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# Prototyping trust in autonomous vehicles (AV)

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This paper reports on the development and validation of a new tool to measure trust in autonomous vehicles (AV), using prototype-based techniques. Four studies, using independent samples, confirmed that safety and reliability of well-tested technologies are central aspects of trust in AV, while features describing outcomes were classified as remote.

## 1. Introduction

Our aim in this paper is to introduce the transport research community to prototype analysis, using as a case study, trust in AV. We report on four studies conducted to understand and confirm the features of trust in AV. The methodology is particularly helpful to "*flesh out the content and structure of a particular concept"* (Fehr, 2005:185), especially when conceptual boundaries are assumed to be fuzzy or ill-defined and to compare them to related concepts (Fehr, 1988). We first present a brief review of the relevant literature, then the results of four studies (feature generation, centrality ranking, best-worst (B-W) type 1 analysis, and reaction time), along with a discussion of the implications of the work and future research directions.

## 2. Relevant literature

Prototype analysis is used to identify features of ill-defined concepts (e.g., emotion, love, spirituality) (Fehr & Russell, 1991; Lambert et al., 2009; Santos & Michaels, 2020), in contrast to a classical definitional approach, in which there is a distinct boundary, and hence, a necessary and sufficient set of attributes that specify a concept/category. For example, the prototype analysis of anger showed that rage and fury were closer forms of anger, than humiliation and indignation (Fehr, 2005). Some features are more central or important, and others are more remote. Another important aspect of prototype structures is their influence on cognition, including attention, recall, and interpretation of situations (Baldwin, 1995). The prototypical method typically includes two stages, with a sequence of independent studies designed to identify and then confirm the prototype. We are applying this methodology here, to reveal features of trust in AV, a concept shown to be distinct from trust in general and under-examined (Kaplan et al., 2021; Kohn et al., 2021).

### 2.1. Stages in prototyping

Although relatively common in psychology, the application of prototype analysis in other domains, including transport, is lagging. This may be explained by marketing, travel behaviour, management, using validated scales, with marginal adjustments to latent constructs. Yet, the prototypical analysis is key in eliciting and confirming features of new and less understood concepts (Fehr, 2005), as well as their relationship with existing concepts and/or categories.

There are two main stages in prototyping: 1) feature generation; and 2) confirmation of the features. The 'ground-up' feature generation stage represents the more exploratory aspect of the methodology. Participants are asked to list all features they can think of with respect to the concept, using a free-response format, but usually with a time limit (Fehr, 1986). A major advantage of a prototype analysis is that, unlike interview data, each feature usually comprises 1-3 words, which makes it easier to code and organise the words and phrases, using root words and synonyms. The frequency of the features determines their relative ranking, and thus, their importance to the concept. Next, a centrality rating assesses the representativeness of the features generated in the first study. The approach involves asking participants to rate the 'centrality' (or closeness/importance) of each feature on a Likert-type scale (Migge et al., 2020). Two indices are commonly used to assess the reliability of the centrality means, including the intraclass correlation coefficient (ICC), and the internal consistency of the ratings, considering the features as cases instead of variables. The features are then ranked from highest to lowest, based on the centrality scores, and when equal means, the standard deviation. As centrality ratings are on a continuum, there is no clear distinction between the central and less prototypical features. However, various rules can be applied to exclude peripheral or remote features from further analysis. In this research, we examined both the average rank, combining the rankings by frequency and by centrality scores, and the median splits (e.g. Gregg et al., 2008; Maher et al., 2020; Migge et al., 2020). Features identified as peripheral by both approaches were then excluded from further analysis, reducing the features from 41 to 36 in our B-W and reaction time confirmatory studies.

Stage 2 aims to confirm the existence of a prototype structure, by assessing the influence of the features on cognition. If a prototype exists it should affect cognition through, for example, the speed and accuracy of cognitive processing. The number of studies conducted in Stage 2 varies from 1 to 3-4, with more confirmatory studies providing stronger empirical evidence for the prototype. The most common studies used in Stage 2 include reaction time, vignette and character description studies, memory recall and recognition tests, and autobiographical recall. We applied reaction time and B-W type 1 experiments and analysis, as further described in section 3. The reaction time refers to the speed of processing; participants are expected to recognise and classify central features more quickly and accurately than the peripheral or remote features (Fehr & Russell, 1991; Gregg et al., 2008). Reaction time studies usually include balanced numbers of true central, true peripheral, and false/decoy statements. ANOVA (repeated measures) or paired t-tests reveal any significant differences between reaction times.

Supplementary applied studies can be conducted to further validate the prototype features and understand relationships between the features. For example, scale development, multi-dimensional scaling or cluster analysis, and survey research can be applied. As with the standard approach to scale development, psychometric analyses can be carried out to assess the scale's reliability, and convergent and discriminant validity (Hinkin, 1995). Another potential approach, not yet used in prototype analyses, is B-W type 1 scaling (Louviere et al., 2015).

## 2.2 Trust in AV

Cutting-edge autonomous and automated systems have captured the imagination and interest of researchers, governments, and the public alike. Substantial efforts have been dedicated to understanding the viewpoints, readiness, governance, and likely adoption of AVs in various countries, as well as their features and their implications for safety, accessibility, urban landscapes, environment, and distribution of activities (Fagnant & Kockelman, 2015; Sun et al., 2017; Lu et al., 2020). They are now a reality and recent examples in China, Singapore, Europe, and North America, show that experience/exposure plays a key role in improving the attitudes and likely adoption (Dai et al., 2021; Dennis et al., 2021; McAslan et al., 2021; Lehtonen et al., 2022; Tan et al., 2023).

Trust has been found as an essential enabler or barrier (Fagnant et al., 2015; Sun et al., 2017; Versteegh, 2019) in the potential uptake of AVs and although it is a well-researched concept in human interactions, the existing scales cannot be directly applied to the AV context. Recently, Kohn et al. (2021) have drawn attention to the lack of clarity and frequent use of ad-hoc measures, which have led to a confusing narrative and a lack of a clear 'state of the art' for trust in automation research. Kaplan et al. (2021) argued that AI is sufficiently distinct from human interaction to warrant its own investigation.

The literature distinguishes between interpersonal trust (Lee & See, 2004; Kohn et al., 2021), and trust in organisations (Mayer et al., 1995), or in technology (Kohn et al., 2021). Trust creates bridges between individuals/agents, organisations and their stakeholders, reducing complexity and transaction costs (Nyhan & Marlowe, 1997; Deferne et al., 2022). When there is a lot of uncertainty and vulnerability, trust is needed to avoid negative outcomes.

Depending on the domain knowledge where they were initiated, there are different components of trust and various ways to analyse it:

- Rational-choice behaviour, affected by various psychological factors, such as disposition, intentions (Lewicki et al., 2006).
- Trust dimensions at a micro-level, highlighting the cognitive and affective nature of trust (Lee & See, 2004) and the influence of emotions, expectations, and attributional motives, during the development of trust between two parties (Costa & Anderson, 2011).
- Antecedents (integrity, benevolence, ability - Mayer et al., 1995), components, and consequences of trust (Lude & Prügl, 2019; Deferne et al., 2022).
- Dynamics (temporal evolution) of trust and its temporal stability (Deferne et al., 2022). Related to this, trust-building is a process that depends on the quality of interactions and the needs and expectations of the parties involved (Lewicki & Bunker, 1996). Positive exchanges are likely to generate, maintain, consolidate/strengthen trust and reciprocity is key for the establishment and maintenance of trust (Costa & Anderson, 2011).

With very few exceptions (Hancock et al., 2011; Sheridan, 2019; Wojton et al., 2020; Malle & Ullman, 2021), there is no research examining trust components in automation. Yet, trust may constitute an important source of competitive advantage across various systems, thus understanding how to build it is essential (Versteegh, 2019; Ferrario et al., 2020). While technological aspects are rapidly being overcome (Motamedi et al., 2020; Raats et al., 2020), psychological challenges prevail in the public adoption of AVs. To make things even more complicated, there are also misunderstandings of the differences between automated and autonomous (self-governance) and overlaps with discussions on mistrust and distrust. Contrary to the general view that they may be at the opposite ends of the spectrum of trust, distrust and mistrust have distinct connotations. Some authors suggest that trust and distrust can co-exist, and that trust may be context- and task-specific (Lewicki et al., 2006).

With an objective to identify the key features of trust from the layperson's perspective, as a potential end user of AV technology, we prototyped trust in AV using four studies with four independent samples from an online panel.

# 3. Methods and data

Four studies, using the Yabble online platform and panel, were conducted in 2022-23. The first two studies generated and ranked the centrality of the features, and the prototypical features were then confirmed with reaction time and B-W type 1 analysis. Participants from distinct samples were given a description and then asked in each study to perform a different task: Study 1) to write down the first 10 words/features that came to their mind in relation to trust in general and trust in AV in particular (each limited to 5 min); Study 2) to rate the relevance of each word on a 7-point scale, to select whether features were significant/relevant or not for the trust in AVs; Study 3) to classify true and false features of trust in AV in a reaction time test; and Study 4) to confirm their selection of the most and least relevant features in a B-W type 1 survey. All studies were independent of each other (to avoid bias and potentially inflating the strength of the relationship between the feature generation and confirmation studies) and included socio-demographics such as gender, age, education, driving licence, as well as previous experience with AV and knowledge of AV technology. The samples were balanced and representative of the population in terms of gender and age group quotas. Results are presented in Table 1. It is important to note the reaction time analysis accounted for the number of characters in a feature, as some self-explanatory features were displayed in one word (e.g., 'Honesty'), while others included several descriptors (e.g., 'Vehicle Quality, high quality interface, quality control).

# 4. Results

The analysis of the four studies highlights the salience of certain elements of trust in AV by crossing the frequency of occurrence and the importance of these elements. The first, the generation study (n=742) identified 41 features, with the highest frequencies for 'safety', 'reliability', 'control', 'performance', 'vehicle quality' and 'vehicle function'. The analysis was performed after lemmatisation. Only words with a frequency > 5 were kept. A median split was used to identify the central features. The most remote features were 'earned', 'negative feeling', and 'sustainability', all with a frequency of 5.

In Study 2 (n=301), we displayed all 41 features in random order to participants, who rated their centrality to trust in AV on a Likert scale 1-7 (1 representing "not at all" and 7 "extremely related"). Two metrics were computed: the average importance of the feature, which is an indicator of the saliency of the evoked words and the standard deviation. The highest centrality means were for 'tested' (av.=5.53, st.dev.=1.4), 'honesty' (av.=5.51, st.dev.=1.41), 'safety' (av.=5.49, st.dev.=1.52), and 'reliability' (av.=5.43, st.dev.=1.46). By contrast, the lowest values were for 'negative feelings' (av.=3.53, st.dev.=1.81), 'dangerous' (av.= 3.75, st.dev.=1.98), and 'worry' (av.= 3.81, st.dev.=1.82). The first two columns of Table 1 show some differences in the ranking, which may be explained by the 'priming' effect. When participants were asked to generate words about AV, their lists may have reflected prior exposure. Certain aspects may have not sprung to their mind, yet, when they were prompted to indicate relevance, they recognised features previously omitted.

Study 3, the reaction time test, (n=459), tested the speed and accuracy of classifying the features. Thirty participants identified false features as related to trust in AV and thus were removed from the dataset, leaving 429 correct responses for analysis. The average reaction time for decoy features was 0.83 seconds (st.dev.=0.48), with a learning/practice test showing an average of 1.29 sec (st.dev.=0.69). The average time for classifying each of the 41 features was 0.97 sec (st.dev.=0.09), however, when accounting for the length of the string or characters, the average became 0.99, with a st.dev. increased to 0.457. The ranking for reaction time presented in Table 1 is weighted by the string length. Results show 'vehicle quality', 'credibility', 'experience', 'vehicle function', as well as 'proven technology' are the top five features, while 'reliability', 'performance', and 'control' show slower reaction times. Reaction time results were inconclusive, and additional analysis is needed.

Study 4, B-W ranking (n=529) is a result of a combination of Max-diff and multinomial logit model estimated using NLogit, as well as the support.BWS, bwsTools, crossdes, apollo in R (Aizaki &Fogarty, 2023). The top 36 features were distributed into 36 sets of four features, using a BIBD design. To reduce cognitive load, participants were randomly presented two blocks of 18 sets out of 36. The B-W allows for relative preference for features to be measured.

The max-diff assumes that the difference in utility between the B and W items selected in the pair of items is the maximum among all utility differences. The multinomial logit considers that the best option has the utility larger than the other options, then after removing the best option, there are other options with utility larger than the worst. The average ranking is shown in Table 1. This ranking has the highest correlations with the centrality ranking (Table 2), showing 'safety', 'tested', 'vehicle quality', 'vehicle function', 'proven technology', and 'performance' in the top 10 central features of trust in AV. Interestingly, 'crashing' appeared as a central feature only in this analysis, while 'guarantee' was in the top 10 only for centrality ranking and B-W. Conversely, 'warning system' was ranked higher in B-W than in the other studies.

**Table 1: Ranking of features using four different studies (top 10 central features highlighted in grey)**

| Feature | Study 1 Frequency | Study 2 Centrality | Study 3 Reaction time | Study 4 B-W | Overall |
|---|---|---|---|---|---|
| Safety | 1 | 3 | 8.5 | 1 | 1 |
| Tested | 13 | 1 | 9 | 2 | 2 |
| Reliability | 2 | 4 | 33 | 3 | 8 |
| Proven technology | 10 | 15.5 | 5 | 4 | 5 |
| Vehicle function | 6.5 | 15.5 | 4 | 7 | 4 |
| Vehicle quality | 5 | 11 | 1 | 8 | 3 |
| Performance | 4 | 13 | 39 | 9 | 15 |
| Control | 3 | 18 | 21 | 12 | 9 |
| Experience | 6.5 | 14 | 3 | 14 | 6 |
| Credibility | 14.5 | 10 | 2 | 15 | 7 |
| Obey regulations | 20.5 | 17 | 12 | 16 | 16 |
| Stress-free | 8 | 19 | 23 | 24 | 19 |
| Guarantee | 34 | 7.5 | 21.5 | 5 | 17 |
| Crashing | 16.5 | 26 | 24 | 6 | 18 |
| Depend on | 29.5 | 5 | 14 | 10 | 11 |
| Honesty | 34 | 2 | 16.5 | 11 | 12 |
| Confidence | 24.5 | 12 | 9.5 | 18 | 13 |
| Positive feeling | 16.5 | 23.5 | 36 | 19 | 26 |
| Integrity | 24.5 | 6 | 6 | 20 | 10 |
| Transparency | 22 | 7.5 | 40 | 21 | 23 |
| Earned | 39 | 9 | 26 | 22 | 27 |
| R & D | 29.5 | 20 | 16.5 | 23 | 21 |
| Smart | 20.5 | 27 | 26.5 | 27 | 29 |
| Belief | 12 | 21.5 | 20 | 28 | 20 |
| Fear | 9 | 32 | 19 | 29 | 22 |
| Distrust | 14.5 | 37 | 27 | 31 | 32 |
| Uncertain | 18.5 | 36 | 33 | 34 | 34 |
| Novel | 18.5 | 35 | 11.5 | 36 | 30 |
| Price | 11 | 30 | 7 | | 14 |
| *Peripheral or remote features* | | | | | |
| Warning system | 39 | 21.5 | 18.5 | 13 | 24 |
| Risk | 29.5 | 23.5 | 33 | 17 | 31 |
| Comfort | 24.5 | 28 | 15 | 25 | 25 |
| Sustainable | 39 | 29 | 38 | 26 | 36 |
| Brand | 29.5 | 25 | 26.5 | 30 | 33 |
| Happy | 39 | 31 | 30.5 | 32 | 38 |
| Exciting | 29.5 | 34 | 35 | 33 | 35 |
| Robotic | 34 | 33 | 37 | 35 | 39 |
| Nervous | 24.5 | 38 | 12.5 | | 28 |

| | | | | | |
|---|---|---|---|---|---|
| Worry | 36 | 39 | 30 | | 40 |
| Dangerous | 29.5 | 40 | 29.5 | | 37 |
| Negative feeling | 39 | 41 | 41 | | 41 |

The last column of the table is a mean ranking of the four studies. With one exception (‘experience’), the features are all related to technology. This is consistent with the literature that identified trust as the main barrier for the development and uptake of AV (Fagnant & Kockelman, 2015; Sun et al., 2017; Lu et al., 2020). Also, it is important to offer the public sufficient experience with AVs to gain trust and support the adoption of the technology. This can be done by intensifying trials, experiencing AVs on the road, seeing them in the streets, in a showroom, watching videos and reading reviews.

Table 2 shows moderate correlations between the rankings, with the strongest alignment between centrality ranking and B-W. This suggests that two confirmation studies may not be sufficient to confirm the prototype. The table also shows that the consistency between studies increases from the generation to confirmation of features stages (B-W and reaction time) yet confounds in the reaction time test deserve further examination.

**Table 2: Rank-correlation between studies**

| | Study 1<br>Frequency | Study 2<br>Centrality | Study 3<br>B-W | Study 4<br>Reaction time |
|---|---|---|---|---|
| **Frequency ranking** | 1 | | | |
| **Centrality ranking** | 0.305 (<0.001) | 1 | | |
| **B-W ranking** | 0.395 (<0.001) | 0.787 (<0.001) | 1 | |
| **Reaction time ranking** | 0.394 (<0.001) | 0.409 (<0.001) | 0.416 (<0.001) | 1 |

# 5. Discussion and conclusion

Through a sequence of four studies we identified the most important features of trust in AV include people feeling safe and confident using them, with the belief that the vehicle technology and the supporting infrastructure will protect the individual. Trust is relevant for AV because the human is uncertain that the ‘machine’/technology will perform competently and reliably when the human does not control the vehicle. Thus, risks are associated with the performance of the AV system. The prototypical features of trust in AV are akin to the trustworthiness (ability, benevolence, and integrity, presented in the trust model by Mayer at al., 1995), and translated by Lee and See (2004) into performance, purpose, and process. We have also found similarities to the human-computer trust scale by Madsen and Gregor (2000), our features incorporating the five facets of trust: reliability, understandability, technical competence/performance, personal attachment, and belief. The analysis also highlighted a few features reflective of outcomes (‘worry’, ‘dangerous’, ‘negative feeling’, ‘fear’, ‘risk’), even if they classify as remote features in all rankings. This suggests that feeling worried and concerned arises when the human is uncertain that the AV technology will perform reliably and competently (and sufficiently tested), in the absence of control. This has implications for technology providers and decision-makers and indicates that perceptions about AV and uptake may be improved if trust is increased and the public has experience with AVs. The findings show that the ‘trust architecture’ in the context of AV is distinct from trust in general and further work is needed to consolidate the central vs peripheral/remote features. Our work will incorporate scale development and vignettes, currently under way. A detailed analysis of the interrelations between personal characteristics, trust, and the outlook of AV technology is required to enrich/complement findings from the aggregated results.

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