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Exploring Trust in Self-Driving Vehicles Through Text Analysis

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Objective: This study examined attitudes toward self-driving vehicles and the factors motivating those attitudes.

Background: Self-driving vehicles represent potentially transformative technology, but achieving this potential depends on consumers' attitudes. Ratings from surveys estimate these attitudes, and open-ended comments provide an opportunity to understand their basis.

Method: A nationally representative sample of 7,947 drivers in 2016 and 8,517 drivers in 2017 completed the J.D. Power U.S. Tech Choice Study^{SM}, which included a rating for level of trust with self-driving vehicles and associated open-ended comments. These open-ended comments are qualitative data that can be analyzed quantitatively using structural topic modeling. Structural topic modeling identifies common themes, extracts prototypical comments for each theme, and assesses how the survey year and rating affect the prevalence of these themes.

Results: Structural topic modeling identified 13 topics, such as "Tested for a long time," which was strongly associated with positive ratings, and "Hacking & glitches," which was strongly associated with negative ratings. The topics of "Self-driving accidents" and "Trust when mature" were more prominent in 2017 compared with 2016.

Conclusion: Structural topic modeling reveals reasons underlying consumer attitudes toward vehicle automation. These reasons align with elements typically associated with trust in automation, as well as elements that mediate perceived risk, such as the desire for control as well as societal, relational, and experiential bases of trust.

Application: The analysis informs the debate concerning how safe is safe enough for automated vehicles and provides initial indicators of what makes such vehicles feel safe and trusted.

Keywords: perceived risk, dread risk, vehicle automation, survey analysis, risk analysis, consumer acceptance

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INTRODUCTION

Self-driving vehicles have the potential to transform transportation. Because transportation plays such a central role in employment, lifestyle, health, and even the structure of cities, this transformation will have widespread economic and social consequences. Like other major technology-induced transformations, consumers' attitudes toward the technology will strongly influence its ultimate success or failure.

Modern vehicles already include sophisticated automation, such as adaptive cruise control and lane-keeping assistance. These systems partially automate some aspects of driving, but the driver remains responsible and in control. Self-driving technology might remove the steering wheel and pedals and transform drivers to riders. Understanding the factors that affect acceptance of this new role represents an important concern for designers and policymakers.

Trust has emerged as a critical variable mediating the relationship between people and technology across domains that include process control automation, human–robot interaction, and decision aids (Hancock et al., 2011; Hoffman et al., 2009; Lee & See, 2004). With vehicle automation, trust is relevant in different ways for different types of automation. For automation that assists drivers and requires them to remain responsible for driving, overtrusting the automation leads to slower and less effective interventions (Beggiato & Krems, 2013; Verberne, Ham, & Midden, 2015). For self-driving vehicles—where the vehicle is responsible for driving—the complexity, risk, and limited opportunity for control might lead to undertrusting the automation (Claybrook & Kildare, 2018; Kaur & Rampersad, 2018). Lack of trust may leave drivers susceptible to dread risk—a heightened feeling of risk when the risk is uncontrollable, not understandable, and has dire consequences

(Gigerenzer, 2004; Slovic, 1987; Sunstein & Zeckhauser, 2010). Dread risk leads to disproportionate negative responses to adverse events and can undermine technology acceptance. Thus, cultivating trust and mitigating dread risk are critical for ensuring the long-term success of self-driving vehicles.

As with other types of automation, three aspects of self-driving technology will likely establish its trustworthiness and will inform feelings of trust: its purpose, the process underlying its operation and creation, and its performance over time (Lee & See, 2004). These aspects of automation can be inferred through experience with the system itself—dynamic learned trust—or with similar systems—initial learned trust (Hoff & Bashir, 2015). This suggests that initial trust of self-driving vehicles will depend on people's experience with analogous systems, most likely their own experiences as a driver interacting with increasingly sophisticated vehicle technology and their experience with computers.

Many studies have considered trust in partially automated vehicles, but existing research regarding people's trust in self-driving vehicles is relatively limited. Several simulator studies have considered how trust depends on lane tracking precision (Price, Venkatraman, Gibson, Lee, & Mutlu, 2016), and how trust and comfort depends on the aggressiveness of vehicle control algorithms (Bellem, Thiel, Schrauf, & Krems, 2018; Lee, Liu, Domeyer, & Dinparastdjadid, in press). Others have considered how interface details affect trust, such as verbal messages that state why the automation responded as it did (Koo et al., 2015). Several surveys have focused on self-driving vehicles and found that trust is strongly associated with the intention use self-driving vehicles, that trust moderates perceived risk (Choi & Ji, 2015), and that trust depends on the reliability of the technology (Kaur & Rampersad, 2018). A cross-national survey also found that trust was an important determinant of driverless vehicle acceptance (Nordhoff, de Winter, Kyriakidis, van Arem, & Happee, 2018).

Surveys provide a valuable method to assess initial trust and estimate how people might respond to self-driving vehicles during their initial deployment. Surveys frequently include quantitative data, such as Likert-type ratings, along with qualitative data, such as open-ended comments. Ratings can be analyzed with traditional statistical methods to assess attitudes, but such analysis fails to explain the basis for those attitudes. Open-ended comments can explain the basis of those attitudes but present a challenge for analysis. Systematic analysis of comments typically requires hand coding and qualitative analysis techniques. These techniques are time-consuming and depend on the personal and theoretical perspectives of the analysts (Mays & Pope, 2000).

Text analysis provides quantitative methods to analyze open-ended survey data (Roberts et al., 2014) and might reveal what factors underlie consumer trust in self-driving vehicles. Techniques, such as topic modeling, treat words as data and make it possible to extract insights from hundreds, or hundreds of thousands of comments, with the efficiency and transparency that traditional statistical techniques provide for ratings data. Text analysis extracts meaning from a collection of documents by estimating the latent or unobserved topics in documents (Dumais & Landauer, 1997).

Topic modeling identifies topics as distributions of words, with those words most related to the topic having higher probabilities. A distribution of these topics describes each document, with those topics most related to the document having higher probabilities (Blei, 2012). Because topic models are mixed membership models, each word contributes to multiple topics and each topic contributes to multiple documents. Topic modeling identifies the words associated with topics, the topics associated with documents, and the overall proportion of each topic across the documents. For our analysis, the documents are open-ended comments that accompany ratings and the topics are themes that appear across these comments.

Typically, topic modeling assumes that topics are independent. It also assumes that the probability distribution of the words in a topic is independent of any metadata that might describe the comment, such as the value of rating associated with the comment. Structural topic modeling builds on topic modeling by relaxing these assumptions, which makes it possible to examine the effect of covariates on the distribution of topics across documents and the distribution of words within topics (Roberts, Stewart, & Airoldi, 2016). For our analysis, the covariates are the Likert-type rating and the year of the survey.

This article uses structural topic modeling to analyze the open-ended comments associated with Likert-type ratings of trust in self-driving vehicles. It extends a previous analysis conducted on a 2016 survey with data from a 2017 survey (Lee & Kolodge, 2018), which makes it possible to assess how attitude of a population changed year over year. Our general hypothesis is that the topics will reveal aspects of trust and risk that underlie drivers' attitudes toward self-driving vehicles. The association of topics with ratings can help explain why some people rate self-driving vehicles positively and others rate them negatively. The association of topics with the year of the survey can reveal changes in how people think about self-driving vehicles.

METHOD

The J.D. Power 2016 U.S. Tech Choice Study[SM] (fielded in February and March) was an online panel survey focusing on vehicle owners that purchased or leased a new vehicle in the previous 5 years yielding 7,947 respondents and was repeated in 2017 (fielded in January and February) with 8,517 respondents. Both samples were nationally representative, and no effort was made to include the same respondents in both surveys. Panelists were provided with an incentive from their respective panel company. Sample quotas were established based on vehicle make. The U.S. Tech Choice Study[SM] examined consumer awareness, interest, and price elasticity of various future and emerging technologies. The survey items covered technology categories including: Entertainment & Connectivity, Comfort & Convenience, Driving Assistance, Collision Protection, Navigation, and Energy Efficiency. The survey also included items regarding consumer interest in emerging concepts such as alternative mobility solutions, cybersecurity threats, and trust in automated technologies.

The purpose of the study was to examine consumers' interest and purchase intention with numerous advanced technologies, including full self-driving automation. Survey questions included both quantitative and open-ended comments to understand consumer sentiment. There were two parts to each item: a Likert-type scale response defined by: "Definitely would not," "Probably would not," "Probably would," "Definitely would," "Don't know" followed up by a free-form text box. Our analysis focuses on the ratings and open-ended responses to the question: "How much would you trust the ability of a vehicle equipped with self-driving technology to operate without a human driver's input?" Of the 16,464 surveys, 15,568 (7,459 for 2016 and 8,109 for 2017) had valid responses to this item, which excluded the "Don't know" responses; of these 6,489 (3,105 for 2016 and 3,384 for 2017) had sufficient text analysis of open-ended responses.

Open-ended comments need to be processed before analysis because they include many typographic errors and misspellings. In addition, similar words or phrases are represented differently, such as "self driving," "self-driving," and "selfdriving" or "tech" and "technology." This processing also includes converting all words to lower case, removing stop words, numbers, punctuation, spellchecking, and stemming. Stemming removes the final letters of the word to reduce words with a similar meaning to a common stem, such as "vehicles" to "vehicle" and "hacking" to "hack." Words that occurred fewer than 12 times across all the comments were removed. Only comments with more than nine characters were retained leaving 6,489 comments for analysis. These remaining comments varied substantially in length, with a 25th, 50th, and 75th percentile of 24, 46, and 84 characters respectively. Such preprocessing can affect the topics composition, particularly with short survey comments. Here, increasing the frequency threshold of words and the minimum length of comments led to more stable topics.

The statistical programming language R was used for the analysis. The ggplot2 package was used for graphs (Wickham, 2016), tidytext for initial text processing (Silge & Robinson, 2016), and the stm package for the structural topic modeling (Roberts et al., 2014). Comments form the unit of analysis for paper. The stm package estimates topics and the prevalence

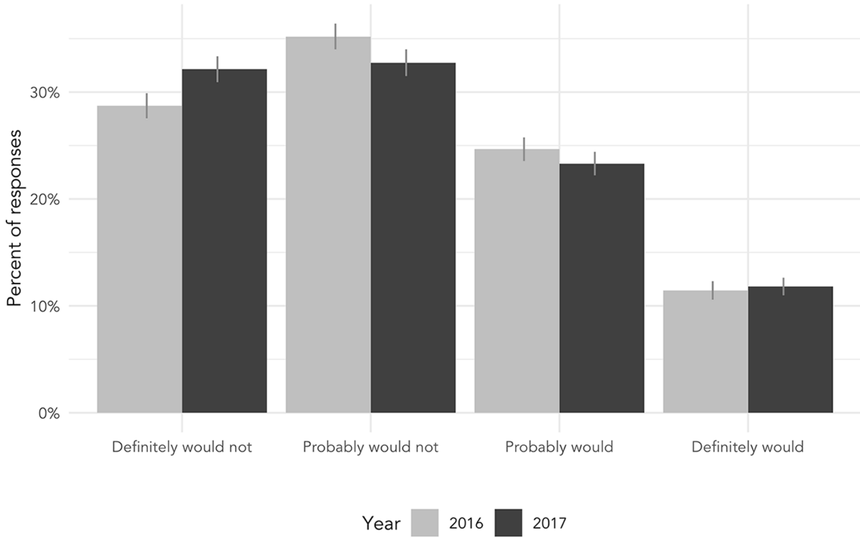

Figure 1. Response to the survey item "How much would you trust the ability of a vehicle equipped with self-driving technology to operate without a human driver's input?" The points show the mean values and 95% confidence interval of the posterior distribution of ordinal Bayesian regression.

of these topics across comments and covariates, such as ratings or the year of the survey. It also produces point estimates of the prevalence for levels of the covariates and credible intervals for these point estimates based on the posterior distribution of the parameter estimates.

RESULTS

Likert-Type Ratings of Trust in Automated Vehicles

Figure 1 summarizes the Likert-type ratings and shows that people generally do not trust self-driving vehicles. Ordinal Bayesian regression using brms (Bürkner, 2017) showed that the proportion of people who "definitely would not" trust self-driving vehicles was greater in 2017 than it was in 2016. The analysis indicates a Bayes factor of 6.3 for survey year, which represents "positive" evidence of an effect (Kass & Raftery, 1995).

Topic Model Selection

Like other statistical modeling approaches, topic model selection involves an iterative process of model verification and refinement. This process typically involves expert evaluation of the words that comprise each topic and the documents that are associated with those topics, and so inspection of models through visualization is a critical aspect of the model selection process (Chuang, Manning, & Heer, 2012). The primary model parameter is the number of topics used to describe the documents. This can range from 50 to 100 topics for corpus of journal articles, but may be only a few topics for open-ended survey responses (Roberts et al., 2014). Model fitting begins with selecting a range of the number of topics that reflects the research question and then assessing the associated models with several criteria.

No precise criteria exist for selecting the number of topics to represent the data, but four metrics generally guide model selection: exclusivity, coherence, residual variance, and held-out likelihood. Exclusivity refers to the degree that each topic is composed of terms that are not shared with other topics. Coherence refers to the degree that similar words comprise a topic. Typically, increasing the number of topics reduces coherence, but increases exclusivity. Similar to a typical regression analysis, the residual variance indicates deviations from the topic model and smaller values of the residual indicate a better

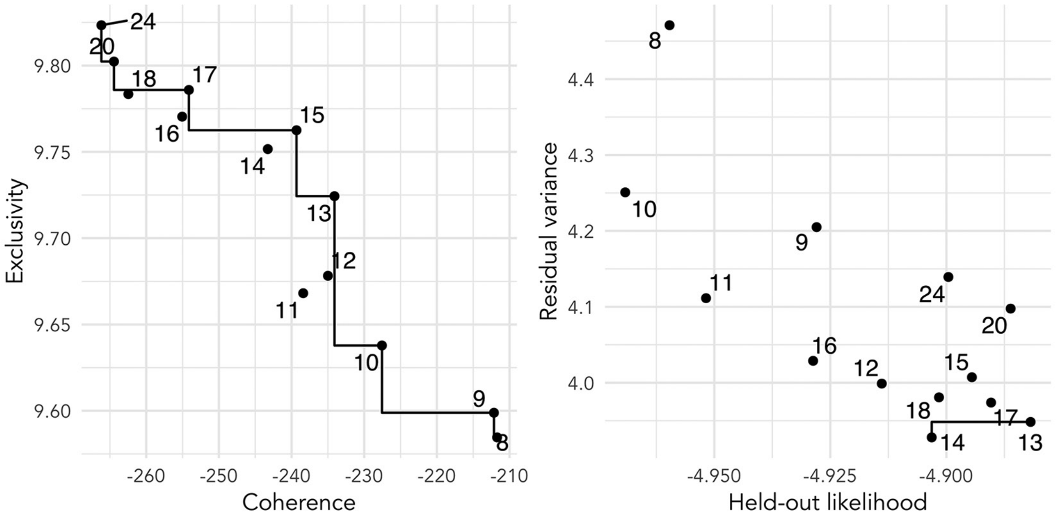

Figure 2. Pareto frontier for selecting the number of topics to include in the analysis. Each point represents a model with the indicated number of topics. Points on the line represent dominant alternatives.

model fit. The held-out likelihood reflects how well the model predicts data that were not included when estimating its parameters and larger values indicate a superior model. Typically, increasing the number of topics will reduce residual variance, but can lead to overfitting, which is indicated by corresponding reductions in the held-out likelihood.

These four considerations guide the choice of the number of topics, but ultimately the choice depends on the judgment of the analyst as to whether the topics reveal useful information about the comments. We considered models with eight to 24 topics. The 13-topic model was chosen because it had much greater exclusivity with only slightly more coherence compared with the 11- and 12-topic models, and it had greater coherence with only slightly less exclusivity compared with the 14- and 15-topic models. Considering the residual and held-out likelihood, the 13-topic model had a higher held-out likelihood than all the models and a lower residual than all but the 14-topic model. The topics from the 13-topic model were also judged to be meaningful.

Figure 2 shows the exclusivity, coherence, residual variance, and held-out likelihood for the models considered, and the lines represent Pareto frontiers. Pareto frontiers show a set of the models that trade-off the performance criteria differently. For example, the 15-topic model has high coherence, but relatively low exclusivity. The 17-topic model has lower coherence, but higher exclusivity. Both of these models are better than the 14- and 16-topic models. For the graph on the left, points below the line represent inferior models meaning there is an alternative that is superior in terms of both exclusivity and coherence for any point under the line. For the graph on the right, only the 13- and 14-topic models merit consideration—all other models have greater residual and lower held-out likelihood. The multiple criteria needed to select a model highlights the complexity of model selection that is often masked by the allure of *p* values as a seemingly objective basis for model selection (Wasserstein & Lazar, 2016).

Topic Content

Structural topic modeling identifies topics in an unsupervised manner—it discovers topics from the data rather than confirms predefined categories. The meaning of the topics must be identified by inspecting the terms that comprise the topics and exemplar comments that include a high proportion of each topic.

Several measures identify terms that define topics: Prob, FREX, Lift, and Score. Prob is the probability that a term occurs in the topic. FREX (Frequency and Exclusivity) identifies terms that occur frequently in a topic and are also exclusive to that topic. Like FREX, Lift weights words more heavily if they occur infrequently in other topics. Score weights words by dividing the logarithm of their frequency by the logarithm of their frequency in other topics. Although FREX, Lift, and Score all consider how words occur in a topic, they do so in slightly different ways, which leads to different words to define topics.

The numeric values of Prob, FREX, Lift, and Score were used to rank the words, and Table 1 shows the seven highest-ranked words for each topic. The right column shows three exemplar open-ended comments for each topic that have a high proportion of the topic. Based on keywords and comments, we identified a label for each topic (Roberts et al., 2014). For example, "Works good?" was used to label comments suggesting such systems often work well, but can be prone to malfunctions in some situations. The words "work," "good," and "malfunctions" all feature prominently as keywords and so "Works good" with a question mark was selected as a label. Overall, the terms and comments define topics that address separate and distinct bases for consumers' attitudes toward self-driving vehicles. These topics provide a window into how people think about self-driving vehicles; some of which suggest an attitude of optimism and acceptance and others, skepticism and distrust.

Topic Links

Topics tend to co-occur within comments, and this co-occurrence defines the correlation between topics. Each comment included a proportion of each topic, but most comments are primarily associated with one topic and included more than 15% of only one or two other topics. For example, the comment "because people r dumb and talk on phones while driving so a robot driver cant be any worse" is primarily comprised of Topic 7 "Scary drivers and robots" but also includes some of Topic 8 "Safer than humans." Figure 3 shows the correlations with an absolute value greater than .30 as links between topics, and the size of the nodes reflects the prevalence of each topic across all the comments. The nodes are positioned with multi-dimensional scaling. Three notable areas of this diagram merit attention. The strongly linked topics of "Trust when mature," "Technology improving," and "Tested for a long time" suggest a conditional, but optimistic view of self-driving vehicles that is predicated on comprehensive testing and technological advances. Two topics suggest that some people think about safety in a relative way and believe it to be "Safer than human" and worry about "Scary drivers and robots." Two other topics reflect a discomfort with the prospect of giving control over to automation: "Feel uncomfortable" and "Control until proven."

Association of Ratings and the Year of the Survey and Topic Prevalence

As the node size in the network diagram indicates, the prevalence of the topics is not uniform. Figure 4 shows that the topic of "Safer than humans" is more prevalent than the topics of "Hacking & glitches" and "Computers make mistakes." The vertical line indicates the mean prevalence—the prevalence if all the topics were equally represented—and visually indicates which topics are over- and underrepresented.

The general hypothesis guiding this analysis is that the topics might describe the basis for the ratings and describe how drivers' attitudes change over time. Figure 5 shows the difference in prevalence of each topic, which was calculated by subtracting the mean prevalence of each topic from the prevalence of the topic in each year. The difference in prevalence for many topics is similar for the two years of the survey, but topics associated with trust and self-driving vehicle crashes were more prevalent in 2017 than 2016 and those associated with computer mistakes and how well self-driving vehicles work were less common. For the topic of "Trust when mature," the topic prevalence changes from approximately 6.6% in 2016 to 8.4% in 2017—a 27% increase in the prevalence of this topic from 2016 to 2017.

Figure 6 places the effect of year of the survey into context by showing how the prevalence of topics depends on the rating and the year of

TABLE 1: Topics, Keywords, and Related Comments

Topic and Keywords	Exemplar Consumer Comments, as Written
Topic 1: Many things go wrong Prob: car, thing, wrong, safety, ready, sounds, total FREX: thing, wrong, ready, sounds, foolproof, total, car Lift: ready, sounds, thing, wrong, freaks, automatic, faith Score: car, wrong, thing, freaks, safety, sounds, ready	"Cruise control and maybe some of the other features would be ok but so many things can go wrong and have in the past so it's best to have a human driver have input" "too many things can go wrong and I want total control of the car" "I don't trust a self-driving car. Something can go wrong and the car owner may not know how to fix or it what to do"
Topic 2: Errors and failures Prob: errors, failure, hackers, made, chances, electronics, mechanical FREX: errors, failure, hackers, made, chances, electronics, mechanical Lift: expect, power, equipment, hackers, information, overriding, world Score: room, errors, failure, mechanical, chances, hackers, electronics	"too much chance for error. driver errors happen, but a mechanical error could be terrible" "It's man made, program by man subject to many errors" "a human had to have made it to start and there is room for human error"
Topic 3: Trust when mature Prob: trust, years, advanced, perfect, point, life, change FREX: trust, point, years, life, early, unproven, perfect Lift: mature, trustworthy, unproven, breakdown, early, unsure, untested Score: trust, mature, advanced, years, perfect, point, life	"I do not trust this type technology at this point of development" "wouldn't trust it 100 percent, but gps are pretty good and so would trust the self-driving technology as much as i trust gps" "I trust the technology will be advanced to the point that it will be safe when it's available for purchase"
Topic 4: Technology improving Prob: technology, fail, putting, improved, develop, fully, interested FREX: develop, interested, technology, fully, fail, proof, improved Lift: extensive, develop, approved, level, proof, interested, fine Score: technology, extensive, fail, approved, develop, improved, fully	"Technology has advanced and improved at such a phenomenal rate that I trust that their would be very few problems associated with this. This technology already exists in some capacity already" "Technology is at a peak and still improving. And all new technologies MUST secure federal permission to function, and NO sane person/agency would approve the use of an unsafe technology" "This country continues to increase the level of technology and the security level is very high"
Topic 5: Hacking & glitches Prob: vehicle, hacking, happen, danger, concerns, glitch, problems FREX: hacking, danger, glitch, potential, happen, crash, software Lift: danger, easy, hacking, scares, trouble, glitch, potential Score: hacking, vehicle, easy, happen, danger, glitch, problems	"Security protection is paramount. Already thieves are able to steal vehicles with password cracking devices. Someone with malicious intent could hack into the vehicle and take over control . . . nope, not happening with me" "Anyone could hack the computer system and then use that vehicle to harm others. It could be used to harm many or just drive the car with it's passengers to a dangerous situation."

(continued)

TABLE 1: (continued)

Topic and Keywords	Exemplar Consumer Comments, as Written
	"System could be hacked. Computer could fail. Never seen a system without a glitch; what happens when the glitch occurs?"
Topic 6: Computers make mistakes Prob: computers, makes, machines, people, program, mistakes, break FREX: machines, mistakes, computers, hands, break, wheel, sense Lift: lazy, mistakes, nervous, sense, wheel, break, computers Score: computers, machines, nervous, mistakes, makes, people, program	"cause machine make mistakes too cause people program them" "Because it is a machine, and machines are programmed by people who can not imagine every instance when programming them. Additionally, they break" "computers can make mistakes"
Topic 7: Scary drivers and robots Prob: driving, driver, input, scary, robot, prefer, smart FREX: scary, robot, prefer, driver, pay, attention, input Lift: touch, attention, prefer, robot, scary, instincts, pay Score: driving, driver, input, touch, scary, prefer, robot	"I think that this could cause the driver to not pay enough attention while driving. Too many distractions." "because people r dumb and talk on phones while driving so a robot driver cant be any worse" "I'm human. this robot [expletive] is new and scary."
Topic 8: Safer than human Prob: human, safer, variables, experience, idea, decisions, distraction FREX: safer, day, idea, judgment, variables, experience, mind Lift: judgment, day, eliminate, faster, fun, mind, respond Score: human, fun, safer, idea, decisions, variables, distraction	"HUMANS ARE DISTRACTED AND EMOTIONAL. AUTODRIVE COULD BE FASTER AND SAFER" "the computer is faster than the human brain and can respond quicker in taffic" "The AI plus the semiconductor can respond than human being quickly. And it is a machine not like human emotional"
Topic 9: Control until proven Prob: control, safe, proven, reliable, issues, giving, worried FREX: proven, issues, giving, worried, safe, control, cost Lift: ensure, giving, guarantees, issues, liability, limit, worried Score: control, safe, proven, ensure, reliable, issues, giving	"I do not like giving up control and do not think the tech has progressed sufficiently at this point to be safe and secure" "not proven fail safe" "not proven enough yet,, would feel out of control"
Topic 10: Tested for long time Prob: tested, time, long, future, completely, depended, properly FREX: tested, long, future, depended, auto, company, assume Lift: open, public, assume, accurately, answer, buy, company Score: tested, time, answer, future, long, depended, public	"I know it's already being tested. I believe comprehensive testing would be performed to ensure safety prior to being released to the public"

(continued)

TABLE 1: (continued)

Topic and Keywords	Exemplar Consumer Comments, as Written
	"It seems safe but would have to be tested a long period of time before I'd fully agree" "The technology has been being developed and tested for a long time and will probably be very safe by the time it is allowed on the road"
Topic 11: Works good? Prob: work, system, malfunction, good, situations, great, react FREX: good, situations, great, malfunction, work, react, hard Lift: excellent, judge, good, great, hard, react, situations Score: work, malfunction, system, good, judge, situations, react	"It works and has been shown to work" "I think it can work, but I do worry some because it doesn't have the process of thinking about what can happen in a situation and then correcting" "Technology is great—when it works! But, if there is too much left to technology, it's bound to break or malfunction sooner or later. And, when it does you could be placed or place others in dangerous or unsafe situations"
Topic 12: Self-driving accidents Prob: road, self-driving, accidents, lot, feature, conditions, responsible FREX: road, self-driving, accidents, conditions, automated, traffic, current Lift: fashioned, pedestrian, prevent, slow, state, Tesla, unpredictable Score: prevent, road, self-driving, accidents, feature, lot, traffic	"The Nation already has to many automobile accidents and traffic on streets and highways are already to heavy, thus having driverless cars will most likely increase both the number of accidents and increase the traffic on streets and highways" "We have already seen accidents involving driverless cars, going at a speed of 30 mph or less. No thank you. I won't ride in a driverless car" "I think its likely possible, but I also have heard about the accidnet with Teslas self driving vehicle so Im a little reluctant"
Topic 13: Feel uncomfortable Prob: feel, operation, comfortable, functions, prove, actions, risky FREX: feel, operation, functions, actions, risky, family, nice Lift: eventually, family, actions, operation, risky, functions, nice Score: feel, nice, operation, comfortable, prove, record, functions	"I don't feel that technology has advanced enough for me to feel comfortable riding in a vehicle that is operating on its own" "I would much rather leave the vehicle in my own control. I don't know if I would feel comfortable completely relying on the vehicle to operate almost blindly" "I can't explain it . . . I just don't feel comfortable with a car operating on its own. I like to be in charge of the car"

Note. FREX = Frequency and Exclusivity.

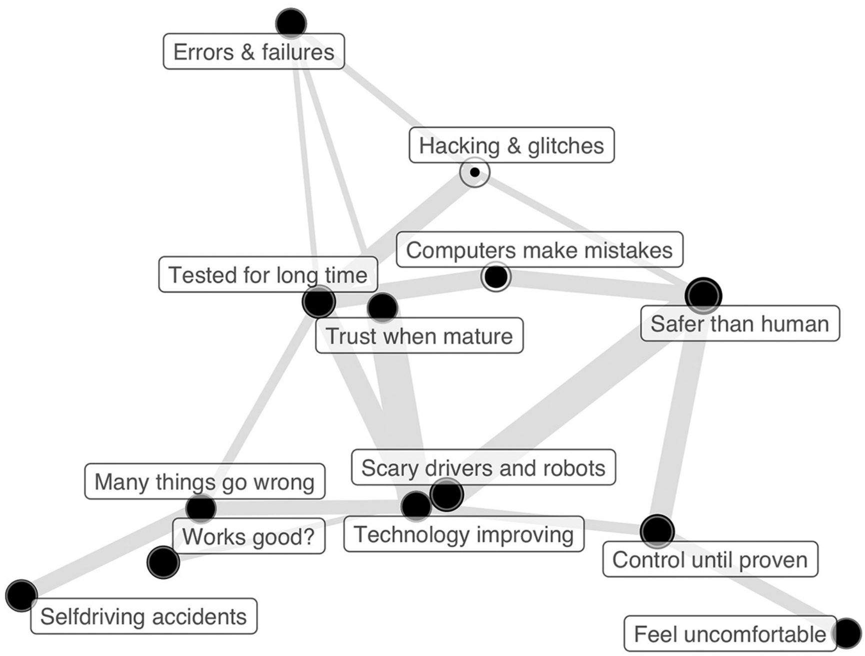

Figure 3. Links between topics based on topic correlations. The width of the link reflects the strength of association, and the size of the nodes reflects the prevalence of each topic.

the survey. The narrow confidence intervals and the orderly effects indicate that topics are meaningfully associated with different attitudes toward self-driving vehicles. The topic "Tested for long time" is most strongly associated with the rating of "Probably would" and so reflects the conditional nature of the rating, as compared with "Definitely would." Interestingly, the topic "Safer than human" is most prominent in the "Definitely would" comments. In contrast, "Hacking & glitches" is strongly associated with "Definitely would not" and "Probably would not." This graph also shows that the year of the survey has a relatively small effect, with many of the lines almost perfectly overlying each other, but "Self-driving accidents," "Trust when mature," and "Computers make mistakes" deviate from this pattern. Overall, the effect of the year is small, but the effect of the rating is large.

DISCUSSION

Our overall objective was to use structural topic modeling to understand trust in self-driving vehicles. The 13 topics show that this technique holds promise for analyzing qualitative data quantitatively. The words and comments most associated with these topics provide a window into how people think about self-driving vehicles that is more nuanced than previous analyses of similar data (Hulse, Xie, & Galea, 2018; Kyriakidis, Happee, & De Winter, 2015). The topics capture the gist of comments in a way that might otherwise require many hours of hand coding. Importantly, these topics help explain what motivates positive and negative attitudes toward vehicle automation and highlight the multi-faceted nature of trust and risk as it relates to self-driving vehicles.

The results support our hypothesis that the topics reveal aspects of trust and risk that change over time and underlie drivers' attitudes toward self-driving vehicles. Topic prevalence varied as a function of survey year and Likert-type ratings. A fatal crash involving a Tesla vehicle on May of 2016 attracted substantial media attention and might have contributed to the less favorable ratings in the 2017 survey (NTSB, 2017), which might underlie the

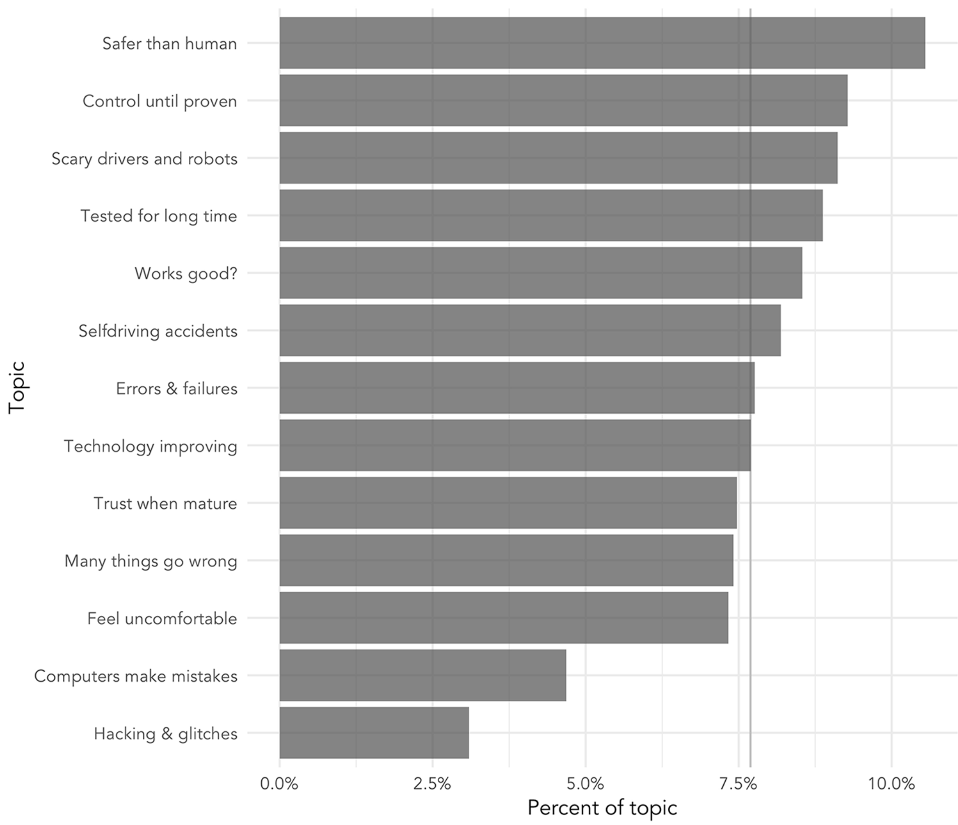

Figure 4. The prevalence of each topic. The gray vertical line shows the overall mean prevalence.

increase in the prevalence of the topic "Self-driving accidents."

Topics reflect both optimism and concern of drivers. The topic of "Technology improving" and "Safer than human" reflects optimism that engineers will address the various challenges facing self-driving vehicles and that they will be safer than human drivers. This optimism contrasts with the topic of "Hacking & glitches," which reflects the feeling that reliability and security problems might plague self-driving vehicles like they do computers and smartphones.

Dimensions of Trust

The results confirm previously identified dimensions of trust (Lee & See, 2004): its purpose, the process underlying its operation and creation, and its performance. Most topics relate to the performance dimension of trust and focus on errors it might make and situations it might not be able to handle, such as "Safer than human" and "Self-driving accidents." Several topics relate to the process dimension of trust, but not in the way the dimension has typically been defined. Instead, topics such as "Technology improving" and "Tested for long time" refer to the process of technology development and reflect the belief that manufacturers and regulatory agencies will assure the safety of vehicle automation. One topic directly touches on the purpose dimension of trust: "Hacking & glitches." Here, the concern is that the automation may be vulnerable to it being redirected in a way that is contrary to its purpose and the drivers' goals.

Performance, process, and purpose represent increasing levels of attributional abstraction and automation infelicities at each level that might correspond to feelings of disappointment, violation, and betrayal (McLeod, 2015). Betrayal reflects a sense that the automation is acting in a manner that is contrary to the person's goals, as

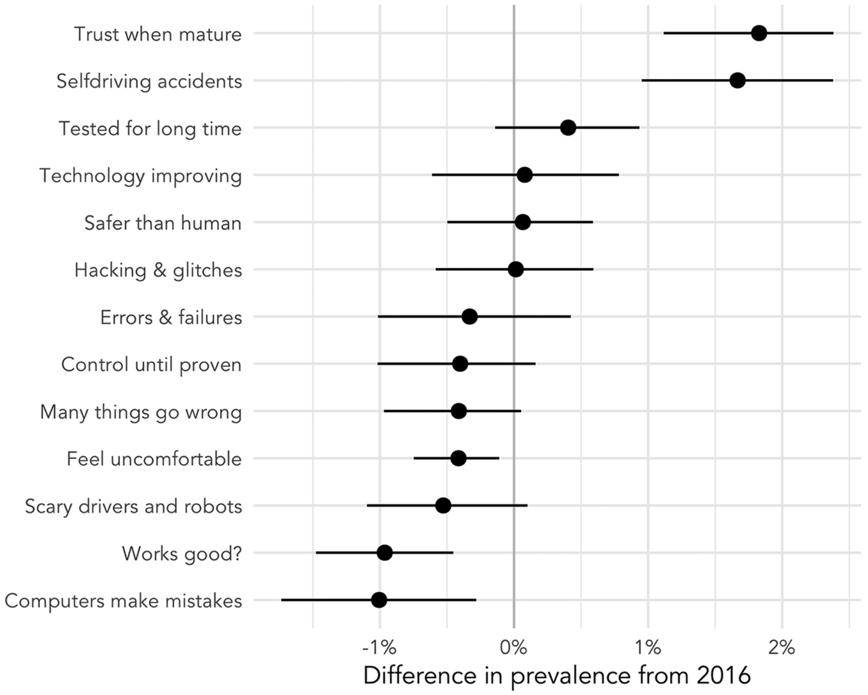

Figure 5. The difference in prevalence of each topic and 95th percentile CIs for years 2016 and 2017. Positive values indicate an increase in prevalence from 2016 to 2017. CI = confidence interval.

when the automation is hacked by a malicious third party, reflected in the topic "Hacking & glitches." A violation occurs when manufacturers or governments fail to uphold social norms for safety assurance, as when the safety assurance processes are revealed to be lacking or have been circumvented. The topic "Tested for long time" reflects such social norms. Disappointment reflects the unpleasant, but to some degree expected, imperfections of automation functioning in a complex world—technical risk. The topics "Computers make mistakes" and "Errors and failures" reflect such technical risk. Violation and betrayal reflect increasing degrees of social risk, which has a greater influence on trust than technical risk (Fetchenhauer & Dunning, 2012; Molm, Takahashi, & Peterson, 2000; Slovic, 1999).

Basis of Trust

The construct of trust in this study differs from that where trust depends on direct experience. Here, respondents reported anticipated levels of trust they will have once the technology is available and had no direct experience to draw upon. When people lack experience with a system, they substitute experiences with related systems—relational trust—as well as expectations regarding government agencies and society—societal trust (Kelton, Fleischmann, & Wallace, 2008).

Without direct experience with self-driving vehicles, people rely on analogous experiences with computers and technology and brands (Hoff & Bashir, 2015; Lee & See, 2004). For example, the topic "Computers make mistakes" and "Technology improving" shows that trust in automated vehicles is grounded in experiences with other computer and mechanical systems. This suggests that people's response to self-driving vehicles depends on their experience accumulated through interactions and associated relationships with other technology—relational trust (Rousseau, Sitkin, Burt, & Camerer, 1998). To avoid being considered as computers that are prone to glitches, privacy, and security problems, manufacturers should stress how different self-driving

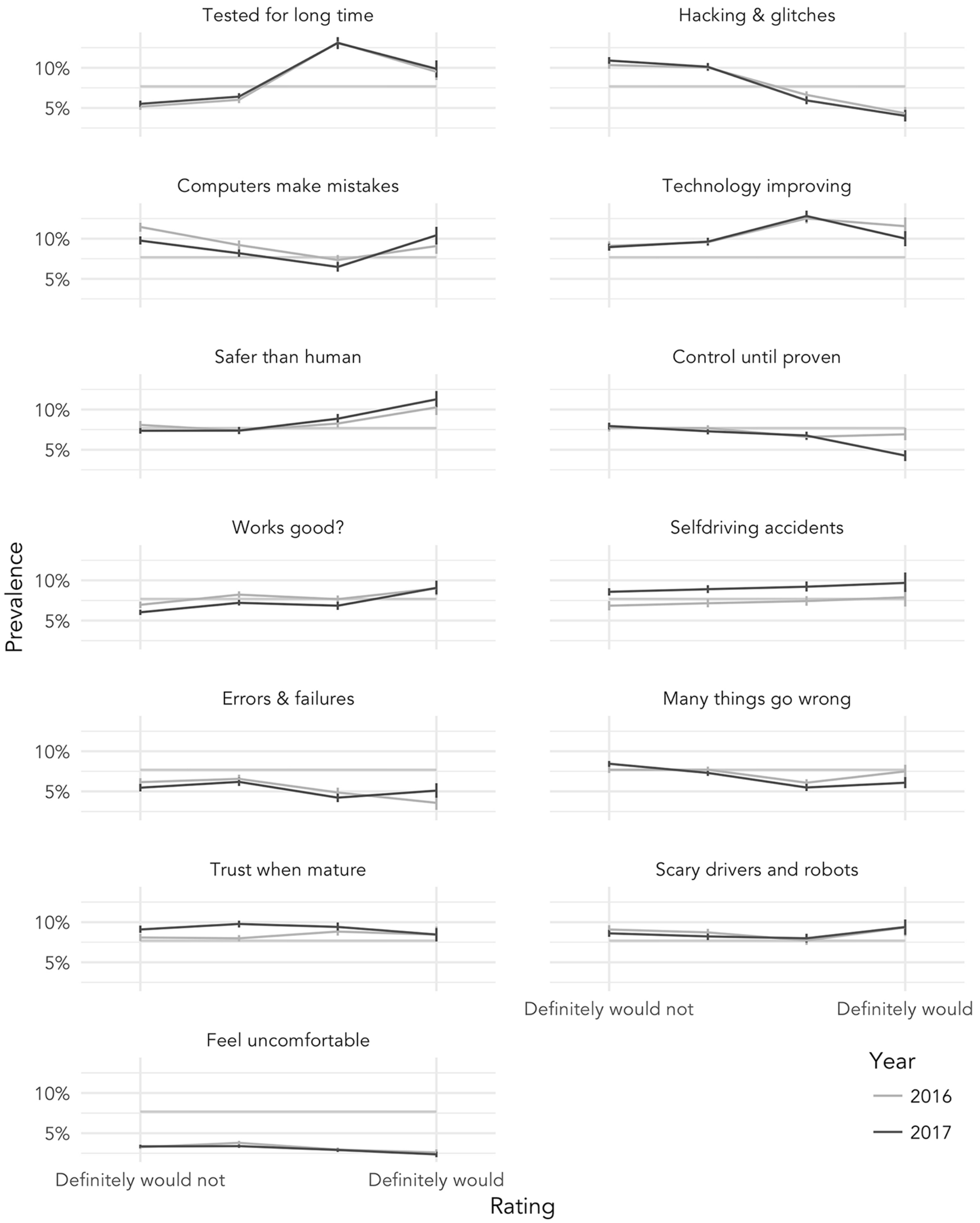

Figure 6. The relative prevalence of each topic and 95th percentile CIs for each rating for the years 2016 and 2017. CI = confidence interval.

vehicles are and how different the associated design process is. For example, manufacturers should develop safety cases, which make the logical arguments for safety explicit and ground these arguments in supporting evidence (Wagner & Koopman, 2015). Different processes are needed for self-driving cars, and the differences need to be communicated to the public.

The lack of direct experience also leads people to base their trust on more general expectations of

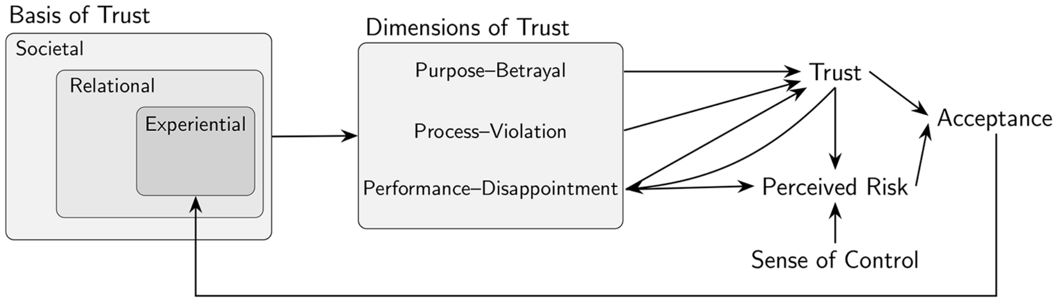

Figure 7. The relationship between trust bases and dimensions and the effect of trust on perceived risk and acceptance.

institutional and societal response to technology, social norms of how government agencies assure safety, and risk measures provided by scientists—societal trust (Zucker, 1986). This suggests a potential backlash if safety benefits are framed in terms of eliminating human error and the associated 94% of crashes. If "automation errors" arise and predictions of a crash-free world fail to materialize, societal trust might suffer. The topic "Trust when mature" reflects this provisional trust that is both conditional on experience with the technology and the intent of developers of the technology. It goes beyond the specific vehicle experience and is grounded in the brands, manufacturers, and government agencies that will ensure its testing and prove its safety (Claybrook & Kildare, 2018). The topic "Tested for long time" reflects comments from some who believe the government and companies will ensure safety through a thorough process testing and certification. Lessons learned from the public backlash to genetically modified food suggests that presenting data is not sufficient to garner public acceptance. Acceptance depends, in part, on building societal trust through institutional transparency and integrating public concerns into policies (Frewer et al., 2004). Perhaps, most importantly, these practices and policies must actually be trustworthy so that the technology provides the advertised safety benefits.

Trust, Control, and Dread Risk

The topic "Hacking & glitches" together with "Control until proven" and "Feel uncomfortable," all suggest that people worry about losing control of their vehicles, succinctly captured in one consumer's comment, "I want total control of my vehicle." Two dimensions of hazardous situations that affect perceived risk: whether it is controlled and limited in its consequences, and whether it is knowable and observable (Slovic, 1987). Uncontrollable, consequential, and unobservable risks constitute dread risk. Nuclear reactor accidents and terrorist attacks are uncontrolled and unobserved and are perceived as dread risk. People perceive dread risks as 1,000 times riskier than known and controllable risks (Slovic, 1987), and so dread risk can disproportionately affect policy and behavior.

Four interacting effects could contribute to diminished trust and the emergence of dread risk (Slovic, 1999). First, events that undermine trust are more salient than those that promote it, as in the overreaction to spectacular crashes caused by self-driving vehicles compared with crashes avoided (Shariff, Bonnefon, & Rahwan, 2017). Second, when positive events are noticed, they are weighted less than negative events. Third, stories about negative events are viewed as more credible than those about positive events. Fourth, diminished trust makes it less likely people will use a self-driving vehicle and experience positive events that might help trust recover. Because of these factors, distrust that develops before people experience a system can persist even after they experience the system.

Figure 7 integrates some of the factors that might change the perception of driving risk from one that is controlled and known, to something closer to dread risk, which can undermine acceptance of automated vehicles. As this figure suggests, trust plays a central role in risk perception, particularly in the absence of direct experience (Earle, Siegrist, & Gutscher, 2010). It also suggests that the basis of trust in early stages of deployment will be societal and relational and that betrayal and violation from these sources could be very damaging for trust (Frewer et al., 2004).

The link from trust to the performance dimension of trust indicates that trust can influence the selection and interpretation of evidence (Horsburgh, 1960; Slovic, 1999). Lower trust makes it more likely that negative performance will be observed and that positive information will be interpreted negatively, undermining trust and further increasing the tendency to monitor the automation for evidence of poor performance. The recursive nature of this feedback loop means that the influence of trust on acceptance affects the experiential basis of trust, leading to either vicious or virtuous cycles. In a virtuous cycle, increased trust can lead to increased use, which can lead to further use and greater trust (Lee & See, 2004). When considering how safe is safe enough for self-driving vehicles, these results suggest that it may be important to not just increase safety but also communicate those achievements in a way that leads to appropriate trust.

Limitations and Generalization

This analysis has substantial limitations that should temper its interpretation. First, the survey sampled drivers who had not experienced self-driving vehicles and so they were forced to imagine that experience. With dramatically transformative technology, the availability bias makes it likely that they will be more influenced by the crashes that have occurred with various types of automated vehicles than the new experiences self-driving vehicles might afford.

Beyond this fundamental limitation, text analysis and structural topic modeling do not reveal a single definitive interpretation of the comments. Selecting a model with a different number of topics might lead to different insights. Likewise, the specific preprocessing of the text such as stemming, spellchecking, term aggregation, and stop word elimination all affect the outcome of the analysis. For example, comments such as "don't trust" and "trust a lot" might both be reduced to "trust" depending on which stop word dictionary was applied to the data set, which would have obvious implications for how a topic associated with trust might be associated with negative and positive Likert-type ratings. Although structural topic modeling provides a quantitative method to analyze qualitative data, it contains many subjective elements that merit attention, just as they do with qualitative methods.

Generalizing from data collected from those who have not experienced a self-driving vehicle is challenging because the basis of trust might change with direct experience. Different driver demographic groups might have different reasons why they trust or distrust automation, and so, the results of this study might not generalize uniformly over the population. Such possibilities could be explored with further topic model analysis. Responding to a survey forces people to imagine possibilities. In contrast, using an actual self-driving vehicle might reveal unimagined possibilities and would provide a visceral experience that cannot be imagined. More generally, the overall assumption that trust guides behavior merits questioning. Most conceptualizations of trust and acceptance assume that attitudes guide behavior (Davis, 1993; Gefen, Karahanna, & Straub, 2003). Trust can be motivated and rationalized, resulting in end-directed trust rather than truth-directed trust that is grounded in the trustworthiness of the system (McLeod, 2015). The practical benefits experienced with the technology can outweigh the need for truth-directed trust. Consequently, end-directed trust can emerge as behavior guides attitudes, which can occur when people align their attitudes with behavior to mitigate cognitive dissonance (Ghazizadeh, Lee, & Boyle, 2012; Sharot, Velasquez, & Dolan, 2010). If automation fills a compelling need and people find themselves using it, their attitudes may shift to align with their behavior.

As people directly experience self-driving vehicles, new challenges to trust may emerge that were not expressed by the survey respondents. Partially automated vehicles exist today, but fully automated self-driving vehicles that operate on all roads and in all weather conditions may never exist. Self-driving vehicles will have a limited operating domain that may lead to "availability anxiety," similar to range anxiety expressed with electric vehicles. Because trust is often specific and contextually grounded—people trust system X to do Y in context Z—it is unclear how experiential, relational, and societal trust will mediate specific trust situations. Likewise, until survey respondents actually experience self-driving vehicles, they might pay relatively little attention to availability, privacy, and fairness, relative to the more salient issues of safety (Kaur & Rampersad, 2018). For example, the algorithms for sending a vehicle to pick up a passenger might be unfair and biased toward certain socioeconomic groups, similar to the biases that have emerged in Uber's ride request algorithms (Hanrahan, Ma, & Yuan, 2017), and algorithms more generally (Courtland, 2018).

CONCLUSION

Structural topic modeling reveals reasons underlying drivers' ratings of vehicle automation, which align with factors typically associated with dimensions of automation trust and trustworthiness. The analysis reveals that the basis of trust differs when the automation has not been directly experienced, leading to a focus on societal and relational bases rather than the more typically studied experiential basis. A particularly important finding concerns whether automation infelicities are viewed as disappointments, violations, or betrayals. Mundane disappointment might annoy, troubling privacy and safety violations might spoil a brand, and betrayal associated with systemic failure to assure safety and hacking might undermine the success of the technology. This and related research suggest that violations and betrayals might have substantially greater consequences than simply disappointing performance. Given the limits of the current technology and the survey, the analysis informs the debate concerning how safe is safe enough for automated vehicles and provides initial indicators of what makes such vehicles feel safe and trusted.

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KEY POINTS

- Structural topic modeling provides a window into what guides people's ratings of trust.
- The comments suggest concerns that reflect dread risk and the associated possibility that people might overestimate the risk of self-driving vehicles.
- When technology has not been directly experienced, societal and relational bases guide trust rather than the more typically studied experiential basis.
- Automation infelicities can be viewed as disappointments, violations, or betrayals, with violations and betrayals being more damaging and more common with societal and retaliation bases of trust.

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