Artificial Intelligence-Driven Convergence and its Moderating Effect on Multi-Source Trust Transfer

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Abstract

AI-driven convergence describes how innovative products emerge from the interplay of embedded artificial intelligence (AI) in existing technologies. Trust transfer theory provides an excellent opportunity to deepen prevailing discussions about trust in such converged products. However, AI-driven convergence challenges existing theoretical assumptions. The context-specific interplay of multiple trust sources may affect users' trust transfer and the predominance of trust sources. We contextualized AI-driven convergence and investigated its impact on multi-source trust transfer. We conducted semi-structured interviews with 25 participants in the context of autonomous vehicles. Our results indicate that users' perceived trust source control, perceived trust source accessibility, and perceived trust source value creation share may moderate users' trust transfer. We contribute to research by contextualizing convergence in AI, revealing the impact of AI-driven convergence on trust transfer and the importance of trust as a dynamic construct.

Keywords: Trust transfer, trust in technology, convergence, AI-driven convergence, autonomous vehicles

1. Introduction

We are witnessing a fundamental change of technologies, becoming more autonomous and intelligent by embedding artificial intelligence (AI). This phenomenon is called AI-driven convergence and is fueled by the interplay of AI (e.g., computer vision, natural language processing, or pattern recognition) with so-called base products (i.e., non-automated technologies like vehicles, healthcare equipment, or production plants; Curran et al., 2010; Klarin et al., 2021; Yoo et al., 2012). The resulting converged products emerge because AI enriches existing base products to increase effectiveness, offers innovative functionalities through automation and augmentation, or transfers users' control over the base product to the AI (Raisch & Krakowski, 2021). For example, AI converges with vehicles (as a base product), resulting in autonomous vehicles (AVs) that provide innovative AI-enhanced driver assistance and infotainment functions (Hengstler et al., 2016). Another example of a converged product are AI-based surgical robots, which can autonomously perform operations in situations where human operators would fail (Haidegger, 2019).

Given the glaring opportunities of AI-driven convergence, the question of how to establish trust in converged products has become a core discussion in contemporary information systems (IS) research (e.g., Berente et al., 2021; Söllner, Benbasat, et al., 2016). Trust has proven to be a key determinant of an individual's willingness to accept and use a system through mitigating uncertainties and risks (Benbasat & Wang, 2005; Gefen et al., 2003; Söllner, Hoffmann, et al., 2016). For example, in the context of AVs, users still perceive conventional vehicles as safer, which is why users are still reluctant to trust AVs (Whalen, 2022).

Trust transfer seems to be a promising, but so far neglected, mechanism to understand how trust may be established in converged AI-based products (Renner et al., 2021, 2022). In essence, trust transfer posits that users' trust in (multiple) already existing and familiar trust sources may be transferred to an unknown target (Stewart, 2003, 2006). We propose that such trust transfer processes are also likely to occur in the case of unknown converged products. They result from AI's convergence with one or more base products that may already be familiar to users as individual trust sources (Glikson & Woolley, 2020; Renner et al., 2021). For example, users may transfer their trust in familiar vehicles—and possibly their trust in AI—to unknown AVs.

Previous research has already examined multiple trust sources and their influence on trust in an unknown target (e.g., Belanche et al., 2014; Leong et al., 2021; Lowry et al., 2014). However, AI-driven convergence specifics put in doubt how trust transfer from AI and base products is achievable. It challenges existing theoretical assumptions of multi-source trust transfer because trust sources are usually perceived as separate entities, contrasting with converged products that result from merging multiple sources (Belanche et al., 2014; Stewart, 2003).

We need to clarify how AI-driven convergence and the resulting interplay of trust sources impacts trust transfer. Depending on how the base product and AI interact to form the converged product, users may perceive one trust source as more predominant than the other, leading to varying strengths of trust transfer. For example, with a low level of convergence, AI augments vehicles by taking over only supportive driving functionalities (Hengstler et al., 2016). Individuals may still perceive failures of vehicles to be severe and therefore consider vehicles as a more important trust source for trusting AVs. However, in the case of a high convergence level and AI-based automation, individuals may perceive AI as the predominant technology. Then, using AVs poses AI-related risks, such as wrong decisions leading to accidents (Koester & Salge, 2020; Raisch & Krakowski, 2021), and users may transfer their trust in AI (as a trust source) toward AVs more strongly. While previous research on trust transfer has analyzed multi-source trust transfer scenarios, they have neglected to consider this interplay of trust sources and resulting moderators (e.g., trust source predominance) that influence trust transfer. Thus, we want to better understand the impact of AI-driven convergence on multi-source trust transfer by examining how possible moderators characterize the interplay of converging trust sources. We ask:

RQ: How does AI-driven convergence moderate the transfer of users' trust into multiple sources toward trust in an unknown target?

We ground our research in trust transfer theory (Stewart, 2003, 2006) and the convergence literature (Klarin et al., 2021) to reveal AI-driven convergence-related moderators in multi-source trust transfer. We focus on the context of trust transfer from known vehicles and AI to unknown AVs. We conducted 25 semi-structured interviews with vehicle users. Our results reveal three moderators: taking a technology perspective, we identified users' perceived trust source control and trust source accessibility as moderators. Besides, we revealed that industry convergence is also relevant. Users' trust transfer may be moderated by the perceived value creation share of the different technology providers as trust sources.

This study has three key contributions. First, we contextualized convergence driven by AI. Second, we contribute to trust transfer theory by explaining the influence of AI-driven convergence on multi-source trust transfer. Third, we highlight the importance of investigating trust as a dynamic construct in AI-driven convergence and its impact on the predominance of trust sources.

2. Background

2.1. AI-driven convergence and the need for trust

Convergence is a complex phenomenon involving multiple layers and interactions of industries, firms, users, regulatory bodies, policy, technology, markets, and media (Klarin et al., 2021). Literature on convergence is interdisciplinary, and convergence has been studied in other emerging technology segments, such as biotechnology, nanotechnology, and digital technology (e.g., Song et al., 2017; Yoo et al., 2012). In essence, convergence describes a phenomenon whereby two or more initially separate items merge, resulting in their interplay, the movement toward unity, and increasing integration with one another (Curran et al., 2010; Duysters & Hagedoorn, 1998).

In the case of AI-driven convergence, AI technologies merge with base products (Yoo et al., 2012), resulting in new converged products that unite AI and the base product. During convergence, base products are enriched with AI to increase effectiveness, provide intelligent features through automation, and enhance or control product functionalities (Raisch & Krakowski, 2021). Prominent examples of AI-driven convergence are AVs, ubiquitous assistants (e.g., speakers embedding natural language processing), intelligent chatbots (e.g., FAQ answering service), and collaboration-based recommender systems (e.g., in video streaming websites like Netflix).

The embeddedness of AI is typically an evolutionary change in which AI is increasingly converging with formerly stand-alone base products. AI-enhanced autonomous driving functionalities in AVs (Koester & Salge, 2020) are a commonly cited example in which the level of convergence is typically divided into six levels of automation, ranging from Level 0 (no embedded AI capabilities) to Level 5 (fully autonomous driving) (SAE, 2018). In the early stages of AI-driven convergence, AI typically supports formerly stand-alone base products while collaborating closely to perform a certain task (Raisch & Krakowski, 2021). In the context of AVs, AI provides supportive driving functionalities, such as lane-keeping assistance, speed control, or infotainment systems, and users remain responsible and in control of their vehicles (Hengstler et al., 2016). As AI-driven convergence increases, AI's impact and embeddedness also increase, assuming more tasks and responsibilities while users' tasks decrease. AI-driven convergence is thus gradually leading to more intelligent, AI-enhanced functionalities as AI takes over the control of tasks that were previously carried out by individuals or base products (Raisch & Krakowski, 2021). For example, AV users relinquish control of their vehicles to AI in predefined situations (e.g., on highways; Koester & Salge, 2020), while autonomous driving functionalities are perceived as intelligent because their decision-making processes and control awareness rely on inherent AI (Hengstler et al., 2016).

However, AI-driven convergence is a double-edged sword that not only offers advantages (e.g., enhanced functionalities such as optimizing traffic or cost-efficient share mobility; Hengstler et al., 2016). It also has several drawbacks, such as AI's inherent risks and challenges, including its complex and opaque nature (Thiebes et al., 2020). For example, the usage of AVs involves significant physical risk, such as accidents on the highway at high speed or with pedestrians in city traffic (Liu et al., 2019; Waung et al., 2021), leading to a sense of uncertainty among users (Liu et al., 2019). Given these drawbacks, trust becomes a key determinant in overcoming uncertainties and risks relating to the vulnerabilities of novel technologies (Benbasat & Wang, 2005; Gefen et al., 2003; Söllner, Hoffmann, et al., 2016), such as AI (e.g., Koester & Salge, 2020; Waung et al., 2021). Unsurprisingly, how to establish trust in AI is central to the current IS debate.

2.2. AI-driven convergence challenges principles of trust transfer theory

Trust transfer processes are valuable for examining trust in products resulting from AI-driven convergence (Renner et al., 2021, 2022). Trust transfer theory explains the relationship between an already known and familiar trusted source and an unknown target (Stewart, 2003, 2006). The beauty of trust transfer theory lies in providing a more externally valid way of looking at how trust works that it goes beyond any single source entity and encompasses a diverse array of source entities as users' trust in (multiple) already existing and familiar sources may be transferred to an unknown target (Stewart, 2003, 2006). Based on previous research, users' trust in a source can be transferred to a relatively unknown target because the target has a strong relationship with the trusted source (Stewart, 2003).

Trust transfer can therefore be characterized as a fundamental form of trust adjustment as users do a form of mental calculus, adding and subtracting trust in various entities toward deciding to rely on an object (Stewart, 2003). To transfer trust, users must perceive the relationship between a source and a target as close and strong. In contrast, users may not trust the target if they perceive the source-target relationship as weak. For example, if users have already established trust in the Internet and public administrations, they are more likely to trust public e-services, given a strong source-target relationship between public administrations, the Internet, and public e-services (Belanche et al., 2014).

For AI-driven convergence, taking a trust transfer perspective is promising because users may have already built trust in base products or AI through former experiences or interactions. As an AI and a base product merge to offer a novel converged product, users may transfer their trust from the base product and AI to the resulting converged product. However, AI-driven convergence challenges existing trust transfer principles.

Related trust transfer research has already revealed that users transfer trust in a multi-source context (e.g., Belanche et al., 2014; Leong et al., 2021). While extant research provides valuable contributions, AI-driven convergence calls for a more detailed assessment because converged products result from uniting a base product and AI as trust sources. This interplay of trust sources may thereby impact how users transfer their trust. We assume that users may perceive certain trust sources as more predominant and important depending on how the trust sources converged. In the context of low converged products, such as when AI augments the vehicle with driver-assistant functionalities (Hengstler et al., 2016), we assume that the vehicle technology is more important for the user because users are faced with uncertainties about whether the vehicle technology functions as expected to ensure safe driving. In the context of highly converged products (e.g., an AV where AI completely takes over the driving functionalities; Koester & Salge, 2020), users may perceive the AI as a more important trust source because the AI introduces novel vulnerabilities during driving, such as wrong decisions that may lead to accidents. Hence, depending on how strongly AI merged with the base product, the predominance of trust sources may change, and users may perceive other sources as more important than others. We thus want to uncover how this interplay of trust sources influences trust transfer and how the predominance of trust sources may be affected by the different levels of convergence (i.e., low vs. highly converged products).

3. Research method

We applied an explorative and inductive research approach to investigate complex circumstances stemming from the interplay of multiple trust sources that the literature on trust transfer has not yet explored and then deepened our understanding of moderators influencing multi-source trust transfer. Research has shown that explorative and inductive approaches are useful when addressing new or poorly understood phenomena (Smolander et al., 2008) and considering the contexts that embed those phenomena (Volkoff et al., 2005), and has shown their usefulness in the context of phenomena related to innovations in the vehicle context (e.g., connected cars; Cichy et al., 2021).

We conducted in-depth interviews with individuals to understand the specifics of AI-driven convergence and how trust sources may interact. In particular, we interviewed 25 vehicle users in Germany (Age: M = 28.9 years, SD = 9.6; gender 31.6% female; higher education = 76.0%; daily interaction with AI functionalities such as voice assistants = 64.0%). Besides, we ensured that participants had a wide range of driving experiences and usage of driving assistants. On average, participants traveled 9,040 km/year (SD = 6,630; min = 1,000; max = 20,000), and 88% of them have also used AI-based driving assistance functionalities (e.g., intelligent lane-keeping, speed control, and braking assistants).

Following Myers (2013), we conducted semi-structured interviews because a semi-structured approach makes the results more comparable and gives the participants the freedom to talk about things that might not have or could have been considered in the preparation of the interviews. We conducted each interview based on an interview guide (Yin, 2014). Starting with an introduction, we ensured that participants had a basic understanding of the technologies and applications of AVs without framing them positively or negatively. We first asked open questions (i.e., "How do you perceive the convergence of AI and the vehicle?") to avoid imposing our point of view. Then, we asked questions that addressed potential moderating effects helping participants to trust an AV and relating to risk and uncertainty (i.e., "What uncertainties come to mind when you think about the process of converging AI and vehicle?").

The interview guideline was derived and discussed by two researchers beforehand. Afterward, three senior researchers reviewed the interview guideline, assessing its comprehensibility and structure. In addition, we made constant improvements to consider preliminary findings gained through ongoing analyses of interviews and improve the clarity and comprehensibility of the questions. Furthermore, we applied a non-judgmental form of listening, maintained distance, and strived to sustain an open and non-directive style of conversation during the interviews to ensure impartiality and avoid bias (Myers, 2013; Yin, 2014).

All interviews were in-person, digitally recorded, fully transcribed (i.e., 93 pages), and analyzed. The interviews lasted, on average, 15.31 minutes (SD = 3.42; min = 10.30; max = 23.10).

We based our coding process on grounded theory approaches to analyze our data: (1) open coding, (2) axial coding, and (3) selective coding (Corbin & Strauss, 2015). The coding procedure was supported by Atlas.ti 22, a coding tool for qualitative data.

First, we applied open coding by searching for concepts in the interview data that may define a significant occurrence or incident about AI-driven convergence and its influence on trust transfer in an AV scenario (Abraham et al., 2013; Corbin & Strauss, 2015). With open coding, we obtained 41 codes related to 219 textual segments from the 25 interviews. For example, the statement, *"so I would not feel safe because I would rather control it myself then."* was coded as *"keeping control of vehicles."*

In the second stage, axial coding was used to develop a more profound knowledge of all concepts, uncover relationships between them, and categorize the emergent first-order concepts into higher-order categories. We reviewed coded text segments to identify the causes and consequences of concepts (Corbin & Strauss, 2015). Causes answer questions about why, when, and how and, thus, refer to individuals' perceived reasons for things happening. For example, we coded *"humans make mistakes are undisputed and for various reasons such as carelessness are a possible source of error."* as a cause for *"concerns about human driving errors."* Consequences refer to anticipated or actual outcomes of concepts, such as the statement *"the automotive industry cannot quite avoid a bit of retooling, especially either researching or developing AI themselves, or cooperating with people who are doing it."* indicating a consequence of the concept *"business model changing."*

After understanding causes and consequences, axial coding enables us to compare concepts to classify them under common categories and, thus, create hierarchical classifications. For example, we grouped the codes *"problem of losing control while using AI functionalities," "risks due to missing training data,"* and *"negative consequences due to the losing control"* into the category *"loss of control"*. Later, we assigned this category to the theme *"perceived trust source control."* During axial coding, initially, 13 categories were identified, which were iteratively condensed into three key themes as moderators (i.e., perceived trust source control, perceived trust source accessibility, and perceived trust source value creation share).

Finally, we performed selective coding (Corbin & Strauss, 2015), allowing us to integrate our analysis and portray a coherent conceptualization of the phenomenon. We seek to integrate all our categories and higher-level themes into one core category, that is, in our case, AI-driven convergence. For selective coding, we drew on the convergence literature (see Klarin et al. (2021) for an excellent literature review) that classifies convergence into different layers. These layers can be divided into technology, market, and industry convergence and represent how convergence manifests. By applying selective coding, we were able to map identified moderators to two layers (i.e., technology and industry convergence). For example, perceived trust source control and perceived trust source accessibility were mapped to the layer of technology convergence. Comparing our results with the convergence layers supported us in understanding how the moderators impact trust transfer and classifying the moderators into different trust perspectives, namely technologies and organizations (i.e., the providers) as trust sources. The following section provides more details on how these two convergence layers and corresponding moderators may impact trust transfer. Besides, Table 1 provides an overview of the codes and their categorization.

To ensure that we identified a reliable set of moderators, we followed researchers stressing that an important goal is to reach theoretical saturation (Sandelowski, 2008). That is the case when we do not learn more about a topic by collecting and analyzing additional data. Since no new moderator emerged in the last four interviews, we are confident that this initial and exploratory study has reached sufficient saturation.

4. AI-driven convergence moderators impacting trust transfer

4.1. Technology convergence

For the technology convergence layer, depending on how strong AI and vehicle technologies are converged, AI augments or automates the vehicle technology (Koester & Salge, 2020; Raisch & Krakowski, 2021). Our interviews revealed two key moderators resulting from the interplay of converged technologies as trust sources that influence trust transfer: users' perceived trust source control and perceived trust source accessibility.

We argue that users' ***perceived trust source control*** moderates users' trust transfer, defined as users' perceived degree of a trust source's control over the functioning of the converged product. In our context, perceived source control indicates which technology source is in (predominant) control and responsible for driving. It can be either the vehicle (together with the user) or the AI technology. For example, in the context of AI automating the vehicle, one participant stated, *"[…] I no longer have to play with the gas all the time, then the AI takes over the driving."* This goes hand in hand with another participant's statement, *"when I think about it now, highly automated. I would think that's probably the AI controlling the vehicle."* Related research on perceived technology control has similarly shown that the influence of users' perception of being in control will positively impact the behavioral intention to accept a technology (e.g., Chau & Hu, 2002). We assume that trust transfer also depends on which source users perceive as controlling the converged technology: users may perceive a high base technology control or AI technology control.

In the case of low converged AV, users are still responsible for the safety of driving decisions while also relying on the underlying vehicle's functionalities and technologies (e.g., brakes, powertrain, and steering unit). Users must trust that the vehicle technologies used in AVs are reliable, will function as expected, and not compromise driving safety. One of the participants points out the uncertainties with the functionality of vehicles because "*of course, there are some weak points, such as tire bursts causing an accident*." Thus, in the context of low converged products, trust in vehicle technologies may be more important to establish trust in AV technologies. In contrast, the impact of trust in AI as a trust source might diminish, given vehicle technologies' predominance. We posit:

Proposition 1 (P1): *Users' perceptions of a high degree of control of vehicle technology (P1a) positively moderates trust transfer from users' trust in vehicle technology toward users' trust in AV, and (P1b)*

Table 1. Commonly stated moderators associated with AI-driven convergence

No	Description	Prevalence*	Concept	Moderators	Convergence layers
1	The superiority of one of the sources in decision making while controlling the AV	High	Decision-making superiority	Perceived source control	Technology convergence
2	The transition and merging of AI and Vehicles as sources	High	Process of merging sources	Perceived source accessibility	Technology convergence
3	AVs cause users to lose control	High	Loss of control	Perceived source control	Technology convergence
4	Changes in classic business models, as more AI knowledge is needed	High	Business model changing	Perceived source value creation share	Industry convergence
5	Users relinquish control of the vehicle to AI	Medium	Control transfer between sources	Perceived source control	Technology convergence
6	Importance of the reputation of the brand and the provider	Medium	Provider reputation value	Perceived source value creation share	Industry convergence
7	Need for knowledge and expertise of AI providers for the AV functionalities	Low	Expertise of AI provider	Perceived source value creation share	Industry convergence

* Low = 5-14 responses (codes); medium = 15-23 responses; high = more than 24 responses

negatively moderates trust transfer from users' trust in AI technology toward users' trust in AV.

However, if AI technology starts to support users with driver assistant functionalities (Hengstler et al., 2016; Koester & Salge, 2020), users perceive a loss of control. This loss of control is indicated through uncertainties and risks, such as one participant's statement, *"I wouldn't feel safe because I would rather control the vehicle myself then."* For another participant, the reason is that *"above all, the more I relinquish control, the more I have to concern myself in principle that something happens and that I can no longer intervene."* Faced with higher uncertainty and vulnerability, users are predominantly elaborating on whether they can rely on AI technologies during driving. Consequently, we argue that users' trust in AI technology becomes a more important trust source when AI technology has taken control and automated driving functions (Koester & Salge, 2020; Raisch & Krakowski, 2021). In such high converged AV, users perceive a stronger relationship between AI and AV technology, resulting in AI technology being a more predominant trust source, diminishing the trust transfer from vehicle technologies. We therefore argue:

Proposition 2 (P2): *Users' perceptions of a high degree of control of AI technology (P2a) positively moderates trust transfer from users' trust in AI technology toward users' trust in AV, and (P2b) negatively moderates trust transfer from users' trust in vehicle technology toward users' trust in AV.*

Second, users' ***perceived trust source accessibility*** is a moderator impacting users' trust transfer, defined by the degree to which a trust source is accessible and observable to users while using the converged product. Technology accessibility has already been identified in prior research as an important factor positively influencing the adoption of new and innovative technologies (e.g., Van Ittersum & Feinberg, 2010). In AI-driven convergence, multiple sources are interplaying, while the predominance as a trust source may also shift. For a low converged AV, users still focus on vehicle technology. One participant stated: *"You can see when you drive modern vehicles that such AI-based functionalities are increasingly available and also become more intelligent."* If AI and vehicle technology have been more converged in AV, the accessibility of sources also changes. AI is predominant, and the importance of vehicle technology decreased as one participant stated *"that these AVs are already driving around and that there are no drivers in them anymore. So, I realize that this is a huge change."*

We argue that multi-source trust transfer depends on the sources' interplay and the resulting accessibility of the single trust sources. If AI technologies (barely) augment vehicle functionalities, users perceive vehicle technology as a predominant source and more accessible. AI technologies perform supporting driving actions such as lane-keeping and speed-control assistants; however, they remain in the background (Koester & Salge, 2020). As a participant associated with AVs, *"the vehicle, so the AI behind it I probably would not perceive."* In this context, users may only establish a strong relationship between vehicle technology and AV technology while perceiving vehicle technology as a predominant trust source. Given that a strong source-target relationship must be present as a condition to achieve trust transfer (Stewart, 2003, 2006), we propose that vehicle technology accessibility increases trust transfer. Then, AI technology will be less accessible, diminishing its trust transfer effect. In sum, we propose:

Proposition 3 (P3): *Users' perceptions of a high degree of accessibility of vehicle technology (P3a) positively moderates trust transfer from users' trust in vehicle technology toward users' trust in AV, and (P3b) negatively moderates trust transfer from users' trust in AI technology toward users' trust in AV.*

However, a trust source's perceived accessibility may differ depending on how strong AI converged into vehicle technologies. One participant stated, *"then, in a scenario with a highly automated vehicle, I perceive the AI as an important technology."* The predominance of trust sources may shift when AI technologies automate the driving functionalities of vehicles. For example, when driving an AV on a highway, AI relieves users of driving tasks, while users perceive AVs less like a vehicle but more like an automated AI-based technology. AI technology is thus more accessible (i.e., performing the driving), and users perceive a strong relationship between AI technologies and AVs. While AI technology is perceived as a predominant trust source, we follow trust transfer's basic assumptions requiring a strong source-target relationship to achieve trust transfer (Stewart, 2003, 2006) and propose:

Proposition 4 (P4): *Users' perceptions of a high degree of accessibility of AI technology (P4a) positively moderates trust transfer from users' trust in AI technology toward users' trust in AV, and (P4b) negatively moderates trust transfer from users' trust in vehicle technology toward users' trust in AV.*

4.2. Industry convergence

Concerning industry convergence, AI-driven convergence describes the shifting and blurring boundaries between two or more industries while AI providers and base product providers are fusing (Curran et al., 2010). Related research on (interpersonal) trust transfer has already examined users' trust transfer from known technology providers toward an unknown provider as a target (e.g., Lowry et al., 2014; Pavlou & Gefen, 2004). However, the interplay and context specifics of AI-driven convergence must be considered. In the case of a low converged product, industries and their associated providers are separate and continue to operate (solely) in their specific industries (Curran et al., 2010). The overlap between the base product industry segment and the AI industry commonly begins in the form of emerging startups and innovative companies, while traditional base product providers also acquire AI startups. With an increasing level of industry convergence, the base product's industry segment and the AI industry more strongly unite, while the boundary between the two is blurring.

AI-driven industry convergence also moderates interpersonal trust transfer. We witness a shift in users' ***perceived trust source value creation share*** of base product and AI providers, that is, the degree to which a provider contributes to increasing users' perceived usefulness and (relative) advantages of a converged product. The results of our interview findings highlight that industry convergence is changing the way users allocate the perceived value of a product to a specific technology provider. Participants explained that *"I would suspect that the vehicle industry will be completely turned upside down"* or *"that the vehicle industry must change competencies, away from what they are now doing classically and more toward competencies in the field of AI and then also have to restructure since other companies that are already good at AI can enter a market easily."* Related research has similarly examined the impact of firms in entering new markets and bringing new products to the market compared to their main competitors (Wang et al., 2012).

The need for mobility changes fuels AI-driven industry convergence while vehicle providers and AI providers are starting to cooperate to innovate vehicles. Our interview findings highlight surprising findings regarding the impact of perceived trust source value creation share and industry convergence, particularly because expected relationships switch compared to the impact of technology convergence-related factors.

Surprisingly, interviewees report that AI providers are more important as a trust source in the case of a low converged product. Users perceive AI providers' value creation share as higher in low converged AV scenarios because they innovate traditional vehicles and offer novel, intelligent functionalities that augment conventional driving. Interviewees perceived an incremental augmentation of AI as more novel for them. Besides, interviewees believe that AI providers contribute more value to AVs because AI providers have high competencies in AI development. According to one participant: *"I think it makes sense because I am simply of the opinion that these AI providers have been doing this for decades. They have completely different experiences compared to when a vehicle provider starts."* With a higher perceived trust source value creation share of AI providers, users elaborate more on the AI provider and its trustworthiness, such as its competence, benevolence, and integrity, when offering the converged product. In low converged product scenarios, the AI provider and its value creation share thus become more pressing in users' assessments, strengthening the trust transfer effect of the AI provider to the AV provider and diminishing the effect of vehicle providers. We posit that:

Proposition 5 (P5): *Users' perceptions of a high-value creation share of AI providers (P5a) positively moderate trust transfer from users' trust in AI providers toward users' trust in AV providers, and (P5b) negatively moderate trust transfer from users' trust in vehicle providers toward users' trust in AV providers.*

If the AV has converged more strongly, the tangled interplay of AI and vehicle providers also changes the predominance of trust sources. Due to increasing industry convergence, *"the automotive industry is undergoing a shift. They are shifting from combustion engines to electric motors and must rethink their business model. It will only be a part of the classic mechanical engineering vehicle. A lot of AI development and AI know-how must be built up because otherwise, there will be a great dependency on AI providers."* With this, a participant emphasizes that vehicle providers must evolve to AV providers, arguing that vehicle providers have the necessary competencies and skills in vehicle development and can learn and adopt new AI-related capabilities. Interviewees associate a (highly converged) AV provider more strongly with a vehicle provider because either the vehicle provider has built up sufficient knowledge in embedding AI capabilities or has acquired an AI provider (i.e., via merger and acquisition). A participant argues, "*I think I would tend to have more trust if a classic vehicle provider developed it completely on its own."* These perceptions align with convergence literature, arguing that industry convergence leads to blurring industry boundaries and stronger cooperation among industry partners (Klarin et al., 2021). In high converged product scenarios, users thus perceive vehicle providers as a predominant trust source for trust in AV providers compared to AI providers. We propose:

Proposition 6 (P6): *Users' perceptions of a high-value creation share of vehicle providers (P6a) positively moderate trust transfer from users' trust in vehicle providers toward users' trust in AV providers, and (P6b) negatively moderate trust transfer from users' trust in AI providers toward users' trust in AV providers.*

5. Discussion

5.1. Principal findings

In this study, we investigated how AI-driven convergence and the resulting interplay of trust sources moderates trust transfer while shifting the predominance of multiple sources. Following research on convergence (Klarin et al., 2021), we first contextualized AI-driven convergence (Hong et al., 2014). We show how AI is reshaping existing products while taking over users' and base products' control and increasingly automating the base product (Raisch & Krakowski, 2021). Interestingly, our findings support the presence of different convergence layers, namely, technology and industry convergence. This aligns with prevalent trust research arguing that trust typically takes an interwoven dual role: trust in an organization and trust in technology with the need to consider them in parallel (Lankton et al., 2015; McKnight et al., 2011).

Elaborating on our findings reveals the importance of considering identified moderators as continuum scales, at the extremes of which users perceive the vehicle or the AI as predominant, e.g., taking control of the vehicle or creating value. We thus witness a competition of the trust sources regarding user perceptions, ultimately increasing the trust transfer effect from the predominant trust source but diminishing the transfer from the subordinate trust source.

Examining the technology layer, we revealed that perceived trust source control and perceived trust source accessibility influence users' trust transfer between AI and vehicle technology toward trust in AV technology. The influence of these two moderating effects is highly dependent on the level of convergence. With low converged products, the vehicle is predominant as a trust source because the technology is more accessible compared to AI, and users tend to trust themselves and the vehicle technologies regarding the steering and control of the vehicle.

However, the manifestations of identified moderators may change depending on the actual usage scenario of the converged product. For example, a user driving in the city may rely less on AI functionalities than vehicle technologies. In contrast, when driving on the highway, AI technology may automate the vehicle functionalities, taking over the control of the vehicle and becoming more accessible to the user (Hengstler et al., 2016; Koester & Salge, 2020). Then, users perceive AI as a more predominant trust source. Such usage- and context-dependent shifts call for a more dynamic perspective on the manifestation of the moderators behind the level of product convergence. More importantly, such dynamic shifting of trust source predominance requires a new perspective on how trust is transferred. During a single interaction scenario (i.e., a driving journey), the predominance of a trust source can change dynamically between the base technology and the AI depending on the context (e.g., driving in the city or on the highway). Prior research, however, has mostly analyzed trust transfer from a static point of view (e.g., Belanche et al., 2014; Lowry et al., 2014; Stewart, 2003), which is why discussing these moderators may support understanding how the interplay of multiple sources affects the trust transfer more dynamically.

Taking an industry convergence perspective, respectively considering trust in providers, we do not see this dynamic shifting, and perceived source value creation share is a rather static construct. What is exciting, however, is that the influence of convergence is reversed compared to the technology perspective. With low converged products, users perceive the AI provider as a predominant trust source because users attribute the development of novel AI-based functionalities to AI providers. However, vehicle providers are more predominant with high converged products as users' trust perceptions of AI providers diminish due to blurring industry boundaries.

5.2. Theoretical and practical contributions

From a research perspective, our study yields several important contributions. First, we briefly contextualize convergence in AI scenarios and categorize the convergence process into technology and industry convergence (Curran et al., 2010; Duysters & Hagedoorn, 1998). Thus, we guide future research in the context of AI-driven convergence to look at AI-related problems from a technology and industry convergence perspective. Second, we contribute to trust transfer literature by showing the influence of AI-driven convergence on multi-source trust transfer. In contrast to prior trust transfer research (e.g., Belanche et al., 2014; Leong et al., 2021; Lowry et al., 2014), we confirm that the interplay between AI and the base product as a trust source must be considered as they form the converged target product. Depending on the level of convergence and the specific interaction scenario, the AI or base product is predominant as a trust source. By conducting various interviews, we reveal three moderators covering this interplay of sources and provide an explanatory description to understand different trust sources' predominance. Third, our research indicates that we require a more dynamic perspective on users' trust and trust transfer. We highlight the importance of looking at the shifting dynamics of the trust sources' predominance, which may change during a single usage of the converged product. In contrast to prior trust transfer research taking a static perspective of the trust source, we argue that the context-specify interplay of trust sources and the related dynamic shift of trust source predominance is important for further consideration and better understanding.

For practitioners, our results provide information on how AI-based converged products are emerging and how to establish trust in such converged products. Providers should be aware of whether they built a low or high converged product because this affects the importance of trust in a particular source. However, not only the technology layer should be considered, but also the shift of industry. To strengthen users' trust, vehicle providers should consider the potential benefits and importance of cooperating with AI providers early in AV development. Involving AI providers in developing converged products may also be helpful in other contexts. The share of value creation may support the trust building in novel AI-based converged products due to specific AI knowledge, such as in the context of AI-based surgery robots.

5.3. Limitations and future research

Our study is subject to limitations that open avenues for future research. First, we conducted 25 interviews with vehicle users. The generalizability of the results needs careful consideration. While trying to understand how users establish trust in AVs, AI-driven convergence specifics depend particularly on the users and their characteristics and attitudes. We collected data from interviewees representing a younger (in our case, average age of 28.9 years) and more educated population (in our case, for example, 76.0% with an undergraduate degree). Thus, future research should employ additional means of data collection that include a more diverse population. Second, we have derived propositions without testing them and proving statistical significance using a quantitative research method. We recommend conducting quantitative research to test our propositions, such as involving online panel providers, conducting behavioral experiments, and investigating related convergence scenarios (e.g., voice assistants) that help triangulate findings.

Further research may also investigate how trust sources as a dynamic construct affect a target and how the interplay of the sources shifts the predominance of trust sources. Looking at other related contexts, such as the healthcare sector or voice assistant usage in e-commerce, may be promising to identify other context-specific effects moderating trust transfer.

6. Conclusion

This study uncovered the context-specifics of AI-driven convergence and their impact on multi-source trust transfer. We investigated the case of AVs emerging due to the convergence of AI with vehicles as a base product. By conducting semi-structured interviews, we revealed that users' perceived trust source control, perceived trust source accessibility, and perceived trust source value creation share moderate users' trust transfer depending on the level of convergence. We contribute to research and practice by fostering a deeper understanding of AI-driven convergence and its impact on the interplay of multiple trust sources in trust transfer. This knowledge can help identify how users establish trust in converged products and show which trust sources are more predominant depending on the context of AI-driven convergence.

7. References

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