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Just one factor?

de Winter, Joost; Nordhoff, Sina

DOI

[10.1016/j.trip.2022.100645](https://doi.org/10.1016/j.trip.2022.100645)

Publication date

2022

Document Version

Final published version

Published in

Transportation Research Interdisciplinary Perspectives

Citation (APA)

de Winter, J., & Nordhoff, S. (2022). Acceptance of conditionally automated cars: Just one factor? *Transportation Research Interdisciplinary Perspectives*, 15, Article 100645. <https://doi.org/10.1016/j.trip.2022.100645>

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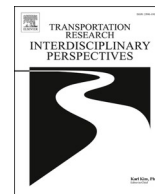
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Acceptance of conditionally automated cars: Just one factor?

Joost de Winter^{a,*}, Sina Nordhoff^b

^a Department Cognitive Robotics, Faculty Mechanical, Maritime and Materials Engineering, Delft University of Technology, the Netherlands

^b Department Transport & Planning, Faculty Civil Engineering and Geosciences, Delft University of Technology, the Netherlands

ARTICLE INFO

Keywords:

Technology acceptance
Method effects
Conditionally automated driving

ABSTRACT

Recent research suggests the existence of a general acceptance factor (GAF), similar to the “big one” in personality research or the general intelligence factor (g). The current study, written in the form of a short commentary, sought empirical support for the GAF by using data from a large multinational questionnaire of the L3Pilot project on the acceptance of conditionally automated cars (CACs). Our analysis provides clear support for a GAF of CACs, as this factor explained 55% of the variance among the questionnaire items. Criterion validity was established by demonstrating an inverted U-curve between GAF scores and respondents’ ages in 17 countries. It is recommended that researchers concerned with technology acceptance consider whether their acceptance constructs are sufficiently unique or merely part of a positive manifold.

Introduction

Recently, Nordhoff et al. (2018) suggested that a General Acceptance Factor (GAF) represents the apex of the factor structure of technology acceptance. Based on an analysis of the eigenvalues of the correlation matrix constructed from 7755 crowdsourced respondents who replied to 58 statements about future self-driving vehicles (e.g., expected usefulness, ease of use, pleasure, social influence, trust, intention to use, etc.), it was determined that a single GAF most appropriately represented the factor structure of their questionnaire. The first factor explained 19.6% of the variance, whereas the remaining factors appeared to be of relatively minor importance (6.0% to 3.2% of the variance was explained by Factors 2 to 5). In the same vein, in their study on the acceptance of highly automated vehicles, Nees and Zhang (2020) identified a general acceptance factor and commented: “Theories of technology and automation acceptance have suggested that sub-constructs of acceptance (e.g., trust, perceived ease of use, intention to use) are distinct. Yet this general factor showed that items to assess these hypothetical sub-constructs loaded on a unitary latent variable”.

An empirical reason for expecting the identification of a GAF is that technology acceptance constructs typically correlate positively with each other. For example, in a study on the acceptance of automated vehicles, Madigan et al. (2017) found that the constructs ‘performance expectancy’, ‘effort expectancy’, ‘social influence’, ‘facilitating conditions’, and ‘hedonic motivation’ of the technology acceptance model UTAUT2 (Unified Theory of Acceptance and Use of Technology 2)

correlated between 0.33 and 0.69. Similarly, positive correlations (0.28 to 0.60) between these technology acceptance constructs were identified in a meta-analysis covering hundreds of UTAUT studies (Blut et al., 2021). The UTAUT2 model represents a synthesis of eight influential technology acceptance models to predict the intention to use consumer technology (Venkatesh et al., 2012) and has received tens of thousands of citations in the academic literature (e.g., Venkatesh et al., 2003, 2012). However, whether the model components are sufficiently unique is a question that deserves investigation.

A conceptual reason for the correlations among acceptance constructs may come from participants’ general positivity, analogous to the reasons behind the general factor of personality (Museum, 2007). Museum described the general factor of personality, or the “big one”, as a mix of socially valued dimensions, including self-esteem, life satisfaction, positive affect, well-being, and motivation. In the same vein, it may be expected that a person’s attitude towards technology, such as automated vehicles, is related to how positive this person is in general towards the technology under investigation without distinguishing between different facets of acceptance.

The current paper uses an international questionnaire dataset from the L3Pilot project (<https://www.l3pilot.eu>), which examined the viability of conditionally automated cars (CACs) as a safe and efficient means of transportation on public roads. Conditionally automated driving, also known as Level-3 automation, automates acceleration, braking, and steering under limited conditions, with the driver having to take over control when requested by the automated driving system (SAE

* Corresponding author.

E-mail addresses: j.c.f.dewinter@tudelft.nl (J. de Winter), s.nordhoff@tudelft.nl (S. Nordhoff).

International, 2021). In contrast to the crowdsourcing study by Nordhoff et al. (2018), the L3Pilot project administered a questionnaire among nationally representative samples involving people aged between 18 and 69 (Nordhoff et al., 2021).

Herein, we examine if the GAF is identified in this large questionnaire, and we establish its generality by determining associations with age among respondents from 17 different countries. Previous research suggests that technology acceptance decreases with age, although the generality of this correlation may depend on the specific type of technology and age group. For example, Künemund and Tanschus (2014) reported that certain technologies tailored to older persons, such as fall detection apparatus, are well accepted into old age. When it comes to CACs, it may be expected that this technology is best accepted among middle-aged users, as this group can be expected to rely on daily road transport to fulfill their mobility needs. In comparison, old persons may be unable or unwilling to learn to use such technology, whereas young persons may not be able to afford CACs.

Methods and results

This study uses a public dataset from the L3Pilot project (Lehtonen, 2021) concerned with assessing the acceptance of CACs among samples that were targeted to be nationally representative in terms of age and gender. The questionnaire was administered in nine European countries (Finland, France, Germany, Hungary, Italy, Sweden, Spain, UK) and eight non-European countries (Brazil, China, India, Indonesia, Japan, Turkey, South Africa, USA). A translation bureau translated the questionnaire to the national languages of the countries. The survey was conducted in two waves; Wave 1 was conducted in April–June 2019 among European countries, and Wave 2 in February and March 2020 among non-European countries.

At the beginning of the questionnaire, the functionality of CACs was described. More specifically, it was explained that such cars can drive automatically under limited conditions, such as on highways. It was also mentioned that the car might request the driver to resume control anytime, for example, when approaching a construction site.

The items of the questionnaire were based on the UTAUT2 model of Venkatesh et al. (2012) and complemented with constructs relevant to automated driving, such as perceived safety and trust (Xu et al., 2018). Items about privacy were added as well. The items were formulated in such a way as to refer to future CACs, e.g., “Using a conditionally automated car would be enjoyable.” More details about the L3Pilot questionnaire can be found in Louw et al. (2019), Metz et al. (2019), and Nordhoff et al. (2020, 2021). For the analysis, all CAC-related questionnaire items from the dataset were included, except for the following ones (item codes based on Nordhoff et al., 2021):

Willingness to pay for CACs (f18). This item was difficult to analyze due to the different national currencies and incomes involved.

Expected effects of CACs (e.g., f21_1: “How do you think CAC will affect your personal mobility?”) since these questions were answered on a different scale (1 = Large increase, 5 = Large decrease) and did not concern the acceptance of CACs.

Questions about concerns.

f19_3: “I think I would monitor the car’s performance the whole time to be sure I can safely take over control from the car when needed.”

f19_8: “I would be concerned about the general safety of a CAC.”

f19_11: “I would be concerned that a failure or malfunctions of a conditionally automated car may cause accidents.”

f19_12: “I would be concerned to take over control from a conditionally automated car after being engaged in activities other than driving.”

These items did not correlate strongly with the other items, perhaps because of their negative wording (i.e., a higher rating suggests lower acceptance). Note that if they were to be included, these four items would cluster as a separate ‘concern’ factor, which may reflect a response style effect due to negative wording rather than a substantive construct.

The 41 included items are shown in Table 1. In our analysis, answers “I prefer not to respond” were set to ‘missing’ values. Respondents with missing data in more than 20 items were removed, leaving 18,590 respondents from the original 18,631 respondents. Missing values of the remaining respondents were imputed using the nearest-neighbor method (1.1% of data were missing).

Fig. 1 shows the scree plot, i.e., the eigenvalues of the 41×41 correlation matrix. It can be seen that one dominant factor emerged, representing 54.6% of the variance. The remaining components each represented only 4.0% or less of the variance. In other words, the scree plot clearly suggests that a single-factor solution is most appropriate.

Table 1 shows the loadings of the first factor (named the general acceptance factor; GAF), as computed by principal component analysis (PCA)¹. It can be seen that the loadings were overall high (mean = 0.73, min = 0.55, max = 0.83).

GAF scores were principal component scores. More specifically, a GAF score was computed for each participant by multiplying the participant’s scores on the 41 items by the corresponding item loadings and subsequently calculating the mean across all 41 items. The item scores and GAF scores were z-transformed so that the mean was 0 and the standard deviation 1. In other words, the GAF score represents a weighted average of the participant’s responses, with the weight being the loading as depicted in Table 1.

An analysis of the association between respondents’ GAF scores and their ages revealed a negative Pearson correlation coefficient ($r = -0.21$, $p < 0.001$, $n = 18,590$). Further examination of the relationship between age and the GAF revealed an inverted U-shape, represented by the parabolic fit indexes ($a = -0.000611$, $b = 0.0365$, and $c = -0.3640$, where $\text{GAF score} = a \cdot \text{age}^2 + b \cdot \text{age} + c$), as illustrated in Fig. 2. In other words, mean GAF scores slightly increased with age and then tapered off. The oldest respondents in our sample (69 years) had a general acceptance score of about -0.74, that is, 0.74 standard deviations below the overall mean. The distribution of the GAF scores for four selected age groups is shown in Fig. 3. It can be seen that the middle age group (21–40 years) is overrepresented for high GAF scores (> 1), while the older age group (61–69 years) is overrepresented for low GAF scores (< -1) and underrepresented for above-average GAF scores (> 0).

In order to evaluate the generalizability of the GAF-age relationship, within-country relations between age and GAF were computed. Table 2 shows that for each of the 17 countries, the inverted U-curve was found, as evidenced by the negative coefficient a of the polynomial.

The above analysis does not imply that a single-factor solution is the only factor solution possible. We attempted to extract a higher number of factors and found that a six-factor solution is well interpretable. More specifically, after using maximum likelihood factor analysis with oblique Promax rotation, the following structure was established (based on items loading > 0.50).

1. Perceived safety & trust (Items 6, 8, 12, 14, 28, 37).
2. Effort expectancy & facilitating conditions (Items 25, 30, 31, 33, 36).
3. Hedonic motivations and other expectancies (Items 2, 3, 5, 9, 10, 17).
4. Behavioral intention (Items 15, 16, 18, 19, 20).
5. Social influence (Items 23, 24, 27).
6. Data privacy (Items 35, 40, 41).

However, these factors are strongly correlated. More specifically, factor scores according to a unit-weight method based on the above

¹ We used PCA instead of factor analysis for reasons of computational simplicity. Loadings obtained using factor analysis (maximum likelihood factor analysis; MLFA) gave nearly identical results ($r = 0.999$ between GAF loadings computed with PCA shown in Table 1 and MLFA loadings). Jensen and Weng (1994) further explained that it hardly matters which method is used to extract a general factor, whether it is PCA, factor analysis, or a hierarchical model.

Table 1

Overview of the 41 questionnaire items. Also shown are the technology acceptance constructs the questionnaire items aimed to represent, the mean item scores on a scale from 1 = strongly disagree to 5 = strongly agree, and the loadings on the general acceptance factor (i.e., one-factor solution).

No	Code	Questionnaire item	Construct	Mean	GAF Loading
1	f16_10	I intend to use a conditionally automated car in the future.	Behavioral intention	3.56	0.83
2	f16_22	I assume that a conditionally automated car would be useful in my daily life.	Performance expectancy	3.70	0.83
3	f16_11	Using a conditionally automated car would be enjoyable.	Hedonic motivation	3.70	0.83
4	f16_21	I would recommend a conditionally automated car to others.	Social influence	3.54	0.83
5	f16_12	Assuming that I had access to a conditionally automated car, I predict that I would use it.	Behavioral intention	3.77	0.83
6	f19_5	I would trust a conditionally automated car for my everyday travel.	Perceived safety & trust	3.51	0.82
7	f16_5	Using a conditionally automated car would help me reach my destination more comfortably.	Performance expectancy	3.76	0.81
8	f19_6	I would feel safe using a conditionally automated car.	Perceived safety & trust	3.47	0.81
9	f16_1	I expect that a conditionally automated car would be useful in meeting my daily mobility needs.	Performance expectancy	3.66	0.81
10	f16_9	Using a conditionally automated car would be entertaining.	Hedonic motivation	3.68	0.81
11	f16_2	Using a conditionally automated car would help me reach my destination more safely.	Performance expectancy	3.63	0.80
12	f19_2	I would feel relaxed during the ride in a conditionally automated car.	Perceived safety & trust	3.45	0.80
13	f16_16	I would use a conditionally automated car during my everyday trips.	Behavioral intention	3.62	0.80
14	f19_1	I would feel comfortable giving control to a conditionally automated car.	Perceived safety & trust	3.42	0.80
15	f20_4	I would use a conditionally automated car for leisure activities (e.g. sport, concert, restaurant, meeting friends).	Behavioral intention	3.69	0.79
16	f20_1	I would use a conditionally automated car for my daily commute to work / school / university / training school.	Behavioral intention	3.65	0.79
17	f16_7	Using a conditionally automated car would be fun.	Hedonic motivation	3.70	0.78
18	f20_5	I would use a conditionally automated car for vacation trips.	Behavioral intention	3.71	0.78

Table 1 (continued)

No	Code	Questionnaire item	Construct	Mean	GAF Loading
19	f20_3	I would use a conditionally automated car to run errands (e.g., going to dentist, or post office, visits to authorities, grocery shopping).	Behavioral intention	3.61	0.78
20	f20_2	I would use a conditionally automated car for business travel	Behavioral intention	3.66	0.77
21	f16_23	I plan to buy a conditionally automated car once it is available.	Behavioral intention	3.18	0.77
22	f17	I plan to use a conditionally automated car on motorways / congested motorways / urban roads / in parking situations once it becomes available.	Behavioral intention	3.48	0.76
23	f16_8	I assume that people whose opinions I value would prefer that I use a conditionally automated car.	Social influence	3.36	0.75
24	f16_20	I expect that people who are important to me think that I should use a conditionally automated car.	Social influence	3.32	0.72
25	f16_6	It would be easy for me to become skillful at using a conditionally automated car.	Effort expectancy	3.76	0.70
26	f16_15	I would expect the use of a conditionally automated car to be compatible with other digital devices I use.	Facilitating conditions	3.80	0.69
27	f16_18	I expect that people who influence my behaviour think that I should use a conditionally automated car.	Social influence	3.31	0.69
28	f19_9	I believe that the actions of a conditionally automated car would be predictable.	Perceived safety & trust	3.58	0.69
29	f19_7	I would expect that a conditionally automated car is reliable.	Perceived safety & trust	3.90	0.67
30	f16_4	I expect that a conditionally automated car would be easy to use.	Effort expectancy	3.92	0.67
31	f16_13	I could acquire the necessary knowledge to use a conditionally automated car.	Facilitating conditions	3.94	0.66
32	f16_14	I plan to use a conditionally automated car in adverse weather conditions such as during heavy rain or fog and in darkness.	Behavioral intention	3.34	0.65
33	f16_17	I would expect to have the necessary knowledge to use a conditionally automated car.	Facilitating conditions	3.85	0.65
34	f16_19	I would be able to get help from others when I have difficulties using a conditionally automated car.	Facilitating conditions	3.59	0.64
35	f15_1	I would feel comfortable with a conditionally automated car collecting	Data privacy	3.72	0.63

(continued on next page)

Table 1 (continued)

No	Code	Questionnaire item	Construct	Mean	GAF Loading
36	f16_3	information about the way I drive to ensure I can manage a safe take-over. Learning how to use a conditionally automated car would be easy for me.	Effort expectancy	3.84	0.63
37	f19_4	I would expect that a conditionally automated car acts appropriately in all situations.	Perceived safety & trust	3.79	0.63
38	f14	I would use the time during which a conditionally automated car is driving for other activities.	Performance expectancy	3.37	0.62
39	f19_10	I think I would be more aware of the traffic environment in a conditionally automated car than when I would drive on my own.	Perceived safety & trust	3.40	0.61
40	f15_2	I would feel comfortable with a conditionally automated car using information about the way I drive for other purposes (following my authorization). This may include information used by insurance companies.	Data privacy	3.30	0.59
41	f15_3	I would feel comfortable with conditionally automated car monitoring my eye behavior to issue warnings in case I become drowsy.	Data privacy	3.89	0.55

Note. Item codes are based on Nordhoff et al. (2021). Items f17 and f19 were asked in four different ways among subgroups, i.e., focusing on different operating design domains (ODDs) (“... if you were using a conditionally automated car on motorways / on congested motorways / on urban roads / in parking situations”); in the present study, no distinction was made between these ODDs.

items intercorrelated ranging from 0.54 (between Factor 5 and 6) to 0.82 (between Factor 1 and 3). These strong correlations make it difficult to establish the uniqueness of the factors. To illustrate, the scores of Factors 1 to 3 correlated negatively with participants’ age ($r = -0.19, -0.12, \text{ and } -0.21$, respectively). However, when attempting to determine their unique contributions by using linear regression analysis to predict age,

we faced issues of multicollinearity, where the regression coefficient of Factor 3 became three times ($\beta = -0.23$) as strong as the regression coefficient for Factor 1 ($\beta = -0.07$), whereas for Factor 2 it became even positive ($\beta = 0.09$). Although the statistical separation of acceptance constructs may be technically correct, whether the regression coefficients are meaningful is doubtful.

A possible counterargument against the GAF is that it is a statistical artifact rather than a meaningful construct (for a similar discussion regarding the general factor of personality, see Just, 2011). Indeed, it is possible that the positive correlations between items arise due to method effects, where a portion of respondents are ‘yea-sayers’ rushing through the questionnaire (see De Winter & Dodou, 2021 for computer simulations illustrating this effect).

To examine this possibility, we re-ran the analysis, but now for fast respondents (those who completed the entire questionnaire in less than 10 min) and slow respondents (those who completed the entire questionnaire in more than 20 min) separately. The results showed that the loadings for fast respondents were higher than the loadings for slow respondents (see Fig. 4). Correspondingly, the variance explained was 60.0% for the fast respondents and 48.6% for the slow respondents. These results provide clear support for the hypothesis that response style, at least in part, explains the GAF factor. However, even for the slowest respondents, who took more time to deliberate on their answers, the GAF still explained nearly half the variance.

Discussion

This study aimed to examine whether a GAF emerges from a variety of acceptance questions about CACs. The results showed that there clearly was a single dominant factor in the data, capturing 55% of the variance. It was also shown that when extracting more than one factor, these factors were found to be strongly correlated and hard to separate statistically.

The generality of the GAF of CACs was examined by its associations with age in 17 different countries. Even though the mean GAF scores differed between countries (differences in the intention to use AVs between countries have been found before, e.g., Bazilinskyy et al., 2015; Kyriakidis et al., 2015; Louw et al., 2021), an inverted U-curve was identified in each country. These findings indicate that GAF-age trends are cross-nationally robust, despite the vast differences between these countries (e.g., type of traffic, infrastructure, income).

The current results provide a sobering outlook on the vast amount of automated vehicle acceptance research currently being published (see Nordhoff et al., 2019, surveying 124 studies, a number that continues to grow). The fact that a single factor represents as much as 55% of the

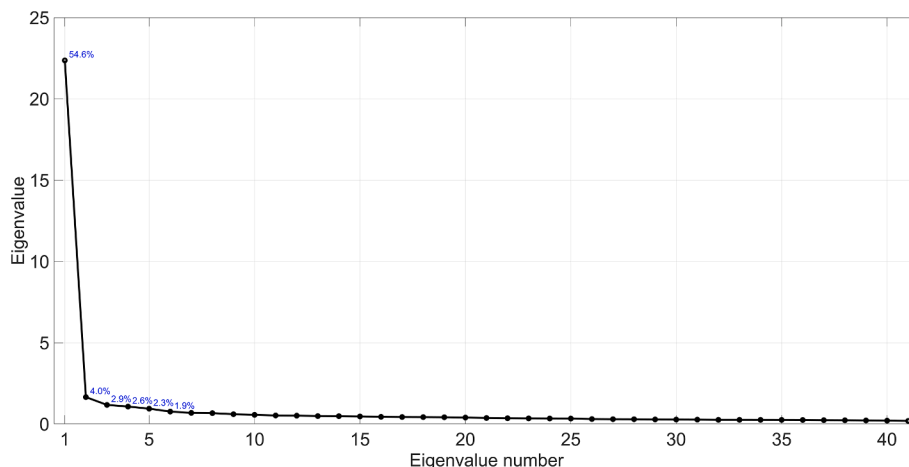


Fig. 1. Eigenvalues of the correlation matrix, sorted in descending order (“scree plot”). Also shown are the percentages of variance explained (being proportional to the eigenvalue) for the first five factors. It can be seen that one dominant factor emerged.

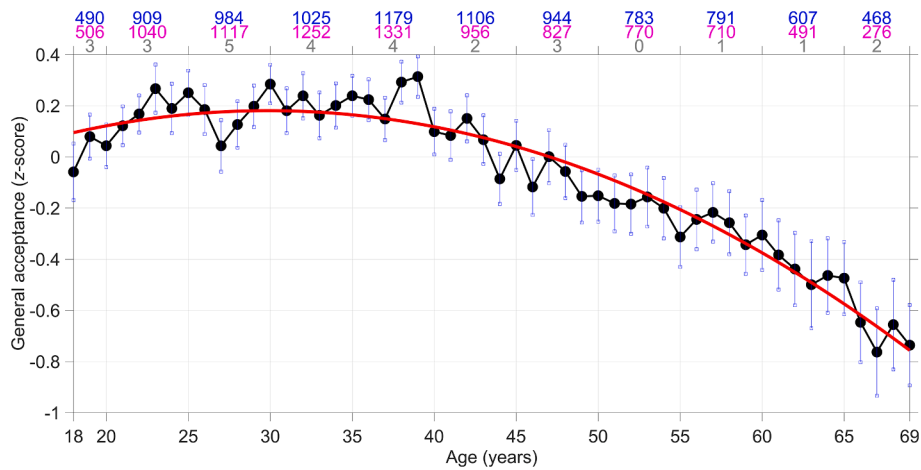


Fig. 2. Mean general acceptance score for each age separately. Also shown is a parabolic fit and 95% confidence intervals calculated for each age separately. The top of the figure lists the number of males (in blue), females (in pink), and participants with the gender “other” (in grey) for the age groups 18–20, 21–25, 26–30, 31–35, 36–40, 41–45, 46–50, 51–55, 56–60, 61–65, and 66–69.

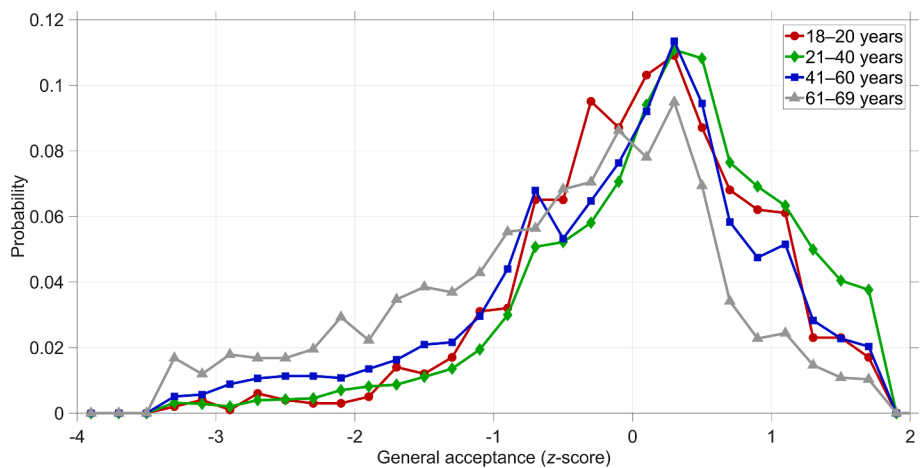


Fig. 3. Distribution of general acceptance scores for four age groups. The horizontal axis shows the general acceptance scores in bins of 0.2 and the vertical axis shows the number of participants, normalized so that the total equals 1.

variance makes one wonder whether the large amount of research examining different facets of technology acceptance (e.g., as part of UTAUT2) is of added value. Researchers are encouraged to determine whether the constructs in their (structural equation) models are sufficiently distinct or whether these constructs should better be seen as one of the same.

The positive correlations may have arisen because respondents found it hard to identify the boundaries of the facets of acceptance, especially as the questions pertained to hypothetical technology that does not exist on the roads at the moment. For example, to them, the item “I expect that a conditionally automated car would be easy to use” representing the construct ‘effort expectancy’ may appear very similar in wording to the questionnaire item “I assume that a conditionally automated car would be useful in my daily life” representing the construct ‘performance expectancy’. In our study, constructs correlated strongly (between 0.54 and 0.82), which is stronger than the correlations observed in the UTAUT meta-analysis by Blut et al. (2021) (between 0.28 and 0.60). The high correlations in our study may be caused by the fact that CACs do not exist on the road yet, so participants had to rely on their imagination. In fact, only after conducting the present survey, Mercedes-Benz claimed to be the first to sell SAE Level-3 automation, where under certain conditions “the driver can focus on other activities such as work or reading the news on the media display” (Daimler., 2021). It is possible that

correlations will be weaker, and the representation of the GAF will be smaller, when participants rate the acceptance of a tangible product with which they have already come into contact.

Our critique of the use of construct proliferation in acceptance research aligns with Schmidt (2017), who provided a similar commentary in the context of the general intelligence factor, also called general mental ability (GMA), or g. Schmidt lamented that many studies exist on specific cognitive abilities such as verbal abilities or spatial abilities and that these studies fail to mention that these specific abilities are indicators of g and that after statistical control for g, the specific abilities retain no criterion validity whatsoever. Schmidt further argued that this form of omission (i.e., the failure to acknowledge g) undermines the credibility of research in psychology.

Finally, this work considered the hypothesis that the GAF is a statistical artifact: If the dominant source of variation in the data arises due to response style, this will cast doubt on much of the published acceptance research in this area since correlations between all items are affected. The present analysis supported the ‘statistical artifact’ hypothesis, as faster respondents, i.e., those who are more likely to provide meaningless answers (see De Winter and Hancock, 2015), yielded a stronger GAF factor. However, as also suggested by Nordhoff et al. (2018), this debate is perhaps of philosophical rather than practical relevance, as a person’s response style (i.e., the ease with which

Table 2

GAF-related effects for respondents from different countries. Shown is the ISO country code, sample size, percentage females, mean age, mean GAF score, GAF score according to the polynomial equation, for three different ages: 18, 35, & 69 years, and the three polynomial coefficients (where GAF score = $a.age^2 + b.age + c$).

	N	% females	M age	M GAF score	GAF @ Age 18	GAF @ Age 35	GAF @ Age 69	a	b	c
GBR	1214	50.7	41.24	-0.41	-0.38	-0.17	-1.44	-0.000968	0.0634	-1.2069
USA	1054	51.9	43.56	-0.36	-0.09	-0.17	-0.93	-0.000351	0.0141	-0.2300
SWE	1167	47.8	42.46	-0.48	-0.28	-0.30	-1.07	-0.000411	0.0203	-0.5110
DEU	1128	50.2	43.89	-0.50	-0.36	-0.35	-0.95	-0.000353	0.0193	-0.5937
FRA	1160	52.1	42.75	-0.34	-0.21	-0.10	-1.21	-0.000774	0.0477	-0.8192
CHN	1003	49.5	37.21	0.44	0.22	0.48	0.43	-0.000324	0.0323	-0.2534
HUN	1138	50.8	41.92	-0.08	-0.19	-0.05	-0.13	-0.000217	0.0202	-0.4866
ITA	1181	49.6	42.71	-0.13	-0.19	-0.02	-0.54	-0.000493	0.0360	-0.6729
FIN	1019	41.1	50.20	-0.69	-0.77	-0.59	-0.90	-0.000386	0.0309	-1.2016
ESP	1074	49.3	42.15	0.06	0.03	0.10	-0.17	-0.000243	0.0171	-0.1968
BRA	1057	50.4	37.48	0.56	0.50	0.61	0.21	-0.000366	0.0263	0.1437
IDN	1059	49.1	35.25	0.59	0.54	0.61	0.30	-0.000266	0.0186	0.2912
IND	1054	48.7	35.33	0.74	0.53	0.83	0.12	-0.000752	0.0574	-0.2595
JPN	1074	50.5	45.04	-0.36	-0.52	-0.33	-0.54	-0.000349	0.0299	-0.9484
RUS	1079	53.8	37.70	0.16	0.24	0.20	-0.29	-0.000234	0.0100	0.1362
ZAF	1069	52.4	35.53	0.36	0.32	0.44	-0.15	-0.000468	0.0313	-0.0880
TUR	1060	49.8	37.11	0.62	0.59	0.64	0.65	-0.000050	0.0056	0.5024

Note. The GAF score is color-coded on a continuum, where the minimum value is red, the median is white, and the maximum value is green.

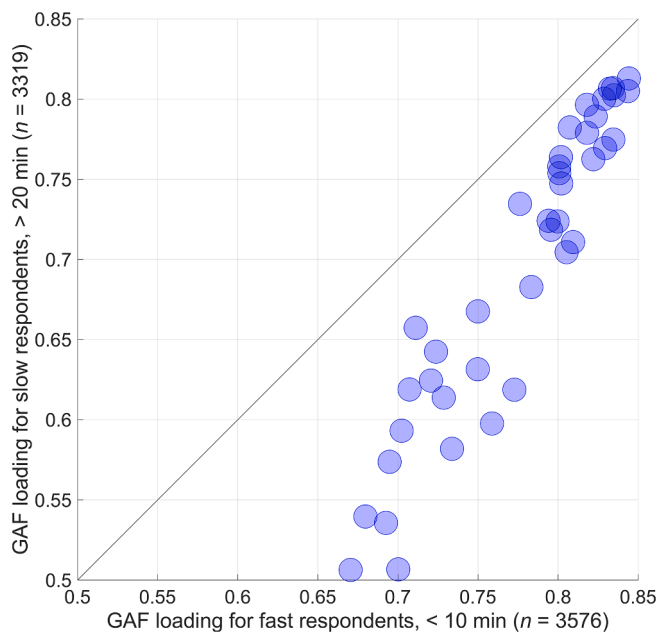


Fig. 4. GAF loadings for fast and slow respondents. Each marker represents a questionnaire item. The diagonal line is the line of unity. The questionnaire completion time data was available for 14,809 of 18,590 respondents. The median questionnaire completion time was 13.75 min.

someone ticks ‘agree’ and rushes through a questionnaire) may be itself a substantive trait that resembles the notion of ‘acceptance’.

CRedit authorship contribution statement

Joost de Winter: Conceptualization, Software, Formal analysis, Visualization, Writing – original draft. **Sina Nordhoff:** Resources, Writing – review & editing.

Supplementary Material

A script that reproduces all results in this paper can be downloaded from <https://doi.org/10.4121/20153585>.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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