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RESEARCH ARTICLE

Moral relevance varies due to inter-individual and intra-individual differences across big data technology domains

Rabia I. Kodapanakkal[1] | Mark J. Brandt[2] | Christoph Kogler[1] | Ilja van Beest[1]

[1] Department of Social Psychology, Tilburg University, Tilburg, The Netherlands

[2] Department of Psychology, Michigan State University, Michigan, USA

Correspondence
Rabia Kodapanakkal, Department of Social Psychology, Tilburg University, Tilburg, The Netherlands.
Email: R.I.Kodapanakkal@tilburguniversity.edu

Abstract

Theories of moralization argue that moral relevance varies due to inter-individual differences, domain differences, or a mix of both. Predictors associated with these sources of variation have been studied in isolation to assess their unique contribution to moralization. Across three studies ($N_{Study1} = 376$; $N_{Study2a} = 621$; $N_{Study2b} = 589$), assessing attitudes towards new big data technologies, we found that moralization is best explained by theories focusing on inter-individual variation (~29%) and intra-individual variation across technology domains (~49%), and less by theories focusing on differences between technology domains (~6%). We simultaneously examined 15 inter-individual and 16 intra-individual predictors that potentially explain this variation. Predictors directly relevant to the technologies (e.g., justice concerns), cognitive styles (e.g., faith in intuition), and emotional reactions (e.g., anger) best explain variation in moral relevance. Accordingly, scholars should simultaneously adopt and adapt moralization theories related to inter-individual and intra-individual differences across domains rather than in isolation.

KEYWORDS
big data, justice sensitivity, moral conviction, moral foundations, moral relevance

1 | INTRODUCTION

Morally relevant attitudes, or moral convictions, are attitudes that people believe are related to fundamental right or wrong and a part of their core beliefs and convictions (Skitka & Morgan, 2014; Skitka et al., 2021). People with morally relevant attitudes are particularly hard to persuade, react with anger when presented with counter-attitudinal positions (Garrett & Bankert, 2020), and show an unwillingness to compromise towards counter-attitudinal positions (Ryan, 2017). One issue that is currently discussed in terms of moral relevance concerns big data technologies that have emerged in different technology domains, like criminal investigations, employment, and healthcare. These technologies have the potential to violate people's privacy and be unfair (Obermeyer et al., 2019). In the current research, we assess sources of variation in morally relevant attitudes towards new big data technologies and from our findings identify predictors that explain this variation. The aim of our research is twofold. First, we aim to provide a more comprehensive picture of moralization by assessing the unique contribution of three sources of variation in moralization that have been typically studied in isolation in earlier research. These sources of variation could either be inter-individual differences, differences due to different technology domains, or an interaction between the two (intra-individual differences across technology domains). Second, based on which sources contribute to the variation, we aim to identify predictors associated with moral relevance that explain variation related to the sources of variation.[1]

1.1 | Moralized attitudes

Moralized attitudes are different from non-moral attitudes, as moralized attitudes are usually perceived to be objectively true (Goodwin & Darley, 2008) and universal (i.e., others must hold the same attitude; Skitka, 2010). Moralized attitudes are also associated with moral emotions like anger and hostility towards those who disagree with the attitude (Garrett & Bankert, 2020; Mullen & Skitka, 2006) and the experience of disgust (Feinberg et al., 2019). They are associated with constructive behaviors (e.g., political engagement; Skitka & Bauman, 2008; see also Van Zomeren et al., 2011), but also less constructive behaviors (e.g., intolerance; Cole Wright et al., 2008; see also Delton et al., 2020; Ryan, 2017) and violence (Mooijman et al., 2018). Notably, these correlates of moral relevance are typically independent of attitude strength (for factor analytic evidence see Philipp-Muller et al., 2020).

Research has focused on the process of moralization and predictors that contribute to the moral relevance of people's attitudes regarding various issues. However, these predictors are typically studied in isolation. Studies have shown that emotions like anger (Mullen & Skitka, 2006) and disgust (Feinberg et al., 2019) are associated with moral relevance. Others argue that an intuitive perception of harm (Schein & Gray, 2018) is associated with moral relevance. The present research takes a more fundamental approach and aims at identifying where the variation in moral relevance comes from. Identifying the sources of variation (and the amount of variation per source) is important as it provides a more comprehensive picture of the underlying characteristics and driving forces of moralization.

1.2 | Sources of variation in moral relevance

We consider three sources of variation that map onto different approaches to morality and moralization in the literature. (1) Differences in moralization due to inter-individual differences are consistent with approaches emphasizing individual differences in morality (e.g., Schmitt et al., 2005), (2) differences in moralization due to domain are consistent with approaches emphasizing consensus in moralization within a society (e.g., Morris & Liu, 2015), and (3) differences in moralization due to intra-individual differences across domains (i.e., the interaction between (1) and (2)) are consistent with approaches emphasizing idiosyncrasies in moralization (e.g., Ryan, 2014). Each of these approaches is useful in explaining variation in moral relevance and moralization; however, some of these perspectives might be more useful than others (i.e., explain more variation than others). So far these models do not specify the extent to which individual differences, domain differences, or an interaction of the two contribute uniquely to moralization. Estimating the amount of variation from each source is theoretically critical as we are able to see which theoretical approach provides the best fit to the data. Moreover, we can also see which approach (or approaches) can best explain elements underlying moralization.

We estimate the variation in moralization through a variance decomposition method using cross-classified models that has been used in other research fields such as impression formation, rater judgments, and situation perception (Hehman et al., 2017; Martinez & Paluck, 2020; Martinez et al., 2020; Rauthmann & Sherman, 2019). Once we estimate the extent of variation in moral relevance from these different sources, we then identify predictors associated with moral relevance related to each source (e.g., justice sensitivity, perceptions of harm, emotions). This allows us to focus on sources that explain the most variation and to simultaneously account for variation from different sources. Below we explain in detail the three different sources of variation.

1.2.1 | Inter-individual differences

Some approaches suggest that moralization is a feature of the individual. Classic work in moral psychology focuses on moral development of an individual (Kohlberg, 1981; Rest, 1986), suggesting that there are individual differences in morality depending on the level of development. Although the surge in moral psychology over the last two decades has largely eschewed this approach, more modern approaches also focus on individual differences in morality. For example, some approaches highlight how some people are much more likely to care about moral behavior and injustice (Schmitt et al., 2005). Less directly, to the extent morality is driven by intuition (e.g., Social Intuitionist Model; Haidt, 2001) and the use of intuition is an individual difference (Ward & King, 2018), moralization may similarly function as an individual difference. Higher moral relevance has also been associated with other individual differences like political party identity (Ryan, 2014). For example, typical studies from this perspective measure traits that vary at an individual level (such as political ideology or Faith in Intuition) and demonstrate that these traits are associated with moralization or moral judgments (Ryan, 2014; Ward & King, 2018). Collectively, these approaches suggest that some people will be more prone to moralization than others. We refer to this as moralization due to inter-individual differences.

In this case, moral relevance appears more like a typical individual difference that generalizes across technology domains for an individual. For example, Figure 1 illustrates a pattern primarily due to inter-individual differences. Overall, Person A finds attitudes towards all technology domains as more morally relevant than Person B, and Person B finds the same attitudes as more morally relevant than Person C.

1.2.2 | Differences in technology domains

Other approaches highlight that moralization can occur at the level of cultures or societies (Morris & Liu, 2015; Rozin, 1999). These approaches highlight how shared historical or cultural features shape which attitudes and norms are moralized. Moralization at the

[1] Note that in the rest of the article, we refer to the different big data technology domains (e.g., criminal investigations, healthcare) as "technology domains". We refer to various predictors that explain variation and are associated with moral relevance as "predictors".

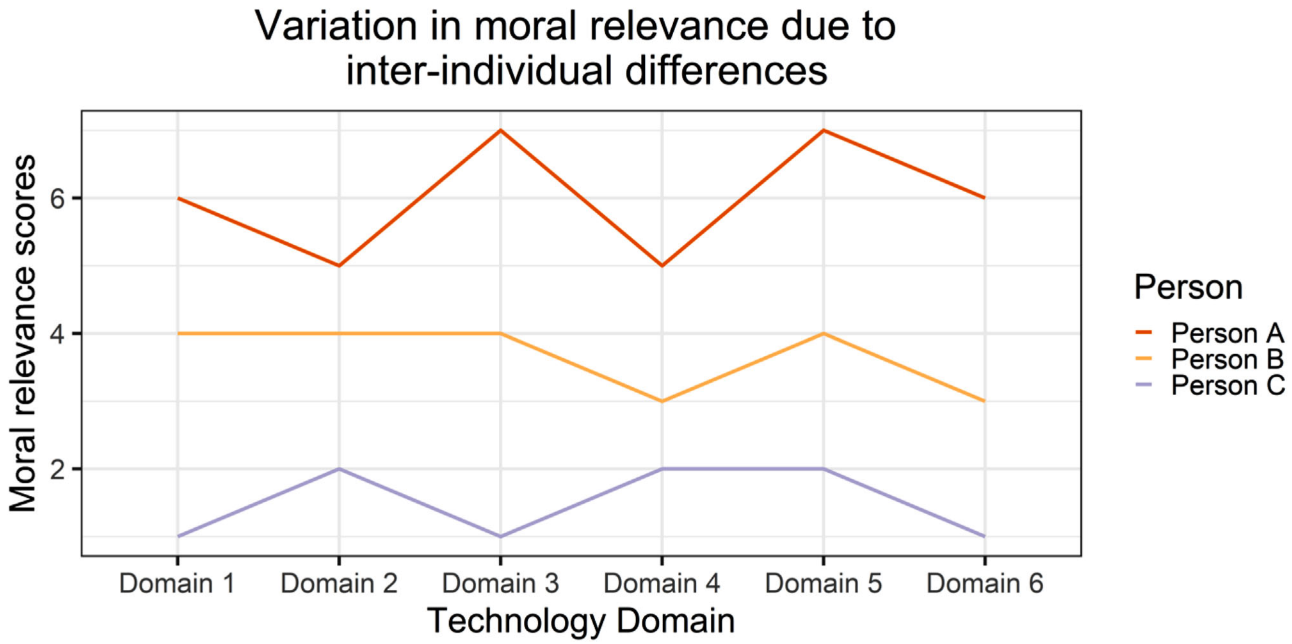

FIGURE 1 An example of variation in moral relevance primarily due to inter-individual differences. The x-axis represents different technology domains, the y-axis represents moral relevance, and the colored lines represent different individuals. All data are hypothetical. We refer to technology domains because this is the focus of our study; however, the idea could be applied to any type of domain

societal level can serve multiple functions, such as helping achieve cooperation and coordination of group goals. This approach suggests that when studying moralization within one society, variation in moralization is likely to be due to differences between attitudes towards different domains, with some attitudes being more moralized by the society than others. For example, typical studies (e.g., Zou et al., 2009) using this approach demonstrate that people adhere to norms and their behavior in a certain context is determined by the norms that govern that context. This implies that variation in moral behavior would then be due to context rather than variation across individuals. This is consistent with the assumption of some scholars that particular attitudes are moral attitudes and other attitudes are mere conventions or preferences (Nucci, 2001; Smetana & Braeges, 1990). We refer to this as moralization due to differences in domains.

Variation due to differences in technology domains would mean that on average the scores of moral relevance in some technology domains will be higher than in other technology domains. Figure 2 illustrates a pattern primarily due to differences in technology domains. Person A, Person B, and Person C find Domain 1 more morally relevant and Domain 3 less morally relevant. In such cases, different levels of moral relevance between technology domains have some consensus in the population.

1.2.3 | Intra-individual differences across technology domains

The final set of approaches we consider suggests moralization is an individual and idiosyncratic approach to a particular attitude (e.g., Ryan, 2014; Skitka et al., 2005). This approach assumes that each and every attitude may be moralized to a different degree by different people such that there will be differences in moralization both across and within domains. Rather than assuming that political issues like abortion, same-sex marriage, or the death penalty are seen as moral issues, research from this perspective assumes that each individual may have their own idea about the moral relevance of these issues. This approach to moralization is consistent with approaches that highlight the potency of idiographic approaches to predict social behavior and personality (Caldwell et al., 2008; Orom & Cervone, 2009). Typical studies done from this perspective demonstrate across multiple contexts that different contexts elicit different reactions (e.g., emotional reactions such as anger or disgust) from different people. For example, people may have moralized attitudes towards a domain if they have strong emotions towards it (e.g., Wisneski & Skitka, 2017); however, not everyone will have the same emotional reactions to the same domains and thus not everyone will moralize the domain. These perspectives all suggest that moralization is not just due to between domain difference or inter-individual differences, but rather an interaction between the two. We refer to this as moralization due to intra-individual differences across domains.

In the case of intra-individual differences across technology domains, moral relevance is idiosyncratic for each person and technology domain combination. Figure 3 illustrates a pattern primarily due to intra-individual differences across technology domains. Person A finds Domain 4 more morally relevant than Domain 1. However, Person B finds Domain 1 more morally relevant than Domain 4. And, Person C has a different pattern compared to Persons A and B.

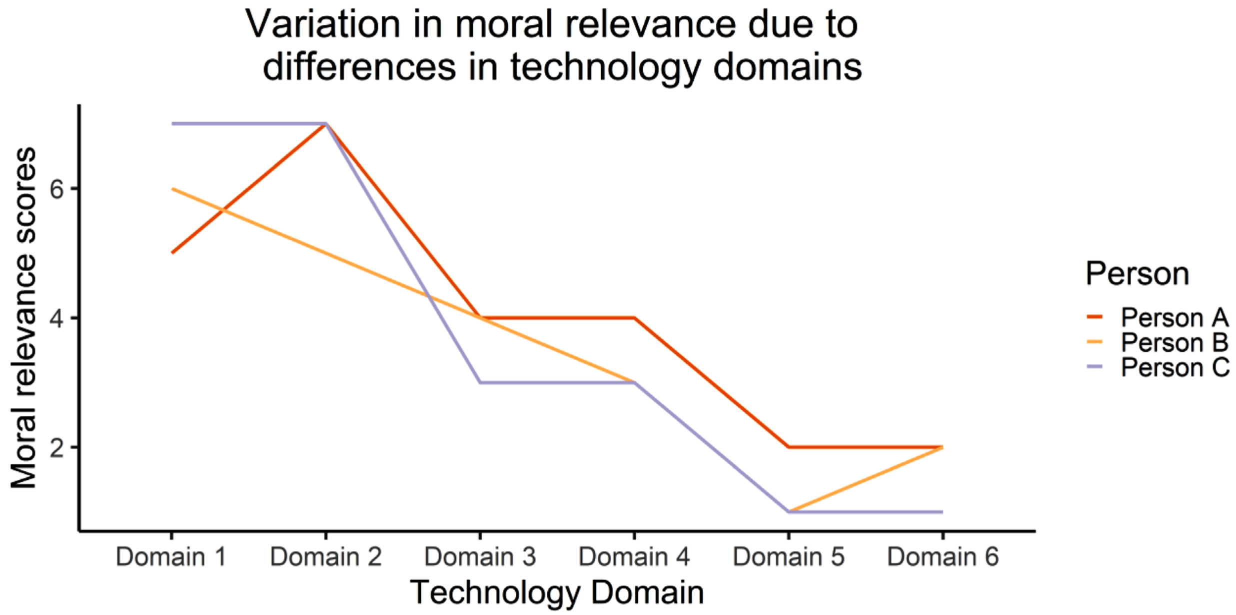

FIGURE 2 An example of variation in moral relevance primarily due to differences in technology domains. The x-axis represents different technology domains, the y-axis represents moral relevance, and the colored lines represent different individuals. All data are hypothetical. We refer to technology domains because this is the focus of our study; however, the idea could be applied to any type of domain

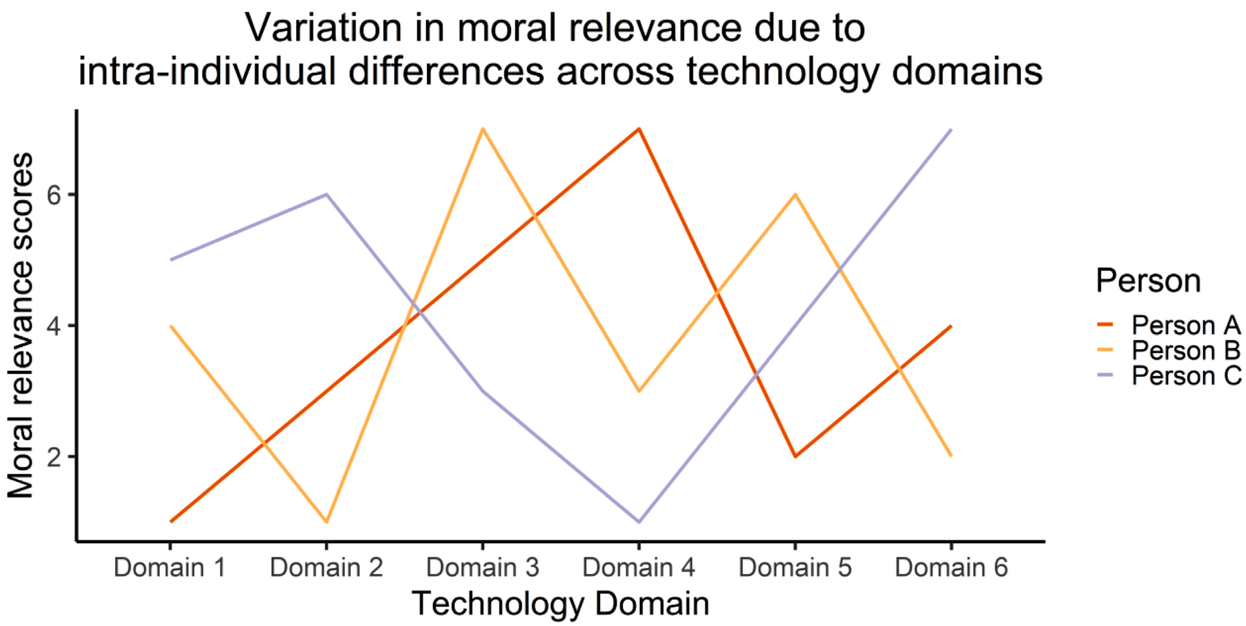

FIGURE 3 An example of variation in moral relevance primarily due to intra-individual differences across technology domains. The x-axis represents different technology domains, y-axis represents moral relevance, and the colored lines represent different individuals. All data are hypothetical. We refer to technology domains because this is the focus of our study; however, the idea could be applied to any type of domain

1.3 | Why big data technologies?

We study the sources of variation by studying attitudes towards a range of new technologies that we refer to as big data technologies. Big data technologies have emerged in technology domains like healthcare, law enforcement, and social media. These technologies share a focus on data gathering and processing at scale, but otherwise cover a wide range of potential issues. Although these technologies provide benefits like improved emergency healthcare and swifter crime solving, they also come with costs of potentially biased algorithms and privacy violations (e.g., Obermeyer et al., 2019). These issues have the potential to be seen with some sort of moral relevance. The present research allows us to delve into relatively new issues using the lens of moral psychology and empirically assess whether people find big data technologies morally relevant or not.

For example, some philosophical works make normative arguments about why privacy should be protected, the value it holds, and refer to it as a moral right (Corlett, 2002; Foley, 2006). Similarly, when big data technologies are discussed in the media, the language used to describe them often suggests moral relevance. For example, privacy violation is referred to as harmful (Guliani, 2019) and moral outrage is expressed towards biased algorithms (Pollmann, 2019). Books have been written showing the "dark side" of big data suggesting the violation of moral values like fairness (e.g., O'Neil, 2016). If these normative arguments hold, then we might expect that there is consensus surrounding the moral relevance of these new technologies and variation would primarily be found between technology domains.

Other philosophical works argue that privacy is a moral value only to those who care about individuality and freedom (Parent, 1983) and so privacy violations may not be considered a moral issue by everyone. Its moral relevance will vary depending on what a person values. Thus, it is possible that big data technologies will not be morally relevant to everyone. This perspective suggests that moral relevance in big data technologies is due to either inter-individual differences or intra-individual differences across technology domains.

1.4 | The current research

We examined six technology domains of existing big data technologies (criminal investigations, healthcare, banking, crime prevention, employment, and government) that covered surveillance and algorithmic technologies in both private and government sectors (see Kodapanakkal et al., 2020). In two studies and three samples, we addressed the following research questions:

First, in both studies we assessed whether there is variation in how morally relevant people find big data technologies. Given the findings of work on other topics (e.g., Ryan, 2014; Skitka & Morgan, 2014), we expect variation in the moral relevance of big data technologies, such that people will not universally see the technologies as morally relevant or irrelevant. Second, using variance decomposition analysis (Hehman et al., 2017; Martinez et al., 2020; Rauthmann & Sherman, 2019), we assessed the extent to which inter-individual differences, differences between technology domains, and intra-individual differences across technology domains explain variation in moral relevance (Studies 1 & 2). In accordance with the current moralization literature, we expected that all three sources would contribute to the variance. However, the current theories on moralization do not provide information on which source explains the most or the least variance. Our analyses fill this gap. In Study 1, we found that (a) there is variation in moral relevance and (b) most variation in moral relevance comes from inter-individual differences and intra-individual differences across technology domains, and very little comes from differences in technology domains. In Study 2 we examined our third research question by testing the predictors related to the main sources of variation that could potentially explain that variation. More details regarding these predictors are presented in the specific description of Study 2.

2 | STUDY 1

In Study 1, we tested the first two research questions: (1) Is there variation in moral relevance of big data technologies? (2) To what extent do inter-individual differences, differences in technology domains, and intra-individual differences across technology domains explain variation in moral relevance? The analyses were preregistered: https://aspredicted.org/jy2bh.pdf.

2.1 | Method

2.1.1 | Participants

This study was conducted online on Mechanical Turk using TurkPrime (Litman et al., 2017) with participants from the United States.

For determining sample size, we used an existing dataset (Ryan, 2019; Study 3 dataset) as the basis for our power calculation conducted via simulations in the R package "simr" (https://osf.io/v3j85/). We used moral relevance as a predictor of attitude change and included other attitude strength measures, similar to our study design. Although this is not what we are predicting in our study, it gave us a reasonable starting point for estimating power of a multilevel design for moral relevance. Since we did not have data from existing research that exactly modeled what we planned to do, we applied an effect size of 0.05 and a 95% power criteria to be conservative in our power analysis. We obtained a sample size of 150 participants. Based on Schönbrodt and Perugini (2013), for stable estimates in between-subjects designs, the sample size approaches 250. However, taking into account dropout rates, we aimed to collect data from at least 300 participants (see Supplemental Materials for more details). A total of 464 participants opened the survey. Three hundred and eighty eight participants fully completed the survey and an additional 25 partially completed the survey. We used all the available data for our analyses. In accordance with our preregistered exclusion criteria, we only excluded participants who failed the attention check leaving 376 participants for the analyses (139 females, 235 males, and 2 people who did not indicate gender) ranging from 19 to 79 years of age ($M_{age} = 35.9$ years, $SD_{age} = 10.6$). Participants received $1.50 for completing the survey which lasted around 10 minutes.

2.1.2 | Procedure and measures

Participants read descriptions of six big data technologies (criminal investigations, crime prevention, healthcare, banking, employment, and citizen scores). These technology descriptions are based on previous research on big data technologies (see Kodapanakkal et al., 2020). We used these technologies because they represent a wide variety of current big data technologies. They include both surveillance technologies (e.g., criminal investigations) and algorithmic technologies (e.g., in employment). They also include technologies in both the private (e.g., banking) and public (e.g., citizen scores) sectors. The technologies differ in their functions and the field they are used in, providing a range of relevant technologies. Prior work shows that the extent to which privacy protection, data sharing, and self-interest predicts people's willingness to adopt the technologies differs across these technology domains (Kodapanakkal et al., 2020), suggesting that they are different from each other. The description of the criminal investigations technology domain was as follows:

> Some city governments use a new surveillance technology to help solve crimes. This technology uses a small plane and a high resolution camera that watches the city 24/7. The camera takes a picture every second. When a crime occurs, the police can zoom into the crime scene at an earlier time to help identify the criminal.

Participants were presented with technologies in a random order (see Table S1 Supplemental Materials for all descriptions). They were of similar length and aimed to describe the technologies in a factual manner without highlighting the moral or privacy implications of the technologies (for previous use see Kodapanakkal et al., 2020). After each technology description, participants answered questions regarding their attitude towards the technology and the moral relevance of their attitude.[2]

The first item after each technology description assessed participants' support for the technology. On a 7-point Likert-type scale (1 = strongly oppose and 7 = strongly support), participants responded to the question, "To what extent do you support or oppose the use of the above technology?" Next, we assessed moral relevance of the technology using a 2-item moral conviction scale (e.g., Skitka et al., 2005; r = .81; r range across technology domains [0.74–0.83]). Participants responded to the items on a scale of 1 to 7 (1 = not at all and 7 = very much), "How much is your position on the use of this technology connected to your core moral beliefs and convictions?" and "How much is your position on the use of this technology connected to your beliefs about fundamental right or wrong?" For Question 2, we treated the items separately and did not combine them. This was necessary to statistically identify the model.

Next, we assessed other facets of attitude strength and potential consequences of moral relevance (see Footnote 2). Finally, participants answered demographic questions that included age, gender, and political ideology.

2.2 | Results

> *Question 1: Is there variation in moral relevance of big data technologies?*

Figure 4 illustrates variation in moral relevance across all six technology domains. Scores of moral relevance ranged from 1 to 7, covering the entire range for every technology domain. The overall *SD* for the measure was 1.77 (range [1.70, 1.90]). The average moral relevance scores for the technology domains ranged from 4.2 to 5.5 (7-point scale). Although average moral relevance was lower in some and higher in other technology domains, there was still considerable variation in moral relevance in all the technology domains. Hence, the assumption (e.g., Corlett, 2002) that people view big data technologies as equally morally relevant is not always true.

> *Question 2: To what extent do inter-individual differences, differences in technology domains, and intra-individual differences across technology domains explain variation in moral relevance?*

2.2.1 | Analytical approach

To answer this question, we used variance decomposition analysis (Hehman et al., 2017; Martinez et al., 2020; Rauthmann & Sherman, 2019). This approach identifies components that contribute to variance of a particular variable, in this case moral relevance, and how these components combine with each other. We used a cross-classified multilevel model and estimated intraclass correlation coefficients (ICCs). The ICC calculated for individuals represents the variance in moral relevance due to inter-individual differences, the ICC for technology domains represents the variance due to differences between technology domains, and the technology domain-individual interaction ICC represents variance due to intra-individual differences across technology domains. The percent variance reported is essentially a standardized ICC for each component, which was calculated by dividing the component ICC by a sum of ICC's of all components (individual, technology domain, interaction, and residual components). For the analysis, we included participant, technology domain, and an interaction between the two as random effects in the model and moral relevance as the dependent variable. The two items of moral relevance were treated separately in the model to have two ratings of moral relevance per participant. This is necessary to distinguish variance by intra-individual differences from residual variance.

2.2.2 | Findings

Figure 5 illustrates that variation in moral relevance was primarily due to inter-individual differences (34.1%, 95% CI [29.4, 38.7]) and

[2] Participants reported other attitude strength measures of importance, certainty, and centrality, and measures that assessed cognitive, affective, and behavioral consequences of moralized attitudes. These measures were included to assess whether moral relevance is a unique dimension of attitude strength for attitudes about big data technologies. This has been demonstrated for other attitudes (Ryan, 2014; Ryan, 2017; Skitka et al., 2005) and was also the case here. See Supplemental Materials for details.

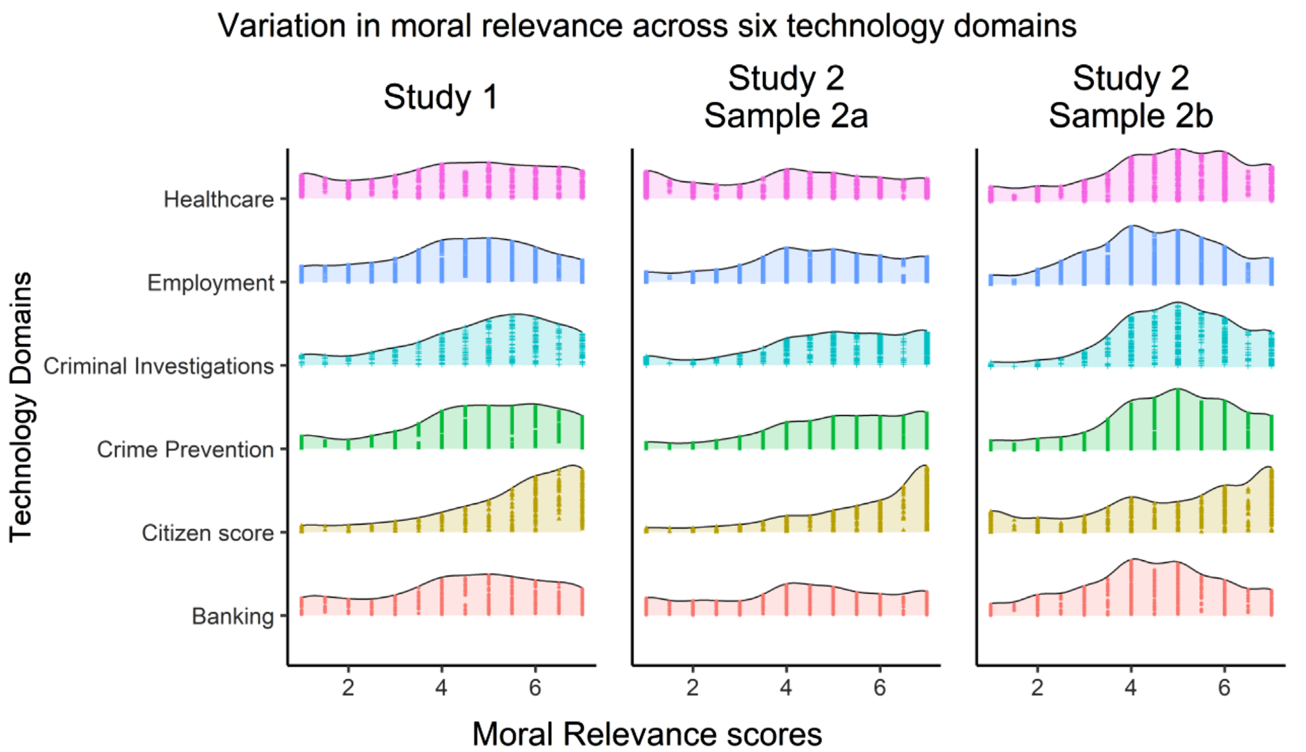

FIGURE 4 Variation in moral relevance across different technology domains in Studies 1 and 2. The x-axis represents moral relevance scores and the y-axis represents the six technology domains

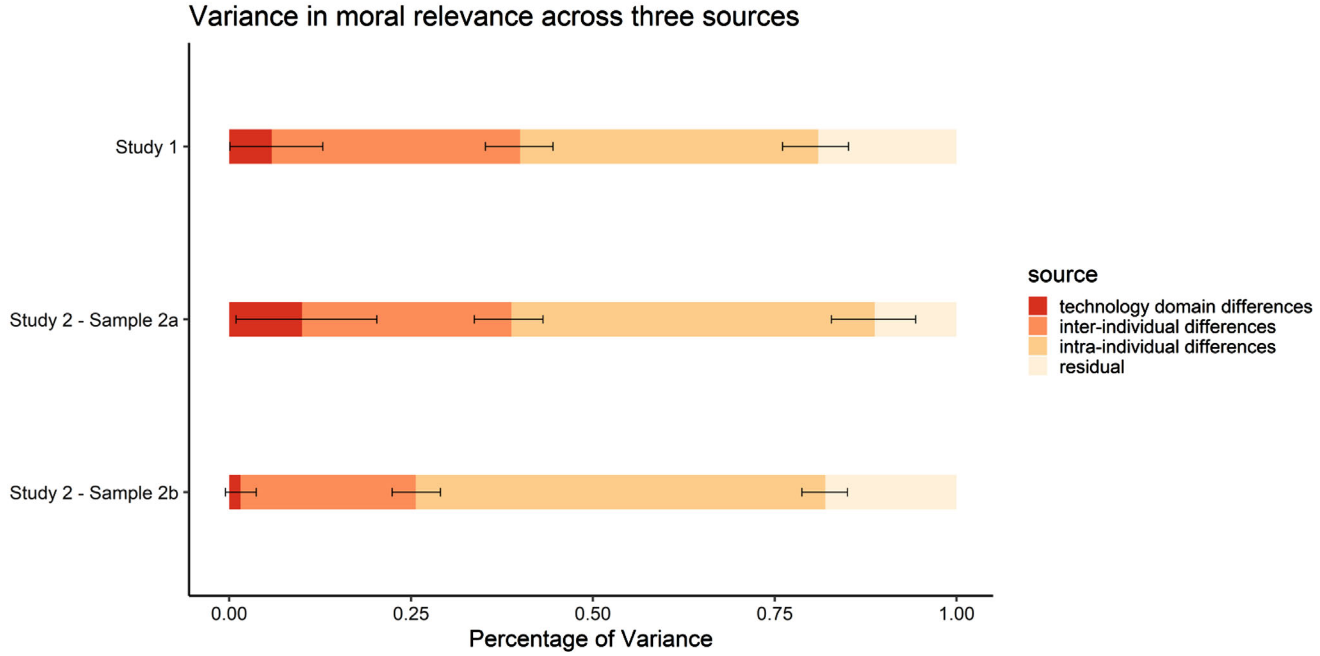

FIGURE 5 Variance in moral relevance due to inter-individual differences, technology domain differences, and intra-individual differences across technology domains in three studies. The x-axis represents the percent variance and the colors depict the sources of variance. Error bars denote 95% confidence intervals

intra-individual differences across technology domains (40.9%, 95% CI [36.1, 45.2]). The technology domains themselves accounted for very little variation (5.8%, 95% CI [0.1, 12.9]), suggesting relatively little consensus in moral relevance in the sample. Individuals seemed to differ in how morally relevant they found big data technologies overall, inasmuch as some people showed lower moral relevance across all technology domains while others showed higher moral relevance across all technology domains. Additionally, the substantial contribution of intra-individual differences towards variance in moral relevance means that individuals are relatively idiosyncratic in the issues they find morally relevant. We also conducted t-tests to compare moral relevance between all technology domains and adjusted the p-values for multiple comparisons using the Tukey method. Moral relevance towards citizen score was significantly (corrected $p < .05$) higher compared to all other technology domains. Moral relevance towards crime prevention was significantly higher compared to employment, healthcare, and banking technology domains. Moral relevance towards criminal investigations was also significantly higher compared to employment, healthcare, and banking technology domains. The remaining comparisons were not significantly different from each other.

2.3 | Discussion

Study 1 showed that there is considerable variation in people's moral relevance towards big data technologies across the six technology domains with responses covering the entire range of the measure. We also found that the variation in moral relevance is largely due to two sources: inter-individual differences and intra-individual differences across technology domains, suggesting a mix between the hypothetical patterns from Figures 1 and 3. We find little variation due to technology domain differences as suggested by the hypothetical pattern in Figure 2. Overall, our results are least consistent with perspectives suggesting that big data technologies are morally relevant for most people (Corlett, 2002; Foley, 2006; O'Neil, 2016) and with moral psychology theories emphasizing consensus in morality within a particular societal context (Morris & Liu, 2015; Rozin, 1999). Our results are most in line with Parent's (1983) argument that people's attitudes towards big data technologies and privacy will depend on what they individually value. In particular, our results underscore prior suggestions that moral relevance has inter-individual variation (Kohlberg, 1981; Schmitt et al., 2005) as well as suggestions that moral relevance is more idiosyncratic across people and domains (Caldwell et al., 2008; Orom & Cervone, 2009; Ryan, 2014; Skitka et al., 2005). We are thus able to narrow the range of plausible theories that can help explain moral relevance and moralization.

3 | STUDY 2

We build on Study 1 to investigate predictors that can explain the observed variation in moral relevance. In particular, given that we know that differences due to technology domain are relatively small, we aim to explain variation in moral relevance due to inter-individual differences and intra-individual differences across technology domains. We used an inductive approach. Using the moralization literature, we identified a number of predictors that could help explain variation in moral relevance due to inter-individual differences and intra-individual differences across technology domains. By casting a wide net, we were inclusive with regard to the theories and perspectives that we tested. This allowed for investigating multiple predictors that could explain the variation in moral relevance. This approach makes it possible to simultaneously test multiple predictors and conclude which of many different theories best explain the variation in moral relevance of big data technologies rather than looking at each theory and perspective separately in a piecemeal approach. We outline our broad rationale below, and list our specific predictions for each predictor in Table 1.

3.1 | Predictors explaining inter-individual differences

To explain inter-individual variation, predictors must be able to vary between individuals. Building on existing theories in both the field of moralization and in the privacy and big data literature, we identified several relevant predictors. We categorized the predictors in three broad areas: (1) differences in personality traits, (2) differences in cognitive styles and attitudes towards others, and (3) differences in specific traits related to big data technologies.

We examined personality traits because the literature on morality links basic personality traits with moral development (Lifton, 1985) and moral behavior (Hilbig et al., 2015). Additionally, personality traits are also robust predictors of a number of behaviors (Soto, 2019) and attitudes (Gerber et al., 2011) in general and they have been associated with privacy attitudes and big data technologies (Charness et al., 2018; Junglas et al., 2008; Sayre & Dahling, 2016). In the case of cognitive styles and attitudes towards others, we identified predictors like political extremity that have been linked to moral relevance in other topics (Ryan, 2014). We also identified cognitive styles that tap into psychological processes that may underlie the formation of moralized attitudes in general (e.g., need for cognition; Cacioppo & Petty, 1982) or attitudes towards privacy in general (e.g., generalized distrust). Using arguments that moral judgment and moral values are processed intuitively (Gray et al., 2014; Haidt, 2001; Ward & King, 2018), we also assessed cognitive measures of Faith in Intuition. Lastly, we chose predictors that were specifically linked to common criticisms of big data technologies, such as concern for privacy and the sensitivity to justice and fairness (cf. O'Neil, 2016). Since privacy violations and discrimination (Obermeyer et al., 2019) are some drawbacks of big data technologies, we argue that people who are more concerned about privacy violations or people who are especially sensitive to justice concerns will find these technologies more morally relevant. Thus, we cover a number of possible predictors of inter-individual differences in the moral relevance of big data technologies.

TABLE 1 Predictions for predictors related to inter-individual differences and intra-individual differences across technology domains

Predictor	Rationale	Prediction
Inter-Individual differences		
Personality traits		
Open-mindedness	People higher in open-mindedness show attitudes with higher concern for privacy (Junglas et al., 2008; Sayre & Dahling, 2016)	Open-mindedness will be positively associated with moral relevance
Negative emotionality	Moralized attitudes have been linked to an expression of negative emotions like anger and disgust (Mullen & Skitka, 2006; Wisneski & Skitka, 2017)	Negative emotionality will be positively associated with moral relevance
Extraversion	Although extraversion has been linked to altruistic behavior (Oda et al., 2014), it does not seem related to moral relevance	Extraversion will not be associated with moral relevance
Conscientiousness	People higher in conscientiousness are more sensitive to unfairness and inequity (Woodley et al., 2016). Big data technologies may be perceived as unfair (O'Neil, 2016; Pew Research Center, 2018) and viewed more morally by those high in conscientiousness	Conscientiousness will be positively associated with moral relevance
Agreeableness	Lower agreeableness is associated with lower levels of belief in the usefulness of a new technology (Devaraj et al., 2008) and people lower in agreeableness also make harsher judgments (Junglas et al., 2008). They could perceive big data technologies as less useful and judge them more harshly for privacy threats	Agreeableness will be negatively associated with moral relevance
Cognitive styles and attitudes towards others		
Political extremity	People who are extreme in their party identification are also more likely to moralize issues (Ryan, 2014). This seems likely in the big data context as well	Political extremity will be positively associated with moral relevance
Need for cognition	People high in need for cognition rely on effortful thought processes to make decisions and are more flexible in their thinking (Cacioppo & Petty, 1982; Evans et al., 2003). People low in need for cognition are less flexible in their thinking and would be more likely to hold rigid moral attitudes. Although this was our preregistered prediction, we came across some literature that states that higher need for cognition is related to higher moral relevance, as moralizers seek more information (cited in Skitka, 2010)	Need for cognition will be negatively associated with moral relevance
Need for closure	Individuals high in need for closure are averse to ambiguous situations and prefer resolving them by making decisions quickly (Webster & Kruglanski, 1994). High moral relevance would provide a clear distinction between two choices and resolve ambiguity	Need for closure will be positively associated with moral relevance
Faith in intuition	Moral judgments and moral values are associated with processing situations intuitively (Gray et al., 2014; Haidt, 2001; Ward & King, 2018)	Faith in intuition will be positively associated with moral relevance
Cynical distrust	Higher cynical distrust is associated with higher concerns for privacy, i.e., those who are generally distrusting of people also show concern for privacy (Liao, Liu, & Chen, 2011)	Cynical distrust will be positively associated with moral relevance
Predictor specific to big data technologies		
Privacy concern	Big data technologies have the potential to violate privacy and people who find these technologies unacceptable name privacy violations as their top concern (Pew Research Center, 2018)	Privacy concerns will be positively associated with moral relevance
Justice sensitivity	Big data technologies can be unfair as algorithms may be biased against certain groups of people (O'Neil, 2016). Those concerned about justice would care about this	Justice sensitivity will be positively associated with moral relevance
Intra-individual differences across technology domains		
Moral foundations		
Purity Loyalty Liberty Harm Fairness Authority	Moral judgment is often rooted in perceptions of harm (Schein & Gray, 2015; Schein & Gray, 2018). Attitudes that are based on perceptions of fairness, loyalty, purity, authority, and liberty could also be associated with moralization (Graham et al., 2011)	Higher relevance of attitudes to the moral foundations of purity, loyalty, liberty, harm, fairness, and authority will be associated with a higher moral relevance

(Continues)

TABLE 1 (Continued)

Predictor	Rationale	Prediction
Risks and benefits		
Perceived risks perceived benefits	Moral relevance is associated with people's perception of risks and benefits of the attitude object (Gray et al., 2014)	Higher perceptions of risks and benefits will be associated with higher moral relevance
Emotional reactions		
Surprise Gratefulness Fear Disgust Curiosity Creeped out Anger	Higher levels of negative moral emotions (Hutcherson & Gross, 2011) of anger, and disgust, are associated with moralized attitudes (Mullen & Skitka, 2006; Wisneski & Skitka, 2017). Positive emotions of gratefulness and surprise have also been viewed as moral emotions (Cohen, 2006) and would also be associated with moral relevance	Higher levels of all emotional reactions will be associated with higher moral relevance
Trust in authorities	Trust towards the parties that use these technologies (e.g., government officials, corporations) could influence people's attitudes	Lower levels of trust will be associated with higher levels of moral relevance

Note: Column 1 indicates the predictor associated with moral relevance, column 2 indicates the rationale behind the prediction, and column 3 indicates the prediction for the predictor.

3.2 | Predictors explaining intra-individual differences across technology domains

We also investigated predictors that are likely to contribute to variation due to intra-individual differences across technology domains. To explain such variation, the predictors must be able to simultaneously vary both across individuals and technology domains to capture idiosyncratic perceptions of the technologies. We investigated cognitive appraisals such as perceived risks and benefits, relevant emotional reactions, relevance to moral foundations, and trust towards the party using the technology (e.g., the police). Cognitive appraisals relevant to decision-making regarding big data technologies (Kodapanakkal et al., 2020), such as the perceived risks/harms and benefits are also central in moral psychology literature (Skitka et al., 2021). Variation in moral relevance is also associated with consequent change in perception of harm (Brandt et al., 2015) and the theory of dyadic morality which argues that moralization is associated with an intuitive perception of harm (Schein & Gray, 2018). Existing work would thus predict that moral relevance would be associated with higher perception of risks. We also investigated relevant emotional reactions (Skitka et al., 2021) towards technology domains. Negative emotions like anger, and disgust have also been associated with moralization (Skitka & Wisneski, 2011; Wisneski & Skitka, 2017). We also investigated predictors that are central in moral psychology literature, such as the relevance of one's attitude to moral foundations (Graham et al., 2011). We argue that these moral foundations are associated with attitudes towards big data technologies as people express concerns about privacy violations, discrimination, and the intrusive nature of these technologies which have links to the foundations of harm/care, fairness, authority, and liberty. All the above-mentioned predictors vary by both individual and technology domain.[3] For example, people may find a particular technology domain morally relevant because they believe it causes harm to people and another technology domain morally relevant because it unfairly discriminates against individuals. Similarly, people may feel anger towards one technology domain and disgust towards another and different people may express different levels of these emotions. These predictors are measured separately for each person and each technology domain.

[3] Because these predictors also vary across technology domain they incidentally can also help explain the (small amount of) variation due to technological domain.

3.3 | Method

3.3.1 | Participants

The study was conducted on Prolific (www.prolific.co) and was preregistered (https://osf.io/npkyt). We recruited two samples (Sample 2a and 2b). Sample 2a consisted of only participants who were born and currently live in the United States. Sample 2a was our intended study; however, we mistakenly first opened the study without restricting by country. To make use of this data, we analyzed it and call it Sample 2b. It was not filtered by nationality or residence and thus had participants from 50 countries. The preregistered analyses were the same for both samples with one exception: in Sample 2b, nationality was included as a control variable which was not preregistered.

We used the R package "simr" for conducting power analysis (https://osf.io/v3j85/). We used the Study 1 dataset in our model and determined the fixed and random effects and input these parameters in the power analysis. We included random effects for an interaction between participant and technology domain in the simulated model which was not included for the power analysis of Study 1. Additionally, we used a more conservative effect size estimate of 0.05. The calculation gave a sample size of 600 participants (~80% power). For the variance decomposition analysis when no fixed effects are included, the Type 1 error rates are close to .05 with six technology domains. These error rates are not affected by the number of domains

(Judd et al., 2012) and six technology domains are sufficient for the analysis.

In accordance with the preregistered exclusion criteria, participants who failed the attention check were excluded leaving 621 participants for the analyses of Sample 2a (309 females and 312 males, $M_{age} = 36.4$, $SD_{age} = 11.5$) and 589 participants for the analyses of Sample 2b (293 females, 294 males, and 2 who did not report gender; $M_{age} = 31.5$, $SD_{age} = 9.8$). Participants in Sample 2b were of 50 different nationalities. Nationalities with fewer than 25 participants were grouped by region. 33.3% were UK nationals, 12.5% from Portugal, 11.5% from Poland, 6% from Italy, 5.7% from Greece, 4.8% from Spain, 17.1% from other European countries (labeled Europe), 3.7% from North and South America (labeled Americas), and 5.3% from other countries. Participants received 2.0 GBP for completing the survey which lasted around 15 min. The same questionnaire was used for both Samples 2a and 2b and for the rest of this section they will be referred to as Study 2.

3.3.2 | Design and procedure

Participants first completed measures intending to account for inter-individual differences in moral relevance. Then they read the same descriptions of technologies that were used in Study 1. The technology descriptions were presented in random order. For each technology, they saw the description, followed by questions related to their attitude towards the technology, moral relevance, and measures intending to account for intra-individual differences across technology domains in moral relevance. This was followed by the remaining five technology domains and demographic questions.

Inter-individual differences

The order in which participants saw the scales was randomized. Participants saw all items of a single scale at once and within each scale, the items were randomized. Table 2 illustrates the scales used to assess inter-individual differences, example items, and reliabilities. Participants responded on a 7-point Likert-type scale to all measures. A correlation matrix for both Samples 2a and 2b is available in the supplemental materials (see Tables S2 and S3).

Additionally, participants reported to what extent they trusted the following institutions (Devos et al., 2002): the police, the government, the legal/judicial system, banks, the healthcare system, and major corporations on a 7-point scale (1 = not at all to 7 = very much). Since it seemed odd to ask this question multiple times within each technology domain, we asked them together before presenting the technology descriptions. Although this question was asked along with the inter-individual difference predictors, for the analyses they were linked to the relevant technology domain as intra-individual differences (e.g., the police was linked to the criminal investigations technology domain).

Next, participants saw the description of a technology domain. The order in which participants saw the six technology domains was randomized. After reading the description, similar to Study 1, participants reported how much they supported or opposed the technology (attitude) and how morally convicted they felt about their position (Sample 2a, $r = .89$; Sample 2b, $r = .82$). This was followed by measures related to intra-individual differences across technology domains.

Intra-individual differences across technology domains

For each technology domain, participants reported the relevance of their position to moral foundations, perceived risks and benefits, and emotional reactions, in that order. All items on one scale were presented together and the items within each scale were randomized. Participants responded to a 7-point Likert-type scale for all measures except emotional reactions, which was on a 100 point scale (0-100). Table 2 lists the scales used to assess these measures, example items, and reliabilities.

Similarly, participants responded to the remaining five technology domains, which were presented in a random order after which they answered demographic questions (age, gender, political ideology, education, and ethnicity). Political ideology was measured on a scale of 1 to 7 (1 = extremely liberal; 7 = extremely conservative) using 4 items: in terms of general, social, economic, and national security policy. We folded each of these four ideology items to create four political extremity predictors, which we included in the analyses as predictors that explain inter-individual differences.

3.4 | Results

> *Question 1 & 2: Is there variation in moral relevance and to what extent does this variation come from inter-individual differences, differences in technology domains, and intra-individual differences across technology domains?*

We replicated the results of Study 1 in both samples. There was variation for each technology domain (see Figure 4). Moral relevance scores covered the entire range of the measure (Sample 2a $SD = 1.85$, range [1.59, 2.01], Sample 2b $SD = 1.63$, range [1.37, 1.94]). The average moral relevance scores across technology domains varied from 3.9 to 5.6 in Sample 2a and from 4.4 to 4.9 in Sample 2b. Similar to Study 1, the average moral relevance was lower for some technology domains and higher for others but with considerable variation in all technology domains in both samples.

Most importantly, the source of variation was similar to Study 1 in both Samples 2a and 2b. Using a cross-classified model (see Figure 5), we again found that this variation came mainly from inter-individual differences (Sample 2a: 28.8% [23.7, 33.1]; Sample 2b: 24.1% [20.8, 27.5]) and intra-individual differences across technology domains (Sample 2a: 50.0% [43.9, 55.6]; Sample 2b: 56.3% [53.1, 59.3]), with little variation due to the difference between technology domains (Sample 2a: 10.0% [0.9, 20.3]; Sample 2b: 1.6% [0.0, 3.7]). Similar to Study 1, these results suggest that the source of variation is a mix between the hypothetical patterns shown in Figures 1 and 3 in the introduction.

TABLE 2 Measures, example items, and reliability

Measure	Example items	Reliability
Inter-individual predictors		
Personality traits (15-item BFI-2-XS scale; Soto & John, 2017)		
Open-mindedness	I am someone who is original, comes up with new ideas	Sample 2a $\alpha = .67$ Sample 2b $\alpha = .52$
Negative emotionality	I am someone who worries a lot	Sample 2a $\alpha = .79$ Sample 2b $\alpha = .74$
Extraversion	I am someone who is full of energy	Sample 2a $\alpha = .61$ Sample 2b $\alpha = .59$
Conscientiousness	I am someone who tends to be disorganized (R)	Sample 2a $\alpha = .76$ Sample 2b $\alpha = .58$
Agreeableness	I am someone who is compassionate, has a soft heart	Sample 2a $\alpha = .56$ Sample 2b $\alpha = .56$
Cognitive styles and attitudes towards others		
Need for cognition (5 items; rational-experiential inventory; Pacini & Epstein, 1999)	I would prefer complex to simple problems	Sample 2a $\alpha = .86$ Sample 2b $\alpha = .75$
Need for closure (15-item scale; Roets & Van Hiel, 2011)	I don't like situations that are uncertain	Sample 2a $\alpha = .88$ Sample 2b $\alpha = .82$
Faith in Intuition (5 items; rational-experiential inventory, Pacini & Epstein, 1999)	My initial impressions of people are almost always right	Sample 2a $\alpha = .91$ Sample 2b $\alpha = .85$
Cynical distrust (8-item scale; Greenglass & Julkunen, 1989)	I think most people would lie to get ahead	Sample 2a $\alpha = .89$ Sample 2b $\alpha = .85$
Predictors specific to big data technologies		
Privacy concern (16-item scale; Buchanan et al., 2007)	Are you concerned about online identity theft?	Sample 2a $\alpha = .95$ Sample 2b $\alpha = .94$
Justice sensitivity (10-item subscale; Schmitt et al., 2010)	I am upset when someone is undeservingly worse off than others	Sample 2a $\alpha = .90$ Sample 2b $\alpha = .85$
Intra-individual predictors		
Moral foundations (1 item per foundation; Graham et al., 2011)		
Question: To what extent is your position on the use of this technology relevant to		
Purity	Violating standards of purity and decency	–
Loyalty	Showing disloyalty	–
Liberty	Interfering in the lives of others	–
Harm	Harm	–
Fairness	Unfairness	–
Authority	Disrespecting authority	–
Perceived risks and benefits (3-items for each; Kehr et al., 2015)		
Perceived risks	In general, the information that this technology gathers to serve its purpose would be risky for people	Sample 2a $\alpha = .92$ Sample 2b $\alpha = .89$
Perceived benefits	This technology will help people obtain services/products they want	Sample 2a $\alpha = .93$ Sample 2b $\alpha = .91$

(Continues)

TABLE 2 (Continued)

Measure	Example items	Reliability
Emotional reactions (1 item per emotion)		
Question: to what extent did the technology make you feel?		
Surprise	Surprised	–
Gratefulness	Grateful	–
Fear	Scared	–
Disgust	Disgusted	–
Curiosity	Curious	–
Creeped out	Creeped out	–
Anger	Angry	–

Note: Measures without an indicator of reliability were single item measures.

We also conducted t-tests to compare moral relevance between all technology domains and adjusted the p-values for multiple comparisons using the Tukey method. For Sample 2a, we found that moral relevance towards crime prevention and criminal investigations technology domain were not significantly different from each other. All remaining comparisons were significantly different from each other. For Sample 2b, moral relevance towards banking was lower compared to healthcare, criminal investigations, crime prevention, and citizen score technology domains. Moral relevance towards employment was lower compared to citizen scores, crime prevention, and healthcare technology domains. All remaining comparisons were not significantly different from each other.

Question 3: What predictors explain the variation in moral relevance?

3.4.1 | Analytical approach

To answer our third question, we used two types of multilevel models. For Model Type I, we included each independent variable separately as a fixed factor, with random intercepts for technology domain, individual, and technology domain-individual interaction, and moral relevance as a dependent variable (the number of analyses we ran with Model Type I is the same as the number of variables; one analysis for each variable). For Model Type II, we included all the independent variables as fixed factors, with random intercepts for technology domain, individual, and technology domain-individual interaction, and moral relevance as a dependent variable. Model Type II assessed the association of the independent variables with moral relevance after controlling for the other variables. In both model types, the variables related to inter-individual differences were mean-centered between participants while the variables related to intra-individual differences across technology domains were mean-centered within participants. Additionally, following the suggestion of a reviewer, we also included grand mean-centered variables related to intra-individual differences to test how much variance these predictors would explain at the inter-individual level. We first calculated a composite score for each measure of intra-individual differences for each individual and we then grand mean-centered each of the composite scores. For example, for disgust for each participant we averaged their ratings of disgust for all of the technologies and then grand-mean entered this composite disgust score. This grand mean-centered score for disgust can then vary between persons and we interpret this effect at the inter-individual level. The inclusion of these grand mean-centered variables was not preregistered, but since they provide a more complete test of our question we have reported these results. The preregistered analysis for this question has been moved to the Supplemental Materials. Region is included as a variable to control for differences between countries in Sample 2b with the following categories: United Kingdom, Portugal, Poland, Italy, Greece, Spain, Europe, Americas, and other countries. The category Americas is treated as a reference.

The results for Study 2 are reported below in Figures 6 and 7 (and Tables S4 and S5 in the supplemental materials). Table 3 summarizes the results for all predictors across both samples.

3.4.2 | Inter-individual predictors

In total, the inter-individual predictors explain 30.1% (Sample 2a) and 33% (Sample 2b) of the variance due to inter-individual differences in Sample 2a (28.8%) and Sample 2b (24.1%) respectively. The predictors at the inter-individual level correlated with each other within a range of −0.42 to 0.90 for Sample 2a and −0.34 to 0.89 for Sample 2b. Figures 6a and 6b illustrate that after controlling for other predictors in Model Type II, we found that no personality traits were associated with moral relevance. Among cognitive styles, only Faith in Intuition had significant positive associations with moral relevance, which was consistent with our predictions (in Sample 2b). Among predictors related to big data technologies, consistent with our predictions, Justice Sensitivity was associated positively with moral relevance across both samples. As opposed to our predictions, Privacy Concerns, Cynical Distrust, and Political Extremity were not associated with moral relevance.

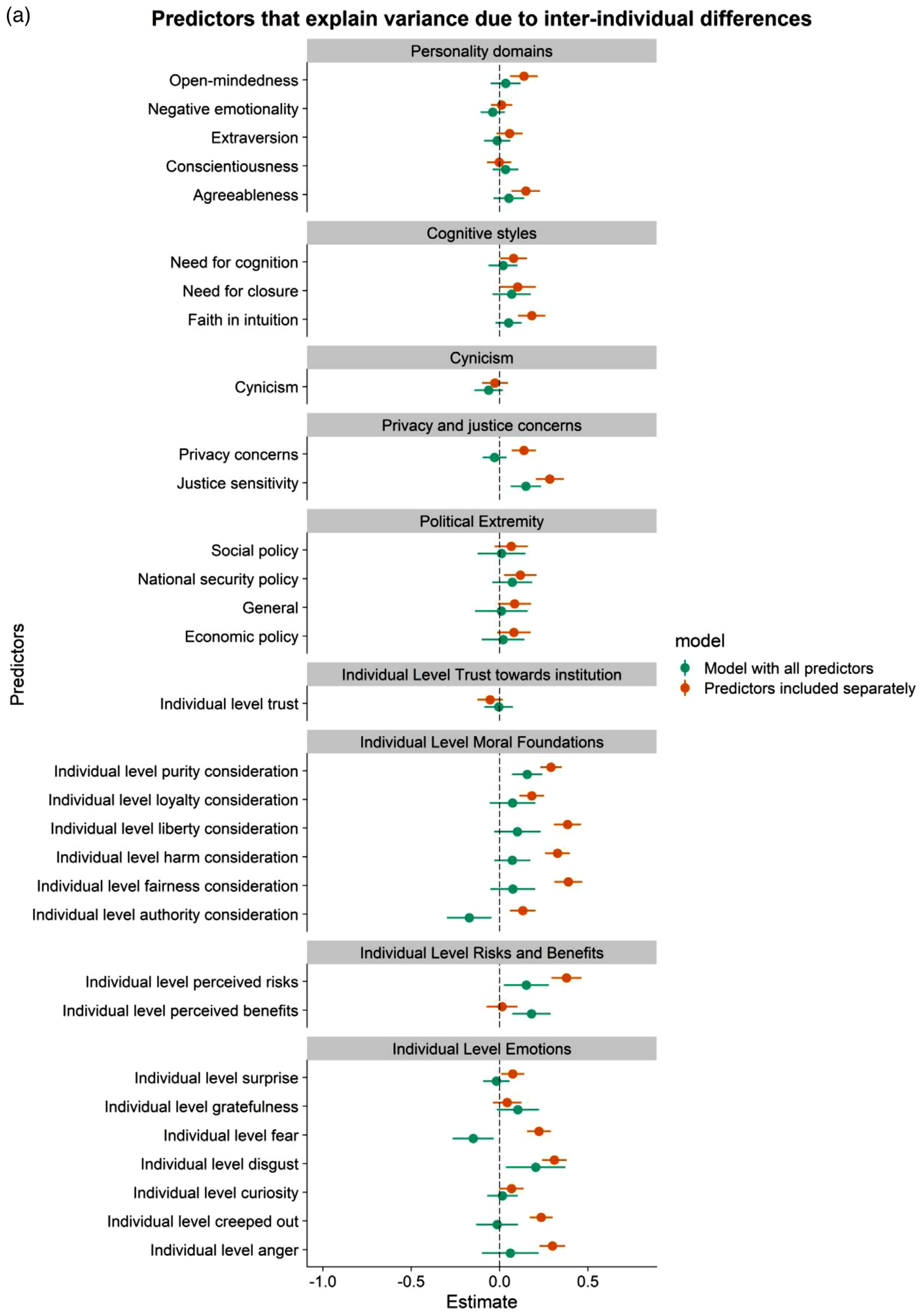

FIGURE 6 (a) Association of moral relevance with predictors related to inter-individual differences for Sample 2a. The orange estimates represent the models where each predictor is included separately and the green estimates represent the model where all predictors are included together. The x-axis represents the coefficient estimate of the predictor with moral relevance and the y-axis represents the various predictors. Errors bars denote 95% confidence intervals. (b) Association of moral relevance with predictors related to inter-individual differences for Sample 2b. The orange estimates represent the models where each predictor is included separately and the green estimates represent the model where all predictors are included together. The x-axis represents the coefficient estimate of the predictor with moral relevance and the y-axis represents the various predictors. Errors bars denote 95% confidence intervals. Region is included as a predictor in Sample 2b

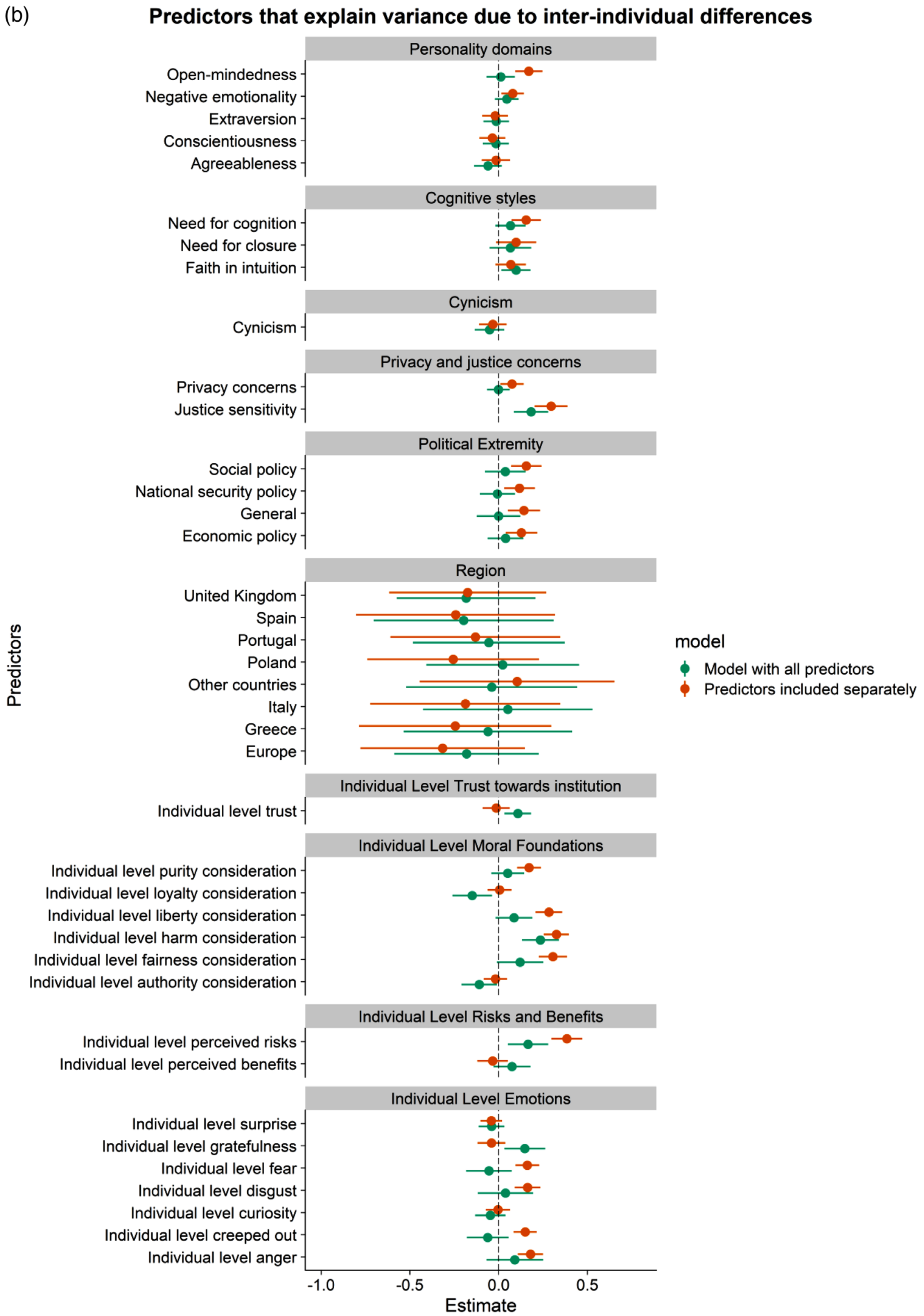

FIGURE 6 Continued

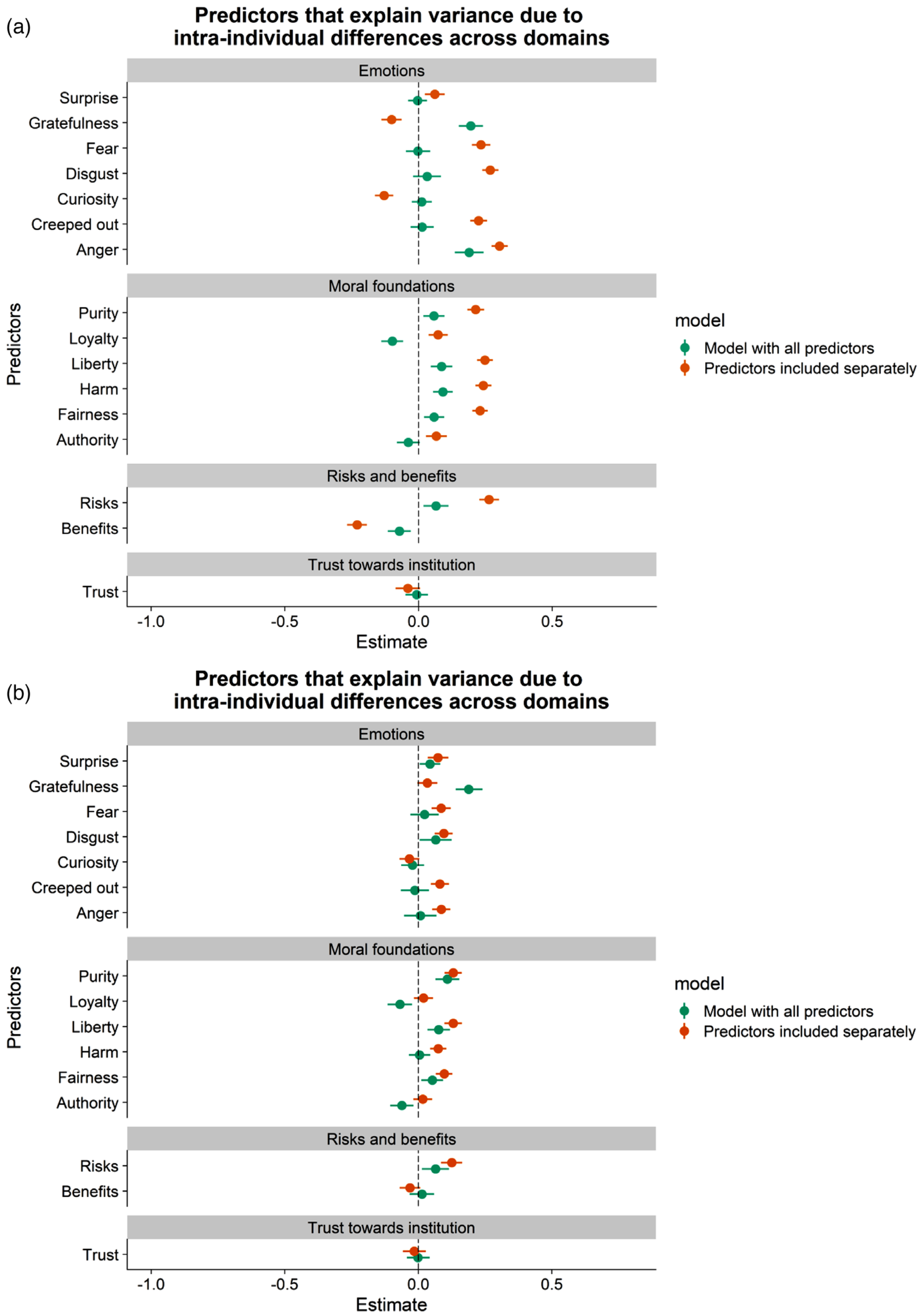

FIGURE 7 (a) Association of moral relevance with predictors related to intra-individual differences across technology domains for Sample 2a. The orange estimates represent the models where each predictor is included separately and the green estimates represent the model where all predictors are included together. The x-axis represents the coefficient estimate of the predictor with moral relevance and the y-axis represent the various predictors. Errors bars denote 95% confidence intervals. (b) Association of moral relevance with predictors related to intra-individual differences across technology domains for Sample 2b. The orange estimates represent the models where each predictor is included separately and the green estimates represent the model where all predictors are included together. The x-axis represents the coefficient estimate of the predictor with moral relevance and the y-axis represent the various predictors. Errors bars denote 95% confidence intervals

TABLE 3 Predictors, predictions, and model outcomes

Predictor	Preregistered prediction	Sample 2a		Sample 2b	
		Model type 1	Model type 2	Model type 1	Model type 2
Inter-individual differences					
Cynical distrust	Cynical distrust will be positively associated with moral relevance	✗	✗	✗	✗
Open-mindedness	Open-mindedness will be positively associated with higher moral relevance	✓	✗	✓	✗
Negative emotionality	Negative emotionality will be positively associated with moral relevance	✗	✗	✓	✗
Extraversion	Extraversion will not be associated with moral relevance	✓	✓	✓	✓
Conscientiousness	Conscientiousness will be positively associated with moral relevance	✗	✗	✗	✗
Agreeableness	Agreeableness will be negatively associated with moral relevance	#	✗	✗	✗
Political extremity – social policy	Political extremity related to social policy, national security policy, general, and economic policy will be associated with higher moral relevance	✗	✗	✓	✗
Political extremity – national security policy		✓	✗	✓	✗
Political extremity – general		✗	✗	✓	✗
Political extremity – economic policy		✗	✗	✓	✗
Privacy concerns	Privacy concerns will be positively associated with moral relevance	✓	✗	✓	✗
Justice sensitivity	Justice sensitivity will be positively associated moral relevance	✓	✓	✓	✓
Need for cognition	Need for cognition will be negatively associated with moral relevance	#	✗	#	✗
Need for closure	Need for closure will be positively associated with moral relevance	✗	✗	✗	✗
Faith in intuition	Faith in intuition will be positively associated with moral relevance	✓	✗	✗	✓
Region	No prediction preregistered	NA	NA	n.s.	n.s.
Individual level surprise	Higher surprise towards technologies will be associated with higher moral relevance	✓	✗	✗	✗
Individual level gratefulness	Higher gratefulness towards technologies will be associated with higher moral relevance	✗	✗	✗	✓
Individual level fear	More fear towards technologies will be associated with higher moral relevance	✓	#	✓	✗
Individual level disgust	Higher disgust towards technologies will be associated with higher moral relevance	✓	✓	✓	✗
Individual level curiosity	Higher curiosity towards technologies will be associated with higher moral relevance	✗	✗	✗	✗

(Continues)

TABLE 3 (Continued)

Predictor	Preregistered prediction	Sample 2a		Sample 2b	
		Model type 1	Model type 2	Model type 1	Model type 2
Individual level creeped out	Higher levels of feeling creeped out towards technologies will be associated with higher moral relevance	✓	✗	✓	✗
Individual level anger	Higher anger towards technologies will be associated with higher moral relevance	✓	✗	✓	✗
Individual level purity	Purity will be associated with higher moral relevance	✓	✓	✓	✗
Individual level loyalty	Loyalty will be associated with higher moral relevance	✓	✗	✗	#
Individual level liberty	Liberty will be associated with higher moral relevance	✓	✗	✓	✗
Individual level harm	Harm will be associated with higher moral relevance	✓	✗	✓	✓
Individual level fairness	Fairness will be associated with higher moral relevance	✓	✗	✓	✗
Individual level authority	Authority will be associated with higher moral relevance	✓	#	✗	#
Individual level perceived risks	Higher perception of risks will be associated with higher moral relevance	✓	✓	✓	✓
Individual level perceived benefits	Higher perception of benefits will be associated with higher moral relevance	✗	✓	✗	✗
Individual level trust	Lower levels of trust towards parties in charge of the technology will be associated with higher moral relevance	✗	✗	✗	#
Intra-individual differences					
Surprise	Higher surprise towards technologies will be associated with higher moral relevance	✓	✗	✓	✓
Gratefulness	Higher gratefulness towards technologies will be associated with higher moral relevance	#	✓	✗	✓
Fear	More fear towards technologies will be associated with higher moral relevance	✓	✗	✓	✗
Disgust	Higher disgust towards technologies will be associated with higher moral relevance	✓	✗	✓	✓
Curiosity	Higher curiosity towards technologies will be associated with higher moral relevance	#	✗	✗	✗
Creeped out	Higher levels of feeling creeped out towards technologies will be associated with higher moral relevance	✓	✗	✓	✗
Anger	Higher anger towards technologies will be associated with higher moral relevance	✓	✓	✓	✗

(Continues)

TABLE 3 (Continued)

Predictor	Preregistered prediction	Sample 2a Model type 1	Sample 2a Model type 2	Sample 2b Model type 1	Sample 2b Model type 2
Purity	Purity will be associated with higher moral relevance	✓	✓	✓	✓
Loyalty	Loyalty will be associated with higher moral relevance	✓	#	✗	#
Liberty	Liberty will be associated with higher moral relevance	✓	✓	✓	✓
Harm	Harm will be associated with higher moral relevance	✓	✓	✓	✗
Fairness	Fairness will be associated with higher moral relevance	✓	✓	✓	✓
Authority	Authority will be associated with higher moral relevance	✓	✗	✗	#
Perceived risks	Higher perception of risks will be associated with higher moral relevance	✓	✓	✓	✓
Perceived benefits	Higher perception of benefits will be associated with higher moral relevance	#	#	✗	✗
Trust	Lower levels of trust towards parties in charge of the technology will be associated with higher moral relevance	✗	✗	✗	✓

Note: Column 1 denotes the predictor, Column 2 denotes the preregistered* prediction, and the remaining columns denote where the prediction was confirmed (✓) or not (✗) in the analyses. "#" denotes significant effects found in the direction opposite to predictions. "NA" denotes that the analysis was not applicable to the predictor region'. "n.s." denotes that there was no effect of region on moral relevance.
*Predictions for individual level trust, emotions, moral foundations, and perceived risks and benefits were not preregistered at the inter individual level so we assume the same predictions for these as the ones made at the intra-individual level.

Among individual level emotions, disgust and gratefulness were positively associated with moral relevance. Among moral foundations at the individual level, Harm and Purity were positively associated with moral relevance. Authority and Loyalty were negatively associated with moral relevance. However, this result should be interpreted carefully as this association switches from positive to negative likely due to suppression effects.

Individuals who perceived higher risk overall were also more likely to find the technologies morally relevant. Individuals who perceived higher benefits overall were also more likely to find the technologies morally relevant. Trust at the individual level was positively associated with moral relevance. However, the results for perceived benefits and trust at the individual level should be interpreted carefully as the association switches from negative to positive likely due to suppression effects.

3.4.3 | Intra-individual differences across technology domains

These predictors together explain 18.1% (Sample 2a) and 6.3% (Sample 2b) of the total variance due to intra-individual differences across technology domains in Sample 2a (50.0%) and Sample 2b (56.3%) respectively. The predictors at the intra-individual level correlated with each other within a range of −0.66 to 0.86 for Sample 2a and −0.69 to 0.87 for Sample 2b. Figures 7a and 7b illustrate that after controlling for all other predictors in Model Type II, emotional responses of surprise, gratefulness, anger, and disgust were positively associated with moral relevance which was consistent with our predictions. Among moral foundations,[4] relevance to Harm, Purity, and Liberty, and Fairness were positively associated with moral relevance in line with our predictions. On the other hand, Loyalty and Authority were negatively associated with moral relevance. The findings of Loyalty and Authority should be interpreted carefully as the association switches from positive to negative likely due to suppression effects. As predicted, perceived risks were positively associated with moral relevance. Contrary to our prediction, perceived benefits were negatively associated with moral

[4] A reviewer suggested testing if the moral foundations interacted with political ideology. In Sample 2a, an interaction between the moral foundation of Liberty and each of the four measures of political ideology significantly predicted moral relevance. Specifically, those who were more liberal and based their attitudes in the moral foundation of Liberty were more likely to show higher moral relevance towards the technologies. No such interaction was found in Sample 2b. These analyses were not preregistered.

relevance. Trust towards the institution that collects data was negatively associated with moral relevance as predicted.[5]

4 | GENERAL DISCUSSION

The present research aimed to quantify the extent to which different sources, namely, inter-individual, technology domain, and intra-individual across technology domains, explain variation in moral relevance. Additionally, it also aimed to test predictors associated with moral relevance that explain this variation. Below is a summary of our findings and their implications.

4.1 | Is there variation in moral relevance towards big data technologies?

Yes. We found considerable variation in people's moral relevance towards big data technologies across technology domains of criminal investigations, crime prevention, citizen scores, healthcare, banking, and employment with responses covering the entire range of the measure. The variation indicates that although issues concerning big data technologies (for example, privacy violations) are viewed as normatively moral in some philosophical works (Corlett, 2002; Foley, 2006) as well as the media (Guliani, 2019; Pollmann, 2019), it is not the case that individuals agree with this assessment. The results also show that variation in moral relevance of big data technologies is similar to other issues. For example, attitudes towards abortion issues (Skitka et al., 2005), genetically modified (GM) foods (Scott et al., 2016), and legalizing euthanasia (Cole Wright et al., 2008) also vary in their moral relevance.

4.2 | What is the source of this variation and to what extent do these sources explain variation?

The variation in moral relevance can be explained largely by two sources: inter-individual differences (~29%) and intra-individual differences across technology domains (~49%). Differences in technology domains explain very little variation (~6%). Participants tend to see all the presented technology domains as more or less morally relevant overall (inter-individual differences) and, at the same time, participants have idiosyncratic perceptions of what is morally relevant across technology domains (intra-individual differences across technology domains).

These results imply that theories that separately emphasize inter-individual differences (e.g., Schmitt et al., 2005), intra-individual differences (e.g., Ryan, 2014), or domain differences (e.g., Morris & Liu, 2015) will not provide a complete picture. The actual pattern of variation is a mix of the hypothetical patterns presented in the introduction that depict inter-individual differences and intra-individual differences across domains (Figures 1 and 3). The idea that moralization is a feature of the individual and is driven by individual differences such as caring about injustice (Schmitt et al., 2005) or individual intuition (Haidt, 2001) is supported. Additionally, the idea that people have idiosyncratic perceptions about what they find morally relevant (Caldwell et al., 2008; Orom & Cervone, 2009) is also supported. However, the idea that there is consensus in morality within a society (Morris & Liu, 2015; Rozin, 1999) and so variation in moralization would come from attitude differences towards different domains is not supported. So instead of focusing on theories that would explain inherent differences between the technology domains (for example, government-related vs. private domains; algorithms vs. surveillance), focusing on idiosyncratic approaches (Ryan, 2014; Skitka et al., 2005) that address how individuals uniquely perceive each domain is more valuable. Studies conducted with single domains as done in previous research do not provide the opportunity to evaluate this idiosyncratic variation.

4.3 | What predictors explain this variation?

4.3.1 | Inter-individual differences

Predictors more specific to big data technologies like the sensitivity to justice explain variation in moral relevance. One of the top concerns that people voice regarding big data technologies are concerns about unfairness due to biased algorithms (O'Neil, 2016). These findings imply that people especially sensitive to justice concerns are more likely to find big data technologies morally relevant. Although people are also concerned about privacy violations (Pew Research Center, 2018), privacy concerns were not associated with moral relevance in the full model.

Among cognitive styles, higher Faith in Intuition was associated with higher moral relevance in line with work which finds that moral judgments and values are associated with intuitive processing of situations or relying on gut feelings (Gray et al., 2014; Haidt, 2001; Ward & King, 2018). Personality traits, in general, were not associated with moral relevance, implying that most broad personality traits do not seem to drive people's attitudes towards big data technologies.

Additionally, at the inter-individual level, people who were overall more grateful also found the technologies more morally relevant in line with the idea that gratefulness is viewed as a moral emotion (Cohen, 2006). Those who showed overall higher levels of disgust also found the technologies morally relevant, tying in with research on affect and moralization (e.g., Feinberg et al., 2019). Fear at the individual level was also associated with more moralized attitudes. This is consistent with research that shows negative affect is related to moralized attitudes (e.g., Skitka & Wisneski, 2011).

People who based their attitudes on the moral foundations of Harm, Purity, Authority, and Loyalty were also more moralized, which ties into moral judgment literature (e.g., Graham et al., 2011). In line with

[5] These predictors also explain around 90% (Sample 2a) and 52% (Sample 2b) of the total variance due to differences in technology domains in Sample 2a (10%) and Sample 2b (1.6%) respectively.

moralization literature (e.g., Gray et al., 2014), we find that overall higher perception of risks is associated with higher moral relevance. Overall, perception of benefits was negatively associated with moral relevance.

We find that among inter-individual differences, moral relevance is associated with predictors that are closely related to the technology domains in question, such as justice sensitivity. Additionally, moral relevance also varies at an individual level, depending on people's overall levels of disgust, perception of risks and benefits, and relevance to moral foundations towards the technologies. It is also associated with more intuitive cognitive styles. Thus, when we think of inter-individual traits related to moral relevance, it is not the case that a person is more or less moralized in general, but rather they are moralized on the basis of inter-individual traits relevant to the topics in question.

4.3.2 | Intra-individual differences across technology domains

We found that predictors measured at this level explained intra-individual variation across domains, and also explained some variance at the individual level (discussed in previous section). We found that moral relevance was based in considerations of Harm, Purity, Fairness, Liberty, Authority, and Loyalty among the moral foundations. Although this is a popular explanation in moral judgment literature (e.g., Christie et al., 2019; Graham et al., 2011), we provide empirical evidence that people's moral relevance is based on these moral foundations for big data technologies.

In line with moralization literature (Feinberg et al., 2019; Gray et al., 2014), we find that higher perception of risks is associated with higher moral relevance. Contrary to the existing literature and our predictions, we find that lower (not higher) perception of benefits is associated with higher moral relevance. One explanation for this finding is that people expect these new technologies to provide benefits by default and will be more moralized about their implementation if they do not find them beneficial. Lower trust towards institutions was associated with higher moral relevance, in line with research that connects trust towards organizations with people's values (Devos et al., 2002).

Overall, these findings show that predictors that vary both between individuals and between technology domains are good predictors of moral relevance at both the intra-individual and inter-individual levels. People have a unique sensitivity to different predictors depending on the domain but at the same time individuals differ from each other in their overall levels of these predictors.

4.4 | Theoretical and practical implications

Our findings build on past research on moralization and provide insights into where the variation in moral relevance comes from. Previous research focuses on multiple distinct theories of moralization that are related to the idea that moralization is a characteristic of the individual, (e.g., Ward & King, 2018), or the idea that moralization occurs at the level of societies (e.g., Morris & Liu, 2015) and differences are due to differences in domains, or the idea that moralization is due to intra-individual differences across domains (e.g., Ryan, 2014). Crucially, the unique contribution of each of these theories has until now not been quantified. Our results address this gap and provide credence to theories related to inter-individual differences and intra-individual differences across domains as the main sources of variance in moral relevance. Moreover, our results indicate a very small contribution due to technology domain differences showing that there is no consensus between people about specific technology domains. This suggests that moralized attitudes towards big data technologies are not just preferences or conventions as proposed by some researchers (Nucci, 2001; Smetana & Braeges, 1990).

Although we used only six technology domains, this was sufficient to assess variance in the variance decomposition model (Rauthmann & Sherman, 2019) to understand how the target sample differs in responding to these technologies. These domains vary in terms of what the technology does (crime surveillance, hiring algorithms, healthcare monitoring) and actors who implement them (police, governments, private organizations), as well as the context they are used in (healthcare, banking, employment). Prior research (Kodapanakkal et al., 2020) finds that there are some similar predictors in what drives adoption across these technology domains, but the strength of the predictors varies considerably across domains. This suggests that it was not a foregone conclusion that the domains were similarly moralized. It might be the case that adding more technology domains will increase differences, but the additional technology domains would need to be different than the broad set we included. It could be that including completely different domains (for example, moral relevance towards issues from abortion or capital punishment to people's preferences for types of swing dance steps) could affect the variance due to domain differences. However, this would be answering a different question from the one we set out to answer in this article. This was not the purpose of our study and our article is specifically focused on big data technologies.

Our findings also have practical implications for policy on big data. The variance decomposition approach helps in breaking down what contributes to the moral relevance of people's attitudes. This information can be very useful to policymakers who are trying to understand aspects of these issues to come up with policies that are acceptable to the public. Knowing that there is variation in moral relevance informs policymakers that not everyone moralizes these issues and this research provides a more nuanced understanding of people's moralized attitudes towards different technology domains. When making new policies and assessing their impact, policymakers should take into account the variation in the moral relevance of these issues rather than assuming that the opposition or support for these technologies is a moral issue for everyone. Additionally, identifying the sources of variation informs policymakers that blanket policies related to big data technologies may not work because individuals idiosyncratically find technology domains morally relevant. Thus, they should take into account those perceptions of risks/benefits and emotional reactions towards technology domains which affect moral relevance and tailor policies for different technology domains based on this information.

4.5 | Strengths and limitations

The current research has a number of strengths. First, the results of the first two research questions replicated across all three samples, showing consistency in the variance in moral relevance as well as the sources of this variation.

Another strength of the current research is the use of the variance decomposition method to quantify variance. This method allows the systematic testing (e.g., Martinez et al., 2020) of which sources of variation more successfully explain the variance in moral relevance. It provides insights into whether theories related to inter-individual differences, domains, or an interplay between the two should be investigated and thus delivers a more precise starting point to understand moral relevance. Future research could use this method for other domains/contexts (outside of big data technologies) to see if the extent of variance explained by the three sources replicates.

This research also has limitations. In Study 2, participants in Sample 2b might have varied in how people from different countries understood the questions. For example, the healthcare technology domain could be viewed as part of the government sector or the private sector. This could especially affect the questions regarding trust towards authorities. Yet, the findings across samples are largely consistent for all three research questions, suggesting that this is not a major issue.

Although Study 2b included participants of different nationalities, we do not have enough participants across different countries to accurately assess how moral relevance varies across regions. The study was not designed to test such a question. Future research could study this in a study powered to detect this variation by including sufficient participants from different regions and including nationality/country as a separate level in the model to assess the contribution of variation due to regions.

Another limitation of this study is that much variation due to inter-individual differences and intra-individual differences across technology domains was unexplained. It is likely that we did not capture all the variance between individuals and within individuals across technology domains. Big data technologies are new and not everyone may have formed opinions about them. How much people already knew about the technology domain prior to our study, the time they had to form their opinions, and personal experiences with these technologies could affect their extent of moral relevance. The difference in inter-individual variance between Sample 2a and 2b could be explained by the heterogeneity of Sample 2b. Moreover, in Sample 2b the variance due to technology domain is less than that in Sample 2a. This could have also allowed room for more inter-individual variance in Sample 2b compared to Sample 2a.

4.6 | Constraints on generalizability

Although our focus is on big data technologies, our research can serve as a starting point for how to examine questions about variation in moralization in other attitudinal contexts as well (e.g., immigration, animal welfare, capital punishment etc.). We propose that our findings would potentially generalize to other contexts as well. Looking at other issues with our framework will help break down the underlying predictors of moral relevance of other issues as well. Given our findings, we can argue that some predictors like consideration of risks/benefits, moral emotions, and relevance to moral foundations would generalize to other issues. But it is also important to consider predictors that could have unique relevance to each unique issue. Each issue may have its own equivalent to predictors like justice sensitivity, which are not broad predictors associated with moral relevance but rather specific predictors relevant to the respective issue. We focus on a topic that is relatively new where attitudes are being formed and the findings could be different from issues like abortion or capital punishment where attitudes may already be more crystallized. Future research could compare different issues to assess whether the findings are similar or different in new issues as compared to older issues that have been more thought out by people.

5 | CONCLUSION

In this research, we found that moralization of big data technologies is explained by theories that focus on inter-individual variation and within-individual variation across technology domains. We find less evidence for theories focused on differences due to technology domains alone. Variation in moral relevance is explained by predictors directly relevant to the technologies (e.g., justice sensitivity, perceived risks and benefits) and cognitive styles (e.g., faith in intuition). For a more comprehensive understanding of moralization, it is useful to simultaneously adopt multiple theories of moralization instead of studying these in isolation.

CONFLICT OF INTEREST

The authors declare that there are no potential conflicts of interest.

ETHICS STATEMENT

The research has been approved by the Ethics Review Board of Tilburg University School of Social and Behavioral Sciences, Tilburg, The Netherlands.

DATA AVAILABILITY STATEMENT

The data and analyses scripts are publicly available at https://osf.io/v3j85/.

ORCID

Rabia I. Kodapanakkal https://orcid.org/0000-0002-3113-332X
Mark J. Brandt https://orcid.org/0000-0002-7185-7031
Ilja van Beest https://orcid.org/0000-0003-2855-3638

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