university of groningen / faculty of behavioural and social sciences / research master

Master's thesis

Risk perception and the earthquakes in Groningen: disentangling the predictors

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Are there deviations of the Master's thesis from the proposed plan?
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Abstract

Psychological science has extensively studied biases of human cognition. The Social Amplification of Risk Framework (SARF) was created to explain various societal processes driving risk perception. However, the interplay of real-life exposure and social factors over time has been studied much less. This paper looks into the temporal development of risk perception in a real-life setting of exposure to earthquakes caused by gas extraction. We analysed four data subsets (N_1 = 750, N_2 = 639, N_3 = 908, N_4 = 2046) from a representative panel of Groningen residents, exposed to varying degrees of seismicity, across fourteen timepoints between February 2016 and June 2019. A structural equation model was iteratively built to observe how much variance in risk perception of earthquakes can be explained by objective exposure to ground motion, personal exposure to damage, and perceived social factors. Substantial variability in risk perception was explained by both objective exposure (between R_2^2 = 39.2% and R_4^2 = 44.6%) and by social factors of involvement and outrage (between R_4^2 = 6% and R_1^2 = 18%). However, objective exposure proved to be a much more potent predictor of inter-personal differences in the perception of risk, than the social factors are.

Keywords: risk perception, SARF framework, earthquakes, structural equation modelling

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Introduction

Humans often perceive risks. Not surprising: life is full of dangers after all. In order to assess whether risks exist, people look around their environments to identify potential dangers. Based on a range of factors, such as information they have available and prior experiences, they form a subjective assessment of risks: risk perception.

In science, risk is defined as the potential for consequence given that a particular event or series of events occur (Aven & Thekdi, 2021). These consequences are uncertain and they can be either desirable or undesirable. To better understand risks, they are typically defined in relation to specific reference values, such as a planned production levels or the number of potential fatalities. Additionally, when assessing risks, the potential consequences are considered for a specific time frame (Aven & Thekdi, 2021).

Risk perception refers to a person's subjective judgment or appraisal of risk and its potential favourable and unfavourable outcomes (Aven, 2019). Since it is an individual's subjective judgement, various psychological, social and cultural factors are believed to significantly shape one's perception of risk. Consequently, while professional evaluations of risks are thought to capture only objective judgement and exclude emotions, laypeople's perceptions are believed to be strongly influenced, and distorted by emotions and past experiences. This approach to risk perception creates a strong divide between the expert risk judgements which are seen as rational, and the seemingly irrational judgments made by laypersons. However, experts can also sometimes overlook certain aspects of risks or misjudge which leads to inadequacies in their professional assessments.

Numerous theories attempted to explain how individual's subjective judgements are formed; what influenc them, and in which way they increase or decrease the perception of something as being risky. The most relevant ones will be explained and reflected on.

The Psychometric Paradigm of risk perception

The *Psychometric Paradigm* is a well-established approach in studying differences in public attitudes towards hazards (Fischhoff et al., 1978; Slovic et al., 1980, 1986). It is also one of the first theoretical frameworks for studying risk perception and one of the most influential models in risk analysis. The Paradigm proposes that risk perception is inherently subjective and subject to various biases. The way that individual perceive (potential) hazards can be represented as a cognitive map with two axes: novelty of the risk and its dread potential (Slovic, 1987). Research in this paradigm identified nine factors related to risk perception and factor analysis identified two dimensions which explain a sizable proportion of variance. Firstly, the model suggests that dreaded risks, which are uncontrollable and potentially catastrophic for future generations, are evaluated very differently from non-dreaded risks. Second, the model suggests that the novelty of a risk makes a big difference in how it is perceived (Slovic et al., 1980). In sum, the Psychometric Paradigm has developed into a key framework for understanding human factors that may influence (and often distort) the way individuals perceive risks.

The Psychometric Paradigm has emphasised that in making risk judgments, individuals are guided by heuristics (representativeness, availability, anchoring heuristics) (Tversky & Kahneman, 1974). Thus, risk perceptions are easily biased. If risks are unknown people tend to overestimate how likely are the risk events to happen to them and they consequently may overreact. This is why experts and laypeople perceive risks differently and often disagree on the magnitude of risks. Laypeople consider a wide range of factors when making their judgments (e.g. catastrophic potential, immediacy of effects, whether they have a choice in facing the risk and control over it (Aven, 2019, p. 163). They are thought to be more easily guided by heuristics and they create rule-governed schemes of risks, while experts base their estimations on probabilistic estimates and historical data (e.g. expected annual mortality (Lichtenstein et al., 1978). Because of this, the psychometric paradigm implies that experts are more capable of balanced risk assessment and of defining “real risks”, and laypeople are more likely to let their risk judgments be clouded by other factors (Slovic, 1987). Laypeople would especially have the tendency to overestimate unusual risks, because such risks have higher cognitive availability, and underestimate common everyday risks (Lichtenstein et al., 1978).

The Psychometric Paradigm of risk perception has been very influential, but various scholars have reflected on its limitations. While some replications suggest high (cross cultural) validity, other authors indicate the need for theoretical and methodological refinement (Boholm, 1998). Sjöberg (2004) drew attention to the fact that the literature on risk perception lacks a strong foundation of empirical data and proper analysis. He states that the explanatory power claimed for the model is artificially inflated because analysis was not conducted for each hazard separately, but relies on comparisons of many widely different hazards to one another. As a result the psychometric factors can explained as much as 70-80% of between-risk variance. However, when perceived risk is regressed on psychometric factors separately for each hazard (i.e., within-risk variance), the psychological factors typically explain much less variance, around 20% or so (Gardner & Gould, 1989; Sjöberg, 2004). Furthermore, Sjöberg (2004) argues that the risk perceptions of laypeople and experts are more comparable than the psychometric paradigm suggests. He underlines the main issue with the Psychometric Paradigm is its assumption that riskiness of different activities is important for forming risk perceptions. Literature however, points out exposure to consequences of different risk, and their severity and frequency, is much more important (Sjöberg, 2000). Finally, and most relevant for the present paper, it has been emphasised that the research upon which the psychometric paradigm is based has focused extensively on cognitive biases, whilst it has overlooked the influence of individual differences to risk perception, such as differences in perception of injustice, trust in stakeholders or knowledge about the risk (Siegrist et al., 2005; Visschers & Siegrist, 2018). Precisely these differences are investigated in the current paper.

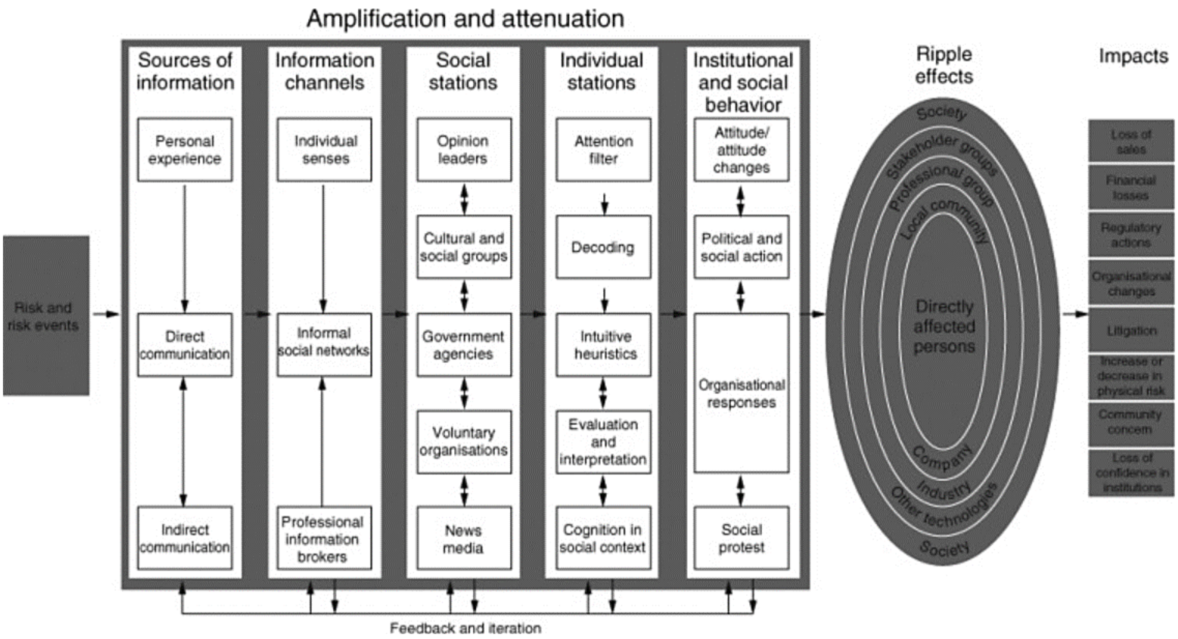
The Social Amplification of Risk Framework (SARF)

Risk perceptions are not just shaped by cognitive biases. The *Social Amplification of Risk framework (SARF)* is a well-established theoretical framework for explaining how risk perception develops as risks are communicated through society (Kasperson et al., 1988; Pidgeon et al., 2003; Renn et al., 1992). Thus, it complements the Psychometric Paradigm by going beyond just quantitative assessments of risk probability in making risk judgement and viewing risk as both an objective threat to people; and as a product of social dynamics (Renn et al., 1992). Risk events interact with psychological, social and cultural processes that can amplify or attenuate public risk perception. As a consequence, risk perception of the public is thought to be biased and even minor events can have large societal impacts (Kasperson et al., 1988).

SARF describes how risk perceptions change over time through processes of interchanging attenuation and amplification (Kasperson et al., 1988). As visible in Figure 1, the main drivers of amplification are media that shape and redefine the public discourse and interpersonal communication about specific risk messages in which this (new) narrative spreads and amplifies the risk. Some of the known risk amplifiers or attenuators are: previous experience of the risk event (Knuth et al., 2014); likelihood of re-experiencing the risk and being personally susceptible to it (Gotham et al., 2018) communication about risks and hazards (Gough, 1990); trust in authorities (Visschers & Siegrist, 2018), feelings of (in)justice (Satterfield et al., 2004), availability of information and media exposure (Kasperson et al., 1988). These factors are included in the present study as well. As Poumadère and Mays (2003) suggest, amplification may be influenced by the degree of prior attenuation, such as denial of a previous risk event. When the risk resurfaces knowledge accumulated during the systematic suppression of risk and the already polarized actors (e.g. industry vs. citizens) intensify the risk signals and this leads to amplification. To conclude, the SARF framework is a key framework used to explain how risk perceptions evolve in society and it was applied to different environmental (Mase et al., 2015; Rickard, Schuldt, et al., 2017), technological (Pidgeon et al., 2003) and health risks (Frewer et al., 2002).

Figure 1

The Social Amplification of Risk Framework (from Pidgeon et al., 2003, p. 14)



Understudied phenomena

In summary, the classic risk perception literature has primarily focused on the biases, heuristics and social dynamics that can distort risk perceptions of laypeople, often compared with judgements of experts who are believed to perceive risks more accurately. Overall, this body of research suggests that various social and psychological factors can contribute to the distortion of risk perception among the general public.

However, the data relied on most often in this literature introduces some limitations to its ecological relevance for real-life hazards and risks. In part this is because many studies in this tradition are cross-sectional, with participants comparing many different risks they may or may not have encountered, often from WEIRD backgrounds. Also, many studies are experimental and based on artificial scenarios. Studies tracing risk perceptions about hazardous events over time are rare, because these events are not always predictable in time to allow for such study designs. As a result, there are relatively few studies which study risk perception in a natural setting where the specific risk event is present and exposure to the risk varies between participants in a systematic and objectifiable manner. For this reason there is a paucity of knowledge about how individual differences, such as differences in exposure, victimization, knowledge or trust might impact risk perception (Siegrist et al., 2005; Visschers & Siegrist, 2018). As a result, we know a lot about how risks are perceived, but less about how risk perceptions develop and change over time in naturalistic settings in which people are exposed to varying degrees of real (as opposed to imagined) hazards. Thus, relatively little is known about the relationship between *objective exposure* and the many subjective and social factors in the SARF framework.

Therefore, my thesis aims to address this gap by focusing on how processes within the SARF framework interact with objective exposure in a real-life risk situation. I seek to explore how subjective and social factors, alongside the actual exposure to risks, influence and shape risk perceptions over time. I will do so by investigating risk perception in the Groningen gas extraction context.

Context: The Groningen gas-extraction

Europe's largest gas field is located beneath Groningen and it has been actively exploited since the 1960's. Due to gas extraction and consequent pressure equalisation hundreds of induced earthquakes have been occurring in the past decades. Earthquakes are not typically part of the of the traditional hazardscape of the Netherlands. Even though the earthquake magnitude on the Richter scale is relatively low, their above-ground impacts are high because of the shallowness of the earthquakes in combination with the soil composition in Groningen (Bakema et al., 2018). Thus, the Richter scale of underground earthquake magnitude grossly underestimates the objective above-ground impact of these earthquakes.

Residents in the earthquake area were exposed to seismicity for several decades. Initially the problem was denied, but when earthquake intensity and frequency rose after 2003, residents increasingly felt the ground motion and suffered damage to homes and buildings. Until 2013, authorities were reluctant to acknowledge the problem. Then, a conflict arose between the public-private partnership of government and oil companies about how to handle damage and risk. Because this denial and subsequent wrangling occurred over two decades of rising seismicity and damage, residents were increasingly having to deal not just with damage, but also with potentially unsafe homes, a bureaucratical mess surrounding damage claims and mounting uncertainty about the future. All this proved to be time-consuming and stress-inducing for residents leading to various health issues particularly among those who have repeated damage and whose homes need to be reinforced (Dückers et al., 2023; Stroebe et al., 2021; Stroebe et al., 2018).

Although the earthquakes in Groningen began as early as the 1990s, the issues of resident safety and trustworthiness of the private-public partnership only became a focus of media and political attention quite late, from 2017 onwards (Tweede Kamer der Staten-Generaal, 2023). The governance system increasingly polarized the country, caused a lot of anger and distrust toward the operator, regulator and the government – all of which central variables in the SARF approach. Because it was clear that government and parliament had mismanaged the gas extraction, a Parliamentary Inquiry Committee was established to investigate the case. Results of the inquiry were recently published and they confirmed how the interests and safety of residents were structurally ignored throughout the years in order for extraction to be continued (Tweede Kamer der Staten-Generaal, 2023). For the present paper most relevant is that risks were (in SARF terminology) initially attenuated and then seemingly amplified through a strong (social) media focus on distrust, injustice and mounting activism. All these factors are central amplifiers of risk perception according to the SARF and we have a dataset which included these factors as well as risk perception, from 2016 to the current day. This makes Groningen an optimal location for exploring the determinants of risk perceptions of individuals exposed to these events and social developments to varying extents.

The present research

The present research aims to address the gap in literature by investigating how risk perception regarding induced earthquakes develops over time. We want to disentangle various predictors of risk perceptions and investigate how much of variance is attributable to objective exposure to seismicity, material exposure (damage) and social exposure (the SARF variables). This provides a perfect opportunity to conduct a real-life test of the SARF approach.

Therefore, in this master thesis we ask the following research question:

What are the predictors of perceived risk(s)? With the following subquestions:

(1) To what extent are perceived risks predicted by:

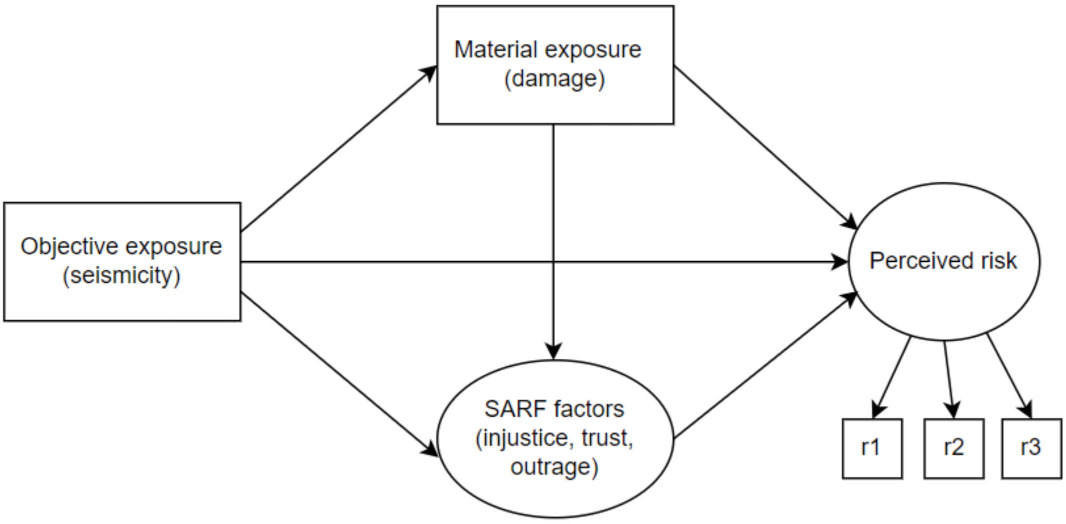
- objective exposure to seismicity
- exposure to material consequences of seismicity (damage to one's home)
- exposure to and interest in communications about risks and hazards
- social perceptions of how government and industry deal with this issue
- social relations to government and industry, in the form of trust
- feelings of injustice?

(2) What is the relationship between the exogenous variable (seismicity), the other predictors, and risk perceptions?

Structural equation modelling (SEM) will be used to test the theoretical model and answer the proposed research questions. A simple representation of the model is visible in Figure 2. This model combines the SARF Framework with objective risk events (seismicity) and material exposure (damage).

Figure 2

Proposed model of exposure predictors of perceived risk: objective (seismicity), material (damage) and social (SARF variables)



Firstly, an exploratory analysis will be conducted and exposure to earthquakes, material damage, SARF variables and risk perception will be described.

Secondly, the proposed model will be tested for two timepoints using two data subsets, the first before the Zeerijp earthquake (January 8, 2018), and the second after this earthquake. These timepoints have been selected because prior to the Zeerijp earthquake there was relatively little seismicity. This earthquake caused a major shift in public perception of the earthquake problem and also initiated a major policy change. Before the Zeerijp earthquake, there had been General elections (March 2017) with (for the first time) some political and media attention on Groningen. At this time there was little consensus about the magnitude of risks: the state supervisor of mines (the regulator) believed that the low seismicity was due to successful risk management. Especially to people outside the earthquake area, the riskiness of the situation was unclear or unknown. Perhaps as a result of these divided opinions, the case was politicized and different political acters had opposing views about what to do with extraction and how to address safety of residents. After the Zeerijp earthquake there was consensus that risk management had failed and that risks were unacceptably high. Groningen had become less politically controversial. The comparison between timepoints will therefore be interesting from the point of both exposure and SARF variables. To assess differences in path coefficients between the timepoints and the changed contexts, models will be compared.

Thirdly, the proposed models will be incrementally adjusted as necessary, guided by the modification indices. This final model will be tested and compared for both timepoints.

To assess the reliability of the final model of step three, the model will be tested in step four on two new timepoints, with two new data subsets collected after July 2018. The selected timepoints are before the Westerwijtwerd earthquake (May 22, 2019), and after the Westerwijtwerd earthquake had taken place. The Westerwijtwerd earthquake is comparable in magnitude to that of Zeerijp because it caused major social upheaval in its aftermath. The change in political controversy and public awareness was less dramatic however. The purpose of this step is model validation. The timepoints were chosen to resemble conditions regarding risk perception prior and after the Zeerijp earthquake. All analysis will be conducted using *R* (version 4.2.2) and *RStudio* (version 2022.7.2.576).

Method

Participants and Design

This study was based on data collected within Gronings Perspectief (GP), a large research project that investigates the psychosocial impact of gas extraction in Groningen, Netherlands, since 2016. Participants of this study were members of a representative panel of inhabitants of Groningen. For the purpose of answering the proposed research question data collected in fourteen timepoints between February 2016 and June 2019 was utilised.

Procedure and participant recruitment

For participant recruitment 25.000 residents of the province of Groningen were randomly selected from the municipal population records. In January 2016 these prospective participants received a letter asking whether they want to participate in the panel study. In the first timepoint the response rate was 16.60% (n = 4149) which increased to 18% in the next timepoint (n = 4556). Because of a large dropout rate in the first two years the panel merged with another panel and was managed by the Social Planning Bureau Groningen. After this change the participant number was kept stable ($n \approx 7000$) by recruiting new participants each year. Data from February 2016 to January 2018 (T1 to T7) was collected by GP, and the data from June 2018 to September 2020 by the Social Planning Bureau Groningen (T8 to T14) but analysed by GP.

Each year two or three questionnaires were distributed to the panel. In case of an earthquake with a magnitude higher than M = 3.00 on the Richter scale, an additional questionnaire was distributed to assess the immediate impact of the strong earthquake. This happened in January 2018 after a M = 3.4 magnitude earthquake in Zeerijp and in May 2019 after a M = 3.4 earthquake in Westerwijtwerd.

Prior to data collection a Data Protection Impact Assessment was conducted, and all performed procedures were in accordance with the ethical standards, and approved by the ethical board of the department of psychology of the University of Groningen. All participants gave informed consent. Participants could choose to either receive the questionnaires by post or via email, and a reminder was sent if they did not fill in the questionnaire within two weeks, leaving four weeks overall to fill in the questionnaire. The majority of data was collected online, and a small number was collected by post (*n* < 10). Responding to the surveys was not incentivised. Figure 3 shows the timepoints in which data for the selected variables was collected.

Figure 3

Timeline of the panel study and variables included in this study

Time point	T1 Feb 2016	T2 Jun 2016	T3 Oct 2016	T4 Apr 2017	T5 Oct 2017	T6 Jan 2018	T7 Jun 2018	T8 Oct 2018	T9 Feb 2019	T10 May 2019	T11 Jun 2019	T12 Sep 2019	T13 Mar 2020	T14 Sep 2020
PGV (ground motion)														
Exposure to damage														
Active involvement (Involvement)														
Media involvement (Involvement)														
Distrust (Outrage)														
Injustice (Outrage)														
Risk perception														
Data subset			1			2		3		4				

Note. T6 – Zeerijp earthquake first cut-off point, T10 and T11 – Westerwijtwerd earthquake second cut-off-point

Demographic characteristics

The whole sample consists of overall 10906 participants recruited over the 14 timepoints and is representative of residents in the Groningen. For the purpose of this paper not all timepoint were used. The number of participants per selected data subset, after exclusion of participants with missing values, varies between 639 and 2046 participants. The questionnaires contained questions concerning demographic characteristics (age, gender and level of education). In the selected subsets participants were between 19 and 95 years old. In relation to gender, a slightly higher number identified as male. Participants were also asked to indicate the highest educational degree they have attained using eight multiple choice options. Responses were further recoded into *low* (1 = no formal education, 2 = primary education and 3 = preparatory secondary vocational education (VMBO) and junior secondary vocational education (LBO)), *middle* (4 = senior general secondary education (HAVO), 5 = university preparatory education (VWO), 6 = secondary vocational education (MBO)) and *high* educational level (7 = higher vocational education (HBO) and 8 = scientific university education (Bachelor, Master, PhD)). Information about the number of participants in each data subset per education level can be found in Table 1.

Table 1

Demographic characteristics of participants in separate data subsets: number of participants, mean age, distribution of education level, gender and material exposure (damage due to gas extraction)

		Subset 1	Subset 2	Subset 3	Subset 4
Total N		750	639	908	2046
Age (mean)		62.37	62.22	63.00	56.87
Education level (N)	Low	148 (19.73%)	125 (19.56%)	167 (18.39%)	333 (16.28%)
	Middle	261 (34.8%)	226 (35.37%)	281 (30.95%)	697 (34.07%)
	High	335 (44.67%)	284 (44.44%)	460 (50.66%)	1013 (49.51%)
Gender (N)	Male	422 (56.27%)	335 (52.43%)	525 (57.82%)	1157 (56.55%)
	Female	324 (43.2%)	281 (43.97%)	377 (41.52%)	867 (42.38%)
Exposure to damage (N)	None	248 (33.07%)	194 (30.36%)	285 (31.39%)	795 (38.86%)
	One time	167 (22.27%)	141 (22.07%)	169 (18.61%)	349 (17.06%)
	Multiple	335 (44.67%)	304 (47.57%)	454 (50%)	902 (44.09%)

Power and sample size

Sensitivity analyses was carried out using G*Power (Faul et al., 2007). The analysis revealed how to investigate the significance of single effects, with 0.95 power and significance level $\alpha = 0.05$, the sample size of the dataset was sufficient for detecting small effect sizes of $f^2 = .02$. Because this means that the power is sufficient to detect even very small effects, the magnitude of effect sizes is more relevant consideration when evaluating the results than statistical significance *per se*.

Materials and Measures

For this study GP data from the panel was enriched with seismological exposure data. We compared two possible sources of exposure data, one based on actual measures of ground motion of a select number of earthquakes, measured using accelerometers and geophones in over 70 locations (so-called "shakemaps" of Peak Ground Acceleration, made by KNMI, see www.knmi.nl), and one based on a calculation of Peak-Ground Velocity (PGV) using an equation based on these data, which can be applied to all earthquakes of $M > 1.7$ (the Ground Motion Prediction Equation (Bommer et al., 2022). The two were very highly correlated, explained approximately the same amount of variance. We decided to use the PGV values in the models because this was the more complete dataset. Using the formula, a separate PGV variable was constructed for all four data subsets accounting for earthquakes occurring up to the specific date[1]. For the first subset this was PGV data up to December 10, 2017, for the second January 9, 2018 (Zeerijp earthquake), for the third April 19, 2019 and for the fourth May 5, 2019 (Westerwijtwerd earthquake). Depending on the location and date, PGV data ranged between $PGV_{min} = 0.65$ and $PGV_{max} = 23.03$.

Exposure to damage

Exposure to damage was measured with one item in each timepoint. Participants were asked to assess how many times they personally experienced earthquake damage due to gas extraction. The reliability of self-reported damage proved to be high, when it was compared to the official damage register in 2019 (Postmes et al., 2020). Results were recorded on a seven-point scale (1 = Never, 2 = 1 time, 3 = 2 times, 4 = 3 times, 5 = 4 times, 6 = 5-10 times,

[1] We wanted to see whether separating acute from historical earthquake data would explain a different amount of variance in risk perception. Following simple linear regressions no differences in variance explained were observed when separating acute from historic data. Thus, sum scores of PGVs accounting for both acute and historic earthquake data up to the specific date for each of the data subsets were used.

7 =or more than 10 times). Results were rescaled to 1 indicating never, 2 having damage one time, and 3 having damage multiple times (see Table 1).

Social Amplification of Risk (SARF)

The SARF framework is very rich and complex and it is largely about social dynamics such as media coverage, social movement formation and so on. The best one can do in an empirical study like this is to include subjective variables that should resonate with these social dynamics to study the between-participant variation in involvement and acceptance of these social dynamics. Accordingly, constructs included in this study were *active involvement*, *media involvement*, perceived *(dis)trust* in institutions, and perceived *(in)justice* (see Appendix A for full a full items list per SARF construct and the original and translated questionnaire version).

Active involvement in the issue was observed in the fifth and twelfth timepoint. These included eight items describing different types of actions taken regarding concern about gas extraction and consequent earthquakes such as supporting and helping others who are struggling, participating in demonstrations and similar (see Appendix A). Responses were measured on a five-point scale (1 = never taken this action, 5 = taken this action often) (α = .85, M = 2.49, SD = 1.09, in the first data subset).

Media involvement was measured only in the fourth timepoint, so this measure is only available for the first two data subsets and models. The items were about the extent to which certain events in the media affected the participants; such as following the topic in the media, watching certain TV shows, or following information about relevant decisions regarding the earthquakes (Appendix A). The responses were collected on a five-point scale (1= never, 5 = very often 5). The Cronbach alpha α =.93 (M = 2.85, SD = 1.09).

Perceived (dis)trust in institutions involved in gas extraction was measured using two items regarding trust in the National Government and the NAM (Dutch Oil Company – operator of the field), the two actors responsible for the earthquake damage by law. Responses were measured in multiple timepoints (see Figure 3), on a five-point Likert scale (1 = no trust at all, 5 = high trust). Most participants reported having low trust in the Government and NAM. 59.47% participants report having no trust at all or little trust in the National Government (no trust at all = 22.8%; little trust = 36.67%, T1), and 84.4% report having no trust at all or little trust in NAM (no trust at all = 54%; little trust = 30.4%, T1). Due to this trend the items were rescaled to reflect distrust and be in line with the SARF framework (1 = no distrust, 5 = high distrust). In the first data these two items were correlated with $r = 0.57$ ($p < .001$, $M = 4.04$, $SD = .78$).

Perceived (in)justice included a scale of four items measured at multiple timepoints (Figure 3) measuring the perception of fairness of the level of gas extracted, decision making about the case and similar (Appendix A). Responses were measured on a five-point scale (1 = very unjust, 5 = very just). Most participants felt the extraction is unjust. In the first timepoint on this scale 84.67% reported they felt the situation regarding extraction was very unjust or a little bit unjust. Because of this the items were rescaled to reflect injustice and be in line with the SARF framework (1 = no injustice, 5 = high injustice). For the first data subset Cronbach's alpha was $\alpha = .86$ ($M = 4.14$, $SD = .94$).

Based on these constructs, two distinct latent variables *involvement* - including *active involvement* in the issue and *media involvement*, and *outrage* - including *distrust* and *injustice* were created in the following SEM models. These constructs are qualitatively different. *Outrage* reflects attitudes toward authorities and institutions involved in extraction that make decisions over extraction levels and compensations for residents. On the other hand, *involvement* reflects personal actions one takes to stay informed, inform others and share experiences while possibly expressing their personal dissatisfaction in different ways (see Appendix A for the list of items per latent construct). These latent constructs are not only qualitatively different but also quantitatively. *Distrust* and *injustice* are highly positively correlated r = .61, as well as *active involvement* and *media involvement* r = .60, but when observing correlations between *distrust* and *active involvement* , or *media involvement* and *injustice* these correlations are lower (Appendix B, Table A1).

Risk perception

Risk perception was measured using a three-item scale measuring perceived probability of experiencing earthquakes related issues. These items included indicating the probability of experiencing these earthquakes in the future (1), probability of damaged property (2) and probability of being injured (3) (Appendix A). Responses were provided on a five-point Likert scale (1 = very small probability, 5 = very high probability). The risk perception scale in the first data subset had a Cronbach's alpha score of α = .87 (M = 2.69, SD = 1.05).

Results

Missing Data

Many missing values were observed in the overall dataset. Stroebe et al. (2021) report a 45.3% attrition rate in November 2017 (T5) compared to the first collected data in February 2016 (T1) in the same dataset. The high attrition level also resulted in adding new participants to the project in June 2018 (T8). For a thorough missingness analysis see Stroebe et al. (2021). Important for the present paper is that attrition was not uncorrelated with the focal variables of the study (e.g., trust, risk perception), although it was correlated with some demographic variables, with higher dropout among younger and less highly educated participants.

Data description

The final SEM model was fitted to four separate data subsets that reflect data collected prior to and after the two major earthquakes - Zeerijp earthquake and Westerwijtwerd earthquake. Table 2 contains the descriptive statistics of *risk perception*, *PGVs*, *material exposure* in form of damage and other SARF variables for the first two data subsets. On average participants' risk perception is moderately low (M_1 = 2.69) and an increase is visible after the Zeerijp earthquake (M_2 = 3.01). Participants on average report having damage at least once, they have growing distrust towards the government and NAM (M_1 = 4.04, M_2 = 4.30) as well as growing sense of injustice about decisions regarding extraction (M_1 = 4.14, M_2 = 4.46). On average participants are moderately involved through speaking up, or participation in demonstrations (M_1 = 2.49, M_2 = 2.52). On average participants report certain events and media coverage of issues regarding earthquakes has concerned them moderately (M_1 = 2.85, M_2 = 2.91).

Table 2

Descriptive statistics of variables before the Zeerijp earthquake and after, corresponding to the SEM Models 1 and Model 2

	Subset 1 (n = 750)				Subset 2 (n = 639)			
Variable	Mean	SD	Skewness	Kurtosis	Mean	SD	Skewness	Kurtosis
Risk perception	2.69	1.05	0.23	-0.73	3.01	1.04	-0.09	-0.78
PGV	3.58	3.50	2.03	4.41	3.90	3.79	2.05	4.8
Exposure to damage	2.12	0.87	-0.23	-1.66	2.17	0.87	-0.34	-1.59
Distrust	4.04	0.78	-0.61	-0.23	4.30	0.71	-1.12	0.99
Injustice	4.14	0.94	-1.09	0.30	4.46	0.72	-1.59	2.33
Media involvement	2.85	1.09	0.29	-0.93	2.91	1.10	0.22	-1.01
Active involvement	2.49	0.76	0.5	0.21	2.52	0.76	0.43	0.04

The third and fourth subset before and after the Westerwijtwerd earthquake do not strongly differ (Table A2, Appendix C). It is important to note the significant increase in the number of participants in the fourth data subset, as new participants were recruited. These participants reported having less damage (Table 1), thus this may be the reason for the decrease in risk perception between the third and fourth data subset. Participants on average have moderate risk perception (M_3 = 2.93, M_4 = 2.76), distrusted the operator and government (M_3 = 4.08, M_4 = 4.02), perceive the decisions regarding extractions as unjust (M_3 = 4.41, M_4 =4.35), and are moderately involved in issues regarding extraction (M_3 = 2.81, M_4 = 2.71).

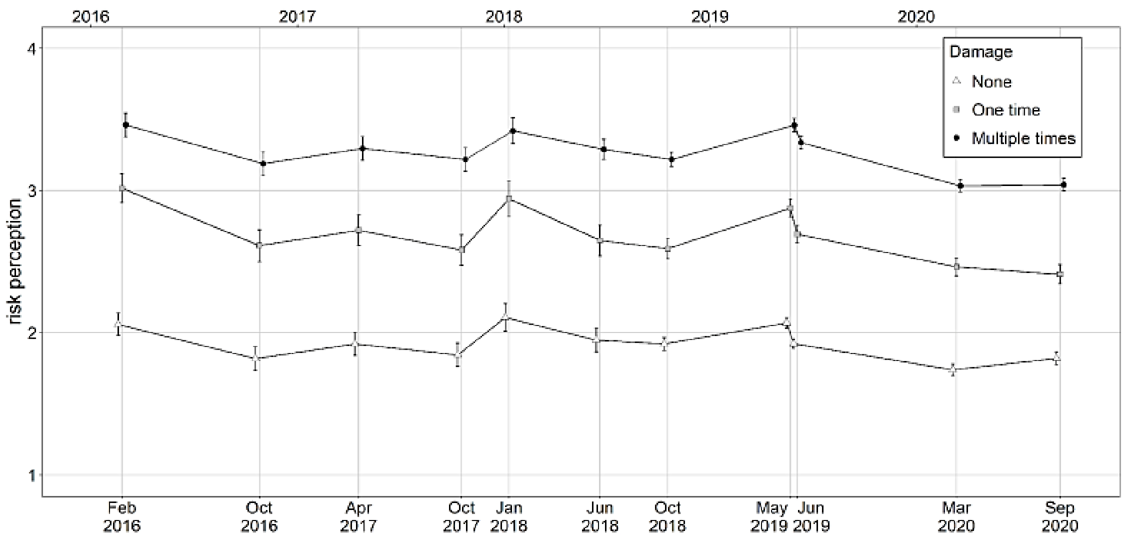
PGV data is the highest on kurtosis and skewness, however that is to expected based on the used formula and how the data is calculated. Perception of injustice also has relatively high skewness and kurtosis, however they are within the threshold.

Dynamics in risk perception and exposure

Figure 4 shows the changes in risk perception between February 2016 and September 2020. Risk perceptions differ strongly depending on whether one has damage or not. For those with no damage, perceived risk tends to be towards the bottom end of the scale (two on a five-point scale). For those with multiple damage, it is above the midpoint, between three and four. This means that these participants have elevated risk perception at all times, with additional increases when earthquakes happen. Also, risk perceptions fluctuate over time. The biggest "jumps" in risk perception happen at the times of the bigger earthquakes that we study in this paper: in January 2018 when the Zeerijp earthquake happened, and in May 2019 when the Westerwijtwerd earthquake took place.

Figure 4

Risk perception over time for different groups of housing damage

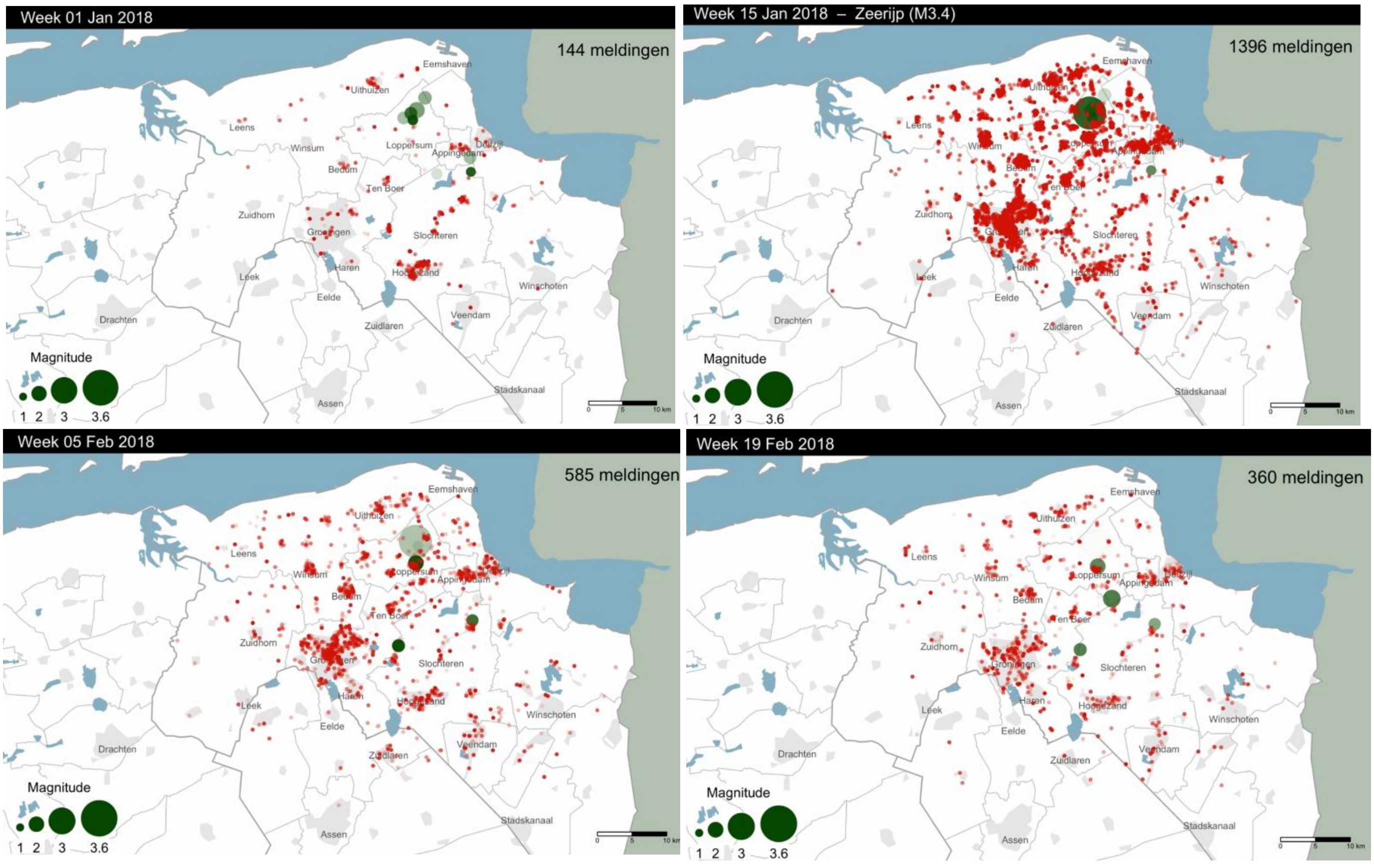


*Note: error bars reflect 95%-CI

Figure 5 presents the spatial distribution of damage claims submitted before and after the Zeerijp earthquake. The figure illustrates temporal dynamics of the number of damage claims and how they fluctuate over time. Moreover, this also shows the significance of incorporating damage as a variable in the model. Even if participants did not experience the earthquake at the location, they do experience the aftermath damage.

Figure 5

Earthquake magnitude and damage claims prior to and after the Zeerijp earthquake



Preliminary analysis

Exploratory factor analysis was conducted to explore the underlying factor structures in constructs that had more than 7 items (active involvement and media involvement). Principal axis factoring and varimax rotation was applied, while observations with missing values were omitted.

For the construct *active involvement* in the first data subset two factors were extracted. First measures of sampling adequacy (MSA) values were observed and the lowest was MSA_{i7} = .79 which is considered as high. Furthermore, eigenvalues and visual investigation of the scree plot was conducted. Items i1 to i5 were extracted and formed the factor i*ssue involvement* (α = .85), while items i6 to i8 formed the factor *taking action* (α = *.71*). However, items i7 and i8 were not measured in the following subsets (Appendix A). These were excluded, and the exploratory factor analysis was reconducted. The construct was now unidimensional and operationalised as *active involvement.*

Exploratory factor analysis was also conducted for the *media involvement* construct, and it is unidimensional (see Appendix A).

Assumptions:

Before fitting the proposed structural equation models, assumptions for SEM need to be considered to ensure that the models are built upon a solid foundation, allowing for valid interpretations of the results.

First, the *sampling* mechanism needs to be known in order to apply appropriate estimation methods (Donaldson, 2015). The sample used in this thesis was randomly sampled using records from the different municipalities in Groningen, although as noted above the attrition was considerable, systematic but apparently inconsequential for the variables of interest.

Second, the assumption of *multivariate normality (multinormality)* for continuous outcome variables (Kline, 2016). In order to assess the normality of individual univariate distributions, skewedness and kurtosis were examined. These results are presented in Table 2 and in Table A2, Appendix C. No variables have |skewness| > 3.0 or have |kurtosis| > 8.0 suggesting that the observed distributions do not deviate greatly from the normal distribution. Normality of continuous outcome risk perception was also observed. Furthermore, homoscedasticity was inspected visually (Figure A2, Appendix D,) and using the *Goldfeld-Quandt* significance test. For all 4 models the test was not significant (p_1 = .085, p_2 = .909, p_3 = .308, p_4 = .703 meaning that there is not enough evidence to indicate presence of heteroscedasticity in the observed data subsets.

Thirdly, no *univariate outliers* were detected. To see if there are extreme atypical scores on two or more variables Mahalanobis distance was calculated and tested on a *p* = .001 significance level (Kline, 2016). Multivariate outliers were observed in all four data subsets ($n(D^2_1)$ = 15, $n(D^2_2)$ = 15, $n(D^2_3)$ = 10, $n(D^2_4)$ = 34, p < .001). These observations were removed from the data subsets and excluded from further analysis as well as the descriptive analysis in the previous section. Furthermore, Cook's distance was calculated to examine whether there are influential observations that could significantly impact the overall models with the .05 threshold (Cook & Weisberg, 1982). None of the four data subsets contained observations exceeding this threshold.

Fourthly, presence of *multicollinearity* was observed as well. R^2 was calculated between all variables in each data subset. Based on Kline (2016) observation that R^2 > .90

suggests extreme multivariate collinearity. In all four data subsets there were no observations over the $R^2 > .90$ threshold, indicating absence of multivariate collinearity. Furthermore, the ratio of total standardized variance over the proportion of unique variance; or the *variance inflation factor* (VIF) was also examined using the VIF > 2.5 threshold (Johnston et al., 2018). No observations were greater than the threshold (Table A5, Appendix D).

To conclude, no significant violations of the assumptions underlying SEM were found.

Main analysis

Bivariate correlations between all variables in the first and second data subset are presented in Table 3, and those for the third and fourth data subset are in Table A3 (Appendix C). Moderate and positive correlations between risk perception and ground motion and exposure to damage were observed in all four data subsets, indicating that risk perception increases with higher exposure to earthquakes and damage. Because exposure to objective ground motion is a true exogenous variable (i.e., there is no way that risk perceptions could make the ground move), it is safe to assume that this is a causal relationship. Moderate positive correlations were observed between risk perception and distrust and injustice (outrage). This means higher levels of perceiving risk are related to higher distrust in institutions responsible for extraction as well as the perception of decision-making surrounding extraction as unjust. This can be observed in the first two data subsets (Table 3), but the correlations between distrust, injustice and risk perception in the third and fourth data subset are weak (Table A3, Appendix C). Risk perception correlated moderately and positively with media involvement and active involvement (involvement), meaning higher levels of risk are related to higher involvement with media and more involvement in the gas extraction case. In the third and fourth data subset media involvement was not measured, but active involvement correlated moderately and positively with risk perception.

Table 3

Correlation matrix for predictor and outcome variables of the first two data subsets

	Variable	1.	2.	3.	4.	5.	6.	7.
1.	Risk perception	1	0.32***	0.58***	0.34***	0.24***	0.45***	0.57***
2.	Ground motion (PGV)	0.33***	1	0.33***	0.15***	0.08*	0.13***	0.23***
3.	Exposure to damage	0.56***	0.31***	1	0.14	0.07	0.22***	0.41***
4.	Distrust	0.37***	0.21***	0.22***	1	0.60***	0.40***	0.31***
5.	Injustice	0.29***	0.11*	0.11*	0.58***	1	0.42***	0.29***
6.	Media involvement	0.46***	0.17***	0.29***	0.42***	0.42***	1	0.61***
7.	Active involvement	0.54***	0.25***	0.46***	0.28***	0.27***	0.61***	1

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

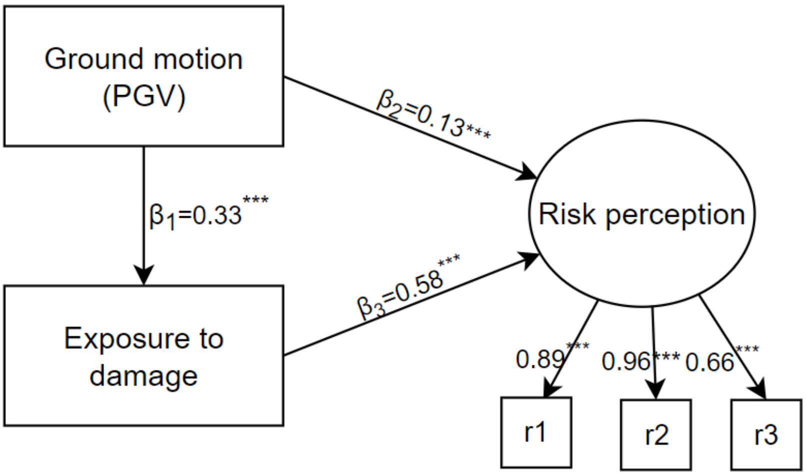
Note: Blue– 1st data subset used for Model 1, green – 2nd data subset used for Model 2

Models

Structural equation models were fitted using a package for SEM in RStudio called Lavaan (version 0.6-12). The Maximum Likelihood estimator was used, because of the data properties and fulfilled assumptions. The first observed model visible in Figure 6 included only risk perception, exposure to damage and PGVs.

Figure 6

Structural equation model of risk perception due to earthquakes and exposure to damage without SARF variables (N = 750)



Note. * $p < .05$, ** $p < .01$, *** $p < .001$

According to Kline (2016) in model fit evaluation model test statistic and three approximate fit indexes need to be reported: the Bentler Comparative Fit Index (CFI; Bentler, 1990) the Steiger–Lind Root Mean Square Error of Approximation (RMSEA; Steiger, 1990) and its 90% confidence interval, and the Standardized Root Mean Square Residual (SRMR). CFI ≥ .95, RMSEA ≤ .05, and SRMR ≤ .08 indicate good model fit.

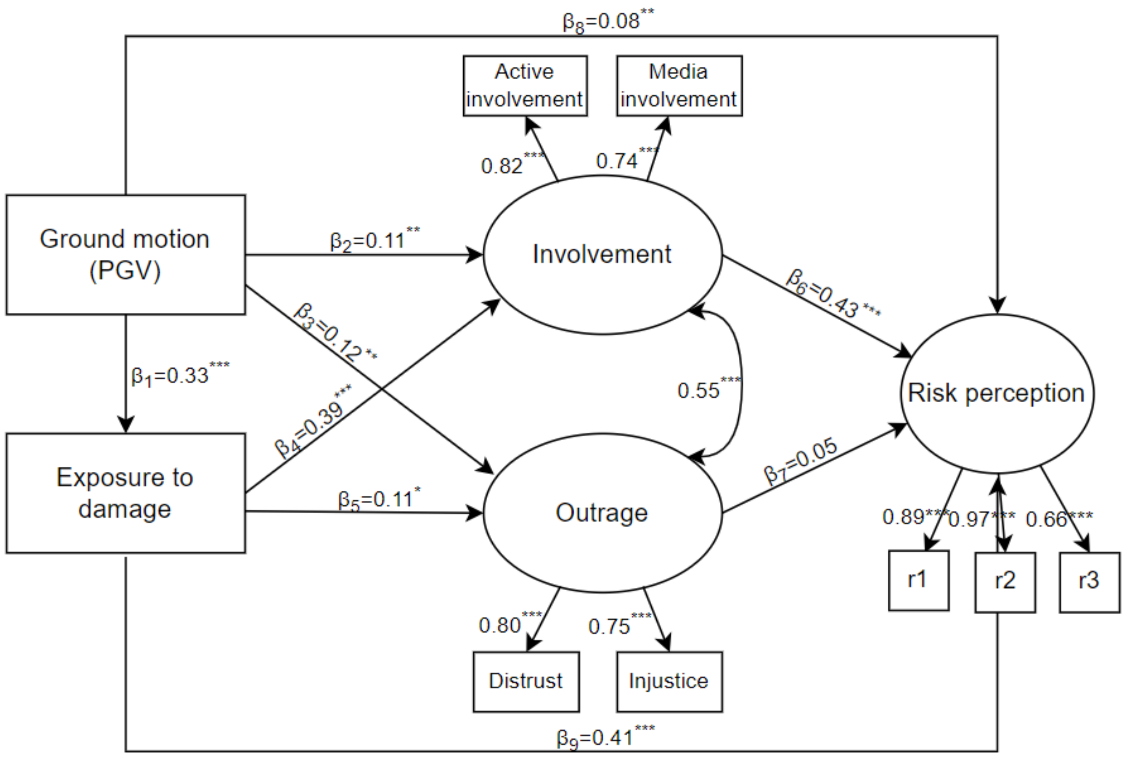
This model was built to investigate the relationships between ground motion, exposure to damage and risk perception, before SARF variables are added to the model. The model was fitted to the first data subset, and it fitted the data sufficiently well ($\chi 2 = 18.33$, $p = 0.01$, $df = 4$, CFI = 0.992, RMSEA [90% CI] = 0.069 [0.04;0.10], SRMR = 0.02). The chi-square test was significant, indicating the proposed model differs significantly from the actual covariance matrix. However, chi-square is sensitive to sample size, so key decisions about model fit should not be based on the model chi-square statistic alone, but based on other fit indexes (Kline, 2016). This was expected due to the large sample size (*N* = 750). The factor loadings and path coefficients are shown in Figure 6. This model with only exposure to damage and PGVs as predictors explained 40.8% variance in risk perception; exposure to damage accounted for 30.4%, and PGVs for 10.4% of variance in the model.

Before and after the Zeerijp earthquake

The models were built iteratively, while taking into account theory and inspecting modification indices. The final model is illustrated in Figure 7, and the results in Table 4.

Figure 7

Full structural equation model of risk perception due to earthquakes, damage exposure, involvement and outrage, first data subset (N = 750)



Note. * $p < .05$, ** $p < .01$, *** $p < .001$

Table 4

Relationships between PGVs, exposure to damage, SARF variables and risk perception in the first (before Zeerijp earthquake) and second data subset (after Zeerijp earthquake)

	Model 1 (N =750)		Model 2 (N =639)	
Regression coefficients	Standardized estimates [95% CI]	Standard error	Standardized estimates [95% CI]	Standard error
β_1	0.33*** [0.26; 0.39]	0.03	0.31*** [0.24; 0.38]	0.04
β_2	0.11** [0.03; 0.19]	0.04	0.14** [0.05; 0.22]	0.04
β_3	0.12** [0.33; -0.204]	0.04	0.18*** [0.09; -0.27]	0.05
β_4	0.39*** [0.31; 0.46]	0.04	0.44*** [0.36; 0.52]	0.04
β_5	0.11* [0.02; -0.19]	0.04	0.11** [0.01; -0.20]	0.05
β_6	0.43*** [0.34; 0.52]	0.05	0.34*** [0.23; 0.45]	0.06
β_7	0.05 [-0.03; -0.14]	0.05	0.14* [0.05; -0.24]	0.04
β_8	0.08** [0.02; 0.13]	0.03	0.08** [0.02; 0.15]	0.03
β_9	0.41*** [0.35; 0.48]	0.03	0.40*** [0.33; 0.47]	0.04

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

The final model fit the first data subset sufficiently, chi-square was significant and RMSEA was above the threshold, but overall, the model fit is sufficient ($\chi 2 = 154.45$, $p < 0.001$, $df = 19$, CFI = 0.96, RMSEA [90% CI] = 0.097 [0.08;0.11], SRMR = 0.05). As well as chi-square, RMSEA is also sensitive to sample size; it imposes harsher penalties on smaller models with few variables and relatively few degrees of freedom (Breivik & Olsson, 2001). This has to be kept in mind when evaluating how the final model fits each data subset and considering the RMSEA value. In line with the theoretical model, we found that PGVs have a direct positive relationship with exposure to damage, a direct positive relationship with *involvement* indicating an increase in PGVs causes and increase in media involvement and taking action regarding extraction. A direct effect of PGV on *outrage* was observed as well, however the effect of PGV on distrust and injustice is descriptively small. The direct effect of exposure to damage and *involvement* is positive and high ($\beta_4 = .39$, $p < .001$). The direct effect of PGVs on risk perception is positive ($\beta_8 = .08$ $p < .01$) and the direct effect of exposure to damage on risk perception is high ($\beta_9 = .41$, $p < .001$) indicating that exposure to damage may be mediating between PGVs and risk perception. Modification indices were inspected again, but based on theoretical background no new paths were added. The theoretically built model fit the data sufficiently, involvement and outrage were identified as distinct SARF latent variables, which was not in the proposed model (Figure 2), and covariance was added between the errors of involvement and outrage, since they measure related concepts.

The final model in the first data subset explained 58.8% variance in risk perception, exposure to damage and PGVs accounted for 40.8% of variance and the SARF variables combined for the remaining 18% of variance. This means a substantial portion of variance in risk perception is explained by PGVs and damage, and not the SARF variables. Unique variances explained per predictor, for each data subset, are available in Table 5.

The final model was fitted to the second data subset that captures data collected right after the Zeerijp earthquake. It can be visualized in the same way as the first model in Figure 7 (with different estimates). The model fit in the second data subset was also sufficient. RMSEA was above the threshold and the *p*-value was significant, but other fit indexes indicated good fit ($\chi2 = 167.39$, $p < 0.001$, $df = 19$, CFI = 0.94, RMSEA [90% CI] = 0.11 [0.10;0.13], SRMR = 0.055). The estimates are visible in Table 4, and are similar to those observed in the first subset. The largest differences are in increased effect of outrage (β_7), and decreased effect of involvement (β_6) on risk perception (Table 4). The model explained 54.6% variance in risk perception. Exposure to damage and PGVs explained 39.2% variance, while involvement explained 12%, and outrage 3% of variance. Again, SARF variables explained additional 15% of variance in the model (Table 5).

Replication: Before and after the Westerwijtwerd earthquake

The final SEM models were also fitted to the third data subset before the Westerwijtwerd earthquake and the fourth data subset capturing data after this earthquake. This was done to validate the proposed model using new data. The visual representation of the third model, and the estimates and standard errors of both the third and fourth model are available in Appendix C.

The third model also had sufficient model fit, RMSEA was above the threshold and the *p*-value was significant, but other fit indexes indicated good fit ($\chi2 = 141.42$, $p < 0.001$, $df = 13$, CFI = 0.96, RMSEA [90% CI] = 0.10 [0.09;0.12], SRMR = 0.05), as well as in the fourth subset ($\chi2 = 295.59$, $p < 0.001$, $df = 13$, CFI = 0.96, RMSEA [90% CI] = 0.10 [0.09;0.11], SRMR = 0.04). Again, we found a direct positive effect of PGV on exposure to damage, a direct positive effect on *involvement* and on *outrage*, however it was descriptively small. The direct effect of exposure to damage on *involvement* is positive and high ($\beta_{4subset3} = .34$, $p < .001$). The direct effect of PGVs on risk perception is positive but small ($\beta_{8subset3} = .11$ $p < .01$) and the direct effect of exposure to damage on risk perception is high ($\beta_{9subset3} = .49$, $p < .001$) indicating once again that exposure to damage is mediating between PGVs and risk perception. There are no substantial differences is these relationships in the third and fourth data subset. The third model explained 52.3% variance in risk perception. Exposure to damage and PGV explained 44.6% of variance, while SARF variables explained 7.7% of unique variance. The fourth model explained 50.2% variance in risk perception. PGV and exposure to damage explained 44.2% of variance, and SARF variables explained 6% of unique variance (Table 5).

In sum, the final model also fit the data well for subsets 3 and 4, which concerned an entirely different earthquake. When comparing the estimates of the final model between the first and second data subset; and the third and fourth data subset, the biggest difference is in the direct effect of ground motion on damage (β_1) and the direct effect of outrage on risk perception (β_7) that are bigger in the third and fourth data subset ($\beta_{1subset1} = .33$, $p < .001$; $\beta_{1subset3} = .47$, $p < .001$; $\beta_{7subset1} = .05$, $p = .211$; $\beta_{7subset3} = .19$, $p < .001$). Furthermore, the direct effect of involvement on risk perception (β_6) was smaller in the third and fourth data subset ($\beta_{6subset1} = .43$, $p < .001$; $\beta_{6subset3} = .19$, $p < .001$). Ground motion and exposure to damage together explain approximately the same amount of variance in each data subset (Table 5). However, the biggest difference in unique variance explained is by involvement and exposure to damage which explain less variance over time, while ground motion explains more (Table 5). To conclude, the theoretically built model, improved by distinguishing two latent variables representing different components of SARF (involvement and outrage) fit the data sufficiently. The model was replicated and validated on four data subsets[2].

[2] A model was also built with perceived safety as the outcome variable instead of risk perception. Results for that model can be found in Appendix E, Figure A3.

Table 5

Unique variance explained in risk perception for the final SEM per predictor for each data subset

	Data subset 1 R^2 (N = 750)	Data subset 2 R^2 (N = 639)	Data subset 3 R^2 (N = 908)	Data subset 4 R^2 (N = 2046)
Ground motion (PGV)	10.4%	11.0%	17.9%	22.3%
Exposure to damage	30.4%,	28.2%	26.7%,	21.9%,
Involvement*	15.7%	12.0%	4.4%	4.0%
Outrage	2.3%	3.4%	3.3%	2.0%
Overall variance explained	58.8%	54.6%	52.3%	50.2%

Note. * In data subsets 3 and 4 do *media involvement* was not measured so the latent variable *Involvement* differs in these subsets compared to the first two data subsets.

Calculating ΔR^2 is not intuitive in SEM models because different restrictions are imposed on covariances between latent variables and their indicators, and the model may not fit the data when a latent variable is included or excluded which is needed to calculate the change in R^2 (Hayes, 2021). However, if a suitable reduced model without latent variables can be configure ΔR^2 can be calculated using this formula: $\Delta R^2 = R^2_{Full} - R^2_{Reduced}$ (Hayes, 2021). Since ground motion is a true exogenous variable, the reduced model with only PGVs predicting risk perception was built. In the next step exposure to damage was added (Figure 6), and in the third step SARF variables were added. Thus, ΔR^2 was easily calculated. This ΔR^2 for each predictor in each data subset is visible in Table 5. It is important to note how this way of calculating ΔR^2 using the hierarchical regression approach is more accurate than just using the Lavaan output for R^2 in the final model. Lavaan output doesn't capture the R-squared change, but only the overall model R^2 for each endogenous outcome calculated when all predictors are included to provide the best model fit based on the covariance matrix, while not reflecting unique variance explained by each predictor when added to the model separately.

Discussion

This paper studied how a representative sample's perceptions of earthquake risks change over time, during a period in which these risks became more widely known and seen as problematic. The traditional literature focuses on how cognitive and social factors bias laypeople's risk perception. We wanted to investigate a broader set of predictors of risk perception in a real-life test of the SARF approach. We investigated the relationship between exposure to objective ground motion, to damage, and what one might call "social exposure" to indicators of involvement and social outrage–variables relevant to SARF. A SEM model that sought to explain as much variance in risk perception as possible was built iteratively using data from one time point, and the final model was fitted to subsets from four different datapoints, so as to replicate the model and to assess coefficient change over time.

The theoretically built model and the final model were conceptually very similar. The theoretical model could be improved by distinguishing two latent variables representing different components of SARF. We labelled these two *involvement* and *outrage.* Involvement predicted how participants scored on items related to media involvement (with items about following media, and how busy certain events and decisions regarding extractions and earthquakes kept them) and active involvement (talking to others about the issue, speaking up, protesting). Outrage predicted the degree to which people thought the events were unjust and their lack of trust of the national government and the operator, who are jointly responsible. Although these two components were not in the initially proposed model, these empirical fact change nothing about the theoretical proposition or about the conclusions. The final model fit the four data subsets sufficiently so we could investigate how much variance is attributable to each predictor of risk perception.

Turning to the relationships between the variables in the model, we shall discuss them in the causal order of the hypotheses, beginning with the exogenous variable of ground motion. First, the results show that the relationship between ground motion and exposure to damage was as could be expected. Ground motion is the direct cause for earthquake damage, so it is logical for these variables to correlate highly and positively.

Turning to the relationship between exposure and SARF, to our knowledge there haven't been prior studies that examined how exogenous measures of exposure to hazards relate to SARF-related variables. SARF proposes that the processing of risk-related information and the societal response are transforming risk perception (either by amplification or attenuation) but it makes no predictions concerning the relationship between risk events themselves and perceptions. Indeed, across all four data subsets only negligible correlations were found between ground motion and SARF variables. This would seem in line with the SARF approach. However, the effect of exposure to damage on involvement is notable; also in line with previous research, those who have direct consequences of the risk event will inform themselves and take more actions as a response to these consequences (Bouman et al., 2020; Bronfman et al., 2020; Lindell & Hwang, 2008).

Now turning to the relationship between exposure and risk perception. Important to note in all this is that we know of no prior research which has distinguished between objective exogenous measures of a risk events in time and personal exposure in the form of damage. Accordingly, the results are bound to be informative. In all four models, the direct effect of ground motion on risk perception was low, because exposure to damage mediated this effect. Exposure to damage was therefore the most influential predictor of risk perception in this paper. This finding is not unexpected. According to literature on a range of possible risk events and hazards, the greater the experienced negative consequences of a risk event are, the higher the associated perception of risk is (Bronfman et al., 2020; Knuth et al., 2014; Lindell & Hwang, 2008; Paton et al., 2000). The finding is also in line with the availability heuristic, and has been confirmed in a study by Tian and colleagues (2014) that specifically investigated earthquake risk perception and showed that those who suffer more earthquake consequences tend to have higher risk perception. Interestingly, in this study those who experienced more earthquakes on average had lower risk perception (in line with the psychometric paradigm's prediction that novel hazards are perceived as more risky). This is not what we see in our data, where, if anything, the relationship between exposure to ground motion and perceived risk gets stronger over time, increasing from $R_1^2 = .10$ to $R_4^2 = .22$. It seems that the repeated exposure to larger earthquakes from Zeerijp onwards increases the relative importance of the physical exposure (ground motion) over the personal exposure (damage). Across the four models, we interpret these results as showing that (a) there is a sizable relationship between ground motion and risk perception, (b) which is mediated by the personal exposure to damage, and that (c) personal exposure amplifies the effect of ground motion on risk perception.

Turning to the relationship between the social factor and risk perception. The effect of involvement decreased over time because media involvement was not included in the third and fourth subset. Based on SARF literature a bigger effect of involvement on risk perception was expected, since the framework poses media as the core amplifier of risk as well as activism and sharing opinions in personal networks (Kasperson et al., 1988). Outrage explains a low but consistent amount of variance across the four subsets. Although previous research within SARF pose both the perception of fairness and trust in the stakeholder as a key risk perception predictor(Visschers & Siegrist, 2018), some authors also only found low trust correlates with risk perception (Sjöberg, 2004).

Finally, turning to the variance explained by the different variables, the results clearly indicate how both the source of the risk (ground motion) and its hazardous consequences (damage) explain the majority of variance, and therefore would be good to include as key predictors of risk perception in empirical research on risk and indeed in theories of risk perception. However, the role of social factors communicated through media and social interactions clearly should be considered as well: they too account for a sizable portion in risk perception variance. In the present research, moreover, it appears that perceptions of risk are less strongly related to distrust and perception of injustice and more strongly to active personal involvement and involvement in media coverage of the event.

When observing differences prior to and immediately after the Zeerijp (first and second data subset) and the Westerwijtwerd earthquake (third and fourth data subset) no substantial differences were found. Both earthquakes generated a lot of adverse consequences for residents and widespread condemnation of the government and corporation’s actions. Media widely covered and politicized the issue prior to the elections, and gave wide birth to residents who expressed outrage over the extraction. Especially notable is the Zeerijp earthquake which did a lot to shift the public perception of the situation in Groningen and initiated major policy changes. For both earthquakes, ground motion explains more variance in risk perception immediately after the earthquakes occur, while exposure to damage explains a smaller portion of variance immediately after the earthquakes. Also, after the first bigger earthquake in Zeerijp, the relative importance of ground motion increases over the personal exposure to damage. A possible explanation for this is that residents became habituated to damage, while their awareness of bigger earthquakes being possible continuously increased (at the time models predicted a maximal earthquake magnitude of $M = 5.0$ (SodM, 2022). But based on the data the objective exposure to the risk event explains a large portion of variance in risk perception over time, indicating that these are the most important factors in predicting risk perception concerning earthquakes among residents in Groningen. These results are unique, we were able to investigate these aspects because the data was continuously collected over a long period of time and paired with real geological ground motion data.

Implications of this analysis are important for the grater scientific community and contribute to the literature on risk perception; but the results also have practical implications for both the residents of Groningen and bodies involved in this issue, and the larger audience. SARF deepens the image of public as irrational and overly influenced by social factors. The consequence of this approach is a theoretical basis for ignoring public risks perception in policy making. While, as the results have showed, the public reacts to real sources of risk in their surrounding (ground motion). Over the years, both government and NAM have sought to manage this problem by downplaying the risks in a manner that suggests they know the SARF risk literature quite well. Concretely, they both for a long time actively downplayed the extent of the damage and the risks involved. When this could no longer be denied, they showed doubt about the extent of the problem as well as about mitigation. Residents, by contrast, began taking action in various ways to contest decisions, raise awareness or signal their disaffection. Whilst all these factors may matter to some degree, they appear to be of secondary influence for risk perceptions in the end: the primary influence is the degree to which people are directly affected.

Limitations and recommendations for future research

The biggest limitation of the present analysis is that this series of cross-sectional analyses would be stronger if a proper longitudinal analysis could be conducted of the changes in risk perception over time. But it proved to be impossible with this data to build a large SEM model over time. This is because of the high attrition level and amount of missing data: new participants were invited to joined the research project in T8. For this reason, the number of repeated measures across all four observations would be very low. Another limitation was that not every variable was measured at each timepoint, so media involvement hasn't been included in the third and fourth data subset which enables a perfect comparison of model fit between the four data subsets. Related to this, we sometimes had to combine measures across different measurement points to be able to test the full model (e.g. in the first data subset distrust and injustice were measured in T2, while media involvement in T4, see Figure 3). Because measures were taken reasonably close in time, this seemed justified but it would still introduce noise. Finally, there is still a portion of unexplained variance in the model. One reason for this is that many more variables could have been included in this research. (e.g. locus of control over earthquakes, controllability of damage,). Moreover, future research should continue investigating risk perception in a natural settings and possibly tracking it over time.

Conclusion

The idea that emotions such as fear and outrage are highly contagious and therefore spread easily among 'the people', clouding their rational judgment, is as old as time. But the current data show nothing of this kind. Based on the findings we conclude that people's perception of risk may be shaped by all manner of cognitive and social factors, but when people have direct personal experience with that hazed we conclude that their perceptions are largely shaped by the magnitude of the events they witnessed and their immediate impact for themselves (and potentially for others who they know well). Accordingly, personal experience deserves to have a central place in the risk perception literature. That is not to say that other factors are irrelevant. Clearly social factors are important for explaining risk perception, but empirically we have shown that the objective exposure to the risk event, in form of ground motion and damage to one's property, explains a lot more variance. The fact that subjective perceptions correlate so well with objective exposure also has implications for theories of risk perceptions that imply that lay perceptions of risk are necessarily biased or ill-founded. The present research suggests that these risk perceptions were fairly accurate, even though over the course of the data collection emotions ran increasingly high, with mounting activism, a persistent sense of injustice and very little trust. Involvement in the issue and outrage over the extraction and earthquakes were shown to be relevant factors in risk perception, for sure, but they were not central. In sum, even though all the ingredients for the social amplification of risk perceptions were present, the present data shows that risk perceptions are grounded in a fairly factual assessment of the degree of exposure to hazardous events and their adverse consequences.

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Appendices:

Appendix A: List of all Questionnaire Items

Scale/construct	Original item(s) in Dutch	Translated item(s)	Scale
Exposure to damage	Hoe vaak heeft u aardbevingsschade gehad? (U mag ook een schatting geven).	How often have you had earthquake damage?(You may also provide an estimate).	never/1 time/ 2 times/ 3 times/ 4 times/ 5-10 times/ more than 10
Risk perception	In het geval van toekomstige aardbevingen: hoe groot schat u de kans dat…	In the case of future earthquakes, what do you estimate the probability that…	
	…u deze aardbevingen zelf meemaakt?	…you experience these earthquakes yourself?	very low probability (1) - probability is very high (5)
	…uw eigendommen worden beschadigd als gevolg van de gaswinning?	…your property is damaged as a result of gas extraction?	
	…u verwond zult raken als gevolg van een aardbeving?	…you will be injured as a result of an earthquake?	
Media involvement (latent involvement)	De gaswinning is de afgelopen maanden veel in het nieuws geweest. Sommige mensen zijn daar erg mee bezig en anderen veel minder of helemaal niet. In hoeverre hebben de volgende gebeurtenissen uzelf de	Gas extraction has been in the news a lot in recent months. Some people are very concerned with this while others are much less concerned or not at all. To what extent have the following events affected	

	afgelopen maanden bezig gehouden?	you in recent months and kept you busy?	
	De uitspraak van de rechtbank dat de Nederlandse Aardolie Maatschappij (NAM) aansprakelijk is voor de immateriële schade van gedupeerden.	The ruling of the court that the Nederlandse Aardolie Maatschappij (NAM) is liable for the immaterial damage of the victims.	Not at all (1) - very much (5)
	De uitzending van "Zondag met Lubach" over de gaswinning.	The broadcasting of "Zondag met Lubach" about gas extraction.	
	De uitspraken van Mark Rutte bij het tv-programma “Jinek”.	Mark Rutte's statements on the TV show “Jinek”.	
	De recente acties zoals de fakkeloptocht en de petitie "Laat Groningen niet zakken".	The recent actions such as the torchlight procession and the petition "Don't let Groningen down".	
	De aandacht voor de persoonlijke gevolgen van de aardbevingen in televisieprogramma's (zoals bijvoorbeeld "De Monitor" en "Brandpunt") en documentaires (zoals "De stille beving").	Attention to the personal consequences of earthquakes in TV shows (such as "De Monitor" and "Brandpunt") and documentaries (such as "De silent quake").	
	Het afwijzen van alle 1800 schadeclaims buiten de "contourlijn" van het aardbevingsgebied.	Denying all 1800 damage claims outside the "contour line" of the earthquake zone.	
	Het besluit om de gaswinning met 10% terug te brengen naar 21,6 miljard m³.	The decision to reduce gas production by 10% to 21.6 billion m³.	

Active involvement (latent involvement)	De situatie rondom de gaswinning houdt velen in Groningen bezig, ook de mensen die niet in het gebied met veel schade wonen. De volgende vragen gaan over uw gedrag omtrent de gaswinning. Kruis op iedere regel het antwoord aan dat het beste omschrijft hoe vaak u dit in de afgelopen 4 weken heeft gedaan.	The situation surrounding gas extraction is a concern for many people in Groningen, including those who do not live in the area with a lot of damage. The following questions are about your behavior in regard to gas extraction. Select the answer that best describes how often you have done this in the past 4 weeks.	never (1) - very often (5)
	Ik zoek er informatie over.	I'm looking for information about it.	
	Ik probeer te begrijpen wat er precies gebeurt.	I'm trying to understand what exactly is happening.	
	Ik steun en help anderen die ermee kampen.	I support and help others who are struggling.	
	Ik praat met anderen die dit meemaken.	I talk to others who are going through this.*	
	Ik laat van mezelf horen (bijv. door een klacht in te dienen over hetgeen me is overkomen).	I speak up (e.g. by making a complaint about what happened to me).*	
	Ik neem deel aan demonstraties.	I participate in demonstrations.*	
Active involvement - Not included*	Ik ondersteun of neem deel aan ludieke acties die de grens van de wet opzoeken.	I support or participate in playful actions that push the boundaries of the law.*	Active involvement - Not included
	Ik werk werknemers en organisaties tegen die voor de	I work against employees and organizations that are responsible for the	

	(gevolgen van de) gaswinning verantwoordelijk zijn.	(consequences of) gas extraction.	
Distrust in institutions (latent outrage)	Hoeveel vertrouwen heeft u in de volgende instanties of personen?	How much trust do you have in the following authorities or persons?	
	…de Rijksoverheid?	…the National Government?	no trust (1) - high trust (5)
	…de Nederlandse Aardolie Maatschappij (NAM)?	… the Dutch Petroleum Company (NAM)	
Injustice concerning extraction (latent outrage)	Hoe rechtvaardig vindt u de door dit kabinet vastgestelde hoeveelheid gas die gewonnen wordt?	How just do you think the amount of gas that is extracted, determined by this government, is?	
	Hoe rechtvaardig vindt u de hoogte van de vergoedingen voor schade en overlast door gaswinning?	How just do you think the level of compensation for damage and nuisance caused by gas extraction is?	very unjust (1) -very just (5)
	Hoe rechtvaardig vindt u de besluitvorming over de gaswinning?	How just do you think the decision-making on gas extraction is?	
	Hoe rechtvaardig vindt u de regelingen voor schade en overlast rondom gaswinning?	How just do you think the regulations for damage and nuisance related to gas extraction are?	

*Note: Since the last two items were not measured in the third and fourth subsets they were excluded from the first two data subsets as well.

Appendix B: SARF correlation matrix

Table A1

Correlation matrix for Involvement and Outrage indicators (N = 750)

		Latent involvement		Latent outrage	
		Active involvement	Media involvement	Trust	Justice
Latent involvement	Active involvement	1	0.60	0.40	0.31
	Media involvement		1	0.42	0.30
Latent outrage	Trust			1	0.61
	Justice				1

Appendix C: Results for the third and fourth data subset

Table A2

Descriptive statistics of variables before and after the Westerwijtwerd earthquake and corresponding to the SEM Models 3 and Model 4

	Subset 3 (n= 908)				Subset 4 (n=2046)			
Variable	Mean	SD	Skewness	Kurtosis	Mean	SD	Skewness	Kurtosis
Risk perception	2.93	1.05	-0.09	-0.83	2.76	1.05	0.04	-0.86
PGV	4.72	4.17	1.83	3.30	4.34	3.97	1.93	3.94
Exposure to damage	2.19	0.88	-0.37	-1.62	2.05	0.91	-0.10	-1.78
Distrust	4.08	0.76	0.84	0.46	4.02	0.76	0.63	0.00
Injustice	4.41	0.79	1.74	3.08	4.35	0.81	1.60	2.51
Active involvement	2.81	0.76	0.31	0.12	2.71	0.76	0.22	0.01

Table A3

Correlation matrix for predictor and outcome variables of the second and fourth data subset

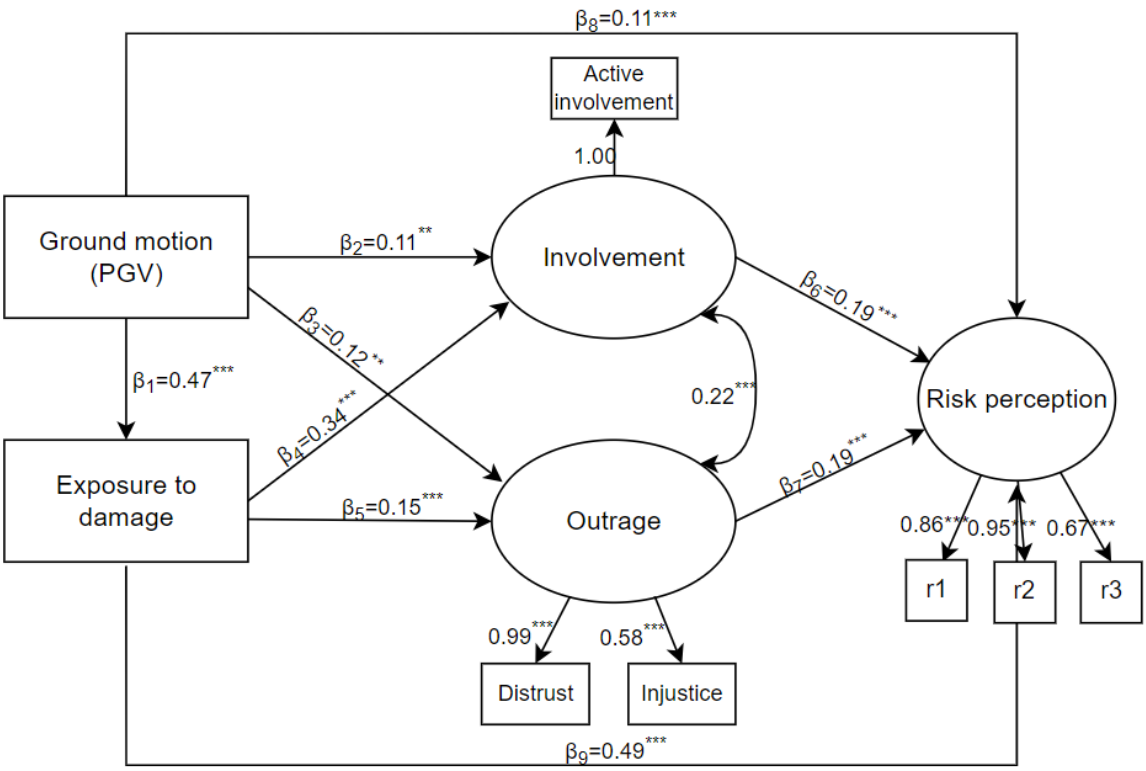
	Variable	1.	2.	3.	4.	5.	6.
1.	Risk perception	1	0.41***	0.60***	0.37***	0.19***	0.44***
2.	Ground motion (PGVs)	0.46***	1	0.47***	0.17***	0.06	0.27***
3.	Exposure to damage	0.59***	0.50***	1	0.19***	0.03	0.39***
4.	Distrust	0.31***	0.17**	0.19***	1	0.58***	0.28***
5.	Injustice	0.18***	0.07**	0.06**	0.56***	1	0.21***
6.	Active involvement	0.44***	0.27***	0.40***	0.28***	0.21***	1

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

Note: Blue– 3rd data subset used for Model 3, green – 4th data subset used for Model 4

Figure A1

Full structural equation model of risk perception due to earthquakes, damage exposure, involvement and outrage in the third data subset (N = 908)



Note. * $p < .05$, ** $p < .01$, *** $p < .001$

Table A4

Relationships between PGVs, exposure to damage, SARF variables and risk perception in the third (before Westerwijtwerd earthquake) and fourth data subset (after Westerwijtwerd earthquake)

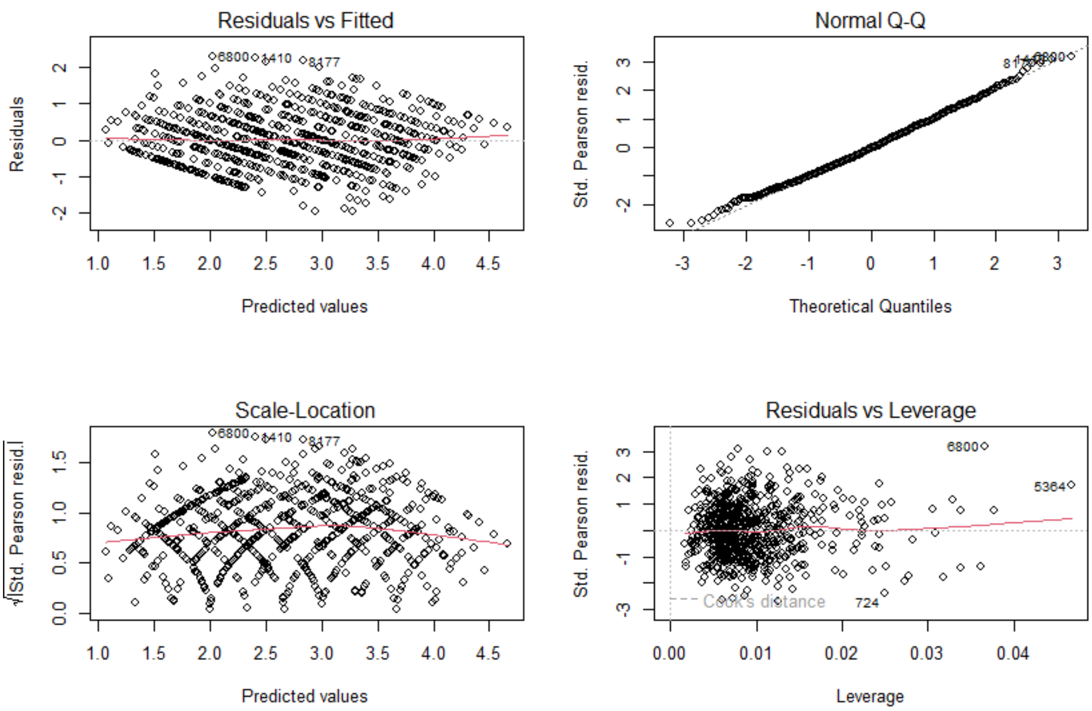
	Model 3 (N = 908)		Model 4 (N = 2046)	
Regression coefficients	Standardized estimates [95% CI]	Standard error	Standardized estimates [95% CI]	Standard error
β_1	0.47^{***} [0.43; 0.52]	0.02	0.50^{***} [0.47; 0.53]	0.02
β_2	0.11^{**} [0.04; 0.18]	0.03	0.10^{***} [0.05; 0.14]	0.02
β_3	0.11^{**} [0.03; 0.18]	0.04	0.11^{***} [0.05; 0.16]	0.03
β_4	0.34^{***} [0.27; 0.40]	0.03	0.36^{***} [0.31; 0.40]	0.02
β_5	0.15^{***} [0.07; 0.22]	0.04	0.15^{***} [0.10; 0.20]	0.03
β_6	0.19^{***} [0.13; 0.24]	0.03	0.18^{***} [0.14; 0.22]	0.02
β_7	0.19^{***} [0.14; 0.25]	0.03	0.16^{***} [0.12; 0.20]	0.02
β_8	0.11^{***} [0.05; 0.16]	0.03	0.16^{***} [0.12; 0.20]	0.02
β_9	0.49^{***} [0.44; 0.55]	0.03	0.46^{***} [0.42; 0.50]	0.02

Note. * p < .05, ** p < .01, *** p < .001

Appendix D: SEM assumptions

Figure A2

Plot of model assumptions for deviations against normality for the first model



*Note: These plots were created for all four models and they look similar so only the first one is presented.

Table A5

*Generalized variance inflation factor (GVIF^(1/(2*Df))) per variable in each data subset*

Variable	Subset 1 (n = 750)	Subset 2 (n= 639)	Subset 3 (n = 908)	Subset 4 (n = 2046)
PGV	1.14	1.07	1.14	1.16
Damage	1.29	1.08	1.10	1.11
Distrust	1.65	1.28	1.27	1.24
Injustice	1.67	1.27	1.24	1.21
Media involvement	1.80	1.37	-	-
Taking action	1.84	1.37	1.13	1.13

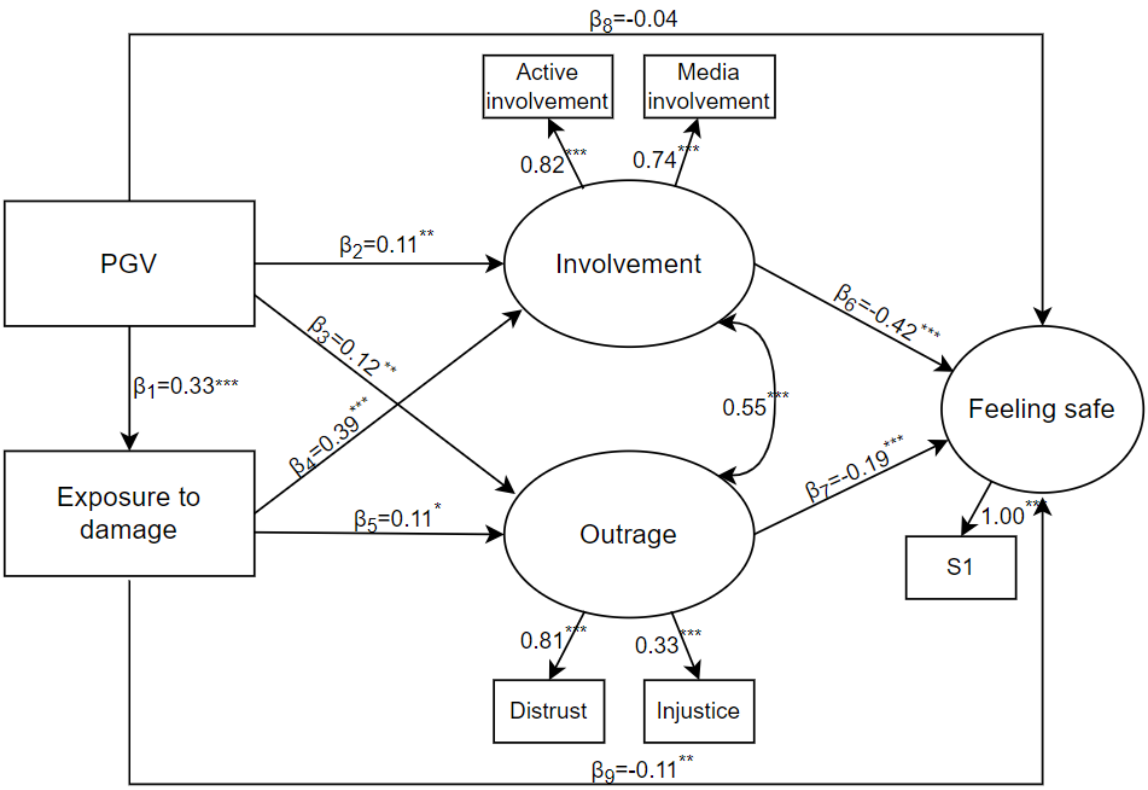
Note: Values of VIF greater than 2.5 are considerate as indicative of considerable collinearity (GVIF>2.5) (Fox & Monette, 1992; Johnston et al., 2018). Analysis was conducted prior to outlier detection.

Appendix E: Safety perception SEM model

- safety perception as the outcome variable

Figure A3

Full structural equation model of Perceived safety regarding earthquakes due to gas extraction, damage exposure and SARF variables (N = 750)



Note. * p < .05, ** p < .01, *** p < .001

This model has sufficient model fit, RMSEA was above the threshold and the *p*-value was significant, but other fit indexes indicated good fit ($\chi2 = 69.31$, $p < 0.001$, $df = 7$, $CFI = 0.96$, *RMSEA* [90% CI] = 0.11 [0.09;0.14], $SRMR = 0.04$). The estimates of this model are similar to those observed when risk perception is the outcome variable (as in Figure 7).

However, β_6 and β_7 have a different operator (- instead of +) compared to when risk perception is the outcome. This is due to the scale used to measure safety. The item was "Over the past four weeks, how safe have you felt in the place where you live in connection with gas extraction? " and it was measured on a five-point Likert scale (1 = very unsafe, 5 = very safe). On the other hand, risk perception was measured with three items, as the probability of experiencing earthquake related issues in the future; also on a five-point Likert scale (1 = "very small probability", 5 = "very high probability"). As visible the meaning of the two scales is opposite because high probability of experiencing risk is related with perception of unsafety. Thus, these items are highly and negatively correlated r = -.60 (p < .001);

The model in Figure A2 explained 38.7% variance in risk perception. Exposure to damage and ground motion explained 12.4% of variance, while Involvement explained 20%, and Outrage 6.3 % of variance. Thus, SARF variables seem to be more relevant for perceived safety compared to risk perception.