Prioritizing Post Disaster Recovery Needs: Academicians versus Practitioners

Ali Nejat
Texas Tech University

Saeed Moradi (smoradi@se3.us)
SE3 LLC https://orcid.org/0000-0002-6163-968X

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PRIORITIZING POST DISASTER RECOVERY NEEDS: ACADEMICIANS VERSUS PRACTITIONERS

Ali Nejat[1] and Saeed Moradi[2]

[1] Dept. of Civil, Environmental, and Construction Engineering, Texas Tech University, Lubbock, United States. ORCID ID 0000-0002-7169-3380.

[2] SE3 LLC, Austin, United States. ORCID ID 0000-0002-6163-968X.

[*] Correspondence should be addressed to ali.nejat@ttu.edu

Abstract

Effective knowledge transfer between researchers and practitioners within the hazards and disaster domain has long been a challenging task. The diversity of hazard researchers and practitioners, as well as the high stakes of applying research outcomes, have contributed to the issue. This research aims to explore potential discrepancies between researchers and practitioners' perspectives regarding post-disaster recovery needs. To achieve the objective of this research, a survey was developed and conducted during the 2019 Natural Hazards Workshop in Broomfield, Colorado, which is host to individuals from various career backgrounds, including researchers, practitioners, policymakers, students, etc. Exploratory factor analysis and elastic net regression were used to provide a link between individuals' awareness of these challenges and their personal attributes. Results highlighted the discrepancies between researchers and practitioners in how they perceive and prioritize recovery needs. Results from this research can be used to bridge the existing perception gap with the goal of devising policies that can improve recovery by addressing the needs more realistically.

Keywords: Natural hazards; Disaster recovery; Convergence

Introduction

The prevalence and severity of disasters worldwide have increased (Bergholt and Lujala 2012; Guha-Sapir et al. 2016). This rise, along with the increase of population density in hazard-prone areas, has contributed to the continuous growth of natural hazard impacts (Aldrich et al. 2018). Since 1980, 279 extreme weather and climate events have impacted the United States and caused over $1.8 trillion in damage (NCEI 2020). While severe events can impact multiple sectors of a community, housing recovery is of vital importance due to its central role in peoples' lives and wellbeing, as well as its ripple effect in the restoration of other sectors such as businesses (Bratt 2002; Moradi and Nejat 2020; Peacock et al. 2007).

Housing recovery is affected by various factors. These factors can be categorized into *internal*, *interactive*, and *external* drivers (Moradi et al. 2020). Internal drivers are the factors directly connected to households' personal attributes. For example, higher-income families are more likely to suffer less from a disaster due to the implementation of mitigation measures (Hunter 2005) and possess a greater capacity for restoration (Hamideh et al. 2018). Racial disparity can also delay the recovery progress, examples of which were observed in the recovery process following Hurricane

Andrew (Zhang and Peacock 2009) and Hurricane Katrina (Bullard and Wright 2009). Education level can also affect households' perception of their community (Nejat et al. 2019) and influence their recovery progress (Burton 2015). Age, gender, and household size make up the other factors that can affect recovery (Henderson et al. 2010; Moradi et al. 2019; Nejat et al. 2020).

On the other hand, *interactive* drivers are created and strengthened through interactions of households with their community, such as social capital and place attachment. Social capital facilitates recovery by fostering trust, collective action, and information and resource flows (Aldrich et al. 2018; Talbot et al. 2020). Place attachment also influences households' recovery decisions, as residents with greater place attachment are more likely to decide in favor of reconstruction than relocation (Mayer et al. 2020; McNeil et al. 2015).

External drivers are the resources and services provided by public or private agencies. Financial assistance from insurance plans, recovery funds from public agencies, and disaster loans boost households' economic power for a timely recovery (Kamel and Loukaitou-Sideris 2004; Moradi 2020). Restoration of services and infrastructure such as businesses, utilities, healthcare, education, and transportation is also vital to households' regular and recovery-specific needs (Comerio 2014; Xiao et al. 2018).

Reducing disaster losses and promoting collective wellbeing requires deep integration across various research disciplines (Peek et al. 2020) and demands convergence of practitioners and researchers as two significant stakeholders involved in the emergency management continuum. The gap between research and practice is not a new observation (Rynes et al. 2001). Knowledge transfer between scholars and practitioners in the field of hazards has long been challenging due to the diversity of their academic backgrounds (e.g., engineers versus planners) and the high stakes of applying research outcomes that can directly affect lives (Fothergill 2000). Yin and Moore (Yin and Moore 1988) analyzed nine natural hazards cases in light of knowledge-driven, problem-solving, and social interaction-based research utilization theories (Weiss 1979). They discovered that among seven cases with superior utilization outcomes, five cases fully satisfied the social interaction theory conditions, one case satisfied three out of four conditions, and one case partially met the conditions. The required conditions were 1) both users and researchers belong to the same network, 2) users are involved early in the research for any potential modifications, 3) users are in continued communication with researchers, and 4) the users are the target of the research (Yin and Moore 1988). One reason behind the current gap between practitioners and researchers is their dissimilar expectations from the discipline. Practitioners generally expect the discipline to provide actionable insights in advisable forms such as standards, policy, and guidelines that could be applied "as is" to facilitate risk reduction. Contrariwise, researchers typically engage in "basic research," to propose more general or ideological ideas and solutions for explaining fundamental processes and their interrelation with disaster context (Trainor and Subbio 2014). Another contributing factor is the difference in knowledge creation and sharing among these two cohorts. Practitioners generally develop their knowledge of disaster based on their own or their peers' experiences working in an agency and share them as "Lessons Learned" reports. In contrast, researchers rely on detailed logical induction or deduction processes to propose abstract ideas from specific experiences and share them as peer-reviewed publications. Lack of common terminology and limited access to the produced knowledge are the other contributors to the gap (Trainor and Subbio 2014).

The objective of this research is to explore the potential gap between researchers and practitioners in how they perceive and prioritize time-varying disaster recovery challenges/needs. To achieve the objective of this research, a survey was developed and conducted during the 2019 Natural Hazards Workshop in Broomfield, Colorado which is host to individuals from various career backgrounds, including researchers, practitioners, policymakers, students, etc. Exploratory factor analysis and elastic net regression were used to provide a link between individuals' perceived recovery challenges and their personal attributes. This section is succeeded by research methodology. Analysis, results and discussions come next. Finally, discussions and study limitations conclude the paper.

Methodology

To collect data on an individual's perception of disaster recovery challenges, an online survey was designed and conducted during the 44th Annual Natural Hazards Research and Applications Workshop (2019) in Broomfield, Colorado in the summer of 2019. This venue was selected mainly due to its diverse participants, including researchers, private and public sector practitioners, and policymakers who attended the workshop with the common goal of reducing the harm and suffering from disasters (Peek 2020). Participants were asked to fill out an online questionnaire approved by the Office of Human Research Protection Program at Texas Tech University. The first question asked the respondents to create a unique ID by adding their two-letter initials to their four-digit birthday month and year (IIMMYY). Follow-up questions were asked to collect data on participants' geographic location of residence, age, gender, ethnicity, education, marital status, household income, employment status, primary occupation, years of experience in various hazard-related fields, and their personal experience with a disaster. Next, they were asked to list the items necessary for a successful short-term, mid-term, and long-term recovery and rate their importance using a five-point Likert scale. Timelines associated with short-, mid-, and long-term were defined as "*immediately after disaster,*" "*six months after disaster,*" and "*a year or more after disaster,*" respectively. The questionnaire together with data descriptive statistics are included in Table 1 below. Data was analyzed using exploratory factor analysis and elastic-net regression, the results of which are presented in the following section.

Table 1. Questionnaire and data descriptive statistics

Question		%	Question		%
ID (IIMMYY)			*10. Household's yearly income*		
Country of residence				$0-$24,999	13
	United States	90		$25,000-$49,999	6
	Others	10		$50,000-$74,999	11
State of residence				*$75,000-$99,999*	*17*
City of residence				*$100,000-$124,999*	*15*
Age				$125,000-$149,999	12
	Less than 30 years	23		$150,000-$199,999	11
	Between 30 and 39 years	32		$200,000-$249,999	11
	Between 40 and 49 years	27		$250,000 or more	4
	Between 50 and 59 years	10		Prefer not to say	1
	Between 60 and 69 years	7	*11. Employment status*		
	70 years and more	1		Employed (full time)	74
Gender				*Employed (part time)*	*7*
	Female	63		Self employed	1
	Male	36		Full-time student	17
	Other	0		Retired	0
	Prefer not to say	1		Unemployed	1

Ethnicity	
American Indian or Alaska Native	0
Asian	15
Black or African American	13
Native Hawaiian and Other Pacific Islander	0
White	57
Hispanic or Latino	8
Other	2
Prefer not to say	4
Highest education level completed	
High school or less	0
High school degree or equivalent	4
Bachelor's degree	19
Master's degree	31
Doctorate	44
Other	2
Marital status	
Single (never married)	32
Divorced	6
Widowed	1
Married/living with partner	61
Other	0
Unable to work	*0*
Other	0
12. Primary occupation	
Researcher	63
Practitioner - Public Sector	18
Practitioner - Private Sector	6
Other	13
13. Years of experience in current occupation	
less than 5 years	24
Between 5 and 10 years	*14*
Between 11 and 15 years	2
Between 16 and 20 years	4
More than 20 years	6
No response	50
14. Been personally affected by any disaster?	
Yes	52
No	*48*
15. short-term recovery needs and their importance level	
16. mid-term recovery needs and their importance level	
17. long-term recovery needs and their importance level	

Analysis, Results, and Discussion

A total of ninety-four participants filled out the questionnaire, among which ten had only completed the demographic section. Of the 84 remaining participants, 57 filled the short-term, mid-term, and long-term recovery items, 12 answered only the short-term and mid-term recovery questions, and 15 responded only to the short-term recovery questions. A summary of the participants' demographic information is provided Table 1. Overall, 63% of the respondents identified themselves as researchers while another 24% indicated they were practitioners.

The limited number of completed questionnaires on mid-term and long-term recovery needs made a plausible quantitative analysis impossible. Therefore, further analysis of the data was limited to short-term recovery needs, which was filled out by the majority of the respondents (84 to be exact). To avoid bias, survey questions were open-ended, allowing for the inclusion of multiple items perceived to be important in various stages of recovery. Consequently, responses included a wide range of topics. To identify the frequency of each need, similar items were grouped together and labeled accordingly. This resulted in a total of 9 groups of short-term needs, the details of which are included in Table 2. As shown in the table, the most frequent needs were *food*, *shelter*, and *social capital,* which were followed by *water*, *financial support*, *health*, *lifelines*, *communication*, and *job*. Table 2 also shows the average importance of each category. Per the results, the top-rated need was *water* (almost critical), and the lowest-rated need, though still important, was *lifelines* (important to very important).

Table 2. Short-term recovery needs and their importance level

Item	Sample responses	Freq. (%)	Importance*
Food	Food, Hot meals	80	4.5
Shelter	Shelter, evacuation shelter, tent, housing	79	4.4
Social capital	Social capital, social networks, social support, social ties, community, engagement, people, family connectedness, help from family and neighbors, leadership, plans	48	4.2

Water	Water, clean water, drinking water, water supply	46	4.7
Financial support	Financial resources, finances, income, cash, funds, money	40	4.2
Health	Health care, health services, health supplies, medical access, medical supplies, medicine, mental health, mental health support	35	4.2
Lifelines	Lifelines, transportation, electricity, power, gas	31	3.5
Communication	Communication, cellphone, communication access, communication device, computers, information, radio	29	3.8
Job	Job, employment, return to work	8	4.1

*Slightly Important = 1, Moderately Important = 2, Important = 3, Very Important = 4, Critical = 5

Next, Exploratory Factor Analysis was used to explore the underlying theoretical structure of short-term needs and reduce data to a smaller set of summary variables. Factor analysis is a common dimensionality reduction technique for identifying latent constructs based on common variances (Bartholomew et al. 2011). The analysis was performed in IBM SPSS Statistics 25. Table 3 shows the Pearson correlation coefficients for the predefined categories. As the results suggest, most items correlate in a degree from $r = -0.491$ to $r = 0.443$, which makes it a good candidate for factor analysis. Moreover, the statistically significant result of Bartlett's test of sphericity ($p = 0.001 < 0.05$) indicated the existence of a pattern among responses (Tabachnick et al. 2007). The above cutoff value of the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy ($KMO = 0.534 > 0.5$) also indicated the suitability of the data for factor analysis (Hair et al. 1998).

Table 3. Pearson correlation coefficients for the short-term recovery items

Items	Communication	Food	Water	Shelter	Lifelines	Job	Health	Social capital	Financial support
Communication	1.000	.382	.269	.168	.013	.066	.315	.192	.098
Food	.382	1.000	.330	.443	.301	-.023	.104	-.140	-.279
Water	.269	.330	1.000	.209	.223	.037	.165	.122	-.383
Shelter	.168	.443	.209	1.000	.188	.231	.241	.113	-.172
Lifelines	.013	.301	.223	.188	1.000	.173	-.073	-.491	-.115
Job	.066	-.023	.037	.231	.173	1.000	-.004	.141	.303
Health	.315	.104	.165	.241	-.073	-.004	1.000	.349	-.028
Social capital	.192	-.140	.122	.113	-.491	.141	.349	1.000	.158
Financial support	.098	-.279	-.383	-.172	-.115	.303	-.028	.158	1.000

A common criterion for selecting the optimal number of factors is to choose factors with eigenvalues greater than one. The total variance explained (Table 4) and the scree plot (Figure 1) suggest that the first three components meet this criterion. Moreover, the first three components explain 60.8% of the total variance, which is above the 50%-60% level commonly agreed in social sciences (Pett et al. 2003). Therefore, the three-factor case was selected as the most parsimonious result. To interpret the results, a varimax orthogonal rotation was employed using IBM SPSS Statistics version 25. Table 5 shows threshold loadings for each item in which loadings with magnitude below 0.5 were excluded.

Table 4. Total variance explained by factor analysis (the pre-play short-term recovery items)

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1. Communication	2.289	25.433	25.433	2.289	25.433	25.433	2.276	25.285	25.285
2. Food	1.825	20.282	45.715	1.825	20.282	45.715	1.769	19.657	44.943

3. Water	1.359	15.097	60.813	1.359	15.097	60.813	1.428	15.870	60.813
4. Shelter	.933	10.363	71.175						
5. Lifelines	.811	9.010	80.185						
6. Job	.716	7.955	88.141						
7. Health	.410	4.559	92.700						
8. Social capital	.358	3.972	96.672						
9. Financial support	.300	3.328	100.000						

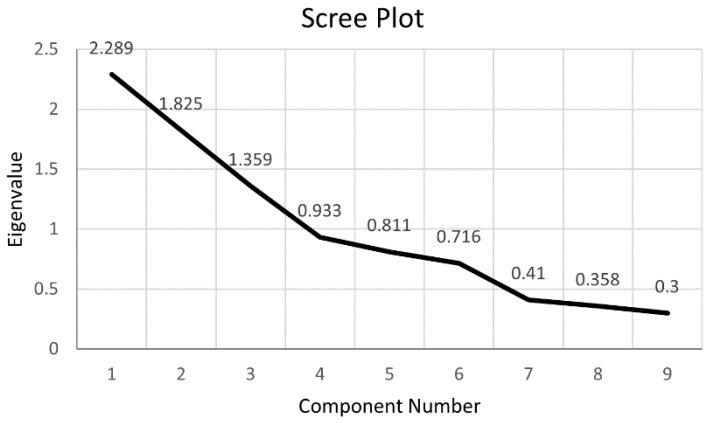


Figure 1. Scree plot (the pre-play short-term recovery items)

A loading cutoff of 0.55 was selected to interpret the results. Although the choice of loading cutoff usually is a matter of researcher preference, a loading above 0.55 is considered acceptable (Comrey and Lee 2013; Tabachnick et al. 2007). Therefore, components with a loading (absolute value) greater than 0.55 were incorporated into the factor. Labeling factors were based on the common theme of the factor constituents and the implied construct. The first factor dealt with items of immediate importance, including food, water, shelter, and communication, and as such was labeled as *basic needs*. The second factor consisted of social capital, lifelines, and health and therefore was identified as *community-related needs*. The last factor brought in job and financial support and hence was named *financial needs*. Although labeling the factors should be descriptive and consistent with other taxonomies in the field (Pett et al. 2003), it is, in general, subjective and inductive (Williams et al. 2010). For example, *job* can be labeled as *basic* needs (Karpman et al. 2018) because it enables individuals to fulfill their basic needs, categorized as c*ommunity-related* needs because infrastructure investment programs can affect the creation and distribution of jobs (Haughwout 1999; Heintz et al. 2009), or marked as *financial* needs due to its association with income, which is a natural fit for financial classification (Jamali et al. 2020). Once loadings are calculated, factor scores for each item are estimated. These scores are regression scores with a mean of zero and a variance equal to the squared multiple correlation between the estimated factor scores and the true factor values. Hence, for each participant, we end up with a tri-variate response matrix.

Table 5. Threshold loadings for each short-term need

Item	Factor 1	Factor 2	Factor 3
Food	.762		
Shelter	.683		
Water	.641		

Communication	.552		
Social Capital		.850	
Lifelines		-.709	
Health		.589	
Job			.815
Financial support			.754

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 6 iterations.

Next, to reveal potential discrepancies among the way researchers and practitioners perceive and prioritize short-term needs in the aftermath of disasters, these factor scores were modeled as a function of the endogenous predictors. As shown in Table 6, predictors included *age*, *gender*, *race*, *education*, *marital status*, *income*, *job status*, and *disaster experience*. As a result, a total of 27 regression parameters were required to be estimated. Due to the relatively large number of parameters compared to the number of participants, the elastic-net regularization model was employed due to its efficient regularization technique. This was implemented through the use of the glmnet package (Friedman et al. 2021) in R statistical software. Proposed by Zou and Hastie (Zou and Hastie 2005), elastic net is a convex combination of Ridge Regression and Least Absolute Shrinkage and Selection Operator (LASSO) Regression. Elastic net takes advantage of ridge models (effective regularization) and lasso models (feature selection). Elastic net has two tuning parameters: α and λ. The α parameter controls the type of regression (0 for ridge, 1 for LASSO, and between 0 and 1 for elastic net). On the other hand, λ is the penalty parameter that controls the weight of predictors in the model by constraining the size of their coefficients. A coefficient can increase if it causes a comparable decrease in the Mean Squared Errors, MSE (Boehmke and Greenwell 2019). In its univariate form, Elastic Net imposes a mixture of $l1$ and $l2$ constraint on the regression parameter with a parameter α ∈ [0,1], determining the relative weights of these constraints, which as previously stated would lead to ridge and LASSO estimates when $\alpha = 0, and\ 1$ respectively. Since we are dealing with a multivariate response, the univariate model cannot be used because it cannot address the dependence among responses. Therefore, the multi-task elastic net (Obozinski et al. 2006) was used to explicitly handle the dependence among responses. This is shown in $Eq.1$ in which the $l1$ norm of the vector of the $l2$ norms of the regression coefficient vectors are penalized.

$$min \sum_{l=1}^{L} \frac{1}{N} \sum_{i=1}^{N} \left|\left|Y^l - X^l B^l\right|\right|_2 + \lambda \sum \left|\left|B\right|\right|_2 \qquad (Eq.\ 1)$$

Where λ is determined based on cross-validation. Multi-task EN attempts to extract the common set of predictors impacting multivariate responses. All the analysis was performed in R statistical software through the use of glmnet package (Hastie and Qian 2016). To allow for multivariate responses, the multi-response Gaussian family was selected, which attempts to find the common subspace of important features shared by the response matrix. The explicit loss function is shown in $Eq.2$.

$$min \frac{1}{2N} \sum_{i=1}^{N} \|y_i - \beta_0 - \beta^T x_i\|_F^2 + \lambda \left[(1-\alpha)\|\beta\|_F^2/2 \ + \ \alpha \sum_{j=1}^{p} \left\|\beta_j\right\|_2\right] \qquad (Eq.\ 2)$$

Where βj is the jth row of the $p \times K$ coefficient matrix β, and the absolute penalty on each single coefficient is replaced by a group-Lasso penalty on each coefficient K-vector βj for a single predictor xj and $||.||_F^2$ is the squared Frobenius norm. The group-Lasso penalty imposes the foregoing common shared subspace constraint.

The minimum MSE was obtained for $\alpha = 0.2$ and $\lambda = 0.4607145$. Figure 2d illustrates the changes in MSE across all the λ values for $\alpha = 0.2$. The model shows improvement in the MSE value for larger values of $\log(\lambda)$. The numbers across the top of the plot indicate the number of predictors. Due to the selected value of α, the model incorporates a heavier ridge penalty. Thus, most of the predictors remain in the model for a wide range of λ values. The vertical dashed line refers to the λ value corresponding to the smallest MSE, i.e., the maximum predictive accuracy.

Figures 2a-c illustrate the estimated coefficients across the range of values for λ. The estimated regression coefficients for the optimal values of α and λ are shown in Table 6.

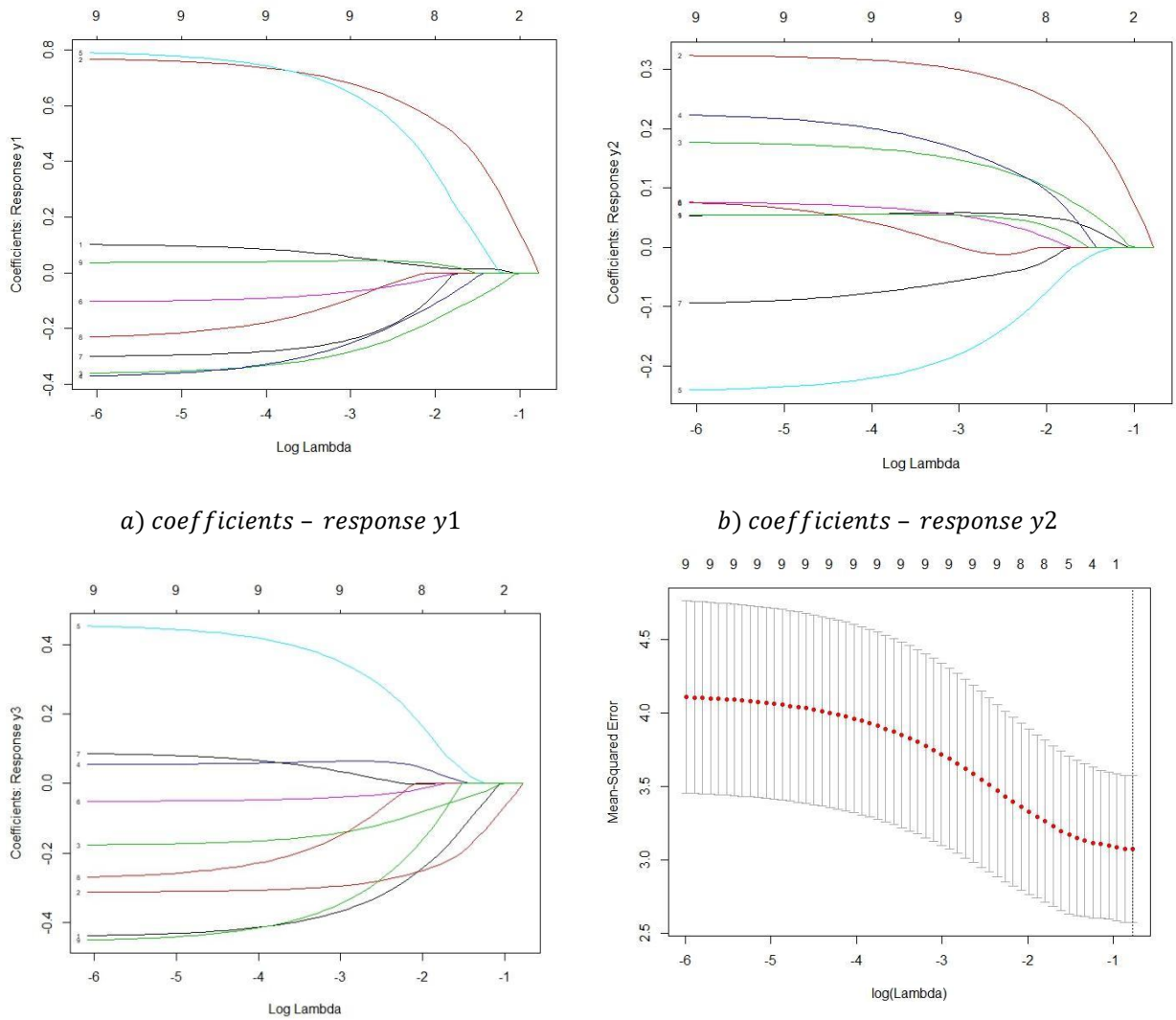
Table 6**.** Estimated regression coefficients ($\lambda = 0.4607145$ and $\alpha = 0.2$)

Predictor	Response		
	1. Basic Needs	2. Community Needs	3. Financial Needs
Intercept	-0.511	-0.841	1.022
1. Age	0.022	0.038	-0.188
2. Gender	0.437	0.204	-0.194
3. Race	-0.142	0.087	-0.076
4. Education	-0.105	0.087	0.03
5. Marital status	0.314	-0.058	0.116
6. Income	-0.017	0.02	-0.019
7. Job Status (student, full-time, part-time)	-0.096	-0.033	0.005
8. Job Type (researcher, practitioner)	-0.009	-0.022	-0.046
9. Disaster experience	0.049	0.043	-0.189

Due to the presence of heavy bias induced by regularization, it is not possible to formally test the significance of the coefficients, and their inclusion trajectories, as shown in Figures 2a-c, indicate the high sensitivity of a few of the covariates to small changes in penalization, denoting their low significance. For example, Figure 2 suggests the triviality of participants' **job status** (predictor #7) to how they perceive the importance of various types of short-term recovery needs. This is mainly due to its low regression coefficient and its hypersensitivity to changes in λ causing it to drop out at a very low penalization level (see Figure 2c).

Additionally, as shown in Figure 2, **gender** (predictor #2) turned out to be the least sensitive covariate to changes in λ, exhibiting the most significant impacts on all the responses. Results indicated that female participants weighted *basic* and *community-related* needs more heavily than their male counterparts while the opposite was the case regarding *financial* needs. The next influential predictor across all responses was **race**. Results revealed that non-white participants tended to assign higher weight to *community-related* needs and lower importance to *basic* and *financial* needs compared to their white counterparts. Respondents' **age** (predictor #1) also exhibited low sensitivity to λ values, especially for the first and second responses. Optimal coefficient signs (Table 5) suggest that older respondents prioritized *basic* and *community-related* needs while younger participants gave more weight to *financial* needs. **Marital status** (predictor #5) also affected the responses. Results suggested that single participants gave more weight to *community-related* needs while others considered *basic* and *financial* needs to be more important. Moreover, participants with higher **education** levels (predictor #4) ranked *community-related* and *financial* needs higher than their counterparts who prioritized *basic* needs. **Disaster experience** (predictor #9) had marginal impact on the first two responses, but was relatively influential on the third signifying that participants with previous disaster experience tended to assign higher weight to *financial* needs compared to those without. **Income** (predictor #6) and **job status** (predictor #7) slightly affected the responses (high sensitivity to λ and low coefficients).

Finally, the coefficient of major interest to this study, **job type** (predictor #8), appeared to be insignificant, having marginal impact on responses which manifested through its high sensitivity across λ values and its fast dropout rate. Nevertheless, the coefficients' negative values at the optimum λ (Table 6) potentially suggest that researchers tend to assign more weights to short-term recovery needs compared to practitioners.



$a)\ coefficients - response\ y1$ $b)\ coefficients - response\ y2$

$c)\ coefficients - response\ y3$ $d)\ MSE\ for\ the\ elastic - net\ model\ (\alpha = 0.2)$

Figure 2. Elastic net coefficient paths as λ goes from 0 → ∞ for the response variable (a) basic needs, (b) community needs, and (3) financial needs

Discussions and Limitations

Knowledge transfer in the field of disaster management has been associated with several advantages, including cohesive communities and response, idealized governance practice, and collective learning about resilience (Curato and Calamba 2020). Considering disasters' social roots (Tierney 2020), it is imperative that relevant science be integrated into institutional arrangements

and policies to provide means for better disaster management (Albris et al. 2020). This cannot be achieved if gaps between science and policy are not identified and addressed. According to Albris et al. (2020), these gaps can be categorized as *epistemological,* dealing with various understanding of relevant knowledge; *strategic,* highlighting the lack of common knowledge to address hazard related planning; and *institutional*, underlining the need for transforming expert knowledge. These gaps are deemed to be caused by knowledge transfer obstacles, lack of disaster expertise, and raising risk awareness barriers (Albris et al. 2020). In a study performed by Kaklauskas et al. (2009), hesitancy of managers to adopt transformational learning together with their tendency to stay within their comfort zone were cited as the major obstacles to knowledge transfer. The importance of knowledge transfer between researchers and practitioners has been highlighted in the work of other researchers as well (Drabek and Hoetmer 1990; Fothergill 2000). Research studies have attributed this multifaceted problem to a diverse set of reasons, including lack of practitioners' early buy-in, lack of specificity in addressing practitioners' needs, and lack of general involvement in research design (Fothergill 2000). Additionally, lack of accessibility and user-friendliness of academic research were among other contributors to the existing gap (Cowan and Beavers 1994). Moreover, social interaction among the two groups was viewed to be critical for the overall process of knowledge transfer (Yin and Moore 1988; Yin and Moore 1985).

Currently, we are witnessing a growing effort to overcome the existing gap. Research foundations, such as the National Academies and the National Science Foundation, have supported the growth of multidisciplinary collaborations among multiple domains (Peek et al. 2020). An example is the National Science Foundation's Growing Convergence Research solicitation (NSF 2021), which aimed at bringing together researchers and stakeholders from the inception to form research questions, share solution frameworks and develop effective transdisciplinary communications. Establishing links between researchers and practitioners, improving accessibility of research, and deciphering research findings to explore their implications for practice are a few strategies that can help achieve a shared understanding to improve disaster management (Trainor and Subbio 2014).

In an effort to identify the existing gap, this research aimed to explore potential discrepancies between researchers and practitioners in how they perceive post disaster recovery needs. To achieve this objective, data was collected from attendees of the 2019 Natural Hazards Workshop in Broom Field, Colorado. The workshop attracts an international audience from various professional backgrounds. The workshop is missioned to decipher and share disaster research for a broader use and create connections between all stakeholders within the domain of hazards/disasters. Analysis of collected data displayed marginal discrepancies in how researchers and practitioners prioritize short-term recovery needs in the aftermath of disasters. Additionally, several personal attributes such as *gender*, *race*, *age*, *marital status*, and *disaster experience* were revealed to be influential on this perception as well.

Even though the research is innovative and intends to fill an important gap within the literature it is not limitation-free. One speculation that can be made regarding the results is the fact that the sample was a convenient sample selected from the attendees of a conference focused on bridging the gap between academics and practitioners, and therefore, such marginal discrepancies between the perceptions of these two groups might have been rooted to this issue. The next main limitation associated with this study is the lack of power due to the limited number of samples, which resulted in exclusion of a statistical significance test for analysis results. More specifically, due to the

presence of bias induced by the penalty function used in glmnet, formal statistical tests couldn't be performed and significance suppositions were not attached to regression coefficients. Therefore, variable selection was used to identify the regressors deemed important and not necessarily statistically significant for predicting the outcome variables. Finally, a lack of complete responses on the other dimensions of post-disaster recovery (mid- and long-term) resulted in the exclusion of quantitative analysis of discrepancies among our targeted group in how they prioritized recovery needs.

To further explore this important matter, another survey in which the participants can answer at their convenience can provide more complete responses suitable for a more comprehensive analysis. Despite the limitations, this research indicated a gap in the perspectives of the researchers and practitioners participating in the survey. A diverse toolset is required to share the academic and practical findings and integrate them into a single body of knowledge that could benefit all the stakeholders more effectively. The next step of this research is to explore potential methods to help with researcher-practitioner convergence.

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Code availability: Not applicable.

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