Measuring Subjective Risk Perception as a Latent Construct: A Semi-Confirmatory Factor Analytic Approach

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Data availability:

Analysis protocols and supplementary files are available at an online repository: https://osf.io/cs97b/.

Anonymised link to online repository: https://osf.io/cs97b/?view_only=5a0b7da9ca0d414b9273988cdd7ee40e.

Original data are available upon request due to data protection regulation.

Abstract

In our paper we analyse risk perceptions of individuals based on data collected as part of the longitudinal survey series Finnish Emergency Attitudes. We propose that in terms of risk perception, risks should be seen as interconnected, intuitively valued, and socially mediated. Using factor analysis, we construct a General Risk Probability Perception Scale (GRPPS) and analyse the variance in risk perception in three different models. We found support for the hypothesis that risk perception is a unitary construct, as opposed to composed of singular risk related perceptions of probability. General risk perception seems to be related to experiences of actual risk, whether direct, near-miss or professional. For social variables, only being male or elderly predicts a higher general perception of risk.

Keywords:

Risk perception, semi-confirmatory factor analysis, General Risk Probability Perception Scale, direct experience, near misses.

Statements and Declarations:

The authors declare no competing interests, either financial or non-financial.

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Author contributions:

Oliver Saal: Conceptualisation, Methodology, Formal analysis and investigation, Writing – original draft preparation, Writing – review and editing, Resources.

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1. INTRODUCTION

Risk perception has been the topic of much research in the past two decades. Investigations have been made into how perception is organised, how hazard events affect subjective judgment, how perception affects preparation efforts, and many more areas. However, most research is focussed on single risk events. There is to date no empirical evidence for whether these singular results generalise from one hazard event to another.

Perception is nonetheless important to study, from a perspective of loss prevention and hazard event management. Flood risk perception has been shown to influence individual behaviour both before, during, and after the hazard event (see Kellens et al., 2013). While the causality is unclear (de Koning et al., 2017), there is a clear understanding that perception, awareness, and behaviour of risk are linked. Thus, understanding how an individual's risk perception arises becomes important for managing hazard-related events.

In this article, we conceptualise subjective risk perception as a unitary latent construct. Risk perception is, in this view, not fully independent between risks, but correlated, with potential amplifying and attenuating effects between different risks. Perceiving one hazard as particularly probable may lead to perceiving other hazards as probable. We test this assumption empirically, using semi-confirmatory factor analysis, and investigate whether previous empirical results in the connection between risk perception and experience generalise to this general system of risk perception.

2. RISKS AND RISK PERCEPTION

The Society for Risk Analysis give multiple definitions of *risk*, where perhaps the most general definition is risk as undesirable consequences related to a future activity[1] (Aven et al., 2018, p. 4). This entails an *uncertainty* about the consequences, which, as we will show, is of particular importance in understanding the individual's perceptions on risk and hazards. The latter, *hazards*, are defined as risk sources "where the potential consequences relate to harm." (Aven et al., 2018, p. 6). In other words: all hazards are risks, and all risks contain some level of uncertainty.

[1] This definition precludes many other definitions. Aven (2022) reviews a six-fold typology of risk definitions. The popular view of risk as the *possibility* of unwanted consequences may also be distinguished from an objective *probability* of an event, as suggested by Lee (2014).

Risk perception is, then, the view an individual has of a given risk. This may be divided analytically into subjective and objective risk perception. *Subjective risk perception* is defined as the individual's estimation of a given risk's probability to occur. It is generally divided into two systems: an analytic and an intuitive system (Slovic et al., 2004). While both are empirically calibrated, the former is slow, methodical, and atomistic, while the latter is fast, general, and holistic. This perception is distinct from a risk's *objective probability*, and the individual's perception of a risk need not align with an expert's appraisal of a risk's probability.

Subjective risk perception has been shown to be biased (Ludy & Kondolf, 2012), empirically calibrated (Dillon et al., 2011; Dillon & Tinsley, 2008), drastically reactive to hazard experiences (Gallagher, 2014), and a derivative function of the time after a hazard event (Atreya et al., 2013; Bin & Landry, 2013; Gallagher, 2014). The perception of flood risk has been shown to correlate with other risk perceptions (Zhai & Ikeda, 2008). Hazard and near-miss experiences have also been shown to be related to risk perception, albeit differently: hazard experience is related to an increase in perceived risk (Kellens et al., 2013), while near-miss experiences has been related to a *decrease* in perceived risk (Dillon et al., 2011; Dillon & Tinsley, 2008).

It has been speculated that divergent research results concerning the connection between behavioural patterns and risk perceptions might be due to the analytic-intuitive dual process model: when research results diverge, it is because the population is using distinctly different ways of modelling subjective risk (Dillon et al., 2011; Dillon & Tinsley, 2008). It has even been suggested that the two systems are opposite, that subjective risk perceptions may arise from a lack of objective risk knowledge (Barberis, 2013; Dillon & Tinsley, 2008; Kellens et al., 2013).

The social amplification of risk framework (SARF) focusses on how objectively defined risk probabilities may become stronger (amplification) or weaker (attenuation) in the public's eye (Kasperson et al., 2022). This framework has been applied widely, and extended among other areas to the analysis of systemic risk (P. Schweizer et al., 2022; P.-J. Schweizer, 2021; P.-J. Schweizer & Renn, 2019).

However, the SARF perspective regards risks as unitary events. We propose that in terms of risk perception, risks should be seen as interconnected. Instead of risk perception arising from the combination of one specific risk probability and an unspecified number of attenuating or amplifying functions, we suggest that risk perception partially arises from the *co-occurrence* of multiple risk perceptions. One could speak of a *phenomenological amplification of risk* framework: the existence of the perception of one risk amplifies or attenuates the perception of another. In a phenomenological framework, this is implied: the individual's interpretations of events in the world are conditioned by their total stock of knowledge, some of which is shared socially, some of which is unique to them, and some of which inevitably includes other risk scenarios (cf. Schütz, 1967, 1970). Phenomenologist Alfred Schütz suggests that such processes of interpretation function through systems of *relevance*, where recognition of similarity and difference is key (Schütz, 2011, pp. 108–128).

This suggested framework is not fully opposed to SARF. We suggest instead that part of risk perception is due to social processes, and part is due to phenomenological processes of similarity and difference. The distinction is necessary, however: the recognition of similarity, which is necessary for a fundamentally uncertain and rarely experienced phenomenon such as risk, is not based on social action, but a prerequisite for it (Schütz, 2011). In other words, for there to be a risk to perceive and socially amplify/attenuate, there must already have been a recognition of its similarity to and difference from other risks.

3. HYPOTHESES

Our primary analysis concerned whether we could observe a singular risk perception construct. For this, we applied factor analysis (see Methods below).

We assessed two hypotheses. Firstly, we hypothesised that <u>the fourteen variables may be explained using a single factor model</u>. Thus, the null hypothesis posits that <u>there is no difference in explanatory degree between a single-factor model and a model using the raw variable scores</u>.

Secondly, we assessed the possibility of a single-factor model arising from acquiescence bias (respondents' tendency to answer positively regardless of question). We assessed the extent of acquiescence bias using a two-factor model strategy (see Methods below). Thus, we hypothesised that the single-factor model fits the data significantly better than the two-factor model. The null hypothesis thus posits that there is no difference in explanatory degree between the single-factor model and the two-factor model.

For our secondary analysis, we consider whether this risk perception construct co-varies with social and phenomenological processes like direct and indirect experience. Since previous research suggested a divergence in how hazard experiences and near-misses affect risk perception (see Risks and Risk Perception above), we test this result in our sample. Further, we presume that, if hazards and near-misses influence risk perception, this should also show indirectly if an individual works in a culture that is more inclined to have said experiences. Thus, the secondary analysis contained three hypotheses:

The Experience Hypothesis

We hypothesised that experiencing a risk as realised leads to an increase in perceived risk probability. Thus, the null hypothesis under test was that experiencing a risk as realised has no effect on perceived risk probability.

The Near-Miss Hypothesis

We hypothesised that experiencing a near-miss situation leads to a decrease in perceived risk probability. Thus, the null hypothesis under test was that experiencing a near-miss situation has no effect on perceived risk probability.

The Culture Hypothesis

We hypothesised that being professionally in or near the emergency services leads to an increase in perceived risk probability. Thus, the null hypothesis under test was two-fold: firstly, being in the emergency services has no effect on perceived risk probability, and secondly, having someone close to oneself in the emergency services has no effect on perceived risk probability. Full support for the alternative hypothesis was found if both nulls are highly probable to be false and partial support was found if either null is highly probable to be false while the other’s test crosses the alpha threshold.

4. MATERIALS

Sample Description

Data were collected as part of the longitudinal survey series Finnish Emergency Attitudes. The series is collected every three years, with the current collection having been conducted in the autumn of 2020 by the polling company Suomen Onlinetutkimus Oy. Sampling is stratified by geographical region, gender, and age, and restricted to mainland Finnish population (excluding Åland Islands) aged 18 to 79 years. Participation in the survey was voluntary and informed consent was retrieved. The retrieved sample consisted of N = 3050 respondents.

Data Preparation

One respondent was missing data on all variables and was removed from the analysis. For each variable, we excluded any “Cannot say”-responses from the analysis. Further recoding is listed under each variable in turn.

Dependent Variables

For the factor analysis, we selected fourteen variables measuring perceived personal risk in different circumstances. Respondents were asked: “How probable do You find experiencing the following risks/threats in Your personal life?”. Respondents could respond on a four-point Likert scale, coded “1” for “Unlikely” and “4” for “Likely”. The risks are listed in Table 1, along with simple descriptive statistics for each variable.

Table 1. Descriptive statistics of perceived individual risks.

Variable	Mean	SD	N
Extreme weather phenomena	2.29	1.01	3008
Traffic accident	2.72	0.75	2915
Fire	2.37	0.78	2922
Nuclear power disaster	1.57	0.77	2928
Workplace accident	2.06	1.01	2862
Leisure-time accident	2.78	0.77	2968
War against Finland	1.71	0.81	2914
Environmental disaster	2.22	0.87	2947
Pandemic	3.24	0.80	2993

Health emergency	2.87	0.80	2895
Violence	2.21	0.83	2919
Societal operational failure	2.69	0.90	2956
Hybrid threats	2.82	0.97	2922
Social polarization	2.67	0.93	2922

Of all perceived risks, a nuclear power disaster was perceived as lowest probability, while a pandemic was distinctly given the highest mean probability. Since the data were collected in the middle of the COVID-19 pandemic, it is not surprising that the risk of a pandemic ranks highly. Traffic accidents presented the lowest variation (as measured in standard deviation), while extreme weather phenomena and workplace accidents tied for highest variation in the dataset. The variables presented similar levels of non-response, with extreme weather phenomena presenting the lowest amount of internal fallout and workplace accident presenting the highest amount.

In the following sections, when we mention relations to the 'dependent variable,' we intend the factor score that we constructed using these fourteen variables (see below for a description of the methodology).

Independent Variables

For the follow-up analyses, we selected three variables of interest as explanatory variables: experience of fire, near-miss experience, and professional engagement with emergency services.

Regarding *experience of fire*, respondents were asked: "Have You or someone close to You encountered a fire?". Responses were coded to "0" for "No" and "1" for "Yes". This variable operationalises the experience hypothesis. The variable was significantly correlated to the dependent variable (r = .122, p < .0001).

For *near-miss experience*, respondents were asked: "Have You experienced a near-miss fire situation, which could have become dangerous?". Responses were coded to "0" for "No" and "1" for "Yes". This variable operationalises the near-miss hypothesis. The variable was significantly correlated to the dependent variable (r = .116, p < .0001).

Finally, respondents were asked about potential *professional engagement with emergency services*: “Are You or someone close to You a part of the emergency services?”. Responses were coded “0” for “No”, “1” for “Yes, I work in the emergency services”, and “2” for “Yes, someone close to me works in the emergency services”. This variable operationalises the professional engagement hypothesis. A one-way ANOVA of professional engagement regressed on the dependent variable was significant ($F_{2, 2940} = 10.101$, $p = .000043$, $\omega^2 = .006$).

Control Variables

We controlled for the following social variables: gender, age, education, income, parenthood, professional category, employment, and form of housing.

Gender was measured as a dichotomy, with “0” representing “Male” and “1” representing “Female”. The bivariate correlation between gender and the dependent variable was significant ($r = .123$, $p < .0001$).

Age was measured in age groups: “30 years or younger”, “31-40 years old”, “41-50 years old”, “51-64 years old”, and “65 years or older”, coded from “1” to “5” respectively. A one-way ANOVA with age regressed on the dependent variable was significant ($F_{4, 2987} = 7.875$, $p = .000003$, $\omega^2 = .009$).

Education was measured in degree levels. “Primary education” is represented by the code “1” and stands for having completed either primary education (9 years in Finland) or comparable pre-basic education reform degree. “Secondary education” is represented by the code “2” and entails having completed upper secondary school or vocational training (both 3 years by default, with slight variation). “Tertiary education” is represented by the code “3” and implies having completed any university of applied science or university degree, from bachelor’s degree onward (a minimum of 3 years by default). A one-way ANOVA with education regressed on the dependent variable was not significant ($F_{2, 2937} = 0.306$, $p = .736$, $\omega^2 = .000$).

Income was measured as yearly gross household income in groups: “Less than 10 001 €/yr”, “10 001 – 25 000 €/yr”, “25 001 – 50 000 €/yr”, and “More than 50 000 €/yr”, coded “1” through “4”, respectively. A one-way ANOVA with income regressed on the dependent variable was not significant ($F_{3, 2482} = 0.961$, $p = .410$, $\omega^2 = .000$).

Parenthood was measured as a dichotomy, with respondents being asked: “Are there children (age 0-17) in Your household?”. Responses were coded “0” for “No” and “1” for “Yes”. The bivariate correlation between parenthood and the dependent variable was significant (r = .036, p = .050).

Professional category partially followed the socioeconomic position standard by the National Statistics bureau (Tilastokeskus, 1989): “Employed in an executive position”, “Upper officer or specialist”, “Lower officer”, “Employed”, “Self-employed or entrepreneur”, “Agricultural entrepreneur”, “Student”, “Stay-at-home parent”, “Pensioner”, or “Unemployed”, coded “1” through “11” respectively. The “Other” category was excluded from analysis. A one-way ANOVA with professional category regressed on the dependent variable was significant ($F_{10, 2919}$ = 3.110, p = .000592, ω^2 = .007).

Employment was measured as being either “Employed full-time” (1), “Employed part-time” (2), “Unemployed” (3), or “Retired” (4). A one-way ANOVA with employment regressed on the dependent variable was significant ($F_{3, 2668}$ = 7.328, p = .000068, ω^2 = .007).

Finally, *type of housing* was measured as a trichotomy: “Apartment complex”, “Semi-detached”, or “Detached”, coded “1” through “3” respectively. A one-way ANOVA with housing type regressed on the dependent variable was not significant ($F_{2, 2949}$ = 0.066, p = .936, ω^2 = -.001).

5. METHODS

The factor analysis was conducted in the FACTOR software, version 12.02.01 (Ferrando & Lorenzo-Seva, 2017). Uni- and bivariate analyses, as well as variance analyses, missing value analyses, and graphics were all conducted in IBM SPSS Statistics version 28.0 (IBM Corporation, 2020).

Factor Analysis

We started the analysis by confirming whether our fourteen dependent risk variables could be considered measuring the same latent factor, representing *general perception of risk probability*. We titled this factor the General Risk

Probability Perception Scale, or GRPPS. We followed the semi-confirmatory factor analysis methodology, because of its ease of interpretation, constructing factor scores, and conducting numerous inferential tests of robustness, one-dimensionality, and model fit (Ferrando et al., 2003; Savalei & Falk, 2014). A summary of indices and their thresholds is listed in Supplementary Material A.

Because our variables to be analysed are measured with Likert scales, and thus ordinal as opposed to quantitative scale variables, ordinary factor analysis based on Pearson correlation matrices are suboptimal. We chose instead to use polychoric correlation matrices, wherein we assume that the Likert scales qualify a latent quantitative scale (Holgado–Tello et al., 2010).

We used Unweighted Least Squares (ULS) as our factor extraction method. While maximum likelihood estimation methods are often more popular, they are not suitable for use with polychoric correlation matrices (i.e., non-linear factor analysis). The ULS method is also robust to multivariate deviations from normality (Brown, 2015), which our ordinal-scale variables by definition present.

To judge how many factors one ought to retain, there are multiple methods. Judging the scree plot as well as the Eigenvalue rule of thumb are both demonstrably non-robust, subjective, and often non-reproducible, and a simulation implementation of parallel analysis is preferred (see Lorenzo-Seva et al., 2011). However, these measures are less important in our analysis as we have theoretical motivation for a single-factor solution. We further retrieved three indices for assessing one-dimensionality: explained common variance, unidimensional congruence, and the mean of item residual absolute loadings (Ferrando & Lorenzo-Seva, 2018).

To judge the quality of potential factor scores, we retrieved several different indices. We use the DIANA method to judge whether scores should be computed as sums or factor-based scores, with the ordinal coefficient of fidelity (Ferrando & Lorenzo-Seva, 2021). We also retrieve construct replicability indices, as well as four psychometric quality indices: factor determinacy index, marginal reliability, sensitivity ratio, and the expected percentage of true differences (Ferrando & Lorenzo-Seva, 2018).

We measured acquiescence bias with a two-factor model, where the solution is rotated to target positive-only loadings on the second factor (Billiet & McClendon, 2000; Ferrando et al., 2003; Mirowsky & Ross, 1991; Savalei & Falk, 2014). This second factor is presumed to measure degree of acquiescence bias (or similar method bias).

Once we had established the adequacy of the single-factor model, we extracted psychometric factor scores for further analysis. These scores became our dependent variable for the follow-up analyses of variance.

Analyses of Variance

We conducted three analyses of variance. For Model 1, we assessed the controlled and corrected relations between the social variables and the dependent variable in a repeated-measures 8-way ANOVA. We use the Hochberg GT2 *post hoc* test for significant group differences based on group size variation (Field, 2018, pp. 550–551).

Model 2 concerned the controlled and corrected relation between the independent variables and the dependent variable. We conducted a repeated-measures 3-way ANOVA, using the same multiple comparison correction methods as for Model 1.

Finally, we constructed Model 3 using the significant social variables from Model 1 and the independent variables from Model 2. Thus, we selected for control only those social variables that had independently shown to significantly relate to risk perception. This resulted in a repeated-measures 7-way ANOVA with controls for multiple comparisons.

6. FACTOR ANALYSIS MEASURING GENERAL RISK PERCEPTION

This section describes the results of the factor analysis, wherein we constructed a single factor measure of general risk perception. We start by describing data adequacy measures and tests pertaining to how many factors ought to be retained statistically. We then move on to the single-factor solution, describing its model fit and characteristics. After this, we present the results from the comparison between a single-factor and a two-factor model. Finally, we present sample descriptive statistics on the psychometric scores we retrieved from the single-factor model.

Data Adequacy and Factor Determination

The determinant was 0.00132, which indicates an adequate correlation matrix for analysis (Field, 2018, p. 799). Bartlett's test was significant (16445.8, df = 9, p = .0001), likewise suggesting good data fit. The Kaiser-Meyer-Olkin value was 0.899 (95% CI 0.882 – 0.903), suggesting good to great data fit (Kaiser & Rice, 1974). No MSA value was below 0.5, suggesting that all variables may be retained. A parallel analysis based on 500 raw data permutations suggest retaining one factor (52.0% variance), with the second factor (10.8%) dropping below simulated variance percentages for both mean (14.0%) and 95th percentile (16.8%) sampling methods.

Both unidimensional congruence and the mean of item residual absolute loadings (MIREAL) suggest that the data may be considered one-dimensional, but the explained common variance does not. The overall unidimensional congruence value was 0.951 (95% CI 0.942 – 0.961), the MIREAL was 0.268 (95% CI 0.247-0.282), and the explained common variance value was 0.817 (95% CI 0.805 – 0.830).

Summarily, we concluded that the data fits a factor analytic approach. We also preliminarily considered the data to be essentially one-dimensional, that is, that acquiescence bias was not a major concern in the survey data.

Model Fit and Description

The root mean square error of approximation (RMSEA) was 0.038 (95% CI 0.037 – 0.040), indicating a close data fit. The LOSEFER chi-square test similarly indicated model fit (χ^2 = 352.408, df = 77, p = .00001). Both the non-normed fit index (NNFI or Tucker & Lewis' index, TLI) and the comparative fit index (CFI) indicated excellent fit (TLI = 0.991, 95% CI 0.990 – 0.992; CFI = 0.993, 95% CI 0.991 – 0.993). Schwartz's BIC is 571.335 (95% CI 558.715 – 954.780).

Table 2 shows the factor loadings for each variable. All factor loadings are reasonably high, with workplace accidents presenting the smallest loading of 0.478 and violence the largest loading of 0.723. The suggested factor accounts for 43.9% of the variance.

Table 2. Single-factor solution factor loadings ordered descending by loading strength.

Variable	**Loading**
Violence	0.723
Fire	0.714
Traffic accident	0.713
Leisure-time accident	0.699
Health emergency	0.681
Environmental disaster	0.673
Societal operational failure	0.653
Nuclear power disaster	0.613
Hybrid threats	0.584
Pandemic	0.583
Social polarization	0.568
War against Finland	0.562
Extreme weather phenomena	0.523
Workplace accident	0.478

Single-Factor vs. Dual-Factor Model

To gauge whether the results are spuriously produced by method bias, we retrieved a two-factor model using a semi-specified target matrix. Variable loadings were constrained to be non-zero positive on both factors. We only report fit indices for comparison.

The first factor represents 43.9% of the variance (same as in the single-factor model), while the second factor represents an additional 9.8%, for a cumulative variance explained of 53.7%. The RMSEA was 0.031 (95% CI 0.030 – 0.032), indicating a close fit. The LOSEFER chi-square test similarly indicated model fit (χ^2 = 218.830, df = 64, *p* = .00001). Both the non-normed fit index (NNFI or Tucker & Lewis' index, TLI) and the comparative fit index (CFI) indicated excellent fit (TLI = 0.994, 95% CI 0.993 – 0.995; CFI = 0.996, 95% CI 0.995 – 0.996). Schwartz's BIC is 547.221 (95% CI 540.025 – 558.674).

Contrasting these results with the single-factor model, the two model options fit virtually as well. The BIC was reduced by 24 points for the dual-factor model (indicating a significantly better fit, as the two confidence intervals did not cross), but we deem reduction practically marginal.

Table 3 shows the rotated factor loadings for the dual-factor model. The solution failed to rotate the second factor to the requested direction (all loadings non-zero positive), which suggests that such a rotation is inappropriate for an orthogonal (factor-uncorrelated) solution. The order of the factors has shifted around. The top three factors changed places but retained similar loadings as before. Social polarization and pandemic also changed places, with the former increasing by 0.018 in strength. The strongest and weakest loadings on factor 1 are very similar to that of the single-factor model (0.734 versus 0.723, and 0.479 versus 0.478, for dual-factor and single-factor models respectively). Summarily, the first factor did not meaningfully change between models.

Table 3. Dual-factor solution loading strengths ordered descending by factor 1 loading.

Variable	F1	F2
Fire	0.734	-0.417
Traffic accident	0.721	-0.304
Violence	0.718	-0.073
Leisure-time accident	0.696	-0.152
Health emergency	0.675	0.017
Environmental disaster	0.669	0.104
Societal operational failure	0.657	0.237
Nuclear power disaster	0.620	-0.150
Hybrid threats	0.619	0.556
Social polarization	0.586	0.421
Pandemic	0.582	0.155
War against Finland	0.557	-0.072
Extreme weather phenomena	0.520	0.009

Workplace accident	0.479	-0.224

We do not deem factor 2 to represent method bias, because of its multivalent loadings. The bootstrapped 95th percentile confidence intervals of five loadings crossed zero: extreme weather phenomena, nuclear power disaster, war against Finland, environmental disaster, and health emergency (see Supplementary Material B). The rest were distinctly on either side of zero, suggesting significant factor loadings. The significance of the factor loadings also does not seem to relate to the order of factor loading size on factor 1, which could have suggested some interrelation. Overall, we thus believe factor 2 to be a statistical artefact.

7. CONSTRUCTING THE GENERAL RISK PROBABILITY PERCEPTION SCALE

Psychometric Quality and Missing Value Analysis

The H index suggests that the single-factor structure is well defined across studies, both in terms of identification from the presumed latent continuous variable structures (H-Latent = 0.907, 95% CI 0.898 – 0.913) and from direct item scores (H-Observed = 0.877, 95% CI 0.869 – 0.885).

For usage in individual evaluation, factor scores should fulfil the following requirements: factor determinacy index (FDI) above 0.9, marginal reliability measures (EAP) over 0.8, sensitivity ratio (SR) above 2, and expected percentage of true differences (EPTD) above 90%. The single-factor solution fulfils all requirements (FDI = 0.953, EAP = 0.907, SR = 3.130, EPTD = 92.8%).

The ordinal coefficient of fidelity is 0.908, suggesting that the following variables may be used to construct a simple sum index with considerable correlation to computed factor scores: Traffic accident, fire, leisure-time accident, environmental disaster, health emergency, violence, and societal operational failure. In other words, creating an additive index with the above variables would result in a 0.9 strength correlation with factor scores, and a consequent Cronbach’s alpha comparable to 0.824. However, the comparative fidelity index for factor score estimates is an even higher 0.953, implying that both retain enough fidelity to measure the latent construct. Stabilities were 1.000 for a reduced sum index and 0.999 for the factor scores, suggesting virtually identical stability across studies.

We saved the factor scores using the ORION method (Ferrando & Lorenzo-Seva, 2016), retrieving Bayesian expected a posteriori factor scores for each respondent. ORION is not possible in cases with too many originally missing values (as Hot Deck imputation becomes impossible); this was the case for 57 respondents, who are missing values on the scale.

Figure 1 shows the approximately normal distribution of the scale (Shapiro-Wilk's statistic = 0.998, DF = 2992, *p* = .0002).

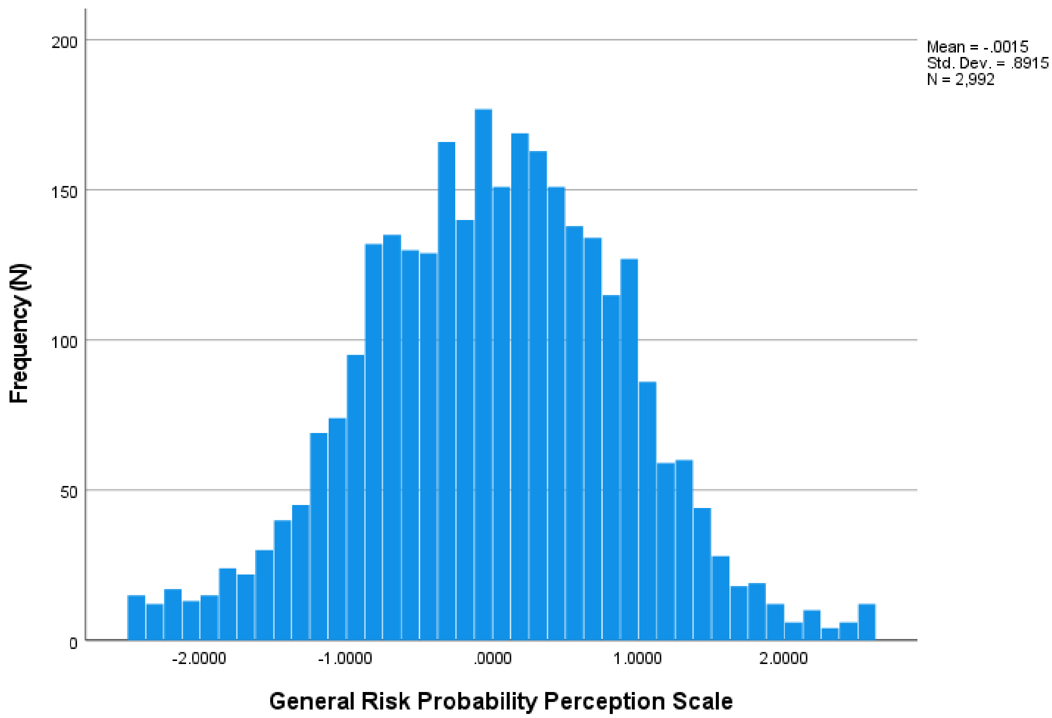

Figure 1. Distribution of General Risk Probability Perception Scale (GRPPS).

We cross-tabulated each of the independent variables in turn with whether a respondent had scored on the General Risk Probability Perception Scale (GRPPS) to judge whether there was a significant difference in proportions between those responding to the dependent variables and those who did not. Table 4 shows the results for each variable, with additional investigations into which group differs where the alpha level is below 0.05. There are slight deviations in group sizes, which ought to be considered in future research.

Table 4. χ2 tests on social and content variables cross-tabulated with dummy variable whether respondent had a GRPPS value. Significant differences investigated with column proportion Bonferroni-corrected z-tests.

Variable	χ^2	**p**	**Difference**
Gender	0.205	.651	
Age	12.368	.015	Ages 31-40 (+[a]), Ages 41-50 (-[b])
Education	36.573	< .001	Primary education (-), Tertiary education (+)
Income	12.499	.006	Less than 10 001 €/yr (+)
Parenthood	0.157	.692	
Professional category	20.228	.027	Upper civil servant/expert (-), Unemployed (+)
Employment	14.469	.002	Part-time (-), Unemployed (+)
Type of housing	0.776	.678	
Experience of fire	0.807	.369	
Near-miss experience	2.626	.105	
Professional engagement with emergency services	3.411	.182	

[a] Significantly higher cell count than expected.
[b] Significantly lower cell count than expected.

Analysing the Variance in Risk Perceptions

Model statistics, estimated marginal means, and ANOVA tables for Models 1, 2, and 3 are available in Supplementary Material C, D, and E, respectively. In this article, we report a summary of relevant statistics for ease of reading.

Model 1: Differences by age, gender, education, income, and professional category

Table 5 presents the results for Model 1, an 8-way between-subjects analysis of variance regressed on the dependent variable. Model 1 is significant (F = 3.535, $p < .0001$, $R^2 = .029$). Significant differences were found in age, education, and income, with marginally significant differences in professional category. We report absolute mean differences (ABS) for comparisons instead of directional mean differences, as in most of our cases, a directional measure is inappropriate due to the comparison's scale level.

Table 5. ANOVA of Model 1.

Variable	**F**	**p**	**Partial η²**
Gender	34.110	< .0001	.015
Age	3.054	.016	.006
Education	0.094	.911	< .0001
Income	1.204	.307	.002
Parenthood	1.224	.269	.001
Professional category	1.756	.064	.008
Employment	3.833	.009	.005
Type of housing	0.140	.870	.0001
Model	3.535	< .0001	.040
Adjusted R^2	.029		

For gender, the estimated absolute marginal mean difference between male and female was 0.220, $p < .0001$, 95% CI [-0.294; -0.146]. Men's score hovered around zero ($\bar{x} = -0.060$, 95% CI [-0.214; .093]), while women's score was distinctly positive ($\bar{x} = 0.159$, 95% CI [0.002; 0.317]).

For age, there were significant mean differences between those 65 or older and other groups. Those aged 65 years or older had a significantly lower estimated marginal mean than those younger than 31 (ABS = 0.231, $p = .010$, 95% CI [0.055; 0.407]), 31 to 40 years old (ABS = 0.156, $p = .082$, 95% CI [-0.020; 0.333]), and 51 to 64 years old (ABS = 0.239, $p = .001$, 95% CI [0.095; 0.382]). The difference between those 65 years or older and those aged 41 to 50 was marginally significant (ABS = 0.163, $p = .059$, 95% CI [-0.006; 0.332]). In *post hoc* tests, those aged 65 or older showed significant differences to all other groups (ABS's 0.205-0.261, p's < .005).

Income was not a significant predictor in the model. However, the lowest earners (less than 10 001 euros *per annum*) presented marginally significant differences to all other groups, with a higher score than each of the compared groups (ABS's 0.145-0.147, *p*'s .063-.099). *Post hoc*-corrected tests were all not significant (*p*'s > .111).

Professional category was a marginally significant predictor in the model. If we contrast those employed (executives, civil servants, employed, and entrepreneurs) against the unemployed, we find significant differences of similar sizes and directions (ABS's 0.237-0.467, *p*'s .099-.001). Similarly, the difference between students and the unemployed was significant (ABS = 0.293, *p* =.033, 95% CI [0.023; 0.562]). The unemployed presented with higher scores in all the above cases. Most other differences were not significant, with minor exceptions (see Supplementary Material C). However, *post hoc*-corrected tests tell a different story. Significant differences were found between pensioners and lower civil servants (ABS = 0.271, *p* = .004, 95% CI [-0.233; 0.181]), as well as pensioners and employees (ABS = 0.168, *p* = .026, 95% CI [-0.328; -0.009]). All other differences were not significant (*p*'s > .101).

For employment, significant differences in estimated marginal means were found for all groups except pensioners. Those in full-time employment were significantly different from both the part-time employed (ABS = 0.134, *p* .037, 95% CI [0.008; 0.259]) and the unemployed (ABS = 0.355, *p* = .003, 95% CI [-0.080; 0.488]). There was a marginally significant difference between those employed part-time and the unemployed (ABS = 0.221, *p* = .059, 95% CI [-0.080; 0.450]). However, *post hoc* tests show other results. Here, only the difference between pensioners and those employed full-time is significant (ABS = 0.191, *p* = .000066, 95% CI [0.077; 0.304]). All other differences are not significant (*p*'s > .120).

Parenthood, educational level, and type of housing were not significant predictors in the model.

Summarily, there seems to be a few relations between social group and general risk perception. Women score higher than men. The elderly score lower than all other age groups. The effect of income might better be attributed to Type I error than a real effect. However, for pensioners, the picture gets murkier. While pensioners present a higher score than civil servants and employees, they concomitantly present a *lower* score than those employed full-time. We suspect this is partially due to the variable not considering different types of pensions: age pension and disability pension might have a differing effect on general risk perception.

Model 2: Actualized risk and near-miss experiences

Table 6 presents the results for Model 2. We included the three independent variables together with all 2- and 3-way interactions. Model 2 is significant (F = 6.478, $p < .0001$, $R^2 = .022$). The only significant difference was for experience of fire. None of the interactions were significant.

Table 6. ANOVA of Model 2.

Variable	**F**	**p**	**Partial η^2**
Experience of fire	4.738	.030	.002
Near-miss experience	0.427	.513	.0001
Professional engagement	1.013	.363	.001
$^{a} * ^{c}$	0.714	.490	.001
$^{b} * ^{c}$	0.343	.709	.0002
$^{a} * ^{b}$	0.096	.757	< .0001
$^{a} * ^{b} * ^{c}$	0.043	.958	< .0001
Model	6.478	< .0001	.025
Adjusted R^2	.022		

[a] Experience of fire; [b] Near-miss experience; [c] Professional engagement.

The experience of a fire was a significant predictor of the dependent variable. Having experienced a fire resulted in an increase of 0.326 compared to not having experienced one (p = .030, 95% CI [0.032; 0.620]). While those without an experience hovered around zero ($\bar{x}$ = -0.026, 95% CI [-0.297; 0.244]), those with an experience were distinctly above the mean ($\bar{x}$ = 0.300, 95% CI [0.185; 0.415]).

Having been in a near-miss scenario did not have a significant effect. The difference was very small, less than 1 % of explained variance.

Professional engagement with the emergency services was not a significant predictor. However, *post hoc* tests revealed many significant differences. Those working in EMS presented significantly higher scores than those not working (ABS = 0.545, $p < .0001$, 95% CI [0.237; 0.853]) and those whose close significant others worked in EMS (ABS = 0.410, $p = .011$, 95% CI [0.073; 0.747]). The difference between those not working and those with significant others in EMS was marginally significant (ABS = 0.135, $p = .092$, 95% CI [-0.145; 0.285]).

Summarily, there are some effects of risk scenario experiences on general risk perception. Those who had experienced a fire in the past ten years presented significantly higher scores than others. Contrary to previous research, near-miss experiences did not seem to influence risk perception. Professional engagement might have an effect directly, but perhaps not when experienced vicariously through a significant other.

Model 3: Combined model

Based on the results, we selected a subset of all variables for inclusion in Model 3, with recoding to better investigate the unique effects of each variable. From the independent variables of Model 2, we included all three, with modifications to the variable measuring professional engagement: we created a binary variable on whether the respondent was directly engaged with EMS or not. From the control variables of Model 1, we selected the following variables: gender, age, professional category, and employment. We recoded age into a binary variable representing whether the respondent was elderly (65 or above) or not. We retrieved Hochberg's GT2 *post hoc* test for professional category and employment and estimated marginal means with LSD correction for all other variables.

Table 7 presents the results for Model 3. The model is significant ($F = 8.722$, $p < .0001$, $R^2 = .054$). Within it, all variables are significant, apart from professional category which is only marginally significant.

Table 7. ANOVA of Model 3.

Variable	**F**	**p**	**Partial η^2**
Gender	50.242	< .0001	.020
Elderly	12.134	.0005	.005

Professional category	1.685	.078	.007
Employment	3.667	.012	.005
Experience of fire	19.394	< .0001	.008
Near-miss experience	11.160	.0008	.005
Employed in EMS	11.303	.0008	.005
Model	8.722	< .0001	.061
Adjusted R^2	.054		

Gender presents the same picture as in Model 1, with a significant difference (ABS = 0.251, $p < .0001$, 95% CI [0.182; 0.321]) between men and women. Men hover around zero ($\bar{x}$ = 0.043, 95% CI [-0.134; 0.219]) while women were distinctly positive ($\bar{x}$ = 0.294, 95% CI [0.112; 0.476]).

The elderly presents a significantly different score to other age groups (ABS = 0.231, $p = .0005$, 95% CI [0.101; 0.361]). Their score is distinctly positive ($\bar{x}$ = 0.284, 95% CI [0.115; 0.453]), while the others hover around zero ($\bar{x}$ = 0.053, 95% CI [-0.151; 0.257]).

Professional category presented a marginal significance in the model. Within it, *post hoc* tests reveal a significant difference between pensioners and lower officers (ABS = 0.021, $p = .007$, 95% CI [0.033; 0.468]), and between pensioners and employees (ABS = 0.156, $p = .034$, 95% CI [0.005; 0.307]). Pensioners present a distinctly positive ($\bar{x}$ = 0.257, 95% CI [0.023; 0.490]) and higher score than either lower officers ($\bar{x}$ = 0.188, 95% CI [-0.005; 0.381]) or employees ($\bar{x}$ = 0.105, 95% CI [-0.065; 0.275]). All other comparisons are not significant (p's > .130).

Employment category shows a significant difference on the dependent variable. *Post hoc* tests reveal, however, that only one difference is significant: that between pensioners and full-time employed (ABS = 0.171, $p = .0002$, 95% CI [0.064; 0.278]). Those employed full-time are distinctly positive on the scale ($\bar{x}$ = 0.319, 95% CI [0.121; 0.517]), while pensioners score lower and less distinctly positive ($\bar{x}$ = 0.147, 95% CI [-0.125; 0.418]).

Having experienced a fire is a significant predictor of general risk perception (ABS = 0.178, $p < .0001$, 95% CI [0.099; 0.257]). Those who have experienced a fire present a larger score ($\bar{x} = 0.257$, 95% CI [0.078; 0.437]) than those who have not ($\bar{x} = 0.079$, 95% CI [-0.101; 0.260]).

Having a near-miss experience is also a significant predictor of risk perception (ABS = 0.136, $p = .0008$, 95% CI [0.056; 0.215]). Those who have been in a near-miss situation score higher ($\bar{x} = 0.236$, 95% CI [0.057; 0.415]) than those who have not ($\bar{x} = 0.101$, 95% CI [-0.081; 0.282]).

Finally, being employed in the emergency services is a significant factor of risk perception (ABS = 0.451, $p = .0008$, 95% CI [0.188; 0.714]). EMS employees present a larger score ($\bar{x} = 0.394$, 95% CI [0.115; 0.672]) than others ($\bar{x} = -0.057$, 95% CI [-0.194; 0.080]).

Summary of Variance Model Results

Table 8 presents a summary of effect sizes in each model, converted into standardised correlation coefficients *r*, with the significant and marginally significant effects marked.

Table 8. Standardised effect sizes (r) for each model.

Variable	Model 1	Model 2	Model 3
Gender	0.12**		0.14**
Age[a]	0.08*		
Elderly[a]			0.07**
Education	0.01		
Income	0.04		
Parenthood	0.03		
Professional category	0.09†		0.08†
Employment	0.07**		0.07*
Type of housing	0.01		
Experience of fire		0.04*	0.09**
Near-miss experience		0.01	0.07**
Professional engagement[b]		0.03	
Employed in emergency services[b]			0.07**
Model adjusted R^2	0.029**	0.022**	0.054**

[a, b] Variables are exclusive. ‘Elderly’ is a recoding of ‘Age,’ and ‘Employed in emergency services’ is a recoding of ‘Professional engagement.’
** $p < .01$ * $p < .05$ † $p < .1$

All effect sizes are small, with gender presenting a small-to-medium effect size in models 1 and 3. This implies that the effect social and experiential variables have on general risk perception is, despite significant, not practically very meaningful. Any intervention strategies would require affecting multiple areas together to enact meaningful change in risk perception.

Controlling for social factors seems to attenuate the effect between risk experience and risk perception. All three experiential effect sizes increase in size, with near misses and professional engagement (measured dichotomously) also crossing the threshold of significance.

8. DISCUSSION

The results are two-fold. Firstly, we found support for the theory that risk perception is a unitary construct, as opposed to composed of singular risk event-related perceptions of probability. Secondly, we found that general risk perception is significantly related to experiences of risk, whether they are direct, near misses, or professional, but not when vicariously experienced. We also found social factors to attenuate the effect that risk experience has on general risk perception.

For social variables, being male or elderly predict a higher general perception of risk. All things being equal, maleness resulted in an increase of 0.25 points on an approximately 5-point-wide scale, and elder age in an increase of 0.23 points.

The variables related to profession and employment status are slightly more difficult to interpret. We found that pensioner-as-profession represented a 0.26-point increase to the mean, but that pensioner-as-status represented a smaller 0.15-point increase. Concomitantly, pensioner-as-profession was significantly related to *higher* scores than lower officers and employees, while pensioner-as-status was related to *lower* scores than those employed full-time.

We believe there to be multiple explanations to this seemingly paradoxical result, all related to sampling and data collection. Firstly, the survey did not distinguish between disability pension and age pension. It could be plausible that there is a divergent effect between disability and age pension, with one increasing risk perception while the other lowers risk perception. In a linear model, we cannot unfortunately investigate this, as splitting the pensioner group by age would violate the assumption of predictor independence.

Secondly, pensioners could plausibly respond to questions regarding profession, salary, and employment in varied ways. Some may consider themselves 'full-time pensioners,' whereas others may respond with what they were employed as prior to pension. This would mix pensioners in with multiple groups, which could lead to inflating (or deflating) effect sizes based on the proportion of pensioners in other categories. The low sample size of some profession categories could even exacerbate the problem.

For the experiential variables, we found divergent results. Modelled alone, only having had an experience of fire is a significant predictor of a higher risk perception score of the three predictor variables. However, all three become significant predictors in a model controlling for social variables, suggesting that they have unique effects that are confounded by gender, age, and employment status (as measured by professional category and employment situation).

9. LIMITATIONS AND FURTHER RESEARCH

We already noted the limitation of a messy operationalisation of retirement in the preceding sections. Further research ought to distinguish between different types of pensions, as well as whether respondents are fully pensioned or part-time pensioned. The difficulties in distinguishing whether a respondent is accurately reporting their current employment status (as opposed to their previous one, or their ideal one) should also be considered.

The general risk probability perception scale ought to be cross validated across time. The data we use were collected in the autumn of 2020, during the COVID-19 pandemic. This may have had unknown effects on general risk perception, which is why the results should be replicated in non-pandemic circumstances.

One important question is how stable psychometric tests are across time, or whether factor loadings vary considerably, to the point that they render final scale scores incomparable. Further research could also consider whether additional items could be removed from, or added to, the scale, as well as if simple sum score procedures could produce an equally robust scale as the complex ORION expected *a posteriori* scoring method we used.

Since we found significances between our scale and the modelled variables, it would also be important to investigate non-response rates using the same variables, i.e., consider whether a lack of response on the items on the GRPPS is significantly related to any of the model variables.

The different interactive relations between the dependent, control, and independent variables ought to be investigated further. Statistically, which control variables interact most meaningfully with the dependent-independent relationship effects, and are there divergent interaction effects where one social variable diametrically opposes the interaction effect of another social variable? Theoretically, what could be the reason for said interactions? In particular, a larger sample of female emergency service workers would be necessary to investigate the particularities of the relationship between gender, risk experiences, and risk perception.

We also could not consider the temporal patterns of risk experiences on risk perception. Further research could investigate how effect sizes change over time (if they do) from the point of experience onward. It is possible that we found no effect for vicarious experiences because their effect is too short-lived, or too small, or both. Similarly, the effect of near-misses may behave differently over time as opposed to the effect of direct experiences.

We only considered the effect of *fire* experiences on *general* risk perception. Since general risk perception is constructed from multiple different risk scenarios, further research could investigate whether different experiences have different effects. Theoretically, we do expect all experiences to have similar effects (albeit perhaps with greater or lesser size). However, what of risks *not* measured on the GRPPS?

There are multiple follow-up questions that could be answered with further research. How does the individual's resilience, defined either as a resistance to affectual reactions to hazard experiences or as the capability to return to normal after a hazard event, affect the relation between risk perception and experiences? Similarly, from a phenomenological standpoint, the awareness of a risk having played out and the awareness of its consequences – they themselves manifold and complex, as opposed to simple linear, objective cause-and-effect relations – may play a large part. Nonetheless, the results show that the division of subjective risk perception into affective and analytical systems is important for understanding how individuals reason about, react to, and prepare for hazard events.

10. CONFLICT OF INTEREST STATEMENT

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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