Multi-Source Trust Transfer in Artificial Intelligence: A Deeper Understanding of the Required Conditions

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Abstract

The concept of trust transfer offers an interesting alternative to the prevalent debates regarding whether or not we can trust AI-enabled devices. However, the integration of AI with various technologies raises questions about the validity of established theories. To begin, it is unclear if faith in AI alone or in the underlying technology is sufficient for trust to be transferred. As a second point, the dual function of trust necessitates a nuanced understanding of the origins of trust. In order to solve these problems, we investigate whether confidence in providers and trust in technology are prerequisites for trust. We used condition analysis to conduct a poll with 432 people on their experiences with autonomous cars. Our findings highlight the importance of having faith in AI and automobile technologies. On the other hand, only car providers qualify as a mandatory input. We provide a contribution to knowledge by offering a fresh viewpoint on trust in AI, using a promising data analysis approach to unearth essential trust sources, and keeping the duality of trust in mind throughout the trust transfer process.

Introduction

The idea of trust has been at the center of technology acceptance studies for decades, and it has been shown to be a major factor in people's decisions to adopt and utilize new technologies [1-3]. Not surprisingly, contemporary information systems (IS) research [e.g., 4, 5, 6] is mostly focused on answering the issue of how to generate confidence in AI-capable technology. By "AI-capable technology," we mean a technology that has benefited from the convergence of AI with other technologies (such as computer vision, natural language processing, or pattern recognition) in some way [7, 8]. For instance, artificial intelligence (AI) is increasingly merging with automobile technology (as foundational tech). As a consequence of these developments, autonomous vehicles (AVs) equipped with artificial intelligence (AI) can now aid drivers and entertain passengers [9]. Researchers, businesses, and policymakers have lately developed and published a number of frameworks and principles to increase public confidence in artificial intelligence [see, for example, references 6, 10]. Recent studies have looked at the factors that lead people to trust AI (such as explainable AI [11]) and how that trust affects their attitudes and actions (such as how satisfied they are with AI technology [5]). Existing research has made important advances, but it has ignored trust transfer procedures necessary to develop confidence in AI-capable technology. According to trust transfer theory [12, 13], people's preexisting confidence in anything (a person, a piece of technology, etc.) may be transferred to something completely new and unfamiliar. Users are more likely to transfer their trust to an unfamiliar entity if they see a close connection between the two [12, 13]. We suggest that innovative AI-capable technologies are also likely to undergo trust transfer procedures because they are the product of the convergence of AI with one or more foundational technologies that are already well-known to consumers and serve as trust sources [14]. By way of illustration, if AI technology is incorporated in the vehicle technology, resulting in AI-capable AVs, users may transfer their established confidence in familiar vehicle technologies and, ostensibly, also transfer faith in related AI technologies (e.g., virtual assistants like Alexa or Siri) to unfamiliar AVs.

However, traditional theoretical assumptions of trust transmission are being tested in two ways by the integration of AI and foundational technologies. It's important to note that people may need to have trusting beliefs in both the base technology (e.g., automobile technology) and AI in order to trust the unknown AI-capable technology. A trust transfer from AI is questionable, despite recent studies validating multi-source trust transfer in comparable circumstances [e.g., 15]. achievable. In particular, for confidence to be transferred, users must already have established credibility with AI [12, 13]. However, because to factors such as their novelty and complexity, consumers may still lack expertise or in-depth understanding of current AI technology [16]. It is still of great interest to learn if users' trusting views in either the base technology or AI are required for trust transfer in an unproven AI-capable system, or whether confidence in either is sufficient.

Second, existing research on trust transfer has often focused on a well-established technology or provider [e.g., 12, 17]. Trust research, on the other hand, suggests that consumers' trust often plays a dual function, with both provider and technology trust being taken into account simultaneously [18, 19]. Since people may be unfamiliar with specific AI yet well-versed in the likes of Google, Microsoft, IBM, and Amazon, the duality of trust is especially pertinent in the context of AI. One example is the partnership between Alphabet (Google) and Daimler on the development of AI-enabled autonomous trucks. Alphabet may be a household name, but the particular artificial intelligence technologies utilized to enhance AVs may be unfamiliar to users. The question of whether confidence in providers and trust in technologies as trust sources are both required to establish trust in an AI-capable technology remains open from the standpoint of trust transfer. Therefore, in the context of AI-capable technologies, a more nuanced approach on multi-source trust transfer is essential, one that takes into account trust transfer of both providers and technologies to allow the comparison of necessary trust criteria. As a result, the following is the research question (RQ) we want to address.

RQWhen looking at AI-enabled technologies from a dual trust viewpoint (i.e., trust in technology and confidence in providers), what trust sources are required for multi-source trust transfer?

We build a theoretical model centered on multi-source trust transmission from a dual trust viewpoint, analyzing whether both trust sources are necessary [19], and we anchor our study in trust transfer theory [12, 13] to answer our RQ. Here, we zero in on the process of extending confidence in established car tech and AI to previously untested AVs. Through an online survey with 432 participants and a required condition analysis (NCA) [20], we put our theoretical model to the test.

Our findings corroborate the importance of confidence in both vehicle and AI technologies as foundational pillars for AV trust transfers. However, our research produces unexpected results at the provider level: only confidence in vehicle providers is seen as a required source, whereas trust in AI providers does not fulfill the necess- ary condition requirement. In three significant ways, our research adds to the existing body of knowledge. To begin, we provide a new theoretical angle on trust in AI by positing the existence of trust transfer mechanisms in the setting of rapidly developing technology. Second, our work adds to the theory of trust transfers by highlighting the significance of the duality of trust and demonstrating how trust transfers may be seen as the product of a combination of provider and technological trust. Third, we emphasize the need of performing NCAs, first proposed by Dul [20] to learn which trust sources are prerequisites for multi-source trust transfer.

1. Background

Autonomous Vehicle Confidence 2.1

AI-enhanced driving capabilities in AVs are a frequent study example of merging AI with foundational technologies [4]. The gradual integration of AI into automobile technology is often broken down into six tiers of automation [21]. A vehicle at level 0 has no autonomous features and no artificial intelligence. Increasing degrees of automation need ever-expanding sets of artificial intelligence capabilities to underpin autonomous driving features [9]. In intermediate degrees of automation, such as lane-keeping assistance, speed control, and entertainment systems, drivers are still accountable for and in charge of their cars, but AI provides help for these tasks. As the degree of automation increases, artificial intelligence (AI) takes over more and more of the driving process, to the point where drivers may hand over control of their car in certain scenarios (such as while driving on specifically upgraded roadways). Convergence between AI and vehicles reaches its pinnacle at level five, with AI boosting intelligent automation to human levels in most driving situations.

The use of AVs contains high physical risks such as accidents at high speeds; and it reflects a step-change from augmentation, where users collaborate closely with AI-capable technology, to automation, where technology is completely taking over complex human tasks, making the convergence of AI and vehicle technologies a double-edged sword. As a result, it is crucial to learn why certain trust conditions are essential for people to feel comfortable with AVs [4].

Two-Faced Trust 2.1

Nowadays, most IS research adopts a dual perspec- tive on trust. First, trust in people or organizations [18, 22], such as trust in a provider [2], team members [23
or those who rent out cars. Second, having faith in a piece of technology, such as a cloud service [18, 22] or in-vehicle technology [19]. Both the object and the assumptions that underlie confidence in humans and technology are different. Beliefs in interpersonal trust stem from assessments that the other party has the qualities and motivations necessary to perform as anticipated in a dangerous circumstance [24], whereas confidence in technology stems from assessments of the device's features rather than its intentions [18]. Individuals can adjust their beliefs about another person's competence (the degree to which they can meet one's needs), benevolence (the degree to which they care about and are motivated to act in one's best interests), and integrity (the degree to which one can be trusted to keep one's word) [25]. As a general rule, when people say they trust a piece of technology, they're referring to its usefulness, dependability, and (in the case of help features) their belief that they'll receive the guidance they need to successfully complete a task [18, 26]. Because consumers may be unfamiliar with AI technology but acquainted with their suppliers, any perspective on trust might be crucial in the case of AI-capable technologies [6]. A concern that arises is whether both trust perspectives are required to transfer users' confidence into a novel AI-capable system, even if trust may be created based on users' attitudes of its technical functions and its supplier. Therefore, we consider the theory of trust transfers.

The Context of Trust Transfer Studies 2.1

Trust transfer theory is an explanation of the bond formed between a familiar trusted source and a new and unfamiliar recipient [12, 13]. Existing studies show that consumers' confidence in a well-known source may be transferred to a less well-known target if the target has a solid connection to the known source [12]. Therefore, trust transfer may be defined as a primary kind of trust adjustment between two entities. For instance, trust is more likely to be transferred when individuals see the connection between a source and a target as close and strong. If the trust between the source and the target is low, however, users may be less likely to engage with the target.

In the domain of AI-enabled technology, there is still a dearth of study (see Gong et al. [17] for a recent overview). To better theorize the formation of trust in AI-capable systems, researchers might benefit from investigating if trust transfer also applies to AI contexts. Nonetheless, due to the complexities introduced by the convergent technologies' multi-source nature and the duality of trust, comprehending the transfer of confidence into these systems remains difficult.

Regarding the multi-source nature, previous research has shown that trust transfer can occur in both single-source and multi-source contexts (for example, from trust in web payment services to trust in mobile payment services [17]) and from trust in public administration and the Internet to the public e-service [27]. In example, previous studies have investigated whether more trusting attitudes toward a source result in more trust in a target. Therefore, a determinant (such as trust in AI) may be sufficient to create the consequence (such as trust in AV) [20, 28]. This understanding of connections between the source and the target follows a suf- ficiency logic. However, this may not be required, and another trust source could be able to make up for the loss. Trust in autonomous vehicles, for instance, might make up for skepticism about artificial intelligence.

In contrast to sufficiency logic, it is assumed in necessity logic "that an outcome-or a certain level of an outcome-can only be achieved if the necessary cause is in place or at a certain level" [28]. To return to our example, it is possible that both trust sources are required to obtain confidence in AV. By focusing on what is absolutely necessary, we can better determine whether or not our efforts will be fruitful [28]. Taking a need logic in the context of trust transfer, then, shows which trust sources are required to establish confidence in an unknown destination, which has been overlooked in the existing literature on trust transfers.

A more sophisticated understanding of essential trust sources is required in light of the emphasized relevance of the du- ality of trust in an AI-capable technological framework. Literature reviews on the topic of trust transfer reveal that previous studies have either concentrated on technological trust transfer (such as trust in websites, e-WOM services, and web shopping services; [17]) or interpersonal trust transfer (such as trust in trusted members and the community; [29]), but not on both at the same time. The question of whether or whether confidence may be transferred at the level of both technology and providers, and which of these trust sources is required, remains unclear. This trust dualism in multi-source trust transfer calls for more study.

Model for Studying

We begin by considering the methods by which trust is transferred in order to ascertain which trust sources are required for faith in a mysterious target. The key idea behind trust transfer is that consumers' preexisting confidence in a source may be transferred to a target via the application of category-based processing [12, 13]. Commonly, users will set items

in various ways to organize, analyse, and comprehend the data they have gathered on these things [30]. A group of similar systems, people, goods, or other items is called a category. Some users may classify 'AI provider' as include companies like Google, Amazon, and Microsoft. Users improve their information processing efficiency and cognitive stability by forming associations between things that are similar in key ways [31]. Similarity is a crucial concept in theoretical theories of categorization and trust transfer [30], since it mediates the transfer of cognitive beliefs from one stimulus to another. Trust is transmitted from a trusted source to a target when the user perceives a high degree of resemblance between the two entities. Users will transfer their knowledge, emotions, and intentions from a more familiar source to a less familiar target item if the two are comparable [12, 30]. Similarity has been characterized in a variety of ways in the prior literature on trust transmission and classification [17], including having a close commercial relationship or providing comparable technological capabilities. These ideas are consistent with the two-sided nature of trust, suggesting that a transfer of trust may occur between people in the event of a strong business relationship, and between people and technology in the event of equivalent functionality.

First, from the standpoint of interpersonal trust, consumers will classify the car supplier, the AI provider, and the AV provider as belonging to the same group if they sense an association and a strong commercial relationship between them [32]. Although vehicle providers may construct the AV themselves—including the intelligent autonomous driving functional- ities—more and more providers are taking a different approach in practice and launching collaborative projects with experienced

and familiar AI providers, such as in the case of [32] where users trust organization A and perceive that organization A and B are partners, so that they experience cognitive balance. As a result, the vast majority of AV suppliers are
partnerships between established automotive firms and AI suppliers. Mercedes is one of Alphabet's many brands, and Waymo is one of its subsidiaries. Therefore, AV providers are often the result of the merging of AI and vehicle suppliers. In keeping with the tenets of the trust transfer theory, we postulate the emergence of trust transfer only when consumers classify the AV provider and the AI and vehicle-hicle provider as belonging to the same group. Users may already be acquainted with AI and car suppliers, allowing for a smooth onboarding process with the AV provider, particularly if they perceive a strong tie between the two. We suggest that customers need to have confidence in the competency, honesty, and compassion of both the AI and vehicle suppliers in order to trust the (converged) AV provider, given the intertwined interaction between the two to supply AVs. In contrast, classification difficulties arise when customers worry that, say, an AI service provider may sell their private driving data to a third party, including GPS coordinates. As a result, the user won't be able to extend their confidence to the AV supplier, which is why we think it's crucial for them to have faith in both parties. Consequently, we postulate:
Trust in car suppliers is a prerequisite for trust in AV providers, hence H1a holds.
Users' faith in AI service providers is a precondition for their faith in AV service providers (H1b).

Second, from the user's point of view, confidence is transmitted depending on how comparable the technologies are that they're using [12, 13]. Based on shared features, users may group together the source and target technologies. We argue that people will classify AV technology alongside automobile technology because they both provide similar mobility features. Initially, AVs will have the steering wheel and pedals for the potential of driver interactions, and they will still have wheels, brakes, and similar driving equipment. Additional artificial intelligence (AI) features, like as voice assistants or the potential for autonomous driving based on intelligent automation without driver inputs, will be introduced as automation levels rise [4]. These capabilities are comparable to those seen in other AI-enabled technologies, such as intelligent automated customer chatbots [e.g., 33] or voice assistants in the home [e.g., 34]. Users may group AVs with other 'trustworthy technologies' if they see technological parallels between AVs and their suppliers (i.e., car technologies and AI technologies). In contrast, if customers have strong faith in automotive technologies but concern about the ability of an AI system to offer safe automated-driving tasks, the latter may be more likely to be adopted. Because of this difference, consumers may lose confidence in AV performance, which in turn disrupts the categorization and trust transfer process. As a result, we suggest that confidence in both AI and vehicle technology is required for the successful transfer of trust in AV technologies.

Methodology, Research

Analyzing Necessary Conditions: An Overview 2.1

To verify our ideas, we use the recently created and increasingly used research technique of required condition analysis (NCA) in the field of information systems. Due of its uniqueness, we will first introduce the methodology.
Dul first proposed NCA in 2016 [20] so that data sets' essential requirements may be identified. Instead of assessing the average correlations, NCA highlights regions in scatter plots of dependent and independent variables that may suggest the existence of a required condition [28]. NCA determines a ceiling line above the data, as opposed to standard least squares-based regression approaches like PLS-SEM, which create a dashed line across the center of the relevant data points [28]. A nondecreasing step-wise linear line (step function) is the ceiling envelopment-free disposal hull (CE-FDH) line, and a simple linear regression line through the CE-FDH line is the ceiling regression-free disposal hull (CR-FDH) line [20]. Both of these ceiling lines serve to demarcate the space with observations from the space without observations.
For a variable to be a necessary condition, the empty space is decisive, whereas the larger the empty space, the larger the constraint of a variable on another. Each variable can be assessed in detail using a bottle- neck table (e.g., Table 4 in Section 4.2.5). For the anal-ysis with NCA, two key parameters are important: ceil- ing accuracy (c-accuracy) and necessity effect size d. The c-accuracy provides the number of observations that are on or below the ceiling line divided by the totalnumber of observations and multiplied by 100. While the c-accuracy of the CE-FDH is 100% per definition, itmay be below 100% for the CR-FDH. Although there isno specific rule for an acceptable level of c-accuracy, estimating with a benchmark value (e.g., 95%) is rec- ommended [20]. The necessity effect size d is calculated by dividing the ceiling zone (i.e., empty space) by the scope (i.e., space containing observations). While dranging between $0 \leq d \leq 1$, a small effect is characterizedas $0 < d < .1$, a medium effect as $.1 \leq d < .3$, a large effectas $.3 \leq d < .5$, and a very large effect as $d \geq .5$. Previousstudies agreed on an effect size threshold of at least $d \geq$
1 (at least a medium effect) to accept necessary condi- tions hypotheses [e.g., 28, 35]. Finally, to evaluate the significance of the meaningfulness of the effect size, a permutation test has to be considered when analyzing a necessary condition [36].However, NCA is limited to only analyzing rela- tionships between observable characteristics (e.g., re- garding scales and

the absence or presence of character- istics) or researchers' created indices (e.g., an index of business performance) [28]. With the help of computing factor scores or composite scores (e.g., via PLS-SEM), the NCA can be extended to measure unobservable, la- tent concepts, such as user satisfaction, use intention, and perceived usefulness [28]. To address this condi- tion, it is therefore recommended to use the composite scores of PLS-SEM [28], while their generation consid- ering the context of the structural model [37]. Using theindicator weights as input, PLS-SEM computes compo- site scores for each construct as linear combinations of the corresponding indicators, which have shown good reliability [38

2.1 Essential use of condition analysis

To conduct the NCA, we used the method outlined by Ringle et al. [28]. To begin validating our assumptions, we created a survey to administer (Sections 4.2.1-4.2.2). For the second part of the survey design, we used Amazon Mechanical Turk's online panel data to perform the cross-sectional survey (Section 4.2.3). It has been shown that online panel data is an appropriate tool for investigating trust-related phenomena [e.g., 34, 39]. High dependability and high-quality data equivalent to student samples or online convenience samples [e.g., 40] have been shown to be produced by surveys conducted using MTurk. To guarantee a high enough quality of data, we only allowed individuals with a solid reputation (at least 95% approval ratings and 5,000 completed tasks) to take part [41]. We limited enrollment to the United States in an effort to lessen the impact of any cultural biases, and we paid all participants no less than the federal minimum wage ($7.25) to do so. After that, we made sure everything was in order with the data and assessed the measurement models' validity and reliability (Section 4.2.4). Next, we used SmartPLS version 3.3.3 [42] to create scores for the latent variables, which we then imported into R to run the NCA (Section 4.2.5). We adopted the CR-FDH line because it is more robust against outliers and measurement errors [20], and the c-accuracy of all variables is more than 95%.

Survey Methods, Version . We did a survey in six easy steps. We began by briefly outlining the study's goals, setting, and illustrative artificial intelligence technologies (e.g., virtual assistants, recommender systems). Since familiarity with the source technology is required to facilitate trust transfer [12, 13], we asked participants to conceive of a trustworthy AI provider and the offered AI technology they know and enjoy. We had participants either think of an AI service provider and tell us its name or choose from a list of options (including Microsoft, Apple, Amazon, Google, and IBM Watson).

The level of confidence that respondents had in the AI service provider and the AI it used was then quantified. Subjects are then asked to identify a reputable automaker whose products they are familiar with and like driving, or to choose one of the brands listed (Toyota, Ford, Volkswagen, Tesla). Be aware that we limited the topic of vehicles in the survey to "cars" for the sake of greater subject comprehensibility. After that, we polled people on how much they trusted the automaker and its innovations. Third, we included a washout time between the assessment of our independent and dependent variables by having respondents read irrelevant material and click on a hidden link [43]. This allowed us to control for ongoing attention. Fourth, we placed participants in a fictitious situation in which they were asked to consider the possibility that they get a business automobile as part of their compensation package. They may either have a vehicle with regular technology or one with autonomous driving technology made possible by artificial intelligence. Brief descriptions of both the provider (i.e., a partnership formed between the AI provider and car manufacturer to demonstrate the strength of business ties) and the technology (i.e., autonomous car technology takes over the complete control of the auton- omous car when driving on the highway and provides additional driver assistant functionalities) were provided to the subjects. Fifth, we quantified our

Table 1. Measurement Items

Label	*Item*	*Loading*
Trust in Provider [Vehicle / AI / AV] [23]		
TP1	Overall, I feel that I can trust [Ve- hicle Manufacturer / AI Provider / AV Provider] completely.	[.818 / .884/ .922]
TP2	I feel comfortable depending on [Vehicle Manufacturer / AI Pro- vider / AV Provider] for the com- pletion of AI-supported tasks.	[.879 / .907 / .931]
TP3	I am comfortable letting [Vehicle Manufacturer / AI Provider / AV Provider] take responsibility for tasks which are critical to [Vehicle / AI / AV Technology] even when I cannot control them.	[.864 / .886 / .908]
Trust in Technology [Vehicle / AI / AV] [18]		
The [Vehicle / AI / AV] technology…		
TT1	... is a very reliable technology.	[.872 / .870 / .898]
TT2	... does not fail me.	[.808 / .859 / .909]
TT3	... is extremely dependable.	[.895 / .891 / *]
TT4	... does not malfunction for me.	[* / .831 / .906]
TT5	... has the functionality I need.	[.866 / .847 / .905]
TT6	... has the features required to ful- fill my needs.	[.843 / .857 / .791]
TT7	... has the ability to do what I want it to do.	[.872 / * / *]
* item was dropped during measurement model assessment		

variables, namely trust in the AV technology and pro- vider. Finally, we collected control variables and de- mographics.

Methods for the Survey. The scales used to measure the components in our survey have all been well tested and are considered reliable and valid (see Table 1). We used instruments developed by McKnight et al. [18] to assess people's faith in technology, and those developed by Staples and Webster [23] to evaluate their faith in service providers. Please take into account that we have reworded and altered the assessment items to match our context, and that we have also included the name of the proposed or chosen car manufacturer and AI supplier (i.e., "I feel comfortable depending on VW for the com- pletion of driving"). We also included items to gauge a latent marker variable (e.g., "Music is vital to my existence," "Bears are incredible creatures," "Rugby is fascinating," and "Paintings are superior to photographs when it comes to art") [44].

Descriptive Statistics . We started with 432 participants but had to exclude 53 since 31 people didn't pay close enough attention and 22 people completed the survey too quickly. In all, 379 reliable replies were gathered in this way. This is more than the median sample size of 200 seen in previous SEM studies [46] and the approximate sample size of 198 we computed using the tool G*Power (power =.95, effect size f2 =.1) [45]. The median age of our respondents was 30.4, with a range of ages from 23 to 67. More men than women filled out our poll. The vast majority of respondents were either college graduates (13.2%) or high school dropouts (18.5%), and they all owned vehicles that were at least three years old and drove them at least once a week or more frequently than that (64.4%). Participants assessed the scenario's realism at 82.5 on a 100-point sliding scale and reported frequent interaction with AI technology (60.7)..

Data interpretation and findings . First, we assessed the measurement model. We assessed univariate and multi- variate normality of the measurement items in our sur- vey. One trust in vehicle technology item had the high- est absolute skewness value of 2.091 (i.e., TT4), fallingbelow the acceptable threshold of 3.0 for skewness [46]. Regarding the highest absolute kurtosis value, items of trust in technology for vehicle (i.e., TT4), AI, and AV (i.e., TT7) exceed the threshold 10.0 for kurtosis [46],

Table 2. Measurement assessment

Construct	*CR*	*AVE*	Fornell-Larcker Criterion (HTMT)					
			1	2	3	4	5	6
1. Trust in AV technology	.947	.780	.883					
2. Trust in AV provider	.944	.848	.813 (.882)	.921				
3. Trust in vehicle provider	.890	.729	.514 (.592)	.508 (.588)	.854			
4. Trust in vehicle technology	.944	.739	.496 (.532)	.320 (.340)	.738 (.845)	.860		
5. Trust in AI provider	.921	.796	.471 (.522)	.530 (.592)	.603 (.713)	.455 (.499)	.892	
6. Trust in AI technology	.944	.738	.581 (.622)	.447 (.478)	.638 (.713)	.653 (.697)	.669 (.738)	.859

which we then removed to ensure that the distributions of our measurement items do not deviate significantly from normality. We also controlled for data outliers and removed two observations exposing extreme outlines (z-score > 3) in trust in vehicle technology.

Second, we assessed the constructs' reliability, con- vergent validity, and discriminant validity (refer to Ta- ble 2). All indicators fulfilled the minimum loading re- quirements (significance and load value) between the in- dicator and its latent construct, achieving convergent va- lidity. The average variance extracted (AVE) was higher than the suggested minimum of .50 [47]. The composite reliability (CR) values were above .70, demonstrating good internal consistency [48]. Regarding discriminant validity, the square root of each construct's AVE ex- ceeded the inter-construct correlations. In

addition, we measured the heterotrait-monotrait (HTMT) ratios of correlations. The HTMT between trust in AV technol- ogy and AV provider (.88) slightly exceeds the recom- mended threshold of .85 [38]. We decided to keep both constructs in our model because the Fornell-Larcker Criterion and the less conservative HTMT threshold of .90 are met, and more importantly, because prior theory has already acknowledged a strong relationship between trusting beliefs in technology and provider [e.g., 25]. We also examined variance inflation factor (VIF) values to test for multicollinearity in our data. All VIF values were below the threshold of 5, except for TT3 in case oftrust in AV technology (i.e., VIF = 6.185), which we then removed to ensure that our data is not subject to severe multicollinearity issue [49].

Third, we account for common method variance (CMV) not only ex-ante through the careful design of the questionnaire, applying the recommendations of Podsakoffet al. [50]), but also ex-post by running a measured latent marker variable (MLMV) test and per- forming a construct level correction [44] relying on PLS-SEM and SmartPLS software, version 3.3.3 [42]. We added a CMV construct comprising the four MLMV items for each construct, modeled them as impacting each model construct, and compared the bootstrapping results. The differences in the path coefficients between

the model constructs were found to be very small (<.200) [51], and we, therefore, conclude that a potential CMV does not pose a significant threat to our results.

Table 3. NCA effect sizes

	Trust in AV provider		
Construct	*CR-FDH (d)*	*p-Value*	*c-accuracy*
Trust in AI technology	.121	<.001	98.7%
Trust in vehicle technology	.255	<.001	98.1%
	Trust in AV technology		
Construct	*CR-FDH (d)*	*p-Value*	*c-accuracy*
Trust in AI provider	.030	.264	99.7%
Trust in vehicle provider	.286	<.001	98.7%

1.1.1. NCA data analysis and results. The NCA's re- sults (see Table 3) show a sufficiently high c-accuracy (c-accuracy > 95%) and indicate that for trust in AV technology, both trust sources are meaningful and sig- nificant necessary condition (d > .100, p < .001). Thus, trust in AI technology and trust in vehicle technology have a medium effect on trust in AV technology, **sup-**

1.1.2. porting H2a and H2b. For trust in AV provider, how- ever, only trust in vehicle provider is meaningful and a significant necessary condition (d = .286, medium ef- fect, p < .001),

1.1.3. supporting H1a. In contrast, trust in AI provider is not significant (d = .030, p = .264), **not sup-porting H1b**.

Table 4. Bottleneck table (percentages)

	Trust in AI technology	Trust in vehicle technology
Bottleneck Trust in AV technology		
0..20	NN	NN
30	NN	0.6
40	NN	10.8
50	1.9	21.0
60	10.8	31.2
70	19.7	41.5
80	28.6	51.7
90	37.5	61.9
100	46.3	72.1
	Trust in AI provider	Trust in vehicle provider
Bottleneck Trust in AV provider		
0..20	NN	NN
30	NN	7.3
40	NN	16.8
50	NN	26.3
60	NN	35.8
70	NN	45.3
80	NN	54.8
90	14.0	64.2
100	36.7	73.7

Each necessary condition can be assessed in detail withthe bottleneck tables [28]. The bottleneck table repre- sent an alternative form of the ceiling line results whileit specifies the level of trust in a source that is neces- sary for a certain level of trust in a target. For example,

Table 4 highlights that in order to reach a 60% level oftrust in AV technology, two necessary conditions needto be in place: trust in AI technology at no less than 10.8% and trust in vehicle technology at no less than 31.2%. In contrast, to reach a 60% level of trust in AV provider, only one necessary condition needs to be in place: trust in vehicle provider at no less than 35.8%.

Discussion

3.1. Important Results

In this research, we looked at the factors that influence the success of trust transfer when many sources are involved. Using trust transfer theory, we demonstrated that people have a high degree of confidence in AVs because they feel a great resemblance to their own vehicles [12, 13]. We demonstrate that confidence in vehicle technologies is a required requirement for transferring faith in AV technologies, which is similar to existing understandings that AVs still resemble ve- hicles based on identifiable mobility features and interior/exterior appearance [e.g., 4, 9]. Our findings suggest that user confidence in vehicle suppliers is also required, since consumers continue to group car providers and AV providers together.

Users' reluctance to link AI with AV technology is surprising and counter to our hypotheses. Despite our ability to detect a moderate impact of confidence in AI technology on faith in AV technology, the impact of trust in vehicles on trust in AV technology was much larger. This might be because people are still cautious owing to trust-related difficulties of these AI-enabled functions [9], and because autonomous driving features have not yet

achieved widespread market penetration [4]. The faith consumers have in AI

technology seems to be a weak but necessary source condition for trust in autonomous vehicles. Despite our best efforts, we were unable to verify our hunch that users must have faith in AI service providers before they would have faith in AV service providers. In the end, customers do not connect artificial intelligence (AI) companies with automobile production. Like the technological viewpoint, this might be because people are still thinking about cars rather than autonomous driving features, which keeps the conventional car companies relevant and necessary. Users seem to place greater faith in a car supplier to create driving-related functions, even when new autonomous driving functionalities are emerging as a result of the convergence of AI with automobiles [6, 14]. However, we demonstrate that trust may be transferred to the target even in the absence of confidence in one source (i.e., trust in AI providers), so long as trust in the other source (i.e., automobiles) is there.

theoretical and applied advancements

Our investigation provides many significant contributions to the field. First, by positing the existence of trust transfer in the context of AI, we expand recent research efforts to explain trust in AI [e.g., 6, 10] by providing a fresh theoretical perspective on developing confidence in emerging converging AI-capable technologies. Multi-source trust transfer provides the theoretical groundwork for incorporating users' trusting beliefs of numerous sources into an examination of the trust transfer process via the convergence of AI with a base technology to create AI-capable technology. Second, we add to the theory of trust transfers by highlighting the significance of trust's dual nature, although most trust transfers studies have focused on either technological or interpersonal trust [17, 29]. Our research shows that the sources required for multi-source trust transfer vary from trust viewpoint to trust perspective. Third, we used a network causality analysis (NCA) to determine what kinds of trust between several sources are required [20]. We demonstrate the utility of this new approach of data analysis by applying it to real-world IS research problems. Thus, we broaden the scope of previous studies on trust transfers that adopt a subjective logic, focusing on the primarily argumentative derivation of essential sources in trust transfers using statistical methods (such as structural equation modeling). In fact, our findings show that gaining consumers' confidence in AV systems requires contributions from both types of technical trust sources. If you're interested in learning how trust is transferred across different AI-capable technologies, you may find the effect-sizes and bottleneck table helpful.

Insights into which sources may be required to generate confidence in AI-capable devices are provided by our findings. Providers of AV systems should keep in mind that both types of technologies are relevant to the question of how consumers will come to trust AVs. This means that traditional car suppliers will need to address confidence in AI as well as vehicle-specific improvements in terms of technological functions. Our findings, on the other hand, may suggest that AI-capable technology providers should prioritize maintaining the user's perception of the need of their connection with the base technology provider. Therefore, any collaboration should still revolve on the supplier of the underlying technology (the manufacturer of the vehicle).

Disadvantages and Prospects for Further Study

There are caveats to our study that provide opportunities for further investigation. To begin, we recruit volunteers for our research using the online platform MTurk. Although previous studies have found MTurk to be useful for behavioral investigations [for example, 40], future studies should make use of a wider variety of data gathering techniques. Triangulating findings may be possible via methods such as using different online panel providers or performing behavioral trials. Second, we saw some little problems with discriminant validity (namely, between confidence in AV technology and AV vendor). In the future, researchers may look at how general trust perceptions compare to multi-source trust transfer procedures on a provider and technology. Third, not all problems with statistical and causal inference have been overcome, and NCA is still a relatively new method. The importance of conditions has to be investigated further via studies of the statistical features of predicted ceiling lines and confidence interval estimation [35]. Fourth, we avoided contrasting the findings of NCA and SEM in order to zero down on determining what makes trust essential.

Our goal in doing this study was to pave the way for future behavioral studies to provide us with novel understanding of how to inspire confidence in AI-enabled systems. To further understand how trust is built in these systems, we further invite academics to examine trust transfer theory from the perspective of necessity logic [12]. To determine which sources are required [20], future research in multi-source trust transfer may use a two-pronged approach (i.e., assessing the SEM and conducting NCA [28]). Finally, the function of the AI provider in trust transfer may be investigated further in future studies in an effort to explain and resolve our unexpected results.

2. Conclusion

Our goal with this research was to identify the key trust drivers for AI-enabled devices. To achieve this, we used a dual trust view and positioned AI and vehicle technologies and providers as trust sources, and AV technologies and suppliers as trust targets, in the context of multi-source trust transfer. To demonstrate the importance of confidence in both car suppliers and vehicle technology, we conducted a network-centric approach (NCA). We demonstrate that, when it comes to AI trust, just faith in the AI itself is required, whereas confidence in AI service providers is completely irrelevant. The essential requirements of trust sources in trust transfer are better understood, which benefits both theory and practice. With the aid of the NCA, this information may be used to determine the best means of establishing confidence in AI-enabled tools and demonstrate how to learn which sources are required for a multi-source trust transfer.

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