On the semantic representation of risk

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There is great theoretical and applied interest in understanding the psychology of risk - but what are defining features of lay people's semantic representation of this concept? We contribute a new approach to mapping the semantics of risk based on word associations that promises to provide insight into individual and group differences. Specifically, we introduce a novel mini-snowball word-association paradigm and use the tools of network and sentiment analysis to characterize the semantics of "risk" from 1,205 respondents (age range = 18-86; 50% female). We find that association-based representations extend those extracted from past survey- and text-based approaches to the semantics of risk. Crucially, we show that the semantics of risk vary systematically across demographic groups, with older and female respondents showing more negative connotations and mentioning more often certain types of activities (e.g., recreational activities) relative to younger adults and males, respectively. Our work has implications for the measurement of risk-related constructs by suggesting that "risk" means different things to different individuals.

Keywords: semantic networks, individual differences

Today's societies require individuals to navigate an increasing number of social and technological risks (Li et al., 2020; Starr, 1969). But how do individuals think about risk? Different disciplines have provided several conceptions that are not fully compatible (Aven, 2012; Boholm, 2017; Boudia & Jas, 2007) – a fact that may have contributed to conceptual and empirical confusion regarding the construct in the cognitive and behavioral sciences (e.g., Schonberg et al., 2011). For example, while some have emphasized risk as being a statistical concept (i.e., variance; Aven, 2012), others have emphasized its subjective character and multiple psychological dimensions (e.g., Slovic, 1987). Crucially, despite a long-standing interest in understanding individual differences in risk-related constructs (e.g., Dohmen et al., 2011; Weber et al., 2002), comparatively little attention has been given to the fact that the meaning of risk may differ between indi-

viduals as a function of different goals and life experiences (e.g., Ravert et al., 2019). In our work, we propose a novel method to uncover the semantic representation of risk and assess potential individual and group-related differences in this concept central to the behavioral sciences.

Past Approaches to the Psychology of Risk

There have been several approaches to understanding the main psychological dimensions associated with risk and risk-related constructs, such as risk perception or risk taking. One prominent survey-based approach uses dimensionality reduction to capture the dimensions of different activities and technologies based on people's ratings of such activities on several aspects (e.g., perceived risk, perceived benefits, controllability; Fischhoff et al., 1978). This work has concluded that different technological risks and activities, from nuclear energy to smoking, can be mapped onto a psychological space composed of (at least) two dimensions, often termed dread and uncertainty. A second survey-based approach also relies on dimensionality reduction to capture the dimensions of the propensity to engage in various risky behaviors covering domains of life for which individuals are thought to have relatively independent beliefs (Weber et al., 2002). This has become a leading approach to measuring individuals' risk attitudes and has concluded that individuals have different psychological representations of the benefits and risks of each life domain, such as the recreational, occupational, financial, or social domains (Weber et al., 2002). A third approach has mapped the semantic representation of

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risk from text corpora by tabulating the most frequent definitions in lexical sources, such as dictionaries and thesauri (Boholm, 2017), or mapping the semantic networks of word associates from other text sources, such as Wikipedia, to obtain a multidimensional space (Li et al., 2020). These text-based approaches have typically revealed more complex semantic representations that can involve dozens of different components or “semantic fields” (cf., Boholm, 2017).

The approaches discussed above have provided considerable insight into the semantic representation of risk but are not without limitations. First, those past survey-based approaches that relied on experimenter-generated aspects or behaviors (e.g., risky technologies and behaviors; Fischhoff et al., 1978; Weber et al., 2002) cannot guarantee that these exhaustively capture all aspects or dimensions of the semantic representation of risk. For example, there have been recent calls to expand the psychology of risk to examine positive risk-taking that has been rather neglected in past research into the topic (e.g., Duell & Steinberg, 2019).

Second, lexical approaches that relied on a naturalistic and broad set of lexical sources are more likely to have identified a full range of aspects or dimensions but their reliance on aggregate information does not allow investigation of the role of individual and group differences in the semantic representation of risk (e.g., Boholm, 2017; Li et al., 2020). A number of past findings, however, suggest that the semantic representation of risk differs across groups and individuals. For example, past work suggests age and gender differences in risk-related constructs, such as risk perception (e.g., Bonem et al., 2015; Marris et al., 1997; Siegrist et al., 2005) and risk taking (e.g., Arslan et al., 2020; Frey et al., 2021; Ravert et al., 2019; Rolison et al., 2014), that may be anchored in different semantic representations of risk.

In this paper, we introduce a novel approach that aims to directly uncover the semantics of risk in a data-driven manner, while assessing potential differences between demographic groups (e.g., younger vs. older, males vs. females). Doing so promises to help uncover to what extent such individual and group differences matter for our assessment and prediction of risk-related behaviors.

The Promise of Word Associations to Mapping the Semantics of Risk

In our work, we introduce a novel approach to uncovering the semantics of risk that utilizes word associations. Word associations are amenable to the investigation of individual differences and arguably provide more direct access to individual subjective meaning than both survey-based approaches based on experimenter-generated stimuli and text-based approaches, while retaining the breadth of the latter approaches (De Deyne, Navarro, Perfors, & Storms, 2016; Mollin, 2009). Past research has found semantic representations extracted from word associations to be more predictive

of human judgments and behavior than those extracted from co-occurrences of words in text corpora (De Deyne, Navarro, Perfors, & Storms, 2016; De Deyne, Perfors, et al., 2016; Vankrunkelsven et al., 2018). This is likely because word association reflects other factors beyond semantic relationships, such as pragmatic communication rules (De Deyne, Navarro, Perfors, & Storms, 2016). Word associations thus promise to enrich existing perspectives on the concept of risk.

Text-based	Association-based
danger	danger
likelihood	game
peril	reward
risky	chance
averse	gamble
threat	money
liability	strategy
probability	take
uncertainty	dangerous
avoid	assessment

Figure 1

Comparison of text-based and free association-based approaches to the semantics of risk. Left column shows the ten words with the highest cosine similarity to the word "risk" based on the fastText pre-trained word2vec representation from Mikolov et al. (2017). Right column shows the ten most frequent associations in the English SWOW free association database from De Deyne et al. (2019). The words' size reflects cosine and retrieval frequency, respectively. The words' color reflects sentiment based on the SentiWordNet sentiment dictionary (Esuli & Sebastiani, 2007).

A preliminary example will help make the case for a word-association approach relative to text-based approaches in uncovering the psychology of risk. We compared text-based and word-association-based approaches to the semantics of risk by analyzing words with the highest cosine similarity to the word "risk" based on text-based representations estimated from large text corpora (Mikolov et al., 2017) and association-based representations estimated from a large-scale citizen-science project involving thousands of free associations (De Deyne et al., 2019) and compared their retrieval frequency and sentiment. Figure 1 shows that there is relatively little overlap in the top ten associates of "risk" in existing text-based and association-based representations. Crucially, associations derived from word associations appear to have more diverse meaning and sentiment than those derived from text; whereas text-based representations mainly

focus on negative consequences and uncertainty, association-based representations also feature positive aspects such as "reward". This suggests word associations may shed light on aspects of the semantic representation of risk that are less accessible through other approaches.

The Current Study

We propose using a mini-snowball, word-association method to map the semantic representation of risk directly from individuals' associations and assess relevant individual and group differences. Specifically, our word-association task asked participants to name five associates of the word "risk" as well as five associates of each of the initially generated risk-associates (for a total of 30 associates per participant). We collected responses from a sample of 1,205 German individuals using a nationally representative online sample from a market research firm. The sample was balanced in terms of age and gender by using sampling quotas for 6 age groups (age range = 17-87, $M = 47.7$, $SD = 16.6$) and gender (50% female).

Our study answers three main questions. The first question concerns the extent to which the components of risk stemming from our approach qualitatively matches the different dimensions and domains that have been typically identified in past research (e.g., Boholm, 2017; Slovic, 1987; Weber et al., 2002). Second, concerning group differences, our analysis aims to describe potential age and gender differences in the representation of risk, including the types or domains (e.g., recreational) and other characteristics (e.g., sentiment) of risk-associates. Past work has identified clear and robust patterns of age and gender differences in risk-related constructs (e.g., Frey et al., 2021), and our study extends such work by considering whether similar group differences are found directly in the semantic representation of risk. Third, and finally, we ask whether individual differences in the semantic representation of risk can be used to better understand and predict individuals' risk taking, thus contributing to the goal of assessing the power of semantic representations in predicting individual and group differences in risk-related behaviors.

The remainder of our article is structured as follows. First, we present a general semantic network of risk created from the responses of all participants and characterize its components. Second, we present results on age and gender differences in the semantic representation of risk at the level of risk components and individual words. Finally, we present results on the link between people's semantic representations and self-reported risk-taking propensity. Note that although English terms are presented in text and figures, all analyses were run using the original German responses. See Appendix for original responses in German.

The Semantic Network of Risk

To identify the semantic components of risk, we constructed a general semantic network of the immediate associates of risk (Level 1) using the data of all participants. Figure 2 depicts our approach (for similar approaches, see Kenett et al., 2020; Siew et al., 2019). In a first step, we characterized each Level 1 response that occurred at least three times (see Figure 2A) by means of the frequency distribution of Level 2 responses that they elicited (see Figure 2B). In a second step, we determined the relatedness of Level 1 responses by calculating a weighted Jaccard similarity between them (Ioffe, 2010), which has been found to perform well relative to other similarity measures in clustering approaches (e.g., Huang et al., 2008; Saad & Kamarudin, 2013; Strehl et al., 2000). In a third step, we represented the similarity matrix of Level 1 responses as a weighted network and extracted the components of risk using the Louvain modularity algorithm (Blondel et al., 2008), which has been found to compare favorably to other modularity and clustering algorithms (e.g., Emmons et al., 2016; Miasnikof et al., 2020; Pradana et al., 2020; Williams et al., 2019). One attractive feature of modularity detection algorithms, such as the Louvain algorithm, is that they also identify an optimal number of clusters. It is important to note, however, that there exists no general, a priori correct clustering algorithm for such problems (Haslbeck & Wulff, 2020; Hennig, 2015).

The semantic network of risk was found to consist of five components. Figure 3 displays the network and its five components along with the five most important words of each component with respect to their PageRank centrality in the entire network. Figure 4A further illustrates the network by showing word clouds for each component, with words scaled by their frequency of occurrence. The largest component encompassing the most distinct words ($n = 82$ of 307), which we labeled *Fortune*, contained words pertaining to positive outcomes of risk, such as "money", "profit", and "fun", as well as many aspects pertaining to life in general, where risks may be involved, such as "health", "occupation", and "children". The second largest component ($n = 64$), labeled *Investment*, contained words pertaining to financial investment, such as "shares", "stock exchange", "stake", and "gambling". An equally large third component ($n = 64$), labeled *Activity*, contained words pertaining to various kinds of activities and activity-related words, such as "driving", "car", "motorcycle", "smoking", and "caution". The fourth largest component ($n = 57$), labeled *Threat*, contained words pertaining to the negative consequences of risk, such as "danger", "fear", "loss", "accident", and "dare". Finally, the smallest component ($n = 40$), labeled *Analysis*, contained words pertaining to the deliberate aspects of taking risks, such as "ponder", "decision", "trade-off", and "assessment".

The five components of risk varied in their distinctiveness according to a clustering stability analysis (Haslbeck

Figure 2

*Construction of the semantic network of risk. Panel A shows the mini-snowball word-association approach used to generate Level 1 and Level 2 associates of the word "risk" (numbers represent each of the 30 word associates provided by each respondent). Panel B illustrates the Level 1 by Level 2 co-occurrence matrix, which served as the basis for determining relatedness among the Level 1 responses (numbers represent unique associates). Panel C illustrates the relatedness matrix between Level 1 associates, determined by calculating the Jaccard similarity between rows in the co-occurrence matrix shown in Panel B, and ordered according to a clustering algorithm (see text for details; C = Component). The asterisk * indicates that only the subset of Level 1 associates are included that were produced at least three times across all participants.*

& Wulff, 2020, also see Supplemental Material). We bootstrapped Level 2 responses and assessed for each Level 1 response how frequently it shared clusters with words from each of the components. Figure 4B depicts the proportion of modal cluster assignments for the words in each component; that is, the component that supplied the majority of fellow cluster members for each word (while controlling for component size). This shows that most words in the components *Fortune* (88%), *Threat* (88%), and *Investment* (78%), were primarily found to share clusters with words from their original component, suggesting high distinctiveness and robustness for these components. Words in the components *Activity* (47%) and *Analysis* (42%) shared clusters with words from their original component much less often, suggesting lower levels of distinctiveness. Notably, almost half of the words of the component *Activity* preferably shared clusters with words of the component *Threat*, suggesting a strong link between these two components.

The components further varied strongly in retrieval frequency. Note that retrieval frequency is different from component size, which is primarily driven by response diversity, not frequency. Overall, words of the component *Threat* accounted for 37.5% of all Level 1 responses and 54.5% of first responses (see Figure 4C). From this component, "danger" is by far the most frequent response, produced by 43.4% of participants and by 27.9% at the first position. Words of the component *Fortune* accounted for 30.4% of Level 1 responses and were the most frequent responses at position four and five. From this component, "money" was the most frequent word, produced by 12.9% of participants. The three remaining components, *Activity*, *Investment*, and *Analysis*,

accounted for 16.2%, 10.5%, and 5.4% of responses, respectively. The most frequently retrieved words from these components were "car" (1.2%), "shares" (1.2%), and "ponder" (.5%).

Finally, and more importantly, as foreshadowed by our preliminary comparison of text- and association-based representations (see Figure 1), the components varied strongly in their semantic and affective content. Figure 4D characterizes the components in terms of the components' similarity to the concept of risk, determined on the basis of the Jaccard similarity matrix and sentiment, with the latter determined using the SentiWS dictionary (Remus et al., 2010, see Methods). Most notably, the two components most similar to the concept of risk, *Threat* and *Fortune*, are at polar ends of the sentiment spectrum, with *Threat* being the most negative and *Fortune* being the most positive component. The three remaining components, *Activity*, *Investment*, and *Analysis*, are less centrally related to the concept of risk and possess moderately negative sentiment.

In summary, the general network of risk revealed five thematically distinct components. A component labeled *Threat*, containing mostly negative consequences of taking risks, emerged as most important in terms of retrieval frequency and similarity to the concept of risk. The second most important component, labeled *Fortune*, consisted of positive consequences and other life-related, mainly positive associates of risk. In addition to these two focal components, three other components capture risky situations, such as financial investment (*Investment*) and risky leisure activities (*Activities*), as well as higher-level considerations associated with deliberating about risks (*Analysis*). All in all, these results support the

Figure 3

The semantic network of risk. Nodes represent the 307 distinct Level 1 associates sized according to their importance for the network (PageRank). Edges represent the relatedness between nodes sized by the magnitude of the Jaccard index. Colors represent the five components identified by the Louvain algorithm (Blondel et al., 2008). For each component the five most important words are shown sized by importance. Gray lines in the background represent between-component edges. The layout of the nodes was determined using the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991) including a minor edge-weight bias for within-component edges to increase visual separation of the components.

idea that the risk concept is multifaceted and associated with both negatively and positively valenced components.

Group Differences in the Semantic Representation of Risk: The Role of Age and Gender

Our association-based approach to mapping the semantics of risk promises to help characterize potential individual and group differences in the psychology of risk. We explored this possibility by characterizing potential differences as a function of the individuals' age and gender.

To characterize the semantic representation of risk across age, we analyzed retrieval proportions for each component and Level 1 responses across the six age groups in our sample (see Methods). As can be seen in Figure 5A, changes in retrieval frequency of components across age were moderate, with the relative order of retrieval proportions of the five components emerging as highly stable across age. Changes across age groups seemed to occur mainly from the transi-

tion between age groups of 38-47 and 48-57, with *Threat* rising in prominence and *Fortune* declining. Minor changes also seemed to occur for *Activity* showing a mild, but steady increase with age.

Figure 5B further illustrates the component trends, by showing the trajectories of individual, prominent words across the life span. Specifically, the figure shows the linear development across age for each of the 86 words of the network that were retrieved at least once by each of the age groups. Positive linear trends imply that the retrieval proportion increases with age. The illustration reveals systematic changes that cut across the components of risk, but clearly correspond to important ecological changes across the life span. For instance, many words more frequently retrieved by older adults center around mobility ("road traffic", "traffic", "driving", "holiday") or health ("disease", "health", "operation"). On the other hand, many words more frequently retrieved by younger age groups center on entertainment

Figure 4

The semantic components of risk. Panel A shows word clouds of all words contained in the respective component, with the size reflecting the retrieval frequency rank of the word. Panel B shows cluster stability. Panel C shows retrieval proportions for each of the five components from the first up to the fifth associate of risk. Panel D shows the average sentiment and proximity to risk for each of the five components. Error bars indicate bootstrapped 95% confidence intervals.

("game", "fun", "adventure", "thrills", "skydiving") and financial prospects ("stock exchange", "money", "shares", "insurance"). Notably the most frequent associates of "risk", such as "danger", "fear", "accident", and "loss" show very small age effects, reinforcing the observation of conceptual stability across age.

Analogous to our analysis of age, we characterized the semantic representation of risk across gender (i.e., males, females) using retrieval frequencies. As can be seen in Figure 6A, differences in retrieval frequencies were mostly restricted to *Threat* and *Fortune*, with females showing a higher proportion for *Threat* and a lower proportion for *Fortune* as compared to males. Females also appeared to produce slightly more responses for *Activity* than males, whereas there were no noticeable differences for *Investment* or *Analysis*.

Figure 6B shows the corresponding word-level differences in retrieval frequencies with positive values indicating a higher proportion for females as compared to males. The word-level differences mirrored the component-level differences with many frequent words for *Threat* ("fear",

"courage", "uncertainty", "danger") being more frequently produced by females, and many characteristic words for *Fortune* ("money", "game", "chance", "profit") being more frequently produced by males, than vice versa. Nevertheless, there also were word-level differences that cut across the components of risk. For instance, the word showing by far the largest difference in the direction of higher proportions for females relative to males was "pregnancy", whereas the largest differences in the other direction was observed for words pertaining to some kind of duty ("policy", "work", "war"), potentially reflecting gender differences in social roles. Notwithstanding these differences, the most frequent associates of risk show comparatively small effects, suggesting relative conceptual stability between males and females.

Linking Group Differences in Semantic Representations and Risk Taking

The previous sections revealed critical group differences in the importance of the components of risk as reflected in retrieval frequencies. Most notably, both older versus younger and female versus male participants tended to produce more

Figure 5
The semantic representation of risk across age. Panel A shows the proportion of retrievals falling into each of the five components across the different age groups. Panel B shows word-level changes in retrieval frequencies of words in terms of the linear effect of age. Specifically, it shows the unstandardized effect of a predictor coding age group predicting the log-scaled relative retrieval frequencies.

associates belonging to the overwhelmingly negatively valenced component *Threat* and fewer associates belonging to the more positively valenced component *Fortune*. Could the associative frequencies account for the established finding that, on average, both older adults and female individuals exhibit lower levels of self-reported risk taking than younger adults and males?

A prerequisite for such an account is that there exists a link between word retrieval and self-reported risk taking. To evaluate this link, we analyzed the correlation between the absence and presence of a Level 1 response (dummy coded) and participants' judgments in the seven self-reported risk-taking items, capturing risk taking in general, as well as in six

Figure 6
The semantic representation of risk by gender. Panel A shows the proportion of retrievals falling into each of the five components across genders. Panel B shows word-level changes in retrieval frequencies of words in terms of the difference of genders. Specifically, it shows the difference between the log relative retrieval frequencies.

specific domains: *Driving, Financial, Recreational, Occupational, Health, and Social*. The analysis revealed a highly systematic pattern of small correlations ranging from $r = -.09$ to $r = .13$. We found that the relationship of words and self-reported risk taking were not affected by domain. That is, words with a positive relationship to one Socio-Economic Panel (SOEP) domain also exhibited positive relationships with other domains and vice-versa for negative relationships. Overall, the word most positively related to higher risk-taking was "courage", which exhibited the strongest relation to the general SOEP item, as well as the domains *Driving, Financial, and Recreational*. For the other domains, "life" (*Health*), "fun" (*Occupational*), and "chance" (*Social*) were found to be most positively related. Overall, the word most

negatively related to higher self-reported risk taking was "uncertainty", which exhibited the strongest relation to the *Driving* and *Financial* SOEP items. For the other domains, the words "fly" (*General*), "investment" (*Recreational*), "recklessness" (*Occupational*), "loss" (*Health*), and "sport" (*Social*) were found to be most negatively related to higher self-reported risk taking. The absence of domain specificity in the link between word retrieval and self-reported risk taking points to word characteristics as the driver of these relationships. In fact, we found that the words' sentiments were strongly predictive of the words relation to self-reported risk taking, with adjusted R^2 ranging from .09 and .29 across the seven SOEP items. Additional details of these analyses are provided in the Supplemental Material.

We next explored whether changes in retrieval frequencies of words across age and gender can account for changes in self-reported risk taking. To this end, we first ran regressions predicting self-reported risk taking of a group i (age or gender) using all Level 1 responses in the network of risk separately for each SOEP item j . Thereby we obtained an intercept b_0 , as well as a vector of effects $\mathbf{b}$, capturing the positive and negative correlations between words and self-reported risk taking. Then, we determined the retrieval proportions of each word in π_i of group i to generate risk taking ratings R_{ij} for each group and SOEP item according to

$$R_{ij} = b_{0,j} + 5\pi_i^T \mathbf{b}_j$$

where 5 is a scaling factor that can be seen as reflecting the fact that it produced five Level 1 responses. Finally, to produce a probable range of predictions, we replaced the observed retrieval frequencies π_i , with bootstrap samples drawn from the retrievals of each group.

Figure 7 shows the ranges produced by the simulation along with the empirical average in self-reported risk taking across age (Figure 7A) and gender (Figure 7B) for each of the seven SOEP items. Figure 7A reveals a close match between age-related changes in self-reported risk taking and those produced by our simulation. The biggest and most consistent empirical changes were observed in the domains of recreational and health-related risk taking. Both age-related developments were accurately captured by our simulation. The other domains, along with the general risk-taking item, showed smaller or less consistent age-related changes that were equally captured by our simulation. Figure 7B reveals a less consistent match between gender differences in self-reported risk taking and those generated by our simulation than found for age. For all domains and, in particular, the domains *Financial*, *Recreational*, and *Driving*, females indicates lower levels of risk taking than males. These trends were captured by our model, albeit clearly not as well as age differences.

Together these results demonstrate links between individual differences in the retrieval distribution of words and in-

dividual differences in self-reported risk-taking propensity. These links, although correlative in nature, are consistent with the idea that associative retrieval processes underlie self-reported risk judgments (e.g., Arslan et al., 2020).

Discussion

We explored the semantic representation of risk and potential individual and group (age, gender) differences in the representation of this concept using a novel mini-snowball word association task. The task asked participants to generate words associated with the concept of "risk" as well as words associated with the initial risk-associates. We then conducted network and sentiment analyses to identify a general network of risk-associates and made use of this network to characterize individual differences across age and gender. In what follows, we summarize our main findings and discuss the main limitations of our work.

Our starting point was the identification of a general semantic network of risk composed of 306 primary associates of risk. This network exhibited a complex organization involving five distinct semantic components, which we labeled *Threat*, *Fortune*, *Activity*, *Investment*, and *Analysis*. In line with extant theories of lay people's representation of risk (e.g., Slovic, 1987), the *Threat* component (consisting of mainly negative consequences of risk) emerged as most prominent in people's semantic network. However, the other components accounted for more than half of people's associations with "risk", even when only considering first responses, which is consistent with the widely held multidimensional perspective on the psychology of risk (e.g., Boholm, 2017). Notably, the *Fortune* component seems to represent positive associations with "risk", echoing recent calls for the need to understand positive aspects associated with risk and risk taking (Duell & Steinberg, 2019) as well as the intrinsically close relation between risk and reward (Pleskac & Hertwig, 2014). Nevertheless, the semantic components of our network have some correspondence to past taxonomies of risk. Specifically, the components *Threat* and *Analysis* align well with Fischhoff et al. (1978) dimensions of dread and uncertainty, as well as the idea that risk refers to potential loss as a consequence of an active decision (Boholm, 2017). Similarly, the remaining three components—*Fortune*, *Activity*, and *Investment*—capture, albeit not perfectly, some of the domain-specific nature of risk taking identified in past approaches (Weber et al., 2002).

One main goal of our approach was to evaluate potential group differences in the semantic representation of risk. Concerning age, we found a striking consistency in the prominence of the components risk across age groups, suggesting that people of different age groups think about risk in similar terms. Yet, there were some noteworthy differences identified at the component and word-level. Specifically, we found that whereas younger adults retrieved words of the

Figure 7

Linking the semantic representation of risk to self-reported risk taking. Panel A shows the empirical age-group averages for each of the seven SOEP domains, as well as the range of predictions derived from our predictive model. Panel B shows the empirical gender averages for each of the seven SOEP domains, as well as the range of predictions derived from our predictive model.

components *Threat* and *Fortune* in nearly equal proportions, there was clear divergence for older adults, with *Threat* being much more prominent than *Fortune*. These results are compatible with the idea that positive aspects of risk and risk taking change across the life span (Duell & Steinberg, 2019; Frey et al., 2021; Ravert et al., 2019). Furthermore, when we inspected age-related changes at the word level, we observed a number of differences, with words concerning mobility and health being prominent among older adults and words concerning entertainment and financial prospects being prominent among younger adults. Thus, despite strong macroscopic level similarities in the semantic representation of risk, there exist systematic differences across age that could be linked to ecological and life circumstances of different age groups (Arslan et al., 2020; Ravert et al., 2019).

Concerning gender, we again observed consistency in the prominence of the different risk components, suggesting that both males and females think about risk in similar terms. Nevertheless, differences emerged for *Threat* and *Fortune*, with the former being more prominent among females and the latter more prominent among males. Thus, similar to older adults, females seem to consider the negative consequences of risk more and the positive ones less frequently than males. Furthermore, when we inspected gender-related changes at the word level, we observed a number of differences, for example, with "pregnancy" being considerably more prominent among female respondents. Thus, despite a similar level of similarities in the semantic representation of risk, there is also evidence of some systematic differences across gender.

Finally, we estimated the potential link between people's risk representations and self-reported risk-taking propensity in general and in specific domains (e.g., recreational, health, driving, financial). We observed that certain risk-associates were consistently related, either negatively or positively, to self-reported risk taking across different risk domains. This link between individual risk-associates was best captured by the word's sentiment, implying the production of associates with more positive valence covaried with higher self-reported risk-taking propensity. Crucially, we developed a statistical model to account for self-reported risk taking on the basis of group-related differences (i.e., age, gender) in the distribution of risk-associates. This exercise revealed that group-related differences in self-reported risk taking can be predicted by differences in the distribution of risk-associates, suggesting that the group-specific representation of risk is indicative of group differences in self-reported risk-taking propensity. Overall, these results suggest that information about the semantic representation of risk can be used to capture typically observed group-related differences in self-reported risk taking, such as those associated with age and gender.

Limitations and Future Directions

Our work has a number of limitations that merit discussion. First, our task uses a lexical approach based on associations of only five associates per individual (with the remaining responses being used to characterize the links between risk-associates). The small set of responses per person

likely limits the richness of the representation and may neglect lower-frequency associates that could in principle be retrieved. Further, it is possible that other approaches, including more focused elicitation methods using experimenter-generated stimuli or dimensions, could provide more fine-grained associations and therefore richer representations of risk. Future work should compare different forms of elicitation to assess the generalizability of our findings in terms of the range of components extracted.

Second, our elicitation method cannot provide truly individual semantic representations. For this purpose, richer sets of data would be needed, requiring more intensive designs (e.g., Morais et al., 2013; Wulff et al., 2021; Wulff et al., in press). Importantly, such approaches could be instrumental in improving predictions about risk-related constructs at the individual level. Recent work has suggested that lexical network approaches may be powerful tools to make predictions about population-level risk perception of novel risks (Bhatia, 2019) and it would be interesting to assess the possibility of extending our approach to make similar, but personalized predictions for single individuals (cf. Wulff et al., in press).

Third, our identification of group differences, such as those related to age or gender, does not clarify the origins of such differences. For example, our data suggest age differences in the types of activities spontaneously associated with risk, such as recreational risk-taking. Several aging theories could be used to explain such a change, including those that make assumptions about motivational changes, concerning the role of activation and excitement (Tsai et al., 2018) or loss avoidance (Depping & Freund, 2011). To distinguish such hypotheses, other survey methods that directly capture the motivation and goals associated with certain concepts could be a better or complementary approach (Ravert et al., 2019).

Fourth, our work does not investigate the mechanisms linking the empirical associations and self-reported risk taking. One possibility is that the predictive power of empirical associations is driven by long-term group differences in semantic representations. Recent work has identified systematic differences in the semantic networks of groups and individuals (Wulff et al., 2018, October 29) and suggested that they can contribute to individual differences in behavior (Ramscar et al., 2017; Wulff et al., 2019). Alternatively, or additionally, situational activation of mental representation can also contribute to such individual and group differences. Additional work that examines ecological and situation-specific risk taking could prove helpful in teasing apart such contributions.

Despite these limitations our results highlight the promise of a controlled free-association approach, in particular our mini-snowball paradigm, to shed light on features of psychology that are less accessible by text or survey-based approaches. We are convinced that this and similar approaches could be employed to further illuminate people's mental rep-

resentations of risk as well as other psychological or social constructs. Our approach could be particularly useful for those constructs for which considerable heterogeneity of perspectives or even polarization exist, from vaccination to sustainability.

Conclusion

Our work contributes to a better understanding of the semantic representation of risk. Our results are in line with past findings suggesting that risk is a multifaceted construct with a rich set of associates that pervades several areas of life. Importantly, our work extends our knowledge of the semantic representation of risk by emphasizing the coexistence of both negatively and positively valenced components, questioning the currently predominant focus on negative aspects of risk. Our results also highlight the importance of understanding individual and group differences such as age and gender in the semantic representation of risk and showcase the promise of using controlled free-association methodology as a means to characterize lay people's representation of complex psychological constructs. One main implication of our work is that the measurement of risk-related constructs, such as risk perception or risk taking, requires an understanding of the many meanings of "risk" and how it differs between individuals and groups.

Methods

Participants

A total of 1,205 (602 female, 50%) participants completed the online study in November, 2016. Participants were between 18 and 87 years of age ($M = 47.7$, $SD = 16.6$). Participants were part of a panel and recruited by a survey company for market research purposes (<https://www.forsa.de>). Participants were sampled evenly from six age bins (18-27, 28-37, 38-47, 48-57, 58-67, 68+), designed to be representative of the German population. The study took an average of 12 minutes (median = 10 minutes) and participants received a 2 EUR Amazon voucher for their participation.

Measures

Word association task

Word associations were collected using mini-snowball word association task. Participants first gave five associations to the word risk and then five associations to each of the five associates of the word risk for a total of 30 associates per participant. Participants were instructed to name the first five words that came to mind when thinking exclusively about the respective cue. They were also instructed to avoid repeating associations while responding to the same cue.

Participants' responses were subjected to manual spelling correction before analysis. Overall, 2.78% of all responses

were corrected with a median string distance between the original and corrected word of 1 (restricted Damerau-Levenshtein distance (e.g., Zhao & Sahni, 2019)). An additional 0.13% of responses were either identified as non-words, e.g., “djebdb”, or clearly expressed failure to produce an associate, e.g., “no idea” (German: “keine Ahnung”) or “?”. These responses were removed from all further analyses.

Inferring Sentiment

Sentiment was determined based on the SentiWS dictionary (Remus et al., 2010). Of the 307 words in the general network of risk only 115 were contained in the SentiWS dictionary. To be able to analyze sentiment for a maximal number of words, the average sentiment of Level 2 responses was used to infer the sentiment of unavailable Level 1 sentiment. Specifically, sentiment was defined as the average between the word’s sentiment and the average sentiment of its associates, or only the latter, whenever the sentiment of the word 1 word itself was unavailable. For the 115 words for which sentiment values were directly available, we found a correlation of $r = .56$ between the word’s sentiment and its inferred sentiment score based on the sentiment of its associates, suggesting that the average sentiment of associates provides a reliable indicator of the sentiment of a target word. This approach delivered sentiment scores for 304 of 307 words.

Risk-taking propensity

Risk-taking propensity was measured using the seven self-report risk items from the German Socio-Economic Panel (SOEP; Wagner et al., 2007). The first item asks participants to judge “Are you in general a risk-seeking person or do you seek to avoid risks?” (translated from German) on a scale from 0 (not risk-seeking at all) and 10 (very risk-seeking). The following six items asked the same question and provided the same scale, but replaced “in general” with text referring to one of six different risk-taking domains including driving, financial investments, leisure and sports, professional career, health, and trusting strangers.

Procedure

Participants were contacted by a survey company to participate in the computerized online study. First, participants were informed about the goals and specifics of the study and gave informed consent. Then, participants completed the word association task followed by the SOEP risk-taking propensity task.

Data availability

The data and analysis scripts are publicly available at an online repository (<https://osf.io/an7dt/>).

Author contributions

DW and RM developed the study idea, DW conducted data analyses, DW and RM wrote the manuscript.

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