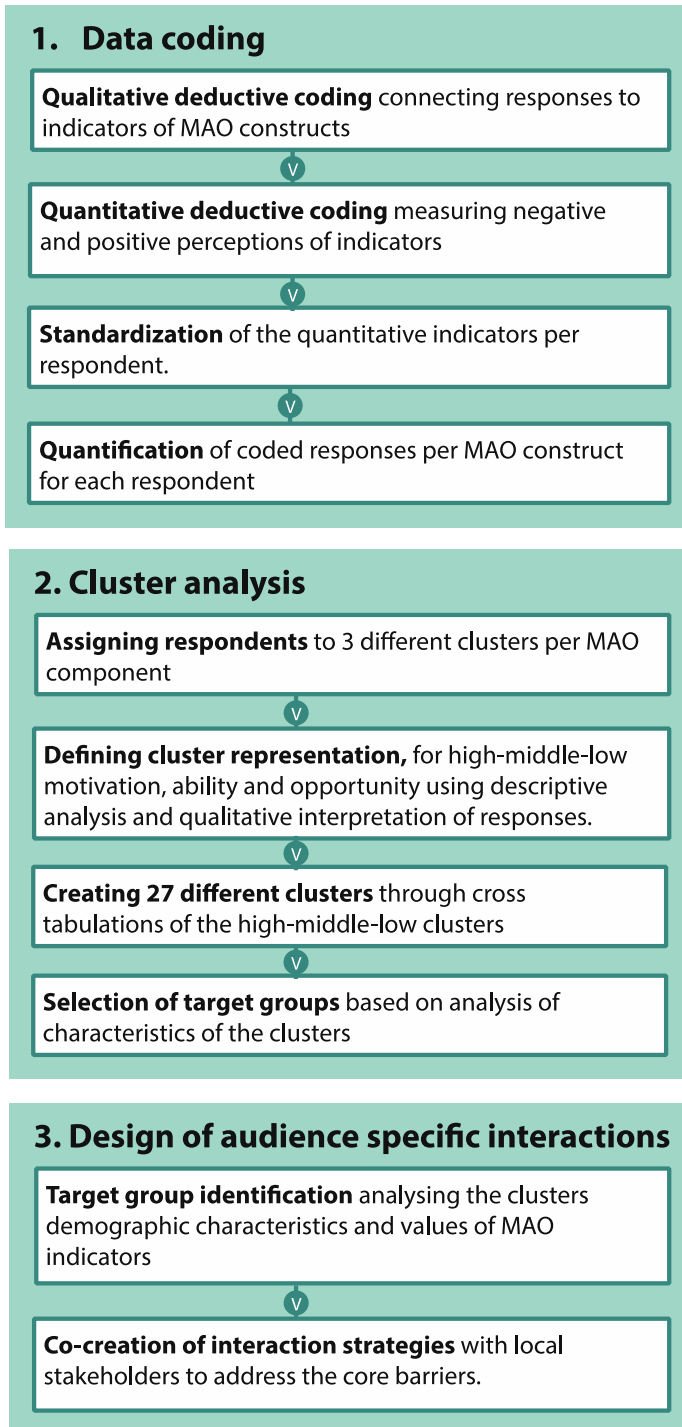
1. Data coding

Qualitative deductive coding connecting responses to indicators of MAO constructs

Quantitative deductive coding measuring negative and positive perceptions of indicators

Standardization of the quantitative indicators per respondent.

Quantification of coded responses per MAO construct for each respondent

2. Cluster analysis

Assigning respondents to 3 different clusters per MAO component

Defining cluster representation, for high-middle-low motivation, ability and opportunity using descriptive analysis and qualitative interpretation of responses.

Creating 27 different clusters through cross tabulations of the high-middle-low clusters

Selection of target groups based on analysis of characteristics of the clusters

3. Design of audience specific interactions

Target group identification analysing the clusters demographic characteristics and values of MAO indicators

Co-creation of interaction strategies with local stakeholders to address the core barriers.

Fig. 3 Methodological overview of the systematic targeted interaction design (STID) method
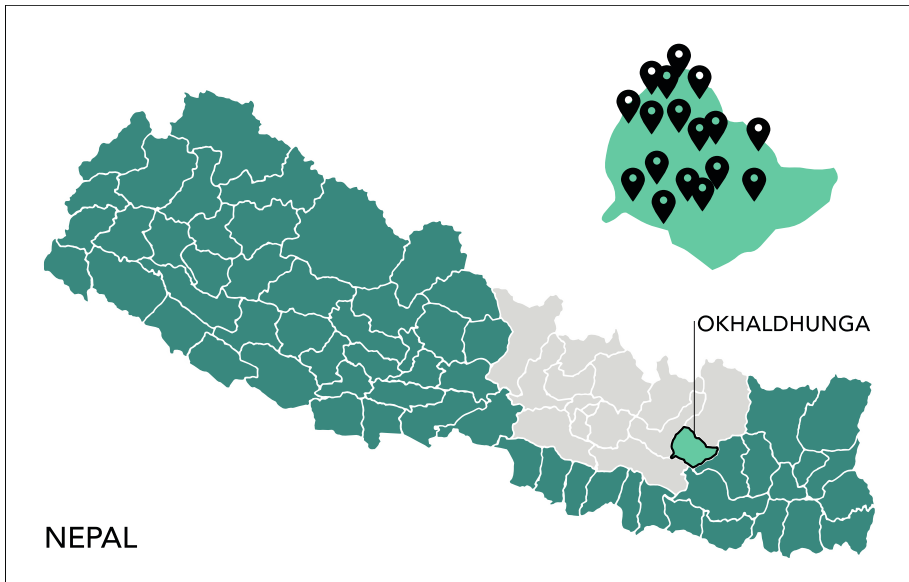
Fig. 4 Case study communities in Okhaldhunga district

constructs: self-efficacy (skill capacity and knowledge capacity), physical capacity, financial capacity, available suitable location, and time available to build. Opportunity is defined as access to external resources that households perceived they needed to build back a safer house. Opportunity is divided between access to training to acquire skills and knowledge, manpower, construction materials, suitable location, and funding to be invested to rebuild.

4 Results design of audience-specific interaction

We will describe the results following the three steps of the STID; (1) data coding, (2) cluster analysis, (3) design of audience-specific interactions.

4.1 Data coding

Through qualitative deductive coding, open-ended responses were linked to the indicators of the three constructs, see Fig. 2. Answers were post-categorized and classified for positive or negative perceptions of individuals. For example, their answers could refer positive to the utility of technical knowledge, or negatively express the lack of utility. Using quantitative deductive coding, for each component a relative quantitative score was connected to each participant (Hendriks 2020; Hendriks and Stokmans 2020).

Our analysis of the data showed that respondents were often extremely outspoken (100%) or not outspoken at all (0%) on certain topics. This resulted in W-shape distributions (see Fig. 5) of the relative scores of each of the components of motivation, ability, and opportunity. The extremes represent strong opportunities and barriers experienced by households and are essential to retain in the data preparation and analysis. In step two of the STID method, respondents are compared with one another to come up with homogeneous groups. However,

the coded data are rather incomparable between respondents, since some talk much more than others. Therefore, we need to standardize a score per component, per respondent.

We use the number of arguments provided for a z-score transformation developed by Pellegrini and Bartini (2000). In doing so, the relative frequency of the number of arguments per respondent were separated into five intervals, as shown in Fig. 5, one for both extremes (0 and 100%) and three equal parts in between the extremes (below the median but not 0, around the median, above the median but not 100). This rescaling avoids loss of extremes and offers a simplified yet still representative reflection of the respondents' intentions. This will result in clusters that reflect those extremes.

4.2 Cluster analysis

4.2.1 Assigning respondents

A cluster analysis can group households based on statistically distinguished differences and similarities (Hair et al. 1998; Bråten and Olaussen 2005), revealing potential commonalities in barriers and drivers experienced during reconstruction. This analysis procedure was selected because it bridges the divide between descriptive case studies and statistical comparison of variables. Notably, cluster analysis retains in-depth knowledge of complexity of differences between respondents in the analysis, offering generalizable findings through robust comparison of underlying constructs (Linnenbrink and Pintrich 2001; Lee et al. 2004).
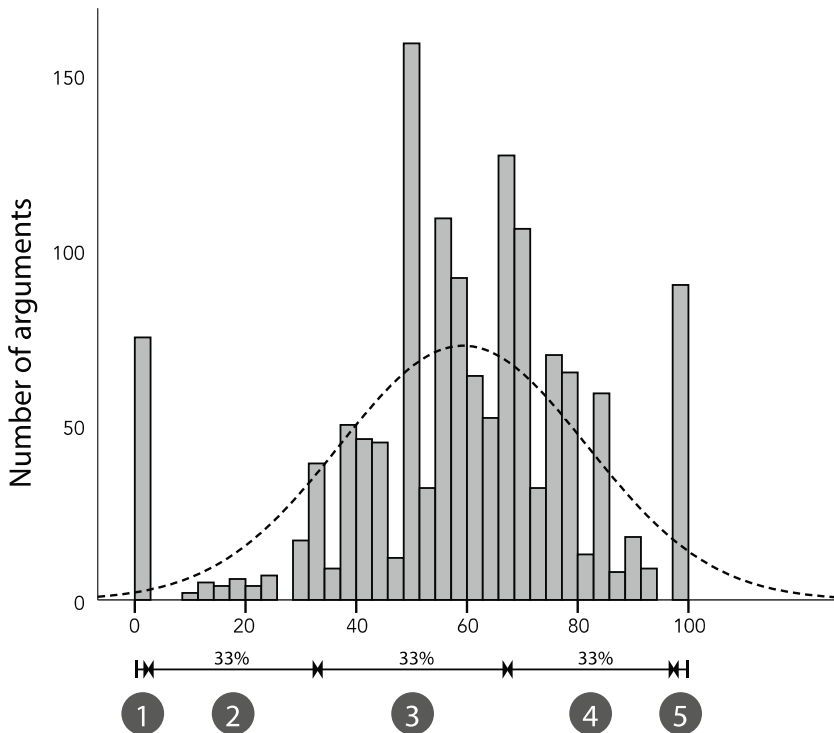

Fig. 5 Example of five interval variables based on interpretation of responses, showing the W-shape deviation of the construct positive perceptions of utility (motivation) for all respondents

Procedures of cluster analysis include K-means, single linkage, centroid, or Ward, whereby different types of distance measures are used as an index of similarity between respondents, such as Euclidian distance or city block (Nunan et al. 2020). This study uses Ward's cluster procedure. In this procedure respondents are assigned to a cluster so distances between respondents within a cluster are minimized and distances between respondents that are assigned to different clusters are maximized (Stokmans 2005). This homogeneity of respondents within a cluster indicates similar intentions to build back safer while their intentions differ from those in other clusters. This cluster procedure aligns perfectly with the intentions of this study.

To arrive at target segments, respondents are first assigned to clusters for motivation, ability, and opportunity separately since motivational aspects are very different from abilities and opportunities. These cluster analyses did not include community membership, only the different aspects of the MOA components. For each cluster analysis, a Ward's procedure using a squared Euclidian distance based on the rescaled data was conducted in SPSS Version 24. While the agglomeration schedule indicated the optimal number of clusters, one should aim at about three cluster for each of the three components of the MAO model (Wiggins 2004; Stokmans 2005) in order to make the procedure manageable. Moreover, the clusters based on a specific MAO component should differ on the aspects of this component (tested with an ANOVA).

We used descriptive analysis and qualitative interpretation of the cluster responses to define which cluster represents low–middle–high perceptions for motivation, ability, and opportunity. Subsequently, clusters of motivation, ability, and opportunity can be combined (cross tabulated) following the scheme in Table 1. Using this procedure, respondents can be connected to one of the 27 different target groups (example is given in Table 5). Target groups represent all possible combinations of low, middle, and high levels of motivation, ability, and opportunity. Households within a target group have a similar MAO profile but differ from the MAO profile of a household in other target groups.

4.2.2 Defining cluster representation

Cluster analysis demonstrated that respondents may be divided into clusters based on their motivation, ability, and opportunity profiles to build back safer. Households are more similar within clusters and are different from households of other clusters due to the Ward's procedure used. Significant differences were found between most groups using a one-way ANOVA; however, a qualitative interpretation was needed to identify which of these cluster represented high, middle, or low perceptions. This interpretation is based on the descriptive statistics of each of the MAO components of a cluster.

Motivation Table 2 indicates that the three clusters of motivation differ significantly ($p < 0.05$) on each of the aspects of motivation distinguished in Fig. 2. Interpretation of

Table 1 Target group classification model based on levels of motivation, ability, and opportunity

Motivation		Low			Middle			High		
Opportunity		Low	Middle	High	Low	Middle	High	Low	Middle	High
Ability	Low	1	2	3	4	5	6	7	8	9
	Middle	10	11	12	13	14	15	16	17	18
	High	19	20	21	22	23	24	25	26	27

these three clusters suggests that cluster 2 has high motivation, cluster 3 has middle motivation, and cluster 1 has low motivation. Cluster 2 is in general most positive and least negative for all three constructs of motivation. While cluster 3 is second most positive for applicability and acceptability and has a rather similar score as cluster 1 for utility, cluster 3 is strongly negative about acceptability (up to 100 points more). Cluster 1 is least positive and most negative for applicability and acceptability. Negative perception of applicability stands out especially in cluster 1 (up to 61.4 points more).

Ability Table 3 indicates that the three clusters of ability differ significantly ($p < 0.05$) on each of its aspects. For ability, we assigned cluster 1 as high, cluster 3 as middle and cluster 2 as low. Cluster 1 has the highest perception of their abilities for all indicators, and perceives the least limitations as reflected in negative indicators of abilities. Cluster 2 and 3 are quite similar, and a closer analysis was needed to decide which of these two has the lowest ability. Cluster 3 is more outspoken, meaning both more positive and negative perceptions than cluster 2. However, cluster 2 is more negative for 3 indicators: location (26.8 points less positive), time (12.0 points less positive), and financial capacity (6.7 points more negative and 6.4 less negative) and slightly more negative on self-efficacy (1.5 point less positive). In consequence, ability of cluster 2 was found slightly lower for more indicators.

Opportunity Table 4 indicates that the three cluster of opportunity differ on all its aspects ($p < 0.05$). Cluster 3 is most positive for all but one positive indicator, and least negative for all but one negative indicator (negative perception of materials). Overall, cluster 1 takes second place and has an "in between" score for almost all indicators. Most negative perceptions are found in cluster 2, especially manpower, materials, and funding (respectively, 6.3, 5.4, and 10.7 points more negative). Only for availability of suitable locations is this cluster more positive (7.2 points) than cluster 1. Therefore, it may be concluded that cluster 3 has a high opportunity, cluster 1 has a middle opportunity and cluster 2 has a low opportunity.

Table 2 Descriptive statistics of clusters based on positive and negative indicators of Motivation

Constructs		Cluster 1			Cluster 2			Cluster 3			ANOVA (significance between clusters)
		n	*M*	SD	*n*	*M*	SD	*n*	*M*	SD	*p*
Motivation											
Utility	+	120	50.81	17.45	**596**	**59.38**	**15.06**	31	*50.21*	*18.77*	***
	–	120	19.44	14.89	**596**	**4.66**	**8.33**	31	*8.86*	*11.27*	***
Applicability	+	120	20.99	21.10	**596**	**60.16**	**12.83**	31	*53.87*	*24.55*	***
	–	120	66.05	27.88	**596**	**4.64**	**11.44**	31	*10.62*	*17.74*	***
Acceptability	+	120	20.26	19.37	**596**	**65.50**	**19.58**	31	*42.88*	*24.05*	***
	–	120	2.78	11.30	**596**	**0.36**	**4.03**	31	*100.00*	*0.00*	***

*$p < .05$, **$p < .01$, ***$p < .001$ strong significant difference between clusters

Bolditalic = High, Bold = Middle, Italic = Low

Table 3 Descriptive statistics of clusters based on positive and negative indicators of Ability

Constructs		Cluster 1			Cluster 2			Cluster 3			ANOVA (significance between clusters)
		n	M	SD	n	M	SD	n	M	SD	p
Ability:											
Self-efficacy	+	105	51.77	14.40	582	24.41	11.52	473	25.94	11.10	***
	–	105	20.68	15.74	582	20.87	13.98	473	22.07	14.57	***
Physical capacity	+	105	92.86	18.61	582	1.74	7.25	473	7.62	17.50	***
	–	105	0.00	0.00	582	15.23	19.22	473	23.31	29.39	***
Financial capacity	+	105	68.96	22.35	582	11.51	12.23	473	17.95	16.69	***
	–	105	3.24	7.52	582	31.34	22.22	473	24.58	21.19	***
Location	+	105	43.24	30.14	582	2.61	7.66	473	29.37	22.83	***
	–	105	6.28	11.81	582	1.01	4.55	473	17.39	16.66	***
Time	+	105	66.06	25.75	582	3.87	7.31	473	15.85	17.79	***
	–	105	0.12	1.22	582	1.71	6.13	473	0.95	4.24	**

*$p<.05$, **$p<.01$, ***$p<.001$ strong significant difference between clusters

Bolditalic = High, Bold = Middle, Italic = Low

Table 4 Descriptive statistics of clusters based on positive and negative indicators of Opportunity

Constructs		Cluster 1			Cluster 2			Cluster 3			ANOVA (significance between clusters)
		n	*M*	SD	*n*	*M*	SD	*n*	*M*	SD	*p*
Opportunity											
Training	+	*208*	*50.09*	*21.00*	**556**	**49.00**	**23.60**	**159**	**71.90**	**16.47**	***
	−	*208*	*23.80*	*17.44*	**556**	**26.75**	**18.18**	**159**	**13.66**	**11.76**	***
Manpower	+	*208*	*38.80*	*23.21*	**556**	**2.81**	**8.79**	**159**	**85.74**	**22.49**	***
	−	*208*	*23.79*	*26.08*	**556**	**30.05**	**26.65**	**159**	**0.00**	**0.00**	***
Materials	+	*208*	*32.77*	*21.32*	**556**	**2.14**	**5.31**	**159**	**43.02**	**26.64**	***
	−	*208*	*21.81*	*18.75*	**556**	**28.85**	**18.66**	**159**	**23.45**	**22.50**	***
Location	+	*208*	*7.36*	*17.62*	**556**	**14.53**	**25.72**	**159**	**71.22**	**29.27**	***
	−	*208*	*8.80*	*14.02*	**556**	**12.64**	**14.86**	**159**	**8.27**	**14.86**	***
Funding	+	*208*	*72.93*	*21.90*	**556**	**52.61**	**20.97**	**159**	**79.23**	**16.92**	***
	−	*208*	*11.38*	*16.34*	**556**	**22.12**	**15.20**	**159**	**9.11**	**14.41**	***

$*p < .05$, $**p < .01$, $***p < .001$ strong significant difference between clusters

Bolditalic = High, Bold = Middle, Italic = Low

4.2.3 Creating 27 different target groups

The representation of the clusters as defined in Sect. 4.2.2 was used for cross-tabulation, resulting into 27 different target groups, see Table 5. Appendices 1, 2, and 3 describe characteristics of all 27 Target Groups in detail.

4.2.4 Selection of target groups

The goal of this study is to illustrate the identification of different target groups to develop audience-specific interaction strategies to enhance intentions to build back safer housing after disasters. By segmenting respondents with similar MAO characteristics in target groups, we identified groups of respondents who experience similar barriers (low scores of MAO), which can be targeted for interaction. As stated by Hoyer and MacInnis (Gruen et al. 2005) interaction *"effectiveness can be proactively achieved by enhancing individuals' levels of MAO elements"*. Therefore, in general, interaction strategies should logically address low levels of motivation, ability, and opportunity.

Table 5 Distribution of households in Okhaldhunga district over the 27 Target Groups (TG)

Motivation		Low			Middle			High		
Opportunity		Low	Middle	High	Low	Middle	High	Low	Middle	High
Ability	Low	*TG1* 19	*TG2* 2		***TG4*** **234**	*TG5* 45	*TG6* 9			
	Middle	*TG10* 3		*TG12* 5	*TG13* 8	*TG14* 3	*TG15* 2	***TG16*** **127**	*TG17* 53	*TG18* 62
	High		*TG21* 7	*TG22* 1				*TG25* 5	*TG26* 14	*TG27* 1

Our results indicate that no interaction will fits all groups identified. Most respondents were categorized in target groups with a middle ($n = 301$) or high motivation ($n = 252$), a low ($n = 309$) or middle level ($n = 263$) ability, and low opportunity ($n = 396$), see Table 5. In reality selecting target groups is a political question as to which group(s) could or should benefit most from an interaction (Rittenburg and Parthasarathy 1997). There is no ideal selection. The selection depends on norms and values of the selecting body and always biased. For the effectiveness of the interaction, we recommend selection in close collaboration with the affected community, seeking motivated and highly trusted parties and respecting local power balances. Individuals trusted for the selection can be identified using a social network analysis. Middle persons between the community and governmental or humanitarian organizations, who understand the community structure and take a role as communicator, such as social mobilisers, could be engaged in the selection. Criteria such as group vulnerability, individuals with the least resources, using demographic indicators or the framework in Table 5, can be used. Another option could be selecting the groups that are considered to have the most "right" on assistance and power, for example commonly marginalized groups. Another option is selecting groups that are most likely to create an effective interaction with, for example not those that score low on motivation.

While selecting the largest groups might overlook the most vulnerable, the choice of the target groups in this study is nevertheless a pragmatic one based on illustrative value and will focus on the two biggest target groups (TG), TG4 ($n = 234$), and TG16 ($N = 127$).

4.3 Design of audience-specific interactions

4.3.1 Target group identification

To understand how to design the interaction with the selected target groups, we explore the target group characteristics. Their MAO components reveal pathways for interaction with and within communities to lower perceived barriers and enhance intentions to build back safer. Gaining an understanding of what exactly is limiting target groups requires exploring two elements: (1) Identifying core elements that the interaction should address based on their MAO characteristics and (2) identifying weak links in knowledge acceptance or communication processes.

Commonalities and differences on the MAO components are described for two target groups in more detail in Table 6, providing the core elements for interactions. Both target groups are almost always located in the same communities (except in one), and both perceive problematic opportunities and abilities to build back safer. People in a community can differ in their motivation, perceived ability, and perceived opportunity to build back safer, although they received the same reconstruction assistance and live in a similar situation.

4.3.2 Co-creation of interaction strategies

Given the characteristics of the target groups selected, we suggest interactions strategy that makes use of four tactics (see also Fig. 6). These tactics are inspired by the framework of social innovations and building community resilience. The reconstruction process can be seen as a joint learning experience that the communities is going through together, where community members share and redevelop norms and values and jointly respond to the same threat. Bowen et al. (2010) describe the process of collaborative, corporative learning, and action as a key element for social innovation. Educational models highlight the

Table 6 Summary of core MAO characteristics of selected target groups to position interaction

|	Group 16 (127 respondents)	Group 4 (234 respondents)
Motivation	High	Average scores, around midpoint of the scale
Ability	Average, close to overall mean. Problematic lack of physical capacity. Insufficient financial resources. Negative about suitability of their own construction plot. Perceived limited time to construct	Low for all indicators, expect availability of a suitable location (little negative). Not positive at all about their physical capacity. Not positive about their own budget. More than average lack of self-efficacy. People did not often refer to location or time as barriers or drivers
Opportunity	Low. Problematic lack of manpower externally. Not very positive about external funding opportunities. Negative about external alternatives for land. Lacking availability of materials	Low. Strongly negative about the possibility to find manpower elsewhere. More than average negative about external funding. More than average to a lack of available materials. People did not often refer to location or time as barriers or drivers
Communities	Identified in all 17 communities, but primarily in 4 of them	Representatives in all communities, except one
Caste	Slightly more households from the Dalit caste (13 vs. 10% on average)	More Janjati, middle caste (67 vs. 56% on average), and less frequently (15 vs. 27%) Brahmin (high caste) and infrequently (9 vs. 10%) Dalit (low caste)
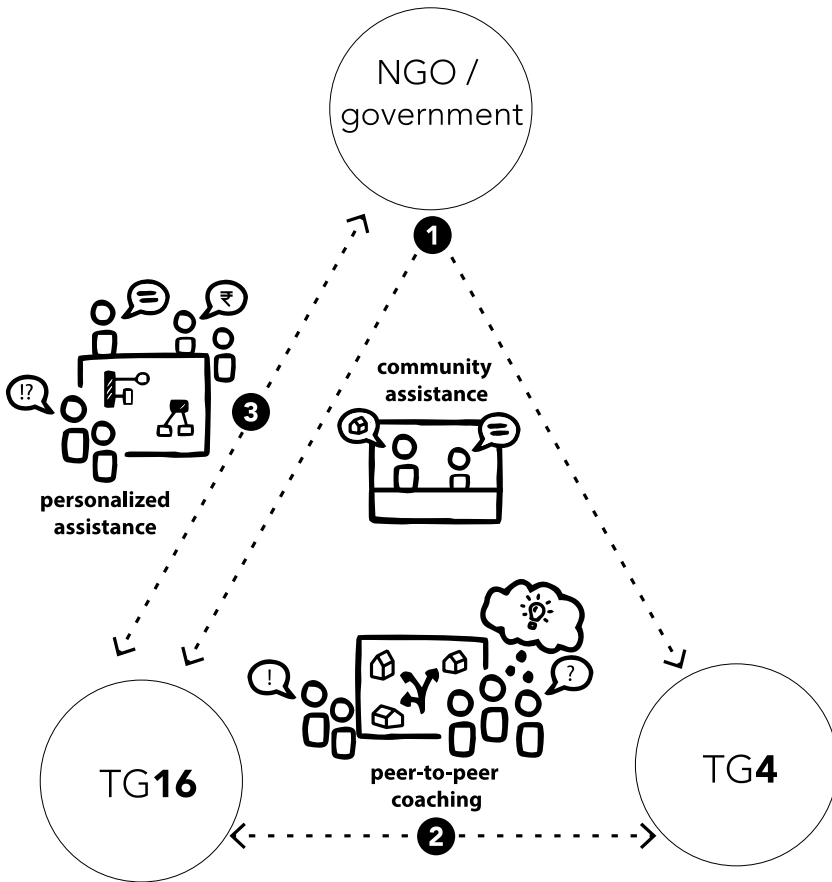
Fig. 6 Interaction strategy; (1) community assistance, linear information sharing by community outsiders to avoid misinformation. (2) peer-to-peer learning, to support community learning through transactional communication between peer target groups. (3) personalized assistance collaborating with key stakeholders in the target groups to act as opinion leaders in a transactional model, to address needs and desires that cannot be solved within the community

effectiveness of peer-to-peer learning aimed at a specific learning objective (Nokes-Malach et al. 2015), learning through experience (Bandura 1977, 1994; Kolb 2015). Therefore, central in our approach is cooperation between community members, before establishing interaction with community outsiders.

> *1. Community assistance* by humanitarian or governmental organizations to address misinformation by means of one-way communication.
> *2. Peer-to-peer learning* within the community between the target groups, transactional two-way communication, sharing solutions to address gaps in motivation, ability, and opportunity.
> *3. Personalized assistance* developed in collaboration between community and outsiders to address needs that cannot be solved within the community.
> *4. National interventions* to change policies that support the reconstruction process.

- Community assistance

To assure that perceptions are not based on misinformation regarding reconstruction opportunities, it can be beneficial that humanitarian and/or governmental organizations share information about existing support programs with the communities. Our analysis shows that the targeted communities required enhanced awareness about procedures to access different types of financial support, construction training, construction materials, and suitable construction plots. Members of one community explained that their damage and progress was incorrectly communicated, resulting in almost no approval of first financial instalments 3 years after the earthquake. Moreover, to avoid extreme construction costs due to the high demand, poorly paved roads and remoteness, information could be shared about retailers, prices, and contact persons to make cost estimations, negotiate prizes and deliveries at a community level. Better access to technical training could be facilitated through selecting locally appropriate training moments, locations, travel funds, or access to food. Attendance motivation and commitment could potentially be stimulated through rewarding certificates (Bowen et al. 2010) or t-shirts, signaling participation to other community members. Vocational training is recommended to deal with contextual complications of accessing a safe construction plot in the mountainous landscape. Strategies include constructing a house on flat surfaces, not adjacent to slopes or edges, away from potential landslides, or next to a retaining wall.

- Peer-to-peer learning

To address perceived lacking opportunities, abilities, and motivation to build back safer, target groups can share knowledge and skills with each other through peer-to-peer coaching. For acceptance of new technologies, social dynamics, trusted actors, and local channels of communication are crucial (Eiser et al. 2012). Peer-to-peer coaching should be facilitated in a transactional, two-way communication and collaboration based on some common grounds and some differences in experiences with Building Back Safer (Stokmans 2005). Power should not be used in a unidirectional manner but rather to simulate stakeholders to both teach and learn simultaneously. Because of their common ground, they will be more likely to trust each other or speak the same language so peer learning will be facilitated. Common grounds were identified analyzing demographics of the case study communities and included language, culture, religion, livelihood, construction materials, and techniques. To effectively stimulate collaborative learning, moderate or high motivation to build back safer is required in the group. Ideal stakeholders to engage in the conversation are highly motivated and already have trust and authority, and positively support application. These stakeholders can be identified using a social network analysis as part of the survey (Hendriks et al. 2021). If those with authority that are negative about application, they could undermine the legitimacy of the exchange and should be motivated before having a large group discussion. TG16 party fits that profile, being highly motivated, regards themselves as more able and perceives more opportunities to build back safer. Due to their higher levels of knowledge, it is easier for them to comprehend incoming information. Through peer-to-peer coaching TG16 could act as steppingstone to support TG4. However, caste differences might affect the interaction. Since TG16 members are often from a lower cast, they could lack local authority to promote build back safer. The presence of different casts could have implications for the interaction strategy, interaction, and tone of voice.

Given the perceived lack of self-efficacy and applicability, peer-to-peer learning could include observational learning and discussion, addressing *what* is being done, *why* it is important, and *how* it can be implemented and adapted it to fit abilities and traditions.

Abstract technical knowledge is often hard for non-specialists to understand. Learning by doing and learning from peers have been found to be effective ways of learning (Foster and Rosenzweig 1995; Fazey et al. 2014). Peer-to-peer communication could address technical complexity by enhancing familiarity with anecdotical solutions through joint visits of construction sites. Self-efficacy (an aspect of ability) is a feeling that one masters the task at hand and is closely connected to exemplary behavior of comparable others. Practical examples and positive feedback on personal performance outcomes are key contributes to self-efficacy (Bandura 1997).

It is essential for disaster resilience to keep motivations high over longer periods of time. After a destructive natural hazard event the motivation of people to reconstruct safer housing is likely to increase at first but reduce over time. Increasing household motivation is relatively complex, involving understanding of why something is instrumental as well as accepting this knowledge as relevant and important. Motivation is not only important for the intention to build back safer, but also for processing the communication about building back safer (MacInnis and Jaworski 1989). In order to increase motivation, interactions should be directed to the *why*, *how,* and *what* (Sinek 2009). By creating a learning environment and organizing regular discussions over a longer period about earthquake resistant construction techniques, motivations and abilities can kept higher.

- Personalized assistance

To identify and address remaining needs and desires that cannot be solved through peer-to-peer coaching. Interaction between key-stakeholders in the target groups and humanitarian or governmental actors can help to developed personalized assistance, identifying problems of community members that are not satisfactory solved, and define opportunities to overcome barriers. In essence, assistance programs are (re)designed based on co-creation through transactional communication. To stimulate social innovation, this type of feedback and interaction is essential. Key stakeholders can act as opinion leaders and push the acceptance of Building Back Safer to the next level. In these target groups, we have found that several problems are embedded in the financial and social conditions of affected communities and are crucial to overcome to build back safer. Main problems are in the domain of skilled and unskilled masons, expensive materials, and lack of possibilities to increase their own income. Cash and voucher assistance could be a solution for required materials, to stimulate the supply chain, and labor, to stimulate people to learn and potentially generate their own income through construction work. Livelihood support could help to develop a secondary source of income.

- National interventions

Some barriers require a national approach. Alignment of the recommended housing design with locally available materials could require co-creation of construction methods and housing designs, for which flexibility needs to be advocated for at a national level. Some examples in our case study call for national interventions. The problematic availability of safe locations to construct can also be addressed through national support of alternative land tenure. The perceived lack of time is closely linked to top–down defined deadlines for reconstruction, overlooking policies and the pace at which people can construct. The feeling of time pressure in the study area was influenced by financial worries. Livelihood recovery and the large percentage of people depending on agriculture and its production cycles, gaining an informal income, limited both time and funding to construct. Adapting

deadlines to the reality on the ground is crucial. Physical capacity was found in many of the communities to be problematic. A large percentage of youth moved to the cities to study and search for work, while elderly often found themselves in problematic situations, unable to provide physical labor or financial resources for the reconstruction. This lack of physical capacity combined with less people in the community to do the physical hard work enhances the problem of external manpower, could be addressed at a national level.

5 Discussion

5.1 Stimulate social learning processes

Research has also repeatedly stressed that aid approaches must adapt to local communication habits, construction practices, and learning mechanisms to be successful (White et al. 2001; Chmutina and Bosher 2015; BBC Media Action 2017). Studies from the fields of knowledge management (Herschel et al. 2001; Graham et al. 2006), education, health prevention (Straus et al. 2011; Pentland et al. 2011), environmental science (Evely et al. 2012; Phillipson et al. 2012; Fazey et al. 2014), and disaster science (Weichselgartner and Pigeon 2015) reveal that exchanging knowledge can increase knowledge development and improve its application. Further studies show that trust in knowledge sources (Spiekermann et al. 2015; Tromp and Bots 2016), and minimal hierarchical differences between stakeholders (Norris et al. 2008) are important for knowledge adoption. We also know that local knowledge networks do not always trust humanitarian or governmental actors (Hendriks and Opdyke 2020). Nevertheless, designing an effective interaction approach remains challenging (UN-Habitat and AXA 2019).

Most households in this study belong to target groups that are already motivated to learn and have good contextual knowledge. Trusted actors provide an entry point for knowledge diffusion within communities and can be best encouraged to take the lead in adapting new technical knowledge to their environmental and cultural context to provide best practices for the community. Peer learning currently appears to be an uncommon process in these communities, since there were substantial differences observed in MAO components within communities. Therefore, we argue based on our results that differences within communities create actionable opportunities for target groups to learn from each other through interaction. This study calls for different forms of social learning processes (Nokes-Malach et al. 2015), such as peer learning and collaborative learning, in which communities co-create or self-develop their knowledge with assistance of NGOs, for example. Facilitation of such learning processes can be a potential role for non-governmental and governmental organizations. In the light of the limited reach of humanitarian aid, an approach to facilitate peer learning can be more affordable than time- and resource-intensive technical assistance. The focus on peer learning and social processes to disseminate and implement build back safer techniques urges regarding these kind of interactions as social innovations which focus on the social dynamic of changing knowledge, beliefs, and values (Cajaiba-Santana 2014) and highlight legitimating actions of different stakeholders involved (Bowen et al. 2010). Interaction strategies should be developed that do not harm social learning processes of communities as enforcement of behavior may disrupt community self-empowerment. It is essential to move away from intervention strategies that force households to conform and standardize behavior (Bowen et al. 2010).

5.2 Further research

The communities in this study have received different intensities of humanitarian technical assistance. Further research could explore the impact of these differences on household intentions. It is possible that medium or even low levels of motivation, ability and/or opportunity can still lead to successful application of hazard-resistant construction knowledge. Further research could connect MAO profiles to the actual application of knowledge by affected households. In such research additional indicators such as the kind of technical assistance received might provide insight into the required levels for hazard-resistant reconstruction action. Our earlier observations in Nepal showed that households applied many of the hazard-resistant construction techniques despite the fact that Okhaldhunga district did not receive intensive humanitarian technical assistance (Hendriks and Opdyke 2021). Further observations have shown that knowledge is often obtained from within the community or from (temporarily) assigned governmental engineers who know the context (Hendriks et al. 2020). Therefore, it is worth exploring what minimal assistance is needed. Our data reflect upon a specific moment in time, 3 years after the earthquake. It is worth exploring how MAO profiles change over time. We expect differences shorter after the earthquake when there is likely more momentum, willingness to change, and less developed abilities and opportunities.

Clustering households based on the MAO-model can be used to explore risk-adaptive behavior in other contexts, including adaptation to climate change and informal housing development. The value of our suggested interactions needs validation in practice and further investigation to widen applicability in other disaster situations. We call for further research understanding, explaining, and assessing decision-making to find effective recovery assistance.

6 Conclusions

Existing technical assistance struggles to enhance reconstruction decisions of households leading to safer housing. Taking affected households as a starting point leads to another perspective to design appropriate interactions. From such a perspective, it becomes evident that households differ in their intentions to build back safer and that those intentions can be acknowledged or changed by social interaction with other community members. This realization led to the development of the systematic targeted interaction (STID) method by the researchers. This social scientific approach, based on the MAO model and STP model, has not previously been used in post-disaster reconstruction. In this study we explored the use of the STID method, to provide an illustration in how the method can be used to identify target audiences based on a set of characteristics that reflect intentions to build back safer. Based on similarities, affected households were segmented into different target audiences, and audience-specific interaction strategies were developed to enhance hazard resistant (re)construction for disaster-affected populations in Nepal. The presence of different target groups living in the same community shows the relevance of mapping needs and barriers at a community level. Facilitating discussion, peer learning, coaching and cooperation between members of the community should be central in assistance approaches, prior to interacting with community external actors. Interactions should be designed in collaboration between communities, policy makers, and NGOs to enhance the safety of reconstructed housing as well as the resilience of communities, while respecting priorities and limitations of the most vulnerable households. The different clusters within the communities show a necessity to take care of the most vulnerable, facilitating connections with community members and addressing their needs with additional support.

Appendix 1

Target groups descriptive statistics of all constructs of motivation in Okhaldhunga.

		Target group 1	2	4	5	6	10	12	13	14	15	16	17	18	20	21	25	26	27
	N	19	2	234	45	9	3	5	8	3	2	127	53	62	7	1	5	4	1
Positive utility	Mean	52.74	53.57	59.20	62.91	59.22	60.99	49.37	45.20	66.67	58.89	57.91	56.25	60.04	47.30	57.14	65.61	55.71	72.73
	SD	24.16	5.05	16.25	15.13	14.18	10.72	10.11	18.32	30.55	26.71	14.32	13.26	14.57	27.92		20.04	21.42	
	SE	5.54	3.57	1.06	2.26	4.73	6.19	4.52	6.48	17.64	18.89	1.27	1.82	1.85	10.55		8.96	10.71	
Negative utility	Mean	21.76	8.33	6.05	3.11	3.63	14.67	15.71	16.61	5.56	0.00	2.85	7.05	1.04	26.99	25.00	9.56	5.00	0.00
	SD	18.37	11.79	8.95	7.39	5.52	3.07	22.81	15.49	9.62	0.00	5.99	10.11	4.07	20.01		9.28	10.00	
	SE	4.22	8.33	0.58	1.10	1.84	1.77	10.20	5.48	5.56	0.00	0.53	1.39	0.52	7.56		4.15	5.00	
Positive applicability	Mean	29.00	50.00	61.13	60.66	58.73	35.71	50.06	47.35	42.22	80.00	59.75	57.51	61.10	11.90	0.00	60.06	58.01	77.78
	SD	24.76	0.00	14.50	10.78	12.75	31.13	11.88	31.10	36.72	28.28	12.43	13.17	10.98	20.89		15.18	10.47	
	SE	5.68	0.00	0.95	1.61	4.25	17.98	5.31	11.00	21.20	20.00	1.10	1.81	1.39	7.90		6.79	5.23	
Negative applicability	Mean	46.54	45.83	68.52	58.67	56.57	48.21	36.67	41.04	33.33	37.50	68.54	60.78	56.47	19.90	50.00	56.67	45.83	50.00
	SD	25.72	29.46	11.32	4.72	0.00	15.03	5.85	23.88	9.62	17.68	11.05	10.88	4.51	25.00		0.00	0.00	
	SE	5.90	20.83	0.74	0.70	0.00	8.68	2.61	8.44	5.56	12.50	0.98	1.50	0.57	9.45		0.00	0.00	
Positive acceptability	Mean	33.77	45.00	68.52	58.67	56.57	48.21	36.67	41.04	33.33	37.50	68.54	60.78	56.47	19.90	0.00	56.67	45.83	50.00
	SD	19.50	7.07	21.33	21.65	20.06	9.94	22.85	30.33	33.33	53.03	16.50	21.04	15.68	22.57		14.91	15.96	
	SE	4.47	5.00	1.39	3.23	6.69	5.74	10.22	10.72	19.25	37.50	1.46	2.89	1.99	8.53		6.67	7.98	

Target group	1	2	4	5	6	10	12	13	14	15	16	17	18	20	21	25	26	27
N	19	2	234	45	9	3	5	8	3	2	127	53	62	7	1	5	4	1
Negative acceptability	Mean 9.65	0.00	5.77	0.00	0.00	0.00	0.00	100.00	100.00	100.00	0.39	1.57	0.00	14.29	50.00	0.00	100.00	100.00
	SD 19.50	0.00	23.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.44	8.18	0.00	24.40		0.00	0.00	
	SE 4.47	0.00	1.51	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.39	1.12	0.00	9.22		0.00	0.00	

Appendix 2

Target groups descriptive statistics of all constructs of ability in Okhaldhunga.

Target group		1	2	4	5	6	10	12	13	14	15	16	17	18	20	21	25	26	27
	N	19	2	234	45	9	3	5	8	3	2	127	53	62	7	1	5	4	1
Positive self-efficacy	Mean	20,86	28,75	23,71	23,02	25,48	16,99	24,52	22,91	33,33	16,67	23,50	30,62	26,78	53,11	40,00	49,17	53,52	62,50
	SD	8,46	12,37	11,37	9,79	7,53	0,57	8,97	9,75	16,67	0,00	8,34	11,46	7,86	11,70		29,32	10,00	
	SE	1,94	8,75	0,74	1,46	2,51	0,33	4,01	3,45	9,62	0,00	0,74	1,57	1,00	4,42		13,11	5,00	
Negative self-efficacy	Mean	16,02	14,93	22,01	19,96	15,89	13,46	24,56	25,89	21,67	9,09	21,73	25,87	25,16	5,16	0,00	22,93	28,06	37,50
	SD	12,63	5,40	13,09	10,78	11,48	4,59	11,88	15,67	20,21	12,86	12,07	12,59	14,45	9,68		14,23	10,56	
	SE	2,90	3,82	0,86	1,61	3,83	2,65	5,31	5,54	11,67	9,09	1,07	1,73	1,84	3,66		6,37	5,28	
Positive physical capacity	Mean	2,37	7,14	0,84	3,70	0,00	0,00	0,00	0,00	33,33	25,00	2,48	20,80	6,55	100,00	100,00	56,67	100,00	100,00
	SD	7,14	10,10	3,84	12,25	0,00	0,00	0,00	0,00	28,87	35,36	8,11	23,84	16,99	0,00		25,28	0,00	
	SE	1,64	7,14	0,25	1,83	0,00	0,00	0,00	0,00	16,67	25,00	0,72	3,27	2,16	0,00		11,30	0,00	
Negative physical capacity	Mean	8,96	30,95	17,49	16,22	27,46	25,76	10,00	12,50	33,33	14,29	31,04	25,19	22,49	0,00	0,00	0,00	0,00	0,00

Target group		1	2	4	5	6	10	12	13	14	15	16	17	18	20	21	25	26	27
	N	19	2	234	45	9	3	5	8	3	2	127	53	62	7	1	5	4	1
Positive financial capacity	SD	11.75	3.37	20.07	22.07	33.44	5.17	22.36	35.36	57.74	20.20	31.02	29.26	23.04	0,00		0,00	0,00	
	SE	2.70	2.38	1.31	3.29	11.15	2.98	10.00	12.50	33.33	14.29	2.75	4.02	2.93	0,00		0,00	0,00	
	Mean	9.73	26.14	6.79	21.59	11.76	4.44	20.00	7.50	43.33	30.56	4.96	31.60	18.75	94.29	100,00	23,71	68,75	100,00
Negative financial capacity	SD	15.53	1.61	10.71	11.15	5.54	3.85	12.64	10.35	5.77	27.50	8.47	18.82	12.44	15.12		3,69	23,94	
	SE	3.56	1.14	0.70	1.66	1.85	2.22	5.65	3.66	3.33	19.44	0.75	2.58	1.58	5.71		1,65	11,97	
	Mean	37.81	17.86	31.61	19.11	12.34	28.24	22.00	52.20	30.56	29.17	24.65	12.13	14.90	0.00	0,00	7,33	5,00	0,00
Positive location	SD	27.28	25.25	20.92	17.33	12.51	5.21	24.65	35.38	33.68	5.89	18.14	12.59	19.98	0.00		10,11	10,00	
	SE	6.26	17.86	1.37	2.58	4.17	3.01	11.02	12.51	19.44	4.17	1.61	1.73	2.54	0.00		4,52	5,00	
	Mean	1.97	10.00	2.78	3.45	22.54	16.93	56.67	32.29	16.67	32.14	19.76	32.19	46.24	26.67	25.00	10.00	30,83	80,00
Negative location	SD	6.27	14.14	7.61	10.07	13.86	10.08	25.28	17.50	28.87	25.25	16.14	21.44	24.11	18,03		22,36	21,67	
	SE	1.44	10.00	0.50	1.50	4.62	5.82	11.30	6.19	16.67	17.86	1.43	2.94	3.06	6,81		10,00	10,83	
	Mean	1.34	0.00	0.38	0.91	5.03	20.63	0.00	32.29	0.00	7.14	16.47	15.10	10.76	3,57	0,00	5,00	5,00	40,00
	SD	4.04	0.00	2.19	3.46	7.57	8.84	0.00	17.50	0.00	10.10	12.07	15.63	13.30	9,45		11,18	10,00	
	SE	0.93	0.00	0.14	0.52	2.52	5.10	0.00	6.19	0.00	7.14	1.07	2.15	1.69	3,57		5,00	5,00	

Target group	N	Positive time Mean	SD	SE	Negative time Mean	SD	SE
1	19	1.54	3.75	0.86	1.23	4.04	0.93
2	2	15.34	4.02	2.84	0.00	0.00	0.00
4	234	1.59	3.92	0.26	0.70	3.06	0.20
5	45	17.43	6.75	1.01	0.25	1.66	0.25
6	9	21.25	6.36	2.12	0.00	0.00	0.00
10	3	0.00	0.00	0.00	0.00	0.00	0.00
12	5	35.67	13.92	6.23	0.00	0.00	0.00
13	8	0.00	0.00	0.00	0.00	0.00	0.00
14	3	21.67	2.89	1.67	6.67	11.55	6.67
15	2	43.06	45.18	31.94	0.00	0.00	0.00
16	127	3.31	6.94	0.62	1.03	4.23	0.38
17	53	26.84	12.57	1.73	0.86	3.72	0.51
18	62	30.87	13.92	1.77	0.58	3.45	0.44
20	7	54.08	16,29	6,16	0.00	0.00	0.00
21	1	75,00			0.00		
25	5	23,71	3,69	1,65	0,00	0,00	0,00
26	4	58,75	11,81	5,91	0,00	0,00	0,00
27	1	100,00			0,00		

Appendix 3

Target groups descriptive statistics of all constructs of opportunity in Okhaldhunga.

Target group		1	2	4	5	6	10	12	13	14	15	16	17	18	20	21	25	26	27
	N	19	2	234	45	9	3	5	8	3	2	127	53	62	7	1	5	4	1
Positive training	Mean	29.89	47.01	51.71	55.00	75.43	30.57	57.11	46.73	44.11	47.50	47.47	54.18	74.95	12.38	37.50	61.47	62.79	28.57
	SD	25.48	12.09	22.79	18.34	18.93	17.04	19.84	32.26	18.96	38.89	20.89	21.54	13.58	13.44		4.55	10.03	
	SE	5.85	8.55	1.49	2.73	6.31	9.84	8.87	11.41	10.95	27.50	1.85	2.96	1.72	5.08		2.04	5.02	
Negative training	Mean	37.86	23.74	27.09	25.41	7.75	33.67	24.44	32.72	33.63	12.50	27.35	24.16	11.77	44.56	28.57	10.54	14.77	33.33
	SD	26.58	17.86	18.55	16.07	6.36	11.62	20.47	27.10	26.28	17.68	17.13	21.39	11.15	14.66		1.31	17.41	
	SE	6.10	12.63	1.21	2.40	2.12	6.71	9.16	9.58	15.17	12.50	1.52	2.94	1.42	5.54		0.59	8.71	
Positive man-power	Mean	1.32	37.50	2.70	47.30	74.07	0.00	80.00	0.00	11.11	75.00	4.46	42.14	84.14	25.00	50.00	0.00	20.83	100.00
	SD	5.74	17.68	8.17	19.83	25.15	0.00	27.39	0.00	19.25	35.36	11.30	19.43	23.26	20.41		0.00	25.00	
	SE	1.32	12.50	0.53	2.96	8.38	0.00	12.25	0.00	11.11	25.00	1.00	2.67	2.95	7.72		0.00	12.50	
Negative man-power	Mean	26.21	25.00	35.93	25.81	0.00	35.56	0.00	43.75	22.22	0.00	30.55	27.70	0.00	37.86	0.00	10.67	12.50	0.00
	SD	30.40	35.36	29.18	23.40	0.00	17.11	0.00	32.04	19.25	0.00	23.39	24.43	0.00	31.47		15.35	25.00	
	SE	6.97	25.00	1.91	3.49	0.00	9.88	0.00	11.33	11.11	0.00	2.08	3.36	0.00	11.90		6.86	12.50	

Target group		1	2	4	5	6	10	12	13	14	15	16	17	18	20	21	25	26	27
	N	19	2	234	45	9	3	5	8	3	2	127	53	62	7	1	5	4	1
Positive materials	Mean	1.54	15.34	1.59	17.43	21.25	0.00	35.67	0.00	21.67	43.06	3.31	26.84	30.87	54.08	75.00	23.71	58.75	100.00
	SD	3.75	4.02	3.92	6.75	6.36	0.00	13.92	0.00	2.89	45.18	6.94	12.57	13.92	16.29		3.69	11.81	
	SE	0.86	2.84	0.26	1.01	2.12	0.00	6.23	0.00	1.67	31.94	0.62	1.73	1.77	6.16		1.65	5.91	
Negative materials	Mean	22.96	32.69	29.06	37.19	44.94	22.81	30.00	9.17	13.89	16.67	29.34	21.49	34.19	14.97	20.00	50.57	8.33	20.00
	SD	15.57	24.48	18.89	17.62	17.31	9.14	32.60	14.56	12.73	23.57	16.51	15.58	21.77	19.13		16.95	16.67	
	SE	3.57	17.31	1.24	2.63	5.77	5.28	14.58	5.15	7.35	16.67	1.47	2.14	2.76	7.23		7.58	8.33	
Positive location	Mean	10.53	0.00	14.95	13.52	71.30	8.33	80.00	8.33	0.00	66.67	20.31	9.94	70.81	3.57	33.33	6.67	6.25	50.00
	SD	25.59	0.00	28.63	28.61	34.64	14.43	27.39	15.43	0.00	47.14	26.01	18.10	28.45	9.45		14.91	12.50	
	SE	5.87	0.00	1.87	4.26	11.55	8.33	12.25	5.46	0.00	33.33	2.31	2.49	3.61	3.57		6.67	6.25	
Negative location	Mean	9.14	7.14	9.24	3.95	6.67	10.00	14.00	3.12	0.00	0.00	11.23	7.74	5.85	6.21	14.29	0.00	6.25	0.00
	SD	10.91	10.10	12.96	9.18	10.00	10.00	21.91	8.84	0.00	0.00	12.54	12.69	11.34	7.84		0.00	12.50	
	SE	2.50	7.14	0.85	1.37	3.33	5.77	9.80	3.12	0.00	0.00	1.11	1.74	1.44	2.96		0.00	6.25	
Positive funding	Mean	40.40	38.10	57.64	79.41	94.07	26.51	57.00	67.50	42.78	83.33	51.66	81.97	84.54	44.05	100.00	69.90	90.00	40.00
	SD	25.32	6.73	21.76	17.39	8.94	14.26	23.35	27.66	35.21	23.57	20.31	16.93	15.17	25.78		16.18	11.55	

Target group	1	2	4	5	6	10	12	13	14	15	16	17	18	20	21	25	26	27
N	19	2	234	45	9	3	5	8	3	2	127	53	62	7	1	5	4	1
SE	5.81	4.76	1.42	2.59	2.98	8.23	10.44	9.78	20.33	16.67	1.80	2.33	1.93	9.74		7.24	5.77	
Negative funding Mean	26.47	18.06	24.64	7.47	7.41	28.03	7.33	27.08	30.56	0.00	18.96	10.75	12.04	27.18	50.00	18.33	6.25	25.00
SD	13.76	9.82	15.99	12.85	11.37	7.07	10.11	32.96	33.68	0.00	14.31	14.25	17.20	34.03		10.87	12.50	
SE	3.16	6.94	1.05	1.92	3.79	4.08	4.52	11.65	19.44	0.00	1.27	1.96	2.18	12.86		4.86	6.25	

Declaration

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