Driven by Trust? An Examination of Trust in Adopting Autonomous Public Transport

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Title: Driven by Trust? An Examination of Trust in Adopting Autonomous Public Transport

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Research question: The current study seeks to investigate (1) to what degree trust impacts intention to use shared autonomous shuttles and (2) whether static and dynamic norms can be applied to impact degree of trust in shared autonomous shuttles.

Abstract

As modern societies face increasing congestion and greenhouse gas emissions due to car usage, autonomous vehicles present promising solutions and new challenges. This thesis investigates the role of trust in the adoption of autonomous public transport systems, particularly small, shuttle-like, on-demand buses seen as a first iteration of self-driving public transport. Introducing novel technology demands a willingness to adopt from the public. As people are affected by what others believe and think, can social norms impact the degree of trust in shared autonomous public transport? The current study investigates to what degree trust impacts the intention to use shared autonomous shuttles and whether static and dynamic norms can be applied to impact the degree of trust in shared autonomous shuttles. An online experimental survey was conducted, where participants (n = 1032) were divided into three intervention groups - control, static norm, and dynamic norm. Each group was influenced by distinct normative statements aimed at shaping their degree of subjective trust in shared autonomous shuttles. Additionally, propensity to trust is examined as an important individual trait. The moderating effect of propensity on social normative influence is further explored. The results from ANOVA and regression analyses indicate that people are influenced by others' degree of trust in a novel service, when making such attributions themselves. Yet only the intervention groups and the control group showed significant differences, while no notable disparities were found between static and dynamic normative statement framing. Safety evaluation of the shuttles was found to substantially affect subjective trust in shared autonomous shuttles. Hence, this study indicates that successful implementation of shared autonomous public transport, especially trust in such a service, can be dependent on normative influences. The study may also help inform future research on the psychological aspects of autonomous public transport adoption and implementation.

Author's Notes

Research pertaining to anything within the field of technology moves at a break-neck speed. Meanwhile, we humans try to catch up to our own inventions and seek out how to best use them. I have always been fascinated by the intersection of psychology and technology, and this project allowed me to take a dive into a small part of those waters.

Writing this thesis has been exiting and challenging. It would have been even harder were it not for all the encouragement and support from so many. First, I want to thank my supervisors, Ole Aasvik and Pål Ulleberg for their excellent guidance. Second, I would like to extend my gratitude to the Institute of Transport Economics for giving me a workspace and a welcoming scientific environment to discuss my ideas. Third, a big thanks to Osloforskning for providing me with a grant for this project.

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Introduction

Mobility for inhabitants is an essential part of modern societies. The introduction of the car brought a new level of freedom and flexibility to individuals' travel behavior. With increasing urbanization, we need new solutions to improve infrastructure. There have been technological advances in the way we interact with transport services, but overall, the basic framework for how we travel using personal and public transport has remained the same for decades (Pooley et al., 2006). With increasing populations, new challenges emerge as to how we travel.

Emissions of greenhouse gases and a dramatic overload of city infrastructure in the form of congestion are examples of challenges faced by modern cities (Chester et al., 2013). At the same time, new possible solutions present themselves. Technology is reaching a point where autonomous driving is no longer science-fiction (Ruter, 2023). Having self-driving cars is believed to reduce the number of accidents (Hult et al., 2016; Nordhoff et al., 2019; Xu et al., 2018), pave the way for more climate-neutral vehicles and transport (Jones & Leibowicz, 2019), and help otherwise marginalized groups live more active lives for longer (Choi & Ji, 2015). However, scenarios in which everyone uses their own private autonomous vehicle for travel will not solve the issues of congestion. On the contrary, having more autonomous private-owned vehicles may increase traffic before they can fully communicate with each other (Cummins et al., 2021; Hyldmar et al., 2019). Autonomous private cars are expected to be used more than their non-autonomous counterparts would be, and even function as a fleet of privately owned robo-taxies, when the owner of the car is not using it (Ruter, 2019). For example, it may drive you to work, and then drive itself home to park, or be ready for other trips. Thus, advertently making it easier and more comfortable than public transport or other means of transportation which further worsens the issues that already exist.

Designing and implementing autonomous public transport alternatives to both private cars and today's public transport solutions that people will use is therefore paramount. Shared autonomous transport can facilitate effective and safe travel, especially on "first-leg" and "last-leg" distances, for example to and from other transport hubs like airports, train stations, or private homes. It can also decrease traffic accidents as computer driving may prove less prone to crashes and be better at avoiding error as the technology improves (Nordhoff et al., 2019). Finally, autonomous public transport can enable off-route travel to allow a more active lifestyle for people who otherwise would have to rely on expensive private travel or taxi services.

A smaller shuttle-like, on-demand bus can facilitate this, and is believed to be one of the first iterations of self-driving public transport to become commercially available in many cities due to the adaptability and size of the vehicle. Having the ability to dynamically plan a route based on the needs of the users creates a more responsive and accessible offer. In other words, function as an automated mobility-as-a-service solution. People living in suburbs may be able to rely less on cars, and the threshold to use public transport can be lowered as less walking is needed. However promising, implementing new solutions in well-established fields introduces challenges.

Availability of a service that introduces a perceived risk for the user will also induce difficulty in getting people to actually use the service. A critical element is whether or not the user *trusts* the technology in question. At its' core, trust is intuitively understood: You can put your trust in others, citizens may trust or distrust their government, and you can trust that the train arrives on time. In this colloquial sense, trust is *an expectation.* This expectation is believed to be affected by many attributions, informed by the knowledge that is available to us, and what we believe others feel about the same thing (Sherif, 1936). When we evaluate novel experiences, the testimonies of others can be crucial in assessing the risk involved, or whether we *trust* the agent in question or not.

The aim of this thesis is to increase our understanding of how trust in novel, technological solutions is formed in the context of shared autonomous shuttles (SASs). More specifically, how social norms and the influence of others play a role in shaping our opinion and attribution of something we lack firsthand experience with ourselves. The study will explore what affects the intention to use a shared public transport service through trust, and the lens of psychology. There are of course many obstacles to overcome when introducing autonomous public transport. However, one of the fundamental initial barriers to actively using a system like this is trust. Without trust in the vehicle and its system, a person will not even try the service. Hence, this thesis will investigate some of the key factors that contribute to building trust in autonomous public transport systems through a psychological framework, with a focus on the role of social norms, the influence of others, and the psychological processes that underlie trust formation, ultimately aiming to provide valuable insights and recommendations for the successful integration and adoption of autonomous public shuttles.

Finally, it should be stated that introducing such a service is not without its risks and downsides. However, this thesis does not intend to focus on this discussion, but rather highlight underlying trust processes given the possible upsides these kinds of innovations may provide society. Hence, the current study seeks to investigate (1) to what degree trust impacts intention to use shared autonomous shuttles and (2) whether static and dynamic norms can be applied to impact degree of trust in shared autonomous shuttles.

Interpersonal Trust, Trust in Automation, Propensity to Trust, and Normative Influence

Trust is called the glue of life and has a large impact on the interactions individuals have with each other, and with the world around us. Trust is a complex construct and is plagued by the same terminological and psychometric issues as other composite and latent psychological terms (Cronbach & Meehl, 1955). Interpersonal trust and trust in automation and technology have been researched for decades. More often than not, the latter has its' roots in the trust we exhibit in human to human interaction (J. D. Lee & See, 2004). Interpersonal trust is an essential part of understanding human behavior in social situations, and functions as a starting point for examining human-automation trust relations. Trust in itself is difficult to define, as it not only differs from one academic discipline to another, but disagreement within the fields is not uncommon either. Within economy, sociology and psychology we find different definitions and conceptual lenses (Harrison McKnight & Chervany, 2001). Even if the surface understanding of the term is similar, the *process* of developing and shaping trust, and what factors influence this process, may differ. In this way, some definitions of trust may be victim to a degree of "jingle-jangle-fallacy", where two constructs are different, even if they bear the same name, or conversely are the same construct while labeled differently (Lawson & Robins, 2021).

Given that the characteristics of trust change from definition to definition, it would be safe to assume the relationship between interpersonal trust and trust in automation also changes with context and theoretical disagreements (Harrison McKnight & Chervany, 2001). Hence, for the sake of consistency and to provide validity to the measures used in this study, trust will be defined through a psychological framework, but not without acknowledging the influence of other disciplines.

Somewhat lesser investigated than trust itself, is the base rate of which the individual exhibit trusting or distrusting attitudes and behavior: their propensity to trust (Frazier et al., 2013;

Schoorman et al., 2007). Propensity to trust is viewed as dispositional trust, or the tendency to trust, when information and other influencing factors are minimal. To understand context specific trust, it is essential to investigate the fundamental structures, such as propensity to trust, because it serves as an underlying baseline that shapes how people perceive and react to trust-related cues in various situations individually, ultimately influencing their trust decisions in specific contexts based on other determinants.

The last component of theory in this study is the influence of social norms in trust formation. When information about something is scarce, we seek other ways to inform an evaluation. Because autonomous vehicles is not yet a common technology, people may rely more on others' testimony and beliefs in their own attributions (Hoff & Bashir, 2015). Hence, social norms may be of great influence to trust in autonomous public transport, given that most people lack any firsthand experience of this technology, and will likely use others' opinion as a gateway to form an evaluation.

In the subsequent sections, I will discuss the foundational elements and definition of interpersonal trust in the current literature, before exploring trust in automation. After defining trust, the propensity to trust is discussed as an important part of trust attribution, both towards other people and automation. Then, frameworks that seek to model how different factors can affect the intention to use shared autonomous shuttles, are presented. Lastly, as a significant aspect of the research objective, literature on the role of social normative influence on attitudes and behavior will be discussed in relation to trust-formation.

Interpersonal Trust

At its core, trust is a construct existing in the form of a social contract between a trustor: the agent that is attributing trust, and the trustee: the agent being evaluated. Trust has been defined as an attitude, a belief, a disposition, a personality trait, and as a mental state (Hoff & Bashir, 2015). No clear interdisciplinary definition has been established (Harrison McKnight & Chervany, 2001), and the construct is largely dependent on the context in which it is being examined. Attempts to define common elements of trust have been made. In an article from 1995, Mayer, Davis and Schoorman propose a model of how trust functions within organizations. Their model has become quite influential in understanding the development of interpersonal "trustworthiness". Mayer et al. (1995) defined the attribution of trust with basis in three factors that the trustor assesses in a trustee: ability, benevolence, and integrity.

The ability of the trustee can be evaluated by the trustor by observing behavior, considering history, achievements or failures, and aptitude. Attribution of ability in one domain does not necessarily translate to another. For example, a trustor may evaluate the ability of a pharmacist to hand out the right prescription. Ability will increase if the trustor has belief in the trustee's *specific* ability, and therefore increase the trust in this area. However, the pharmacist's ability to stop a robbery will not affect this attribution in this specific domain, because these abilities are unrelated. Benevolence refers to the trustee's inclination to do well by the trustor, free from any personal gain (Mayer et al., 1995). Following the same example, a trustor may attribute the benevolence of the pharmacist as high, if they advise the change of a drug even if the drug is cheaper for the customer. Lastly, the integrity of the trustee is attributed based on the trustor's normative behavioral expectations. In other words, a standard of which the trustor holds the actions of the trustee against. Previous actions also impact this factor, in line with ability. The pharmacist may receive a high integrity attribution by stopping the aforementioned robber, for example. As such, ability, integrity, and benevolence are not isolated factors. They will affect each other and interact, and the overall trustworthiness of the trustee will depend on a collective attribution, or a combination grounded in the context of the evaluation.

Further categorization by Harrison McKnight and Chervany (2001) supports the factors proposed by Mayer et al (1995). In a cross-disciplinary review of trust definitions, they proposed benevolence, integrity, competence, and predictability as main elements of trust based on analysis of 65 articles which defined trust. Benevolence and integrity are conceptually similar to Mayer's model. Competence is very similar to ability, encompassing the skills to achieve a given task or desired behavior. The fourth category, predictability, refers to whether the trustee acts consistently across different events or behaviors, and is an addition to the model proposed by Mayer et al. (1995) It differs from integrity in that it does not differentiate between subjectively good or bad behavior, but simply relates to the trustee's consistency in relation to the complete attribution of trustworthiness. It will be harder to assess the other attributes if predictability is low, given that a trustor would be unsure if the trustee would behave as predicted. Harrison McKnight and Chervany (2001) further elaborate on the typology of trust by defining five trust types divided among dispositional, institutional, and interpersonal trust, which build on each other.

Institution based trust is based in the belief that societal factors or systems are designed in a way that the actor believes are in favor of desired outcomes in a given situation. This will affect how the trustor behaves when in the relevant context. Interpersonal trust holds three of the trust types: Trusting beliefs, trusting intentions and trust-related behavior. These follow the logic of the Theory of Reasoned Action (Fishbein, 2011), where beliefs is the antecedent of intention, and intention the predictor of actual behavior. Trusting beliefs consist of the four subconstructs earlier mentioned: Benevolence, integrity, competence, and predictability, and make up a solid footing for trusting intention, argue Harrison McKnight and Chervany (2001). If trusting intention is sufficient, the trustor will exhibit trusting behavior, and hence accepting the possibility that the trustee may fail, betray, or not exhibit the expected behavior. This underlines what is perhaps one of the most fundamental elements of trust: the existence and acceptance of risk.

A Reason to Trust: Risk

Risk is a necessity for trusting behavior to exist. More specifically, risk that entails a negative consequence or disadvantage for the individual. Mayer et al. (1995) argue that risk-taking in a relationship is the manifestation of the willingness to be vulnerable. A trustor can exhibit a large degree of willingness, but not necessarily trust the trustee enough because the risk evaluation is too high. The behavioral output of trust is therefore defined by comparing the sum of ability, benevolence, and integrity attributions against the total evaluated risk. The appropriate factors may also be weighed differently from one contextual setting to another, based on what the current task or behavior is. Third parties and changes in the situation not yet known to the trustor will change attribution and risk evaluation accordingly when they become clear to the trustor.

The risk evaluation can be described as a continuous and repeating process: After the trust behavior is resolved, new attributions are made for each of the three factors, and "updated" to match the outcome. In other words, Mayer et al. (1995) propose that ability, benevolence, and integrity are re-calibrated with information and history from the behavior and will change the willingness to be vulnerable to the trustee in future interaction and trust evaluations. Colloquially speaking: How much the individual trusts the agent in question.

Further building on these constructs proposed by McKnight and Chervany, the fifth trust-type is dispositional trust, which is proposed to make up the base rate of all further trust attribution. This construct is mostly referred to in the literature as the propensity to trust.

Propensity to Trust

Mayer et al. (1995) propose that propensity to interpersonal trust, or the general willingness to trust others, affect or moderates all three factors of trust attribution, meaning that a person that has a high propensity to trust, will make more positive attributions of the trustworthiness of the trustee when concrete information about what is being attributed is not available or lacking. Hence, propensity functions as a *baseline* for trusting different trustees.

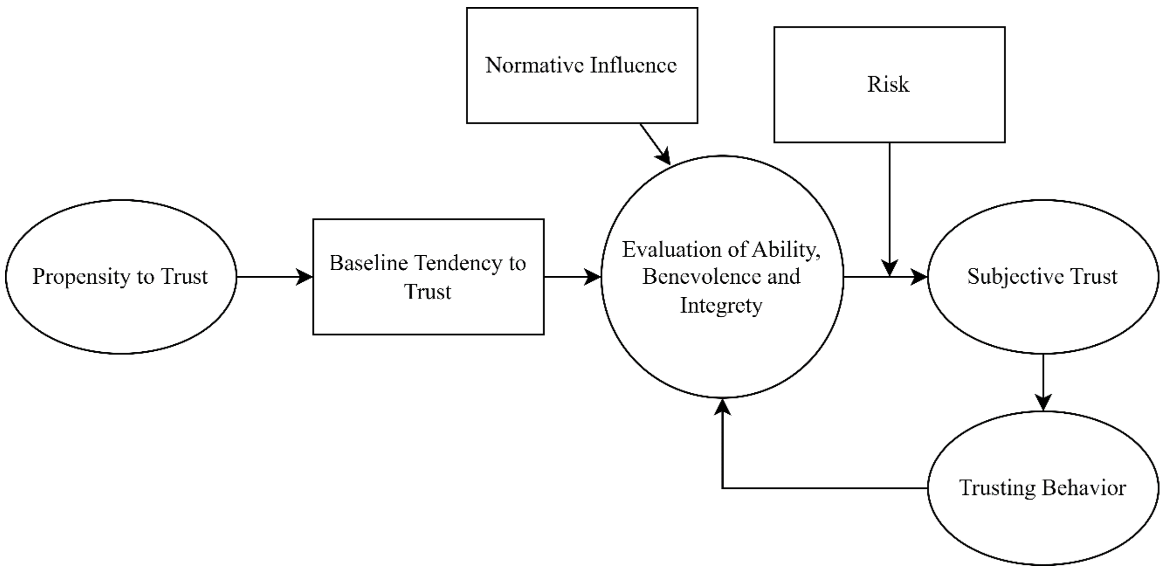
Propensity to trust is believed to be stable (Mayer et al., 1995; Rotter, 1967) and function as a personal trait, however not in the same vain as a *personality* trait, but a general tendency tied to one's person. It develops through socialization and learning, with a feedback loop from encounters and situations leading to either a generally trusting, or distrusting disposition (Harrison McKnight & Chervany, 2001). This trait functions as a substitute for lack of information and moderates the degree of negative or positive influence from new information. A trustor that meets someone for the first time will exhibit trust appropriate to their own propensity in addition to any available information. If the trustor has a low propensity to trust, the more lack of information contributes to *distrust*. It should here be noted that distrust also bears different connotations and definitions. Some argue that distrust is the negative form of trust, and exist only when there is no trust because they are a part of the same construct (Rotter, 1980). Others have put forward that trust and distrust are separate constructs and may exist in tandem (Harrison McKnight & Chervany, 2001). Logically, this makes more sense: you may trust that the bus will arrive sometime, but express distrust in its ability to arrive *on* time, in the same instance. However, whether this distinction actually contribute to expand understanding and explanation of trust as a construct is debated (Schoorman et al., 2007). Increased complexity is not necessarily equal to increased comprehension.

As new information is gathered, low propensity may entail that it is harder to increase trust for the trustee than for someone with a high propensity. Still, propensity to trust is believed to be at its' most influential in novel interactions and trusting behaviors (Harrison McKnight & Chervany, 2001; Jessup et al., 2019).

Ultimately, propensity to trust can be understood from the perspective of dispositional psychological theory. It is a foundation which affects the individual's outlook, perception and understanding of the world within a construct domain. Consequently, it is an important part in understanding trusting-behavior. The theoretical understanding of trust formation is illustrated in Figure 1.

Figure 1

Theoretical Overview of Trust Formation



The figure displays theoretical trust formation from baseline, affected by propensity, to the active attribution of trust in relation to an agent. This attribution is affected by many factors, including normative influence. Risk is the "opposition" to subjective trust. The evaluation leads to a trusting (or distrusting) behavior. New evaluations are made on the basis on feedback from this behavior.

Trust in Automation

Automation has become a prominent feature of modern society, as technology has advanced to the point where many tasks can now be performed by machines. From vending machines to advanced computers, and elevators to planes: automation saves precious time, increases effectiveness, and can be much safer than letting humans perform the same task.

Research has exploded on human-automation trust and interaction, and we have reached a point where automations seamlessly intertwine with our lives (Fröhlich et al., 2019). In human-automation research, the user is often presented as the "operator", bearing the connotation that they are an active user of the automation. However, more automation is utilized with a more passive role, and while still being used as tools, many functions as extensions of already well-established entities. Shared autonomous shuttles are examples of this. This type of use may naturally lower the demand for knowing the workings of the automation, simply because there is no need or capacity for the average user to hold this information. Because of this, trusting the automation becomes more reliant on other elements, such as borrowing others' beliefs through social influence, conformity, and social norms (Hoff & Bashir, 2015). Beyond this, the main components of a trusting relationship between humans and automation do not differ all that much from interpersonal trust. However, it is not unproblematic to extrapolate *findings* from interpersonal trust to trust in automation.

When trusting or distrusting automated technology, some components are alike to those encompassing interpersonal trust. Lee and See (2004) expanded on the model by Mayer et al. (1995) and defined three factors that translate to trust in automation: Performance, process, and purpose. *Performance* relates to ability and denotes what tasks the automation is able to perform, and what it is expected to do. The end-goal is essential, as the feedback-loop for an automation is based on the results of the automations behavior, similar to the reattribution in interpersonal trusting relationships. *Process* relates to integrity, as it describes the basis of the automation's actions. In other words, it is the algorithms, code or design that make up the automation. Lastly, *purpose* relates to what Mayer et al. (1995) defined as benevolence. It is the element of "why" this automation exists, and what it is intended to achieve for the user. Lee and See (2004) argue that these attributes would be derived from the intentions the designer or creator of the automation holds, or at least what the user or trustor thinks the designer intended. The lines between trust in automation and interpersonal trust are blurred when interpersonal elements confound the attribution. There are, however, similarities that may function as heuristics in this process.

Hoff and Bashir (2015) highlight the likeness in human-automation trust and interpersonal trust: Both processes are specific to situations, and both rely on a dyadic interaction where risk or uncertainty is present. When engaging with automation, the risk is often much more clearly stated and understood by the trustor than in human-to-human trust relations. Especially with automation that serves a clear *purpose* for the user. This changes the dynamic between trustor and trustee, as reliability and predictability become increasingly important, even if the risk evaluation is still the same. Mayer et al. (1995) defines the risk-element of trust through risk taking in relationships, which entails that the trustee must have some agency, some degree of freedom, to either break or protect the expectations of an outcome of trusting behavior. This complicates the relationship with automation. Does the trustor trust the person who designed or programmed the automation as a proxy? Do they view automation as an acting agent of its own? Individuals may use heuristic judgements and techniques to answer these questions, without being reflexive of it themselves.

Intuitively, automation differentiates from interpersonal trust because an automation does not have autonomy over the actions taken in specific situations. However, a problem arises with newer automation relying more and more on artificial intelligence (Sarmah & Shekhar, 2019). At what point is an automation equipped with machine-learning capabilities no longer restrained by pre-determined functioning? Additionally, some people tend to anthropomorphize automation, which can be defined as giving nonhuman entities human characteristics, motivations, or even emotions (Epley et al., 2007). This may stem from a lack of understanding in the automation, and instead artificially induce a sense of benevolence and sometimes even perceived sentience (Luscombe, 2022). Recent technological advances have made some technologies remarkably good at emulating human behavior, especially within the realm of language processors or "chat-bots". While there are only so many human characteristics one can attribute to an autonomous vehicle, it is not unlikely that the systems will be *perceived* as having autonomy. As large-scale deployment of this technology becomes reality, many people will use the service without having any knowledge of the functioning or technical detail, just as many people use computers without understanding how it works on a component-level.

Another difference between interpersonal trust and trust in automation is the formation and maintenance of trust. In interpersonal trust, individuals start at a baseline defined by propensity to trust and contextual factors, and build on that trust through feedback loops and trusting behavior situations (J. D. Lee & See, 2004; Mayer et al., 1995; Rotter, 1967). Formation is hence a bottom-up process. With automation, interacting is already a trust-behavior. Evaluations of performance, process, and purpose are already "integrated". Trust in automation functions more as a top-down process, with the baseline being more neutral or centered, and then being weakened or strengthened after first interaction (J. D. Lee & See, 2004). This makes errors and faults of the system more detrimental than in an interpersonal relationship, especially in the first interaction (Robinette et al., 2017).

The affective processing of trust attribution ultimately relies on thoughts. Lee and See (2004) argue that trust formation depends on analytical, analogical, and affective processes, with affect both being influenced by, and influencing the two former processes. Analytical trust formation is informed and happens when the trustor actively evaluates the available information and makes an argument for whether or not the trustee can be trusted. The necessary information needed to make such a calculated attribution is rarely present, and people generally do not have access to all the necessary information demanded. Much in line with heuristics-theory, analogic processes are the evaluations which replace these information-driven attributions where data is lacking. Analogical processes rely on testimony of others, previous engagements and experience with similar agents, and category-based trust. Gossip, word of mouth and social normative influence are examples of this. Category-based trust is dependent on a heuristic-like processing where the trustee is grouped with other similar entities. For example, an autonomous shuttle may be grouped with an autonomous ferry, should the trustor have previous experience with the latter, and not the former. This kind of trust is particularly fragile to situations that weaken the trust, such as accidents or erroneous behavior from the automation. This is in line with the top-down formation and maintenance of human-automation trust. Finally, emotions are the results of the attribution of the trustee. Since humans are not computers, the *emotion of trust* (or lack thereof), provides feedback from the more or less subconscious evaluation, and informs the answer to the question: "Should I trust this machine?"

To highlight the intertwined workings of interpersonal trust and trust in automation, different processes can be exemplified through Harrison McKnight and Chervany's (2001) proposed typology of trust. As established, trusting intentions contain a form of resignation of power. The trustor needs to accept that the trustee has influence over the outcome of something involving one's person. Take for example a passenger on a plane. When entering the plane, a contract between the passenger and arguably three agents has been made: The plane (trust in technology/automation), the pilot (human, an interpersonal actor) and the airline company (an example of structural and situational trust). Each instance requires risk taking and relinquishment of control. Fundamentally, both interpersonal trust and trust in automation ultimately boils down to this central component: risk taking. It is the processes and evaluations along the way which encourage or discourage the risk that make up the construct we call trust. This trust is, in the same vein as interpersonal trust, affected by an individual's intrinsic beliefs and propensity.

Propensity to Trust Automation

Propensity to trust automation is defined similarly to propensity for interpersonal trust, serving as a general tendency or baseline for placing trust in automated systems (Jessup et al., 2019; J. D. Lee & See, 2004). Despite its importance, measuring this construct has been less prevalent in the literature than its interpersonal counterpart, an issue that the current study aims to address by further the understanding of the gap between propensity to trust and propensity to trust automation.

A three-layered approach to trust proposed by Hoff and Bashir (2015) defines dispositional trust, or propensity to trust, as one of the central influencing elements to trust formation in relation to automation, parallel to situational trust and learned trust. Whilst drawing research from, and parallels to, interpersonal trust to inform their model, it proposes to summarize the make-up of propensity to trust automation through other factors. Age, for example, can affect the disposition dependent on a person's needs, or their cognitive ability (Hoff & Bashir, 2015). The personal-trait-factor is perhaps the closest related to propensity to interpersonal trust. A defining difference is the effect of, and on, the feedback loop from concrete trusting-situations. Empirical evidence suggests that the propensity to trust automation has a greater influence on early trust-attributions compared to propensity to interpersonal trust, and taking a correspondingly large hit when automations act erroneous or make mistakes that breach this trust (Hoff & Bashir, 2015).

Culture is also believed to impact the disposition and might for example have an influence on the effect of age. If a country has a historically significant culture of innovation and forward-thinking societal values, individuals who identify with that culture might be more inclined to conform to cultural norms, regardless of, or even dependent on, their age. The propensity to trust automation is, similar to interpersonal trust propensity, also believed to be a stable characteristic, which is formed by learning and socialization, and *informed* by experiences and outcomes of trusting-behavior in relevant scenarios.

Another central element in examining propensity to trust automation is specificity versus generality. Jessup et al. (2019) argue that more specific measures that pinpoint a specific type of automation, or more explanation of the context within the measure, provides a more valid estimates of the propensity. However, creating a more specific measure also dilutes the practical use of a propensity scale. In contrast, the interpersonal propensity measures used yield a high construct validity (J. D. Lee & See, 2004; Rotter, 1967) without being specific to any *type* of person. As propensity is supposed to be a general tendency, the measurement cannot stray too far from the understanding of an automation without hurting the scales' generalizability.

In this context, the challenge lies in clearly defining the concept of automation. A vending machine being as much an automated system as a self-driving vehicle, in technical terms, may not be immediately obvious when simply considering the term "automation." However, to provide a general measure, these two entities must be of equal standing without changing the definition. Lee and See (2004) defined automation as "technology that actively selects data, transforms information, makes decisions, or controls processes"(J. D. Lee & See, 2004, p. 50). Whilst this definition does cover most entities that would replace the need for a human's action, it is rather broad. Ultimately, automations can be complex and composite of several different technologies, and most importantly is that some common understanding of what an automation is and isn't, is established in the research context.

Regarding propensity to trust automation however, the proposed definition does not entail that a person who scores high in propensity to trust automation should trust a vending machine and a self-driving vehicle equally. This is where the attribution of trust through performance, purpose, and process becomes the crucial determinant, and active attribution replaces intrinsic tendencies.

Defining Trust

In this thesis trust will be construed as a sum of its attributional parts defined by the theory discussed. Interpersonal trust is defined as the *willingness to accept a form of risk, given the attribution of another person's ability, reliability, and benevolence*. Trust in automation is defined as the *willingness to accept a form of risk, given the attribution of an automation's performance, purpose, and process.* It is important to be reflexive in the actual measure of the latent variable trust. Going forward, I acknowledge that trust as a construct is indeed defined by the context in which it is examined and must be carefully evaluated and measured appropriately. As argued by McKnight and Chervany (2001), conceptualizations of trust must be adequately comprehensive and adequately context-specific, in order to function in the actual study and at the same time be able to build on previous research and theory. The perfect definition of trust is not achievable, and it is more appropriate to adhere to definitions that function properly with the theoretical framework surrounding it. Further, this study is based on the notion that there is a common denominator between trust in other people and trust in automation. Lastly, the concept of separating distrust and trust into separate constructs is beyond the scope of this study, and the main focus will be to examine the formation of trust in its positive description, not focus on the formation of distrust.

The complex nature of trust clearly demands a solid contextual foundation. Numerous theoretical models and frameworks have been developed to provide comprehensive explanations for human behavior, and technology acceptance is not an exception. To ground my definitions in the context of autonomous vehicles, I now turn my attention to the concrete frameworks that inspired this study.

Predicting Autonomous Vehicle Adoption: Integrating UTAUT and MAVA

Since the Theory of planned behavior was introduced by Ajzen (1985), intention has been seen as a solid predictor in models that seek to explain behavior. One such model is The Unified Theory of Acceptance and Use of Technology model (UTAUT) proposed by Venkatesh et al. (2003). It is an attempt at unifying eight different models that seek to predict the acceptance of new technology. The models, hailing from psychology, information-systems research and sociology, include the Theory of Reasoned Action and the Technology Acceptance Model (Venkatesh et al., 2003). After conducting a comparison and synthesis of the models, the authors argue that four constructs are dominant in predicting technology acceptance: *performance expectancy*, *effort expectancy*, *social influence* and *facilitating conditions*. Performance expectancy encapsulates the degree of belief the individual has that the technology in question would provide a benefit, a performance boost or be useful to them. Effort expectancy refers to the level of effort one would have to invest to use the technology, or the ease of use. Social influence is defined through social interaction regarding technology, and whether or not the individual perceives the use of relevant technology as normatively correct or acceptable. Influence from significant others and peers affect this construct. Venkatesh et al. (2003) also notes that the complexity in social situations and the sheer number of influencing factors make this a broad construct. Social situations are also highly culturally dependent and may be affected by, for example, normative influence. Lastly, facilitating conditions refers to the surrounding framework and infrastructure that facilitate the use of the technology.

Interestingly, trust is not explicitly declared a factor in the proposed model. It can be argued that trust would play a large role in Effort expectancy as well as facilitating conditions and that social influence would depend on others exhibiting trust in the technology in question. However, the UTAUT is not necessarily context specific enough to be applicable to, for example autonomous vehicle adoption, where extensions of the model become more suitable.

The Multi-level Model on Automated Vehicle Acceptance (MAVA)

The Multi-level Model on Automated Vehicle Acceptance by Nordhoff et al. (2019) proposes a combined model to predict automated vehicle acceptance. It is fundamentally based on the third iteration of the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), and the Car Technology Acceptance Research Model (Osswald et al., 2012). The model postulates a process overview which results in either adoption of autonomous vehicles (AVs), or rejection or undecided regarding AVs. 28 acceptance factors within seven acceptance classes encompass the model through a four-stage pipeline.

Stage 1 is the individuals' exposure to autonomous vehicles. Stage 2 is divided into three sub-stages: Domain-specific system evaluation, symbolic-affective system evaluation and moral-normative system evaluation. Stage 3 encapsulates the actual intention to use autonomous vehicles, and finally, stage 4 is the use of AVs. The Unified Theory of Acceptance and Use of Technology model is represented in stage 2, where safety, social influence and benefits and risks are also believed to be deciding. In line with the theory of planned behavior (Ajzen, 1985), intention is the final gateway to behavioral change, or in this case: acceptance of autonomous vehicles.

The model is hierarchical, and it is theorized that the individual will try to "realize" or evaluate, the conditions of the preceding steps before continuing to later stages in the model (Nordhoff et al., 2019). Because of this, it is postulated by the authors that trust is essential for adoption in the early stages given that uncertainty and initial distrust decline after engaging with, and having own experiences with autonomous vehicles (Hartwich et al., 2019). However, trust may be important in *all* stages, as a determinant to engage or choose to disengage with an autonomous vehicle.

In the MAVA, trust is categorized under the factor-class personality, and hence a micro-level individual factor which may affect all stages in the model. Alongside trust, technology-savviness is identified as a personality-related trait that may affect the intention to use AVs. Socio-demographical factors are also postulated to have a role. Age for example, has been shown to affect tech-savviness (Zhang et al., 2022).

There is no doubt that trust is essential in the adoption process of autonomous public transport. Additionally, social or subjective norms play a part in determining how trust in these automations is evaluated.

Social Normative Impact on Trusting Intention and Behavior

Formation and maintenance of trust in novel actors and situations is a complex process. As discussed so far, there are a myriad of factors at play, and context affect the attribution to a large extent. However, the subjective norm element, or social norms are a cornerstone component in several behavioral models in psychology, including the aforementioned UTAUT and the MAVA. If people believe that a certain behavior or attitude is normatively acceptable or significant others share the same viewpoint, they are more likely to shape their behavior in line with those beliefs (Ajzen, 1985).

In line with this, seeing significant others use and endorse autonomous vehicles have been found to increase personal decision making regarding adoption of the technology, and people tend to view the normative consensus as a guide to the perceived benefits of autonomous vehicles (Acheampong & Cugurullo, 2019). Even the perceived ease of use of autonomous vehicles is believed to be affected by how normative the use is in the population.

As normative information is theorized to be of importance in analogic trust formation (Hoff & Bashir, 2015), social norms could be a major influential factor regarding trust too. This is especially true when little information is available, and the testimony and experience of others are a primary source of information.

Dynamic Norms

Social norms and their ability to affect behavior is well documented (Cristina Bicchieri et al., 2018; Sherif, 1936). However, dynamic norms, or the conformity to others' change in behavior or beliefs over time, is less researched. Some studies have shown potential in changing climate-positive behavior with dynamic norm interventions (Sparkman & Walton, 2017). Additionally, overcoming personal psychological barriers to change can be assisted through dynamic norm intervention (Sparkman & Walton, 2019). Given that pre-conformity can impact sustainable behavior, could the same interventional strategy be applied to increase trust in shared autonomous vehicles? The current study seeks to explore this, however, as discussed, trust attribution is heavily reliant on the context in which it takes place.

Autonomous Public Transport (in Norway)

As now established, mobility is no exception to the automatization of society. Automation of personal transport, both public and private, is regarded as an important step in potentially reducing accidents, emissions, and making a more sustainable infrastructure for the future (Acheampong & Cugurullo, 2019; Nordhoff et al., 2019). Realistically, the first iteration of fully autonomous public transport to become available to the public are smaller, first-leg/last-leg shuttles (Ruter, 2019), which are the ones being piloted in Norway. These function as transport for a few people (six to eight passengers) on routes to and from other high capacity means of transport like airports or train stations. These shuttles are more intimate and travel on smaller roads at lower speeds. Ideally, an automated fleet of shuttles like this can be used without traditional bus-stops and run on an on-demand basis, in contrast to having traditional bus-stops.

In the Oslo-region, several pilots with smaller shuttles like this have been conducted (Ruter, 2022). The shuttles drive on a predetermined route with a safety driver that may intervene, if necessary, but are otherwise fully autonomous in operation. These trials have uncovered several challenges with implementation, including understanding and managing the interaction with the public. The shuttles are to a large extent a foreign element in an otherwise well-established mobility infrastructure. Furthermore, studies from these pilots have revealed challenges with trust in the systems, particularly regarding decline in trust over time (Aasvik, 2023). Exposure to the technology does not necessarily increase the trust in the systems, contrary to other findings (Choi & Ji, 2015). Limitations and less than ideal implementation may help explain this effect, however, which is consistent with theory of trust in automation (Hoff & Bashir, 2015). Indeed, launching pilots that are not functioning well may damage the public's attitude and trust towards self-driving in general (Pigeon et al., 2021). The ambiguity and uncertainty in relation to research on trust in autonomous vehicles further emphasizes why this deserves attention and clarification.

Trust in automation is heavily dependent on context, both regarding the trustor (J. D. Lee & See, 2004) and the cultural environment (Hoff & Bashir, 2015), and it is important to understand the circumstances in which this study is conducted. Norway is relatively reliant on car usage due to low population density, with a large variation between rural and city environments. Excluding city centers in big cities, most people have access to and use cars as their main means of transportation (Nordbakke & Nilsen, 2021). Norway is also far ahead in shifting its' fleet of cars into electric vehicles, with a 16% share of fully electric vehicles as of 2021, and a further increase to 20% at the end of 2022 (Tjernshaugen & Halleraker, 2023). With electrification and renewal of the car-fleet, newer technologies are more accessible and more common, which may affect the viewpoints on autonomous vehicles and novel transport technologies since people are more knowledgeable and familiar with newer technologies. Most people prefer to travel using personal cars (SSB, 2022). Making public transport the most viable option for more of the population would therefore have a large positive impact on reducing personal car usage. In The Oslo Study (Ruter, 2019) it was simulated how the transport demands of the future may be shaped by the introduction of automated vehicles. An essential prerequisite for a successful implementation highlighted in the study is avoiding the use of personal autonomous vehicles in favor of public transport implementation. The worst-case scenario may lead to a traffic overload with a complete breakdown of infrastructure.

The focus of the current study is hence *Shared Autonomous Shuttles (SASs).* Defined as automated smaller vehicles more resembling minibuses than traditional on-route buses. These are likely the first encounter many in Norway and other countries will have with autonomous public transport. Altogether, the presented theoretical background is what leads to the following hypotheses for this study.

The Current Study

The current study seeks to investigate (1) to what degree trust impacts intention to use shared autonomous shuttles and (2) whether static and dynamic norms can be applied to impact degree of trust in shared autonomous shuttles. To examine this, I will use an experimental-design survey, with one control-group and two intervention groups. I postulate nine hypotheses:

H1: Static norm intervention increases subjective trust in SASs compared to control. First, it is postulated that influence from static, social norms that indicate a viewpoint or normative behavior, will increase the subjective trust in shared autonomous shuttles (SASs). The goal is to explore if being presented with a normative statement is enough to affect a person's subjective trust in a novel technology. It is worth noting that this does not affect *subjective norm* directly, but rather inflicting a *social normative influence.* The former is referring to the latent variable present in for example The Theory of Planned Behavior (Ajzen, 1985), while the latter is referring to the social process. I expect a small to moderate effect of the intervention.

H2: Dynamic norm intervention has a larger impact on subjective trust in SASs than static norm intervention. Perceiving that a social norm is in the process of changing should increase the effect of the intervention. Promoting a pre-conformity with a dynamically framed social norm should increase trust further, compared to a static-framed social norm. A small to moderate effect is expected here as well.

H3: Higher propensity to interpersonal trust will increase effect of intervention as a moderator effect. The propensity to trust is established as a baseline for the tendency to trust others. While trusting individuals and automation are expected to be different constructs, I hypothesize that individuals with a higher propensity to trust others should be more affected by the social-norm prompt, given a higher trusting tendency.

H4: Higher propensity to trust automation will increase effect of intervention as a moderator effect. As with interpersonal trust, the propensity to trust automation should moderate how individuals are affected by normative statements, especially in novel situations. The effect of moderation is expected to be small.

H5: Propensity to trust automation has a positive direct effect on subjective trust in SASs. In addition to moderating the effect of the intervention, I predict that individuals that score high on propensity to trust automation should also have an increased subjective trust in SASs.

H6: Propensity to interpersonal trust has a positive direct effect on subjective trust in SASs. Similarly to H3, the propensity to trust is hypothesized to overflow to other domains, in this case automation, with people that are high in propensity to trust others also trusting automation more.

H7: Safety evaluation is positively correlated with subjective trust. As contextual considerations are paramount, I postulate that safety is a central element in trust formation of autonomous vehicles and should be accounted for when exploring trust formation. Other empirical evidence has found that safety evaluation of these kinds of services have a large impact on trust, and as to isolate the effect of social norms should be taken into consideration (Nordhoff et al., 2019). Safety evaluation of shared autonomous shuttles is expected to correlate strongly with subjective trust in SASs.

H8: Subjective trust in SASs positively predicts intention to use SASs. To see if there is a possibility that subjective trust in shared autonomous vehicles predicts real-world behavior, trust should predict intention to use shared autonomous shuttles. Again, this follows the principles of theoretical and empirically supported assumption that intention is a meaningful predictor of behavior (Ajzen, 1985).

H9: Propensity to interpersonal trust and propensity to trust automation are positively correlated. I postulate that the two types of propensity are different but related constructs and should therefore correlate to some degree.

Since propensity is believed to be especially important in novel situations, and in early interactions, it is a focal point in the study. It may perhaps therefore also moderate the effect of social normative influence. If you have a higher propensity, you should more easily trust "others", hence be more easily affected by their testimony.

Method

Recruitment

Recruitment was conducted through three main channels: social media, posters, and a mailing list with potential respondents from a previous study. Social media yielded 159 respondents, email 835 and posters 38, for a total of 1032 responses. Most respondents from social media were recruited through student-groups and peers including word-of-mouth. The respondents were not directly compensated for participation, however, all participants could choose to enter a raffle for three gift cards, should they wish to. This was communicated through all recruitment channels as an incentive to take part in the study. Email recruitment was conducted in two waves, yielding a response rate of 60.5% and 53.6% respectively. A total of 1460 emails were sent. Social media recruitment was conducted via posts in Facebook-groups as well as LinkedIn. Posters were displayed at different locations, including on a university campus. Recruitment started on the 9. of November and concluded the 14. of December 2022.

Procedure

When partaking in the survey, the participants reported on the following measures in their respective order:

First, they recorded three sociodemographic variables: (1) age (2) gender and (3) education. Then, three independent measures were presented: (1) propensity to trust others (2) technical competence and (3) propensity to trust automation. After this, the participant was randomly assigned one of three experimental conditions: (1) control group (2) static norm group, or (3) dynamic norm group. The participants in the intervention groups also received a rumination task right after, as well as a reminder of the presented vignette. Then, two dependent variables followed: (1) subjective trust in shared autonomous shuttles and (2) intention to use shared autonomous shuttles, further followed by a safety evaluation of shared autonomous shuttles and a short-hand version of the MAVA-scale, then lastly a measure of exposure to pilot projects that are testing SASs.

Measures

Gender, Age, and Education

Three demographic variables were collected. Gender had four alternatives: "Female", "Male", "Other", and "Do not wish to answer". Age was collected in intervals to ensure anonymity. There were seven categories, with the first being "18-29" and the last being "80+", and the remaining were intervals of ten years. Education was also collected as a categorical variable, asking the participant to note their highest completed educational level. The options were "elementary", "high-school", "1-3 years university or higher education", and "over 3 years of university or higher education".

Propensity to Trust

There are many scales and measures that aim to capture propensity to interpersonal trust (Frazier et al., 2013; M. K. O. Lee & Turban, 2001; Rotter, 1967). The scale used in the current study to measure propensity to trust consists of five items adapted from Frazier et al. (2013), measured on a seven-point Likert scale where one and seven are denoted by strongly disagree and strongly agree respectively. The scale of Frazier et al. (2013) has been validated through a series of four studies, where the items with the highest loading are retained and used in the current study as a short form measure of propensity to trust (e.g., "I usually trust people until they give me a reason not to trust them" and "Trusting another person is not difficult for me."; $\alpha = 0.84$). As an established measure, propensity to trust should yield a high reliability. A Cronbach's alpha value of .84 is therefore somewhat weaker than what is expected given the scale used and its framework. However, it is an acceptable value. All items selected for the current study had a loading of .74 or higher in the study by Frazier et al. (2013). Additionally, a fifth reversed item was added ("I have little trust in other people's promises.") to decrease the likelihood of pattern responses and further strengthen the measure. Additionally, the items used were sourced from validated previous work by Lee and Turban (2001) and McKnight et al. (2002). Overall, the five items used should provide a good measure of people's tendency to trust others.

Propensity to Trust Automation

There is scarcity in the literature regarding scales that measure the propensity to trust automation (Jessup et al., 2019), especially in comparison to propensity to trust other individuals. Some argue that even if propensity to trust automation is high, contextual elements may lead to vastly different evaluations of different systems, or that the systems in question introduce noise in the evaluation (Lewis et al., 2018). More accurate psychometrics is therefore in demand. The propensity to trust automation scale used in this study was developed by drawing from the shortened propensity to trust scale (Frazier et al., 2013) and converting them to relate to automation. The items follow the same structure but are adjusted to target trusting behavior tendencies towards automated systems and are as such context specific in this regard. The scale had a seven-point Likert scale where one and seven are denoted by strongly disagree and strongly agree respectively. The respondents were instructed to answer with general automation-systems in mind, like computers or elevators (e.g., "I usually trust automatic systems until they fail" and "It is not hard for me to trust automatic systems"; $\alpha = 0.90$). This was to avoid priming of very advanced technology, since the goal was to measure propensity in relation to more "everyday" automation. However, this might also introduce some priming as to what kinds of automation they evaluate. Avoiding the problems of contextual differences is difficult, but aligning the items with the propensity to interpersonal trust may yield a more proper general tendency measure. Still, this scale needs further testing. Because propensity to trust automation is a less tested scale, it was expected to yield a somewhat lower internal consistency. However, the scale had an Cronbach's alpha value of 0.90, indicating a solid scale, with few redundant items (Tavakol & Dennick, 2011).

Technical Competence

Technical competence, also called tech-savviness, is a measure which aims to capture the respondent's subjective ability to handle, and their interest in, technology in general. The measure is included as a control variable when assessing trust. In this study, three items were developed to assess the construct ("I am among the first to hear about new technology", "Friends and family come to me for help with technology", and "I am above average interested in technology"; α = 0.89). These items function as an aggregate to how technology-savant the individual sees themselves and how comfortable they are with interacting with technology. The scale had a seven-point Likert scale where one and seven are denoted by strongly disagree and strongly agree respectively. Regarding consistency, the scale was just short of the .90 mark but is however a shorter scale which might not completely capture all aspects of the latent variable, hence making .89 acceptable.

Safety Evaluation of SASs

Safety Evaluation included five items which aimed to measure the subjective degree of how safe a shared autonomous shuttle would be in use, both from a personal perspective (e.g., "A bus like this would be safe to use") and a societal perspective (e.g., "A bus like this would increase traffic safety"; α = 0.95). The scale is developed for this survey, with inspiration from Nordhoff et al. (2019) using a seven-point Likert scale where one and seven are denoted by totally disagree and completely agree respectively. The variable is designed to be a controlling variable, as safety is assumed to be of importance in trust evaluation of shared autonomous shuttles. The scale had a Cronbach's alpha score of .95 which may entail that some items are redundant (Tavakol & Dennick, 2011). The measure may be concrete enough to not demand a five item scale.

Multi-Level Model on Automated Vehicle Acceptance (MAVA)

A short-form scale containing seven items representing the domain-specific system evaluations in the Multi-Level Model on Automated Vehicle Acceptance was included. It aims to measure the most central parts of the model, such as safety, performance expectancy and effort expectancy (e.g.," I think it would be easy for me to use this bus service", "I think this type of bus will be useful for me", and "I think others would find it good that I use a bus like this"; $\alpha = 0.88$). Because the scale contains several sub-constructs, it was somewhat surprising that it had a Cronbach's alpha of .88. The items are arranged on a seven-point Likert scale where one and seven are denoted by totally disagree and completely agree respectively. The items are derived from Nordhoff et al (2019) and Aasvik et al (2023).

Subjective Trust in Shared Autonomous Shuttles

The first dependent variable was comprised of three items, specifically aimed at assessing the extent to which respondents would have trust in shared autonomous shuttles. The items were measured on a seven-point Likert scale where one and seven are denoted by totally disagree and completely agree respectively. The scale was developed for this survey, with inspiration from Choi and Ji (2015): "Self-driving buses are reliable", "Self-driving buses will mostly do what is expected" and "All in all, I can trust self-driving buses"; $\alpha = 0.95$. It represents the willingness to trust and be vulnerable, and not the actual trust-behavior, hence a proxy for probable behavior. The argument can be made that this is a form of institutional-based trust, more specifically a form of structural insurance (Harrison McKnight & Chervany, 2001), since it represents an expectation that the government and service operator have conducted the necessary testing. Still, the variable should capture the essence of trusting the technology in this context. The scale had a somewhat high Cronbach's alpha score, possibly indicating some redundancy.

Intention to Use Shared Autonomous Shuttles

The second dependent variable was also comprised of three items. This measure was developed for this scale, with the belief that intention is a viable predictor of behavior (Ajzen, 1985). It represents the trust-behavior as best as can be done without observing real-world behavior. This is in line with Theory of Planned behavior, Reasoned action, and intention as a predictor of behavior (Fishbein, 2011). The reason for including a three-item measure is to fully capture intention to use SASs given that this offer is not available yet. For example, the intention may be masked by the respondent's belief that this offer would not be applicable in their context or local area, and hence not measure their intention free of contextual boundaries. The items were measured on a seven-point Likert scale where one and seven is denoted by totally disagree and completely agree respectively: "I would be comfortable riding a bus like this", "If I had the opportunity, I would be fine with riding on a bus like this", and "I would avoid driving with a bus like this, even if it was the fastest and cheapest alternative (Reversed)"; $\alpha = 0.93$.

Lastly, seven-point scales were used for all the measures as they are better for detecting moderation effects as suggested by Memon et al. (2019). Additionally, it increases the accuracy of the measures, and allows for more nuanced responses than five-point scales. Regarding inter-item reliability, all seven measures had an adequate Cronbach's alpha score overall.

Manipulation

After the independent measures, each respondent was randomly assigned to one of three conditions: Control, Static Norm, or Dynamic Norm. All groups were shown an informative vignette (Here translated from Norwegian):

> *A bus-service is now being developed in Norway, which will consist of small, self-driving busses. The busses drive on normal roads and in normal traffic but will not need a driver. Pilots (tests) with a service like this are now being tested.* (See full survey in appendix A)

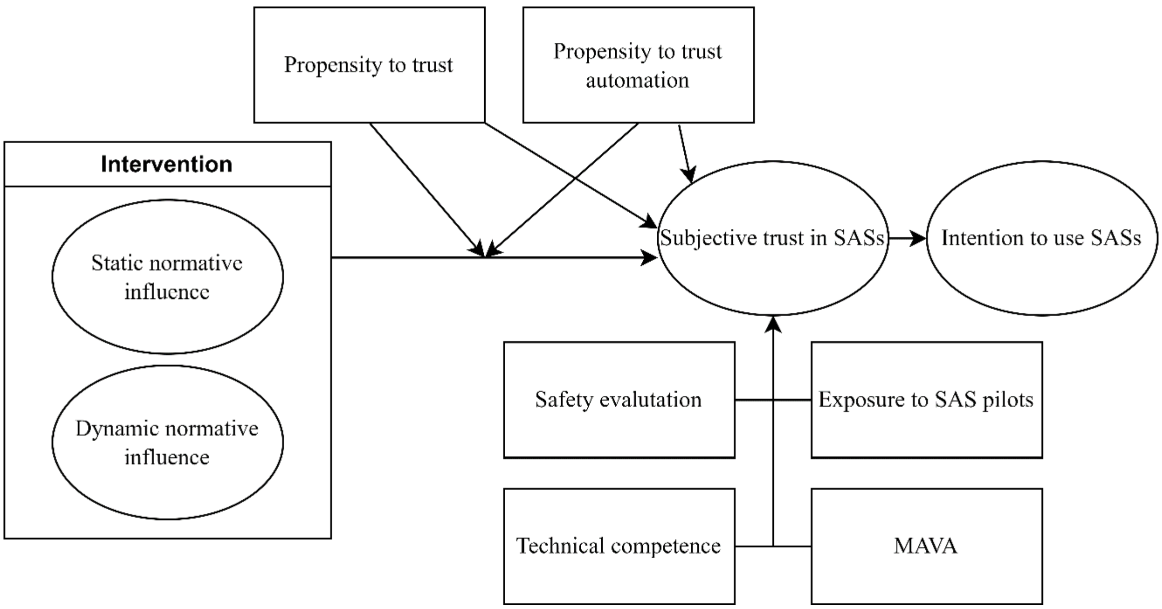
In addition, the control group was shown a neutral text (In the same vignette): "The tests have been done in relevant areas with moderately dense populations. Most of the buses are red." The static norm group was presented with the information, and additionally: "Recent studies by the Institute of Transport Economics show that more than 7 out of 10 Norwegians trust that self-driving buses work as they should." Finally, the dynamic group was presented with the above information, as well as:

> *More people are positive towards a service like this, and recent studies by the Institute of Transport Economics show that more than 7 out of 10 Norwegians trust that self-driving buses work as they should. People are changing their opinion about a self-driving public transport offer.*

After one of three vignettes, the respondent was given a rumination prompt, asking what they thought about the amount of people trusting a bus service like this. This was to foster reflection of the normative statement and to make the respondent interact actively with the information. The control group did not receive any rumination prompt. Before continuing to the dependent measures, the participants were shown a reminder vignette, identical to the one they were presented, which they could navigate back to if they wanted. Figure 2 presents an overview of the relationships between the intervention, control variables, and the dependent variable.

Figure 2

Overview of Intervention and Variables



The intervention is hypothesized to affect subjective trust in shared autonomous shuttles, whilst the two types of propensity moderate the effect. The other variables act as controls. Subjective trust in SASs is hypothesized to predict intention to use SASs.

Manipulation Checks and Exposure to Shared Autonomous Shuttles

All groups were displayed one of two manipulation checks which had the goal of establishing whether the respondent had properly read and contemplated the vignette. The intervention groups were asked "How many Norwegians trust that self-driving busses work as they should?", with the alternatives being over 3 out of 10, over 5 out of 10 or over 7 out of 10. The control group were presented with the following question: "What color does most of the busses in the testing of self-driving busses in Norway have?", with the alternatives red, green, or yellow.

Lastly, the respondents were asked to estimate their exposure to self-driving busses in Norway: "Did you know of trials with self-driving buses in Norway before you participated in this survey?". The scale was on a seven-point Likert, with "1" representing "None", "2" representing "A little", and then a gradually increase until "7", which represented "A lot".

Pre-Registration and Power Analysis

The study was pre-registered using asPredicted.org on the eighth of November 2022 to promote transparency and minimize potential biases in the research process. The pre-registration contains the hypotheses of the study, key dependent variables and their measures, procedure of the experiment, analyses, and outlier-handling. The full pre-registration can be found in appendix B. There were some minor divergencies that should be noted.

First, the hypotheses regarding propensity to trust automation (H4, H5 and H9) was initially referred to as "propensity to trust technology". This was changed to "propensity to trust automation" for clarity, as this is more accurately describing what is being examined. Second, ANCOVA was determined as the analysis to use for examining multivariate relationships and intervention groups. Regression was applied instead, as it is functionally similar, but provided an easier comparison between models. Additionally, the full script and anonymous dataset used can be found in Open Science Framework (https://osf.io/e279h/?view_only=03c6413ac7414b718264af986799d49f).

To determine the necessary sample size for the moderation analysis, an a-priori power analysis was conducted using G*Power (Faul et al., 2009). The analysis was based on a small effect size ($f^2 = 0.02$), a significance level of 0.05, and a desired power of 0.80. The power analysis indicated that a minimum sample size of 395 was required to adequately detect the expected effect. To address the potential impact of dropouts and nonresponse to questions, the aim was to recruit a sample of 600 respondents (see appendix C for plot).

Lastly, the study in its entirety was evaluated and approved by NSD - Norwegian Centre for Research Data, as well as the Department of Psychology's internal research ethics committee (see appendix D).

Analyses

First, I examined the characteristics of demographic variables in order to understand the sample's composition. To determine if there were any significant differences between these demographic variables, I employed a chi-square analysis. Next, reliability of the scales used in the study were assessed by analyzing their internal consistency, and subsequently, the descriptive statistics of these scales, to grasp the central tendencies and dispersions of the measures.

To investigate the relationships between the measures, I conducted a correlation analysis. Both a parametric and a non-parametric ANOVA were performed to examine the effect of the intervention on subjective trust in shared autonomous shuttles.

To further analyze the data, I utilized multiple regression to examine the model with hypothesized covariates, which provided insight into the predictive relationships between the independent and dependent variables. Finally, to assess potential moderation effects, I conducted a moderation analysis using regression to identify any significant interaction effects between the predictor variables and the two hypothesized moderators: propensity to trust and propensity to trust automation. Lastly, an explorative analysis was conducted, investigating the effects of the intervention on MAVA, safety evaluation, and intention to use SASs scores.

Response Rate and Filtering

A total number of 1032 responses were collected, and 958 completed the survey. Removing all responses which had a response time of less than three minutes, in accordance with the pre-registration, left 920 total responses. When controlling for failed answers to the manipulation checks, 630 valid responses remained and were retained for further analysis, well within the required 395 assessed with the a priori power analysis. After filtering, the control group had 230 participants, the static norm group 198, and the dynamic norm group 202.

Results

The analyses are presented following the order of the hypotheses, with some exploratory analyses at the end.

Sociodemographic Descriptive Statistics

This section presents the sample’s characteristics. I investigate whether the sample shows any patterns across treatment groups in sociodemographic statistics. Table 1 lists descriptives for gender, age, and educational levels.

Table 1

Sociodemographic Characteristics of Participants for Each Intervention Group from Retained Responses (N = 630)

	Control Group (N= 230)		Static Norm (N=198)		Dynamic Norm (N=202)		Full sample (N=630)	
Variable	*n*	%	*n*	%	*n*	%	*n*	%
Gender								
Female	110	47.8	81	40.9	82	40.6	273	43.3
Male	116	50.4	117	59.1	120	59.4	353	56.0
NA	3	1.3	0	0.0	0	0.0	2	0.3
Other	1	0.4	0	0.0	0	0.0	1	0.2
Age								
18-29	29	12.6	26	13.1	24	11.9	79	12.5
30-39	20	8.7	24	12.1	18	8.9	62	9.8
40-49	32	13.9	31	15.7	28	13.9	91	14.4
50-59	54	23.5	38	19.2	46	22.8	138	21.9
60-69	61	26.5	38	19.2	52	25.7	151	24.0
70-79	28	12.2	34	17.2	33	16.3	95	15.1
80+	6	2.6	7	3.5	1	0.5	14	2.2
Educational level								
Elementary	6	2.6	1	0.5	4	2.0	11	1.7
High school	43	18.7	27	13.6	23	11.4	93	14.8
1-3 years higher education	60	26.1	54	27.3	54	26.7	168	26.7
Over 3 years higher education	121	52.6	115	58.1	120	59.4	356	57.0
NA	0	0.0	1	0.5	1	0.5	2	0.3

Gender was fairly evenly distributed, with 43 percent female and 56 percent male respondents.

Inspecting the distribution, age was a bit skewed to the left, with a dip in responses between the age of 30 and 39. Education distribution was even more skewed to the left, with 57 percent of respondents reporting 3 or more years of higher education. 26.7 percent had 1-3 years of higher education. There was also a skew in age dependent on which recruitment channel the participant was from. Most were in the lower to medium ranges in the social media channels, which were primarily comprised of students, the same being true for the participants recruited through posters. The email respondents were more evenly distributed but skewed towards older age, with most respondents being in the 60-69 age group. Education was similar across channels; however, the total was very skewed towards higher education. Only 22 respondents reported "elementary school" as their highest completed education, and 170, 281, and 543 for "High-School", "1-3 years higher education" and "Over three years higher education" respectively.

Differences in demographic distributions across the groups were investigated using Chi-Square tests, including age given that age was collected as intervals. The results showed that there were no significant differences among the three groups, suggesting that the randomization process was successful.

Scale Analysis: Distribution and Normality Insights

I investigated descriptive statistics for all measures, including Cronbach's alpha, means, standard deviations, skewness, kurtosis, and the Shapiro-Wilk test to explore normality. An overview can be found in table 2.

Table 2

Descriptive Statistics for Independent, Dependent, and Control Variables. (N = 630)

	Propensity to trust	Propensity to trust automation	Technical Competence	Safety evaluation of SASs	MAVA	Subjective Trust in SASs	Intention to use SASs
N	630	630	630	623	623	630	630
Missing [a]	0	0	0	7	7	0	0
Mean	5.23	5.18	4.06	4.54	4.15	4.59	4.99
Median	5.20	5.20	4.00	4.80	4.14	5.00	5.33
Standard deviation	0.994	1.07	1.57	1.44	1.28	1.37	1.57
Cronbach's alpha	0.84	0.90	0.89	0.95	0.88	0.95	0.93
Minimum	1.20	1.00	1.00	1.00	1.00	1.00	1.00
Maximum	7.00	7.00	7.00	7.00	7.00	7.00	7.00
Skewness	-0.588	-0.657	-0.0569	-0.526	-0.288	-0.510	-0.753
Kurtosis	0.606	0.615	-0.897	-0.362	-0.293	-0.160	-0.168
Shapiro-Wilk W	0.973	0.967	0.974	0.965	0.987	0.964	0.928
Shapiro-Wilk p	< .001	< .001	< .001	< .001	< .001	< .001	< .001

Note. [a] Safety evaluation and the MAVA scale did not require an answer to proceed in the survey, which lead to some missing data. All scales had a range of 1-7.

The average scores for all the scales leaned towards the higher end, with participants exhibiting a strong inclination to trust. Propensity to trust not only had the highest average but also the smallest variation, suggesting that most participants consistently scored homogenous in this aspect. On the other hand, tech competence displayed the lowest average and a considerable variation in scores. The two dependent variables, subjective trust and intention to use shared autonomous shuttles, showed similar averages and variations in scores, with subjective trust being slightly lower than intention to use. It should also be noted that overall, people were positive to use a service like this as implied by the score of intention to use SASs.

Propensity to trust, propensity to trust automation, subjective trust in SASs, intention to use SASs, and safety evaluation all exhibited a slight leftward skew. However, the skewness value for each scale remained within the conventional range deemed unproblematic, as per Field (2013). Among these, Intention to use SASs had the highest skewness value, slightly below -0.753. Both measures of propensity displayed a positive kurtosis just above 0.6, indicating a heavier-tailed distribution. Importantly, all the scales had values between -1 and 1, which are conventionally considered acceptable (Field, 2013).

Lastly, each scale was tested with the Shapiro-Wilk test to investigate if the sample follows a normal distribution. All tests were significant. However, this test is sensitive to larger sample sizes and tend to easily become significant with sample sizes above 50, and given that the sample is well above that, it is more informative to look at the distribution visually than put too much emphasis on the significance of non-normality (Field, 2013). Inspecting the quantile-quantile plots of the variables reveals that both measures of propensity have values below the normal distribution in both lower and higher end of the scale. This suggests that the main deviation from a normal distribution is due to kurtosis. The rest of the scales all show a tendency to an "S-shaped" distribution, pointing towards a higher skewness (Field, 2013). All Q-Q plots and histograms and distributions of the scales can be found in appendix E.

Assessing the Effect of Social Norm Intervention

One-way ANOVA was applied to test the effect of the manipulation predicting subjective trust in shared autonomous shuttles, testing hypothesis one and two. Both a parametric and non-parametric test is used.

Levene's test was not significant ($p = .188$) which entails that the items’ variances across groups are equal. ANOVA is robust against non-normality (Schmider et al., 2010). Still, to avoid the possibility of obscuring significance due to non-normality, a Kruskal-Wallis test was employed as an additional test, as it does not necessitate the assumption of normality (McKight & Najab, 2010).

Analysis

The parametric one-way ANOVA was significant, signaling a difference in the means of subjective trust in SASs dependent on which group the participant belonged to. The results revealed a significant effect of the intervention group on subjective trust in SASs (F (*df* = 2, 627) = 10.4, $p < .001$). Tukey's post-hoc test was used to compare the mean differences between the groups, as presented in figure 3 and table 3.

Figure 3

Descriptive Plot of Means for Subjective Trust in Shared Autonomous Vehicles for Each Group With 95% Confidence Intervals

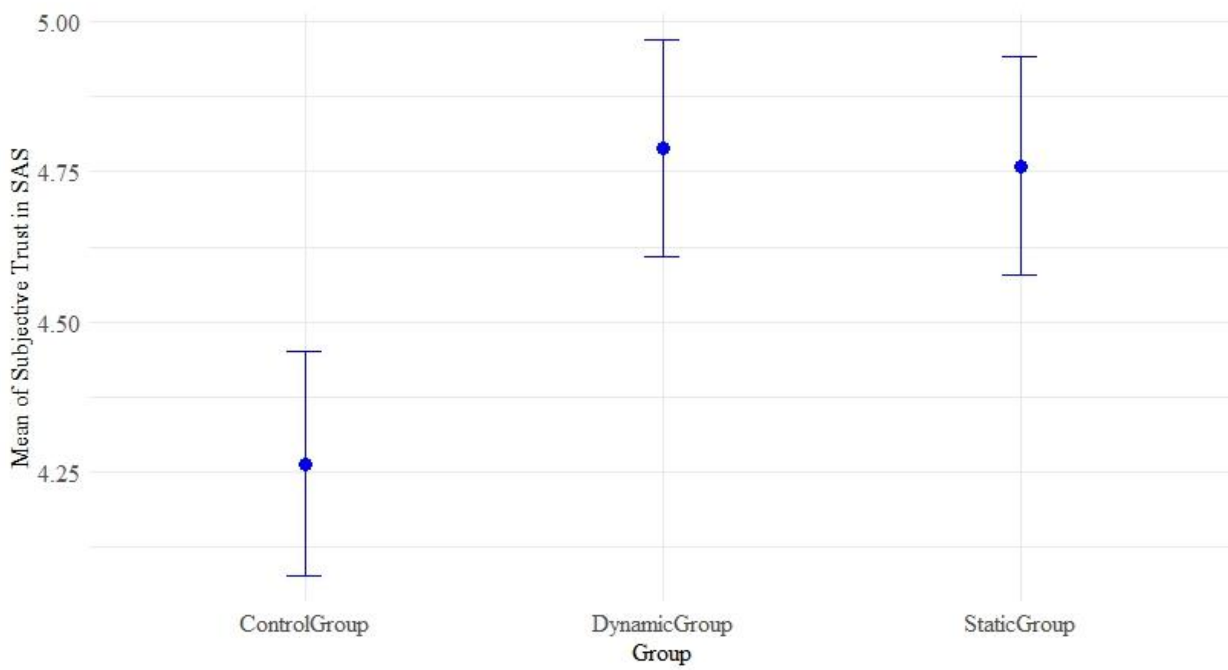


Table 3

Multiple Comparisons of Mean Scores on Subjective Trust in SASs for the three Conditions (Tukey's HSD Test)

				Pairwise comparisons		
	N	Mean	*SD*	1 vs. 2	1 vs. 3	2 vs. 3
1. Control Group	230	4.26	1.43	-0.53**	-0.50**	0.03
2. Dynamic Group	202	4.79	1.30			
3. Static Group	198	4.76	1.30			

** *p* <.001

The post-hoc test shows a systematically lower mean for the control group compared to the intervention groups of half a point. The higher level of trust in the static group supports hypothesis one, whilst the lack of significant difference between the intervention groups means that hypothesis two is not supported.

For the non-parametric test, the Kruskal Wallis test was applied. It also proved significant differences between the means. The results showed a significant effect of the intervention group on subjective trust in SASs, $\chi^2 = 18.7$, $p < .001$, with an effect size of $\varepsilon^2 = 0.0297$. Dwass-Steel-Critchlow-Fligner pairwise comparisons of means were used to investigate the relationships between the groups. The difference in means for the control group and static group was significant ($W = 5.05$, $p < 0.001$), the same was true for the control and dynamic group ($W = 5.41$, $p < 0.001$) and the difference between static and dynamic groups were non-significant ($W = -0.26$, $p = 0.98$). Notably, the dynamic and static group means were very similar, while both had a significant difference from the control group.

Overall, the results suggest that the intervention had an effect, as indicated by the significant chi-squared value and p-value. However, the effect size is small ($\varepsilon^2 = 0.03$), suggesting that other factors are likely to be important in determining subjective trust in shared autonomous shuttles.

Correlations Between the Study Variables

To examine the relationships between the independent, dependent, and control variables, as well as investigate hypothesis seven, eight, and nine, Pearson's correlation coefficients were calculated. These are displayed in Table 4.

Table 4

Correlations for Independent, Dependent, and Control Variables

Variable	1	2	3	4	5	6
1. Propensity to trust						
2. Technical competence	-.01					
3. Prop. to trust automation	.29***	.29***				
4. Subjective trust in SASs	.26***	.25***	.51***			
5. Intention to use SASs	.22***	.30***	.47***	.82***		
6. Safety evaluation	.26***	.26***	.48***	.88***	.87***	

7. MAVA	.26***	.34***	.42***	.75***	.81***	.82***

Note. *** indicates p < .001.

Propensity to trust was significantly correlated with all other scales except technical competence, with small correlations. This included propensity to trust automation, supporting hypothesis nine. Technical competence had a moderate positive correlation with intention to use shared autonomous shuttles, and the MAVA-scale according to conventional interpretations (Cohen, 1988). Additionally, small positive correlations with propensity to trust automation, subjective trust in shared autonomous shuttles, and safety evaluation were found. Propensity to trust automation had a notably high correlation with subjective trust in shared shuttles, and moderate to high correlations with intention to use SASs, safety evaluation, and the MAVA-scale. Subjective trust in SASs had large correlations with intention to use SASs, safety evaluation, and the MAVA-scale in addition to propensity to trust automation. This indicates a strong relationship between subjective trust in, and intention to use shared autonomous shuttles, supporting hypothesis eight. Safety evaluation had notably high correlations with subjective trust in SASs and intention to use SASs, supporting hypothesis seven. The full table with confidence intervals can be found in appendix F.

Multivariate Regression Analysis of Intervention Effects: Controlling for Other Factors

To further examine hypothesis one and two, multiple regression was used to test the effect of the intervention when controlling for safety evaluation, exposure, MAVA, and technological competence. Two models are presented: Both keeping intervention group as a fixed factor with subjective trust in SASs as the predicted variable. Model 1 includes all the hypothesized covariates, while model 2 presents a more parsimonious model, given high correlations between safety evaluation, MAVA, and the subjective trust in shared autonomous shuttles.

Assumptions of multivariate regression were assessed to ensure the robustness of the analysis. First, the variable inflation factor (VIF) and tolerance levels were investigated. All variables have a VIF well below any level of concern (Myers, 2000) with all values ranging from 1.01 to 1.82. Tolerance levels ranged from 0.55 to 0.99. Levels above 0.1 are considered to not be problematic (Field, 2013). Therefore, multicollinearity does not seem to be present in the current model.

Normality was assessed by inspecting the quantiles-quantiles plot of the model. There seems to be signs of heavy tails in several variables (see plots in appendix E and G), and light tails in others. This is expected, as most of the variables are somewhat skewed to the left, and some exhibit more peaked values. Subjective trust in SASs in model 2 was especially left-skewed. However, combined with the earlier investigation of kurtosis and skewness, I choose not to apply any transformation of the data.

Furthermore, two points stand out as particularly extreme when inspecting the residual plots. These two observations were identified, and it seems that both of them score low on safety evaluation while high on both subjective trust in SASs and intention to use SASs, which may explain the extreme residual values. Cook's distance was calculated (Mean = 0.002, max = 0.047), and using a threshold of 1 (Field, 2013), no substantial influence from any extreme values was indicated. Excluding the two divergent observations from the analysis would be unfortunate, given that they do not qualify as outliers outright. The complete analysis was run without the two points to investigate if they had a major impact. The residual plots did naturally become better clustered, but elsewise the results did not differ that much when the points were excluded, and I chose to include these observations in further analysis.

Multiple Regression Analysis – Model 1

The result of the analysis is presented in table 5.

Table 5

Regression Results Using Subjective Trust in SASs as the Dependent Variable (Model 1, N = 630)

Predictor	*b*	*SE*	*t*	*β*	*p*
Intercept	0.66	0.11	6.35		< .001***
Group (Control = 0)					
Dynamic	0.17	0.06	2.68	0.12	0.008**
Static	0.16	0.06	2.54	0.12	0.011*
Safety evaluation	0.78	0.03	25.11	0.82	< .001***
Exposure	-0.03	0.01	-1.80	-0.03	0.072
MAVA	0.08	0.04	2.13	0.07	0.034*
Technical Competence	0.01	0.02	0.82	0.02	0.414
R^2	0.795				
Adjusted R^2	0.793				

Note. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$

The analysis predicting subjective trust in SASs revealed significant effects of both interventions, safety evaluation, and MAVA, while controlling for other variables. Safety evaluation had the decidedly largest impact, with an estimate of 0.78 and a standardized estimate of 0.82. Comparatively, the effect of the intervention was markedly lower than in the ANOVA tests, but still significant when controlling for the other factors. The effects of the treatments were still very similar, with an identical standardized estimate. MAVA was significant, but not by a large margin. The standardized estimates were also relatively low, even lower than the intervention effects. The multivariate model explained a total of 79.3% of the variance in subjective trust in SASs.

Multiple Regression Analysis – Model 2

Because the MAVA-scale and safety evaluation correlated highly with subjective trust in SASs and each other, there is reason to believe they explain a fair share of the same variance. Hence, a model without these two is calculated and presented in table 6.

Table 6

Regression Results Using Subjective Trust in SASs as the Dependent Variable (Model 2, N = 630)

Predictor	*b*	*SE*	*t*	*β*	*p*
Intercept	3.39	0.18	19.08		< .001***
Group (Control = 0)					
Dynamic	0.45	0.13	3.49	0.33	< .001***
Static	0.41	0.13	3.18	0.30	0.002**
Exposure	0.04	0.03	1.22	0.05	0.222
Technical Competence	0.19	0.03	5.70	0.22	< .001***
R^2	0.087				
Adjusted R^2	0.081				

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Model 2, all predictors are significant except for exposure to shared autonomous shuttle pilots. The interventions have the largest standardized estimates, indicating that they account for most of the variance in subjective trust in SASs. Additionally, technical competence has become significant: the more technically competent a person sees themselves to be, the higher the reported trust. While the effect of the intervention is even more evident in this analysis, Model 2 only explains 8.7% of the variance in subjective trust in SASs. This represents a substantial reduction compared to Model 1.

Examining Moderation Effects of Propensity

To investigate hypotheses three, four, five and six, I performed regression analyses that included interaction terms in order to test possible moderation effects. Hypothesis three and six, postulating a moderating effect and a direct effect of propensity to trust on subjective trust in SASs is tested in the first model. The second model tests hypothesis four and five, postulating the same relationships for propensity to trust automation.

Analysis of Propensity to Trust - Model 1

Table 7 presents the results of a regression analysis testing whether propensity to trust moderated the effect of the interventions on subjective trust in SASs. The table is divided into two parts: the top part shows the main effects, while the bottom part presents the interaction effects.

Table 7

Moderation Analysis of the Effect of Propensity to Trust on the Relationship Between the Interventions and Subjective Trust in SASs (N = 630)

Variable	*b*	*SE*	*t* value	*p*
Intercept	2.56	0.29	8.91	< .001***
Group (Control = 0)				
Dynamic	0.47	0.13	3.69	< .001***
Static	0.50	0.13	3.96	< .001***
Propensity to trust	0.33	0.05	6.24	< .001***
R^2	0.089			
Adjusted R^2	0.087			
Variable				
Intercept	2.52	0.44	5.72	< .001***
Group (Control = 0)				
Dynamic	0.42	0.71	0.60	0.552
Static	0.66	0.65	1.00	0.316
Propensity to trust	0.34	0.08	4.10	< .001***
Dynamic × Prop. to trust	0.008	0.13	0.06	0.950
Static × Prop. to trust	-0.03	0.12	-0.24	0.812
R^2	0.089			
Adjusted R^2	0.081			

The main effects were all significant, signaling a direct effect of propensity to trust on subjective trust in SASs. Hence, hypothesis six was supported. Both interaction terms had small and non-significant impacts on subjective trust, thus indicating no support for a moderation effect of propensity to trust (hypothesis three). The overall model without the interaction term had an R^2 of 0.087, explaining 8.7% of variance. Adding the interaction terms did not result in any increase in R^2.

Analysis of Propensity to Trust Automation - model 2

Table 8 presents the results of the second regression analysis examining the moderation effects of propensity to trust automation on subjective trust in SASs based on intervention group. Like model 1, the top part of the table presents the main effects, whilst the latter the interaction terms.

Table 8

Moderation Estimates of Propensity to Trust Automation Predicting Subjective Trust in SASs Based on Intervention Group (Model 2, N = 630)

Variable	*b*	*SE*	*t* value	*p*
Intercept	0.84	0.23	3.66	< .001***
Group (Control = 0)				
Dynamic	0.41	0.11	3.70	< .001***
Static	0.38	0.11	3.46	< .001***
Propensity to trust automation	0.67	0.04	15.70	< .001***
R^2	0.306			
Adjusted R^2	0.302			
Variable				
Intercept	0.84	0.39	2.16	0.031*
Group (Control = 0)				
Dynamic	0.72	0.56	1.29	0.196
Static	0.11	0.55	0.20	0.842
Propensity to trust automation	0.68	0.08	9.03	< .001***
Dynamic × Prop. to trust auto.	-0.06	0.11	-0.56	0.575
Static × Prop. to trust auto.	0.05	0.11	0.50	0.618
R^2	0.307			
Adjusted R^2	0.301			

All main effects are significant, as in model 1. However, propensity to trust automation has a much higher estimate than propensity to trust. The interaction terms for both groups are included in the same manner, neither being significant. Thus, there is no support for a moderation effect of propensity to trust automation rejecting hypothesis five. The overall model fit explains around 30% of the variation, which is substantially larger than model 1.

Exploratory Analyses

Because the intervention was applied before the measurements of safety evaluation, MAVA and intention to use SASs, in addition to subjective trust in SASs, I wanted to investigate if the intervention had any systematic effects on these variables as well. An exploratory analysis with the aim of uncovering intervention effects on safety evaluation, the MAVA-scale and intention to use was conducted using ANOVA.

Effects of Intervention on Safety Evaluation, MAVA, and Intention to Use SASs

Three analyses examined the differences in means for safety evaluation, MAVA, and intention to use SASs, with each variable serving as the dependent variable in separate tests. Table 9 presents the three ANOVA's, all of which are significant. This indicates that there is a significant difference in means between groups for the variables.

Table 9

One-Way ANOVA (Welch's) with Intervention Group Predicting Safety Evaluation, MAVA, and Intention to use Shared Autonomous Shuttles

Variable	*f*	*df1*	*df2*	*p*
Safety evaluation	6.19	2	412	0.002
MAVA	7.01	2	411	0.001
Intention to use SASs	6.40	2	418	0.002

To examine the relationship between the groups, Tukey's HSD was used as a post-hoc test. The results indicate a comparable significant effect of both intervention groups compared to the control group for all three dependent variables. The means, standard deviations, and standard error for each group in each test is presented in table 10.

Table 10

Means, Standard Deviation and Standard Error of Each Group in the ANOVA Model for each Variable

Variables	*Group*	*N*	*Mean*	*SD*	*SE*
Safety evaluation	Control Group	226	4.27	1.49	0.0990
	Dynamic Group	200	4.71	1.44	0.1016
	Static Group	197	4.68	1.34	0.0957
MAVA	Control Group	228	3.89	1.32	0.0875
	Dynamic Group	200	4.29	1.28	0.0904
	Static Group	195	4.30	1.20	0.0857
Intention to use SASs	Control Group	230	4.69	1.72	0.1137

Table 10

Means, Standard Deviation and Standard Error of Each Group in the ANOVA Model for each Variable

Variables	*Group*	*N*	*Mean*	*SD*	*SE*
	Dynamic Group	202	5.17	1.49	0.1045
	Static Group	198	5.17	1.41	0.1002

Notably, the means for the intervention groups are very similar across all three variables, compared to the control group. The discrepancies between the static groups and control were also very similar, 0.41, 0.41, and 0.48 for safety evaluation, MAVA, and intention to use SASs respectively.

Discussion

In this thesis, I have investigated the impact of social norms on subjective trust in shared autonomous public transport using an experimental online survey. The main takeaway is that trust in shared autonomous shuttles (SASs) can be influenced by social normative impressions, as demonstrated with the use of normative vignettes. However, no significant differences were found between statically framed normative statements and dynamically framed statements, only between the intervention groups and the control group. Secondly, the results highlight the importance of propensity to trust others and propensity to trust automation in trust attribution, with the latter significantly affecting trust evaluation of SASs. Further, safety evaluation of the shuttles has the most substantial impact on subjective trust in SASs in the composite model. Subjective trust has a strong correlation with intention to use SASs, which has significant practical implications in planning, implementing, and optimizing autonomous public transport solutions. It should also be noted that both intention to use SASs and subjective trust in SASs was measured after the intervention, so a causal relationship should be cautiously interpreted. Lastly, the results reveal no moderating effect of either type of propensity on the intervention.

To summarize the findings in relation to the hypotheses proposed: It was found that static norm interventions positively impacted subjective trust in shared autonomous shuttles (H1), while the dynamic norm intervention did not have a larger effect compared to the static norm intervention (H2). Contrary to expectations, propensity to interpersonal trust and propensity to trust automation did not enhance the intervention effect as moderator variables (H3 and H4). However, both types of propensity exhibited direct positive effects on subjective trust in shared autonomous shuttles (H5 and H6). Furthermore, a positive correlation was found between safety evaluations and subjective trust in SASs (H7). Subjective trust in SASs predicted intention to use shared autonomous shuttles (H8), and finally, a positive correlation between propensity to interpersonal trust and propensity to trust automation was observed (H9). The upcoming discussion will delve further into these findings and their implications, following the order of the hypotheses, starting with the intervention effects.

Intervention Effects: The Impact of Social Norms

This study investigated the level of subjective trust in shared autonomous shuttles when primed with a statically framed normative vignette or a dynamically framed normative vignette compared to no normative statement. The degree of trust among participants who were presented with a normatively loaded statement, regardless of static or dynamic, was higher than those presented with a control text, supporting hypothesis one. The results from the two ANOVA tests strengthen the first hypothesis that static norm intervention would increase subjective trust in shared autonomous shuttles. The dynamic group scored a bit higher on trust, however, it was a non-significant difference and may simply be a coincidence.

Even if there was no significant effect separating the dynamic intervention from the static, the fact that there was such a similar effect of *both* normative vignettes compared to the control-group strengthens the first hypothesis further, and the notion that trust in shared autonomous shuttles is impacted by what others believe about them. They can be viewed as two types of normative influence, and in this way, bolster the overall effect. This is also in line with the analogical trust formation (J. D. Lee & See, 2004) where the testimony of others is an important part in making quick assessments of an actor or trustee. The lack of knowledge and hands-on experience should increase this effect, as the less information available, the more heuristic judgement is necessary to make an evaluation (Bruhn, 2019). Autonomous public transport is a very novel service. Subjective norms and leaning on others experience and their perceived evaluations should therefore be prevalent in the attribution process (Hoff & Bashir, 2015), as displayed in this study.

There could be several reasons for the lack of significant effects between the static and dynamic norm intervention. First, it may simply be too weak of an effect to display in the design used in this study. Even with a high sample size, the effect of simply reading a normative statement may not be sufficient to imprint an actual change in perception of trust, however this explanation is not very likely as there are clear effects of both normative interventions. Second, there is, to the best of the authors knowledge, little-to-no literature examining if a dynamic norm influence has a significant effect on trust attribution, at least in this context. The effects found related to for example more environmentally positive behavior (Sparkman & Walton, 2019) may not translate to trusting behavior and attribution, and deserves more thorough examination. The context in which trust is being exhibited can also impact the degree of effect, as people may be more wary of changing norms regarding some attitudes and not others. For example, how "futuristic" or forward leaning one wishes to identify as, may change the degree of conformity to such norms. Other values may directly counteract the effect in this context, such as the fear that more automation may lead to less workplaces, and simply does not have anything to do with the trust in the technology itself. Other factors may also be more important than normative influence, simply because the individual may assign higher priority to these factors in that particular moment. Lastly, the amount of dynamically loaded phrasing may have been too subtle to invoke any change that differed from a static normative statement.

The interventions exhibited a consistent and systematic impact on the other variables presented to the respondent following the vignettes, these being safety evaluation, MAVA, and intention to use SASs. The explorative analysis shows that the means of the dynamic and static norm groups were strikingly similar, whilst the control group displayed consistently lower means in all three of these variables. On one hand, the fact that the social norm vignettes had a significant effect on all measures that succeeded the intervention is an indication that individuals are indeed influenced by others to a large extent in their attributions in this context. On the other hand, all of the control and dependent measures except technical competence correlated highly, which means that they probably share much of the same explanatory capabilities. As such it is no surprise that the intervention influenced the intention to use shared autonomous shuttles directly. Whilst strengthening the validity of the intervention, it also means that using safety evaluation as a controlling variable was somewhat less informative, given that the respondents who read a normative statement evaluated the busses as safer than those in the control group.

The Significance of Safety Evaluation and MAVA-Factors

Two regression models are presented in the findings. The first model includes the hypothesized covariates safety evaluation and the MAVA-scale, and model two explores the effects without the covariates. Because of the intervention effect on safety evaluation and MAVA, and the high correlations between safety evaluation, MAVA, intention to use SASs and subjective trust in SASs, it makes sense to examine subjective trust without these variables. Additionally, comparing the two models may provide insight as to what variables contribute to predicative power without the controlling effect of safety evaluation and the MAVA scale.

In model one, it is found that the effect of the intervention persists even when controlling for other factors. Still, the safety evaluation of the shuttles had the decidedly largest impact on trust. This makes sense, as the perceived safety permeates almost all aspects of using such a service. As both a passenger and a pedestrian or cyclist, one will likely consider the operational safety of the vehicle to be the most prominent element. Given that trust is formed when individuals willingly accept risks (Harrison McKnight & Chervany, 2001; Mayer et al., 1995), safety is a crucial factor in mitigating risk within the context of autonomous shuttles, in some way serving as a natural opposition. The safer the shuttle, the less risk-taking is necessary. Hence, the safer the individual perceives the shuttle, the more initial trust is exhibited.

The most striking finding may be that social normative statements can affect trust in autonomous shuttles regardless of if safety evaluation is accounted for or not. While the effect is rather small, it means that it is a factor that should not be overlooked. Normative influence may be increasingly important as technology advances and the understanding of the tools and services individuals use becomes weaker. Increased adoption should hence predict a larger acceptance from the public, because more people will observe that others are using the service.

Furthermore, it was surprising to not find an effect of exposure in either model. Other studies have pointed to interaction with automation as a source of increased trust, barring unsuccessful implementations (Aasvik, 2023). However, the exposure measure in this study measures *knowledge* of pilots, not necessarily hands-on experience. In fact, most people would not have had the opportunity to test a service like this. Another explanation may be that given how theory predicts an evaluation of the system, exposure to systems does not play a large role. The other predictors may also eliminate any effect of exposure if the effect is small.

Finally, there is a substantial decrease in explained variance from model one to model two. Again, this supports the notion that safety evaluation is particularly important in this context.

Propensity: Direct Effects and the Absence of Moderation

Hypotheses three through six postulated effects of propensity as moderators and direct effects of propensity. No moderation effects were found in either model. Given this, hypothesis three and four is rejected. There was, however, a direct effect of propensity and propensity to trust automation, supporting hypothesis five and six.

Because propensity is such an integral part of the trust process (Mayer et al., 1995), it is surprising that neither of the two types proved to moderate the effect of the intervention, even when only a small effect was expected. Being more inclined to trust others was believed to increase the impact of the intervention vignettes. There could be several possible explanations for a lack of effect. First, it may entail that the propensity to trust does not increase the impact of others' opinions when making a trust attribution, because the propensity has already "made its mark" on the attribution. Because both types of propensity are believed to be a deeply ingrained and learned part of a person's disposition, it seems that the influence of others may prove more of an *additional* source of data, on top of the baseline evaluation. Second, there might not be grounds for "using" or tapping into ones' disposition when attributing trust in this context, as the variable assessing this assumes that the individual can clearly imagine what the transport service will be like and how they personally will use and interact with it. The testimony of others may be informative enough on its own. This further emphasizes the direct effects of propensity and is also supporting the notion that context-specific measures are better at predicting an outcome regarding trust-attribution. For example, the propensity to trust automation explained much more of the variance in the moderation models.

This also emphasizes that these two variables are distinct enough that they demand different measures and must be studied independently. Moreover, propensity to trust automation had a higher effect than the intervention when investigating the main effects, indicating that a solid baseline-trust in automated systems can have a similar impact on shaping people's perceptions as norm-based interventions. Thus, it is of importance to understand and address both individual dispositions and automation-specific factors.

Interconnected Constructs: Predicting Intention

Excluding technical competence and propensity to trust, all other variables exhibited significant correlations with one another. A modest correlation was observed between the propensity to trust automation and the propensity for interpersonal trust, supporting hypothesis nine. This may entail that they exhibit a degree of interdependence, while still being clearly separate constructs. Propensity to trust automation also had moderate to high correlations with subjective trust in SASs, intention to use SASs and safety evaluation as well as the MAVA scale. Intriguingly, propensity to trust others had a similar pattern, but the correlations were weaker overall. Perhaps the two constructs share some common elements, or that propensity to trust automations is functioning as a context specific propensity measure of the elsewise same tendency. Propensity to trust others may be general enough to affect trusting behavior regardless of context, while propensity to trust automation exhibits a high validity in the specific context of autonomous vehicles.

Additionally, technical competence correlated with propensity to trust automation, but not with propensity to trust others. This may indicate that more technically competent people have a higher tendency to trust automation, or that people who trust automation easier will have more exposure to technology and hence get increased competence through experience. However, the correlation was low.

The MAVA-scale and safety evaluation demonstrated a strong correlation, suggesting that there might be some overlapping aspects in their explanatory capacities. This makes sense, as both constructs correlated strongly with subjective trust and intention to use shared autonomous shuttles. The purpose of the MAVA-scale is after all a composite measure of intention to use (Nordhoff et al., 2019), which is supported in this study as well. However, it becomes problematic to separate the measures in regard to trust, especially when the MAVA items are as intertwined as they are. Hypothesis seven is supported with safety's correlation with subjective trust in SASs, but the issue of separating effects is present here as well.

Not surprisingly, subjective trust and intention to use shared autonomous shuttles correlated highly, supporting hypothesis eight. The measure of intention is a strong indicator of real-world behavior (Ajzen, 1985), and the fact that subjective trust is closely related validates the measure as an important decider in trusting autonomous vehicles.

Sample Demographics and Trust Implications

There were no significant differences in gender, age, or education levels between the three intervention groups. It is worth noting the high educational level across the full sample, which is most likely a result of the sample primarily being distributed in channels among individuals with higher education (e.g., university and people who have responded to similar surveys before). There were more female respondents in the control group than in the static and dynamic intervention groups, which may be a result of the different influence of the manipulation check.

Furthermore, the propensity to trust and the propensity to trust automation both displayed a left-skewed distribution, with nearly no responses in the lowest ranges. This may indicate that people are generally a bit high in propensity to trust. Cultural elements may be an important explanatory factor, as people in Norway simply may tend to trust others as well as automations to a larger extent. They typically exhibit a heightened level of trust towards the government and societal structures, which can be reflected in a confidence in the nation's public systems (OECD, 2015). Additionally, people tend to relate the public transport systems in their local area to government institutions, and trust in them may then result in a heightened trust in shared autonomous shuttles due to testing and piloting being taken for granted as a measure to ensure correct implementation.

Limitations

Sample and Group Differences

Even though the groups were randomly filled as the survey was distributed, there was a discrepancy in the number of respondents in each intervention group, with the control group having 230 participants, dynamic 202, and static 198. This is most likely due to the exclusion criteria tied to the manipulation check. A possible explanation for this is that the manipulation check in the intervention groups were more prone to unsuccessful answers than the control check. The check for the control group had a more distinct categorical difference (asking what color the buses had), while the check for the intervention groups had numbers which may have been more easily interchangeable (how many people trust the shuttles, see appendix A for full survey).

Interestingly, it seems that this may be reflected in the tech competence score for the participants. Both intervention groups had a higher tech competence score than the control, (however only the mean of the static-norm group was statistically significantly different) which may signal that the more technology competent respondents had an easier time answering the manipulation check correctly. While it is not ideal that this creates an artificial effect of the group on technical competence, which should not be possible given that the intervention is administered after measuring technology competence, it can be argued that it strengthens the construct validity of the technical competence scale. The intended measure is an aggregate of tech-savviness, ability to interact with technology, and interest in technology. Hence, it is reasonable that individuals who score slightly lower on this measure would have a marginally increased risk of failing such a check, although this aspect should not be overly emphasized, and would need testing in a follow up study. Overall, it has most likely not affected the analysis to a large extent but should not be overlooked.

There may also be some demand characteristics present, as people may want to think that they are more trusting than they are, as it is perceived as a positive trait. The difference in technical competence may also impact this result, as it correlates with propensity to trust automation.

Normality, Scales and Measures

As presented in the results, non-normality was present in several of the scales used. This may have led to a reduction in power, or more inaccurate measures than what is optimal. However, adjustments and alternative tests were applied to counteract these effects.

The majority of the scales used in the study were partly or completely constructed from the ground up. While the measures had a good reliability, some should be explored further, and validated to assure their precision. Propensity to trust automation, for example, is extrapolated from interpersonal trust research and should be further tested in future research. Additionally, it may have been affected by the propensity measure proceeding it in the survey, which may have primed similar answers based on the likeness of the two scales. There is also a lack of a solid and validated scale for measuring propensity to trust automation in the literature, and the scale developed in the current study may provide an excellent starting point.

Additionally, the respondents were asked to evaluate something that few or none of them had prior knowledge about. This may be a threat to the validity of the measures, as it may be difficult to accurately assess something without firsthand experience. Still, a central goal of this study was to examine if normative influence could affect a novel or unknown agent. The results may have been different if the sample was more experienced or exposed to shared autonomous shuttles.

The variable that measures exposure may not be the most accurate way to examine the effect of knowledge related to shared autonomous shuttles. The way the item was constructed excluded all forms of self-driving that was not directly related to the pilots mentioned in the study. Additionally, it did not measure experience, but rather knowledge. It may have been more informative to measure any hands-on experience in addition.

Lastly, the assumptions for moderation-models were assessed, and several of the assumptions were not met in both models. Violation of skewness and heteroscedasticity may affect the precision of estimates and test validity, while skewness is a primary concern in model two. Hence, caution is necessary when interpreting results from both moderation models.

Generalizability, Future Research and Conclusions

In light of the findings highlighting the influence of social norms on trust in shared autonomous public transport, the most essential takeaway for stakeholders is perhaps the potential negative effects of a failed or badly implemented pilot. Because of the top-down nature of trust formation in automation, the public may quickly form negative opinions and resist adoption of autonomous public transport if they experience negative interactions with them. Additionally, as this study indicates, a bad reputation that spreads will potentially have impact, and affects other's opinion and subjective trust attributions, because people may rely on others testimony when attributing foreign things.

Findings from this study may also be generalized to other autonomous methods of transport or inform further studies and experiments, including larger vehicles and other use cases. Even if the small shuttle design introduces some unique interactions and caveats that may not be present in other modes of transport, trust can have a spillover-effect, especially when attributing similar services and trustors.

As for future research avenues, examining static and dynamic norm influence in an experiment with more external validity would be highly informative. The effects shown in this study will benefit from organic reproduction to assess whether there is an effect in real-world trusting-behavior. Finally, it should once again be emphasized that technology advances at a pace unmatched by corresponding research in the field. The literature regarding autonomous vehicles will probably constantly fall behind the leaps in technology and emphasizes the need for more research efforts to effectively address the evolving challenges and opportunities automation brings. Perhaps especially related to the psychological aspects of implementation.

In this thesis, I have discussed the potential benefits of shared autonomous shuttles as a public transport option, and what may contribute to the successful adoption of such a service, through trust. Using an experimental survey design, the degree of subjective trust in shared autonomous shuttles was influenced by a normative intervention. Whether the normative statement was statically or dynamically framed, the effect persisted. However, there was no difference between the two intervention conditions.

The study indicated that the propensity to trust others, and the propensity to trust automation influences a person's attribution of shared autonomous shuttles. Propensity to trust automation had a larger effect, suggesting that propensity is context specific. Neither type of propensity moderated the influence of social norms, contradictory to expectations. Safety evaluation seems to be of great importance, but the effect of social normative influence persists even when controlling for this factor. Conclusively, safety concerns are one of the most important barriers to trusting an autonomous shuttle, however, the way we perceive that others attribute trust in autonomous public transport can also affect our own opinion and attributions, especially in novel trusting situations.

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Appendix

Appendix A – Complete Survey as Distributed

Introduction and Consent

Takk for at du har lyst til å svare på undersøkelsen!

Her kommer litt informasjon om hva undersøkelsen innebærer:

- Det tar 8 minutter å svare på undersøkelsen.
- Alle svar er anonyme og du kan trekke deg når som helst.
- Ingen spørsmål er vurdert som sensitive.
- Dersom du ønsker, kan du delta i trekningen av 3 universalgavekort på 200,- etter at du har gjennomført undersøkelsen.
- Under følger detaljert informasjon:

Informasjon om forskningsprosjektet

Prosjektet har som mål å avdekke ulike faktorer knyttet til holdninger om teknologi og fremtidens transportmidler. Prosjektet er en del av en mastergrad ved Universitetet i Oslo.

Hvem er ansvarlig for forskningsprosjektet?

Universitetet i Oslo er ansvarlig for prosjektet.

Hvorfor er du inkludert i studien?

Utvalget i studien er alle personer over 18 år som ønsker å delta. Det har blitt gjort rekrutering i ulike offentlige grupper via internett og sosiale medier, forespørsler på bakgrunn av deltagelse i andre undersøkelser, og plakater. Deltagerne representerer befolkningen generelt, og du som deltager er ikke valgt ut på bakgrunn av noen spesifikke kriterier. Vi ønsker deltagere med ulike bakgrunner, alder, kjønn og andre demografiske faktorer.

Hva innebærer prosjektet for deg?

Studien innebærer å svare på et spørreskjema og lese noen korte tekster. Det tar cirka 8 minutter å gjennomføre spørreskjemaet. Alle svar er helt anonyme, og kan ikke kobles til deg som person på noen måte. Dersom du ønsker, vil det være mulig å legge igjen epost hvis du ønsker å bli kontaktet om lignende spørreundersøkelser i fremtiden, eller du ønsker å delta i trekningen av gavekort. Eposten vil ikke knyttes til svarene på spørreskjemaet.

Det er frivillig å delta:

Det er frivillig å delta i prosjektet. Hvis du velger å delta, kan du når som helst trekke samtykket tilbake uten å oppgi noen grunn. Alle dine personopplysninger vil da bli slettet. Det vil ikke ha noen negative konsekvenser for deg hvis du ikke vil delta eller senere velger å trekke deg.

Ditt personvern – hvordan vi oppbevarer og bruker dine opplysninger:

Vi vil bare bruke opplysningene om deg til formålene vi har fortalt om i dette skrivet. Vi behandler opplysningene konfidensielt og i samsvar med personvernregelverket. Det er kun forsker, veileder og biveileder som har tilgang til datamaterialet. Ingen data kan spores tilbake til den som svarer på skjemaet. Epost som lagres blir ikke knyttet til svarene på undersøkelsen.

Hva skjer med opplysningene dine når vi avslutter forskningsprosjektet?

Eposter slettes senest 12 måneder etter innsamlingens slutt, noe som etter planen er i mai 2023, eller hvis du ønsker å fjerne eposten din fra listen. Ellers lagres ingen personidentifiserbare data.

Hva gir oss rett til å behandle personopplysninger om deg?

Vi behandler opplysninger om deg basert på ditt samtykke. På oppdrag fra Universitetet i Oslo har Personverntjenester vurdert at behandlingen av personopplysninger i dette prosjektet er i samsvar med personvernregelverket.

Dine rettigheter:

Så lenge du kan identifiseres i datamaterialet, har du rett til:

- innsyn i hvilke opplysninger vi behandler om deg, og å få utlevert en kopi av opplysningene

- å få rettet opplysninger om deg som er feil eller misvisende
- å få slettet personopplysninger om deg
- å sende klage til Datatilsynet om behandlingen av dine personopplysninger

Svarene fra spørreskjemaet er helt anonyme, og du kan ikke identifiseres. Dersom du velger å delta i trekning av gavekort, eller legge igjen epost hvis du ønsker å bli kontaktet om lignende spørreundersøkelser i fremtiden, gjelder rettighetene listet over.

Hvis du har spørsmål til studien, eller ønsker å vite mer eller å benytte deg av dine rettigheter, ta kontakt med:

- Universitetet i Oslo ved Mastergradsstudent, Sander Vassanyi (sanderva@student.sv.uio.no, tlf: 90961800) eller
- Hovedveileder, Ole Aasvik (ole.aasvik@toi.no) eller
- Vårt personvernombud: Roger Markgraf-Bye (personvernombud@uio.no).

Hvis du har spørsmål knyttet til Personverntjenester sin vurdering av prosjektet, kan du ta kontakt med: Personverntjenester på epost (personverntjenester@sikt.no) eller på telefon: 53 21 15 00.

○ Det er greit, fortsett

Sociodemographics

Hvor gammel er du?

○ 18-29
○ 30-39
○ 40-49
○ 50-59
○ 60-69
○ 70-79
○ 80+

Hvilket kjønn identifiserer du deg som?

○ Kvinne
○ Mann
○ Annet
○ Ønsker ikke å svare

Hva er din høyeste fullførte utdanning?

○ Grunnskole
○ Videregående
○ 1-3 år universitet eller høyskole
○ Over 3 år universitet eller høyskole

Independent Variables

De neste fem spørsmålene handler om tillit til andre personer.

Vennligst svar på hvor godt utsagnene beskriver deg:

	1 Stemmer ikke	2	3	4	5	6	7 Stemmer helt
Jeg pleier å stole på folk frem til de gir meg en grunn til å ikke stole på dem	○	○	○	○	○	○	○
Det er ikke vanskelig for meg å stole på en annen person	○	○	○	○	○	○	○
Vanligvis stoler jeg på nye bekjente frem til de viser at jeg ikke burde stole på dem	○	○	○	○	○	○	○
Jeg har en høy tendens til å stole på andre	○	○	○	○	○	○	○
Jeg stoler lite på andre folks løfter	○	○	○	○	○	○	○

Du vil nå få presentert noen utsagn knyttet til beslutningstaking, teknologi og tillit.

Vennligst svar på hvor godt utsagnene beskriver deg:

	1 Stemmer ikke	2	3	4	5	6	7 Stemmer helt
Jeg er blant de første til å høre om ny teknologi	○	○	○	○	○	○	○
Venner og familie kommer til meg for å få hjelp med teknologi	○	○	○	○	○	○	○
Jeg er over gjennomsnittet interessert i teknologi	○	○	○	○	○	○	○

De neste fem spørsmålene handler om automatiske systemer. Her er det snakk om for eksempel en datamaskin, en heis, eller en brusautomat.

Vennligst svar på hvor godt utsagnene beskriver deg:

	1 Stemmer ikke	2	3	4	5	6	7 Stemmer helt
Jeg pleier å stole på automatiske systemer frem til de feiler	○	○	○	○	○	○	○
Det er ikke vanskelig for meg å stole på automatiske systemer	○	○	○	○	○	○	○
Vanligvis stoler jeg på nye automatiske systemer, frem til jeg får en grunn til å ikke gjøre det	○	○	○	○	○	○	○
Jeg har en høy tendens til å stole på automatiske systemer	○	○	○	○	○	○	○
Jeg stoler lite på at automatikk gjør som den skal	○	○	○	○	○	○	○

Control Block

Du vil nå få informasjon om et transporttilbud som vil bli tilgjengelig i fremtiden:

Det arbeides nå med et busstilbud i Norge som vil bestå av små, selvkjørende busser. Bussene kjører på vanlige veier, og i normal trafikk, men vil ikke trenge noen sjåfør. Det gjennomføres nå piloter (prøveprosjekt) der en slik tjeneste testes. Testene har blitt utført på aktuelle områder i middels befolkede strøk. De fleste bussene er røde.

Se for deg et slikt tilbud når du svarer på de neste spørsmålene.

Static Norm Block

Du vil nå få informasjon om et transporttilbud som vil bli tilgjengelig i fremtiden:

Det arbeides nå med et busstilbud i Norge som vil bestå av små, selvkjørende busser. Bussene kjører på vanlige veier, og i normal trafikk, men vil ikke trenge noen sjåfør. Det gjennomføres nå piloter (prøveprosjekt) der en slik tjeneste testes. Nylige undersøkelser av Transportøkonomisk institutt viser at flere enn 7 av 10 nordmenn stoler på at selvkjørende busser fungerer som de skal.

Se for deg et slikt tilbud når du svarer på de neste spørsmålene.

Rumination

Hva tenker du om at så mange stoler på et slikt tilbud?

- ◯ Det er overaskende
- ◯ Det er forventet
- ◯ Har ingen formening

Dynamic Norm Block

Du vil nå få informasjon om et transporttilbud som vil bli tilgjengelig i fremtiden:

Det arbeides nå med et busstilbud i Norge som vil bestå av små, selvkjørende busser. Bussene kjører på vanlige veier, og i normal trafikk, men vil ikke trenge noen sjåfør. Det gjennomføres nå piloter (prøveprosjekt) der en slik tjeneste testes. Flere og flere blir positive til et slikt tilbud, og nylige undersøkelser av Transportøkonomisk institutt viser at flere enn 7 av 10 nordmenn stoler på at selvkjørende busser fungerer som de skal. Folk er i ferd med å endre sin oppfatning av et selvkjørende kollektivtilbud.

Se for deg et slikt tilbud når du svarer på de neste spørsmålene.

TextReminder

Du kan navigere tilbake til denne informasjonen om du ønsker når du svarer på de neste spørsmålene:

Det arbeides nå med et busstilbud i Norge som vil bestå av små, selvkjørende busser. Bussene kjører på vanlige veier, og i normal trafikk, men vil ikke trenge noen sjåfør. Det gjennomføres nå piloter (prøveprosjekt) der en slik tjeneste testes. Testene har blitt utført på aktuelle områder i middels befolkede strøk. De fleste bussene er røde.

Du kan navigere tilbake til denne informasjonen om du ønsker når du svarer på de neste spørsmålene:

Det arbeides nå med et busstilbud i Norge som vil bestå av små, selvkjørende busser. Bussene kjører på vanlige veier, og i normal trafikk, men vil ikke trenge noen sjåfør. Det gjennomføres nå piloter (prøveprosjekt) der en slik tjeneste testes. Nylige undersøkelser av Transportøkonomisk institutt viser at flere enn 7 av 10 nordmenn stoler på at selvkjørende busser fungerer som de skal.

Du kan navigere tilbake til denne informasjonen om du ønsker når du svarer på de neste spørsmålene:

Det arbeides nå med et busstilbud i Norge som vil bestå av små, selvkjørende busser. Bussene kjører på vanlige veier, og i normal trafikk, men vil ikke trenge noen sjåfør. Det gjennomføres nå piloter (prøveprosjekt) der en slik tjeneste testes. Flere og flere blir positive til et slikt tilbud, og nylige undersøkelser av Transportøkonomisk institutt viser at flere enn 7 av 10 nordmenn stoler på at selvkjørende busser fungerer som de skal. Folk er i ferd med å endre sin oppfatning av et selvkjørende kollektivtilbud.

Dependent Variables

Hvor enig er du i følgende påstander:

	1 Helt uenig	2	3	4	5	6	7 Helt enig
Selvkjørende busser er pålitelige	○	○	○	○	○	○	○
Selvkjørende busser vil stort sett gjøre som forventet	○	○	○	○	○	○	○
Alt i alt kan jeg stole på selvkjørende busser	○	○	○	○	○	○	○

Hvor enig er du i følgende påstander:

	1 Helt uenig	2	3	4	5	6	7 Helt enig
Jeg ville vært komfortabel med å kjøre i en buss som dette	○	○	○	○	○	○	○
Hvis jeg fikk muligheten, ville det vært greit for meg å kjøre med en slik buss	○	○	○	○	○	○	○
Jeg ville unngått å kjøre med en slik buss, selv om det var det raskeste og billigste alternativet	○	○	○	○	○	○	○

Safety and MAVA

Hvor enig er du i følgende påstander:

	1 Helt uenig	2	3	4	5	6	7 Helt enig
En slik buss vil være trygg å bruke	○	○	○	○	○	○	○
En slik buss vil fungere godt sammen med annen trafikk	○	○	○	○	○	○	○
Alt i alt er en slik buss sikker	○	○	○	○	○	○	○
En slik buss ville økt trafikksikkerheten	○	○	○	○	○	○	○
Denne bussen ville være risikabel å ta i bruk	○	○	○	○	○	○	○

Hvor enig er du i følgende påstander:

	1 Helt uenig	2	3	4	5	6	7 Helt enig
Jeg tror det ville vært enkelt for meg å bruke denne busstjenesten	◯	◯	◯	◯	◯	◯	◯
Jeg ville følt meg trygg mens jeg ventet på en slik buss når det er mørkt	◯	◯	◯	◯	◯	◯	◯
Jeg tror denne typen buss vil være nyttig for meg	◯	◯	◯	◯	◯	◯	◯
En sånn buss ville vært bedre enn en tradisjonell buss	◯	◯	◯	◯	◯	◯	◯
Jeg tror andre synes det er bra at jeg bruker en sånn buss	◯	◯	◯	◯	◯	◯	◯
Jeg tror folk flest vil ønske å bruke en sånn buss	◯	◯	◯	◯	◯	◯	◯
Å bruke en slik buss ville vært underholdende	◯	◯	◯	◯	◯	◯	◯

Manipulation check

Hvor mange Nordmenn stoler på at selvkjørende busser fungerer som de skal?

◯ Over 7 av 10

◯ Over 5 av 10

◯ Over 3 av 10

Hvilken farge har de fleste bussene i testingen av selvkjørende busser i Norge?

◯ Gul

◯ Grønn

◯ Rød

	1 Nei	2 Litt	3	4	5	6	7 Mye
Kjente du til forsøk med selvkjørende busser i Norge før du deltok i denne spørreundersøkelsen?	◯	◯	◯	◯	◯	◯	◯

Appendix B – Pre-Registration

ASPREDICTED

Wharton CREDIBILITY LAB
University of Pennsylvania

CONFIDENTIAL - FOR PEER-REVIEW ONLY

Examining Trust in Autonomous Vehicle Acceptance Trough Dynamic Norms (#112191)

Created: 11/08/2022 05:29 AM (PT)

This is an anonymized copy (without author names) of the pre-registration. It was created by the author(s) to use during peer-review.
A non-anonymized version (containing author names) should be made available by the authors when the work it supports is made public.

1) Have any data been collected for this study already?
No, no data have been collected for this study yet.

2) What's the main question being asked or hypothesis being tested in this study?
1. To what degree does interpersonal trust impact trust in automation and intention to use autonomous vehicles? 2. Can dynamic norms be applied to impact degree of trust in automation?
H1: Static norm intervention increases Subjective trust in SAS compared to control.
H2: Dynamic norm intervention have a larger impact on subjective trust in SAS than Static norm intervention.
H3: Higher propensity to interpersonal trust will increase effect of intervention as a moderator effect.
H4: Higher propensity to trust technology will increase effect of intervention as a moderator effect.
H5: Propensity to trust technology has a positive direct effect on Subjective trust in SAS.
H6: Propensity to interpersonal trust has a positive direct effect on Subjective trust in SAS.
H7: Safety evaluation is positively correlated with subjective trust.
H8: Subjective trust in SAS positively predicts Intention to use SAS.
H9: Propensity to interpersonal trust and Propensity to trust technology are positively correlated.

3) Describe the key dependent variable(s) specifying how they will be measured.
Subjective trust in shared autonomous shuttles: Three items on a 7-point Likert scale (in Norwegian). (1) Self-driving busses are reliable. (2) Self-driving busses will more often than not act as expected. (3) Generally, I can trust self-driving busses. Intention to use shared autonomous shuttles: Three items on a 7-point Likert scale (in Norwegian). (1) I would be comfortable riding in a bus like this. (2) If I got the opportunity, it would be ok for me to ride in a bus like this (3) I would avoid riding with a bus like this even if it was the quickest and cheapest alternative for me.

4) How many and which conditions will participants be assigned to?
Three randomized groups: (1) Control: Given a brief explanation of the self-driving busses, with some filler info. (2) Static-norm: The same info as the control group without the filler info, and a static-social-normative statement (in Norwegian): Recent research by the Institute of Transport Economics show that more than 7 out of 10 Norwegians trust that self-driving busses work as intended. (3) Dynamic-norm: The same info as the control group without the filler info, and a dynamic-social-normative statement (in Norwegian): More and more people are becoming positive to an offer like this, and recent research by the Institute of Transport Economics show that more than 7 out of 10 Norwegians trust that self-driving busses work as intended. People are in the process of changing their opinion about a self-driving public transport offer.

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
To test H1 and H2, ANCOVA will be used to compare the treatment groups (Controlling for Safety evaluation, exposure, MAVA, and technological competence), along with post-hoc tests to identify differences between the groups should there be a significant difference. H3, H4, H5 and H6 will be tested with moderation analysis. H7 and H9 will be tested with correlation analysis. H8 will be tested using regression.

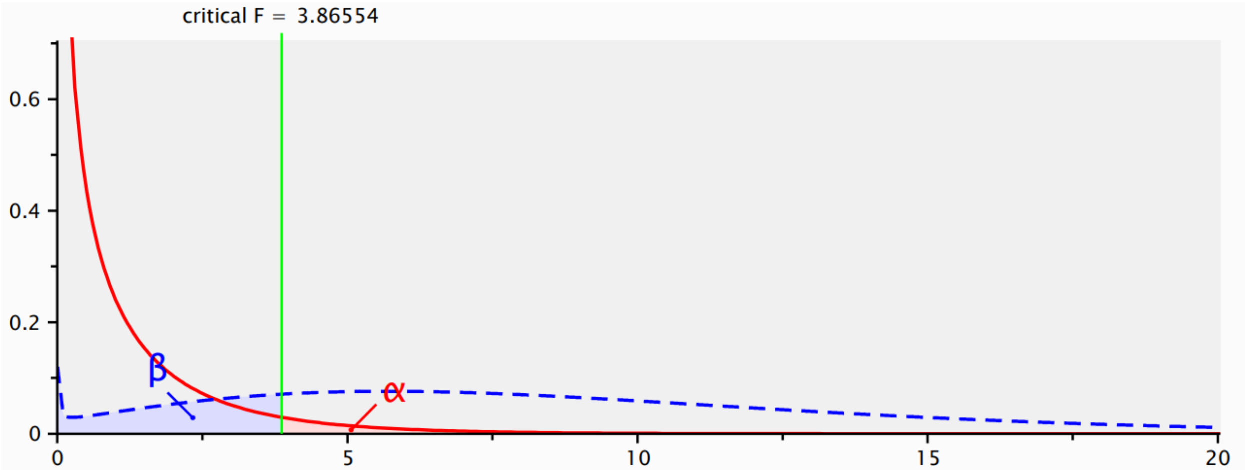
6) Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
(1) Two manipulation checks are included. Should a participant fail a check, they will be excluded from the analysis. (2) Respondents with an answer time below 3 minutes will be excluded, as this would indicate not having read the instructions and questions properly. (3) Straight-lined answers spanning reversed questions will be excluded, as it would indicate not properly reading the questions and answers.

7) How many observations will be collected or what will determine sample size? No need to justify decision, but be precise about exactly how the number will be determined.
Power analysis for moderation and comparable small effect-sizes were established. A minimum of 600 participants is the target. Data-collection will stop when reaching 1000 respondents or at 15.12.22, whichever comes first. If the minimum is not achieved, the collection period may be extended until 31.12.22.

8) Anything else you would like to pre-register? (e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)
Items created to test various aspects of MAVA, age, gender and educational level will be collected to allow for exploratory analysis.

Available at https://aspredicted.org/PSJ_Q93

Appendix C – Plot of Power Analysis from G*Power



Appendix D – NSD and REK Approvals

Vurdering

Referansenummer	Type	Dato
868180	Standard	05.10.2022

Prosjekttittel
Tillit til delt, selvkjørende transport

Behandlingsansvarlig institusjon
Universitetet i Oslo / Det samfunnsvitenskapelige fakultet / Psykologisk institutt

Felles behandlingsansvarlige institusjoner
Transportøkonomisk institutt

Prosjektansvarlig
Pål Ulleberg

Student
Sander Vassanyi

Prosjektperiode
01.10.2022 - 31.05.2023

Kategorier personopplysninger
Alminnelige

Rettslig grunnlag
Samtykke (art. 6 nr. 1 bokstav a)

Behandlingen av personopplysningene kan starte så fremt den gjennomføres som oppgitt i meldeskjemaet. Det rettslige grunnlaget gjelder til 01.10.2023.

Meldeskjema

Kommentar
OM VURDERINGEN
Personverntjenester har en avtale med institusjonen du forsker eller studerer ved. Denne avtalen innebærer at vi skal gi deg råd slik at behandlingen av personopplysninger i prosjektet ditt er lovlig etter personvernregelverket.

Personverntjenester har nå vurdert den planlagte behandlingen av personopplysninger. Vår vurdering er at behandlingen er lovlig, hvis den gjennomføres slik den er beskrevet i meldeskjemaet med dialog og vedlegg.

VIKTIG INFORMASJON TIL DEG
Du må lagre, sende og sikre dataene i tråd med retningslinjene til din institusjon. Dette betyr at du må bruke leverandører for spørreskjema, skylagring, videosamtale o.l. som institusjonen din har avtale med. Vi gir generelle råd rundt dette, men det er institusjonens egne retningslinjer for informasjonssikkerhet som gjelder.

DEL PROSJEKTET MED PROSJEKTANSVARLIG
For studenter er det obligatorisk å dele prosjektet med prosjektansvarlig (veileder). Del ved å trykke på knappen «Del prosjekt» i menylinjen øverst i meldeskjemaet. Prosjektansvarlig bes akseptere invitasjonen innen en uke. Om invitasjonen utløper, må han/hun inviteres på nytt.

TYPE OPPLYSNINGER OG VARIGHET
Prosjektet vil behandle alminnelige kategorier av personopplysninger frem til den datoen som er oppgitt i meldeskjemaet.

LOVLIG GRUNNLAG
Prosjektet vil innhente samtykke fra de registrerte til behandlingen av personopplysninger. Vår vurdering er at prosjektet legger opp til et samtykke i samsvar med kravene i art. 4 og 7, ved at det er en frivillig, spesifikk, informert og utvetydig bekreftelse som kan dokumenteres, og som den registrerte kan trekke tilbake.

Lovlig grunnlag for behandlingen vil dermed være den registrertes samtykke, jf. personvernforordningen art. 6 nr. 1 bokstav a.

PERSONVERNPRINSIPPER

Personverntjenester vurderer at den planlagte behandlingen av personopplysninger vil følge prinsippene i personvernforordningen om:

lovlighet, rettferdighet og åpenhet (art. 5.1 a), ved at de registrerte får tilfredsstillende informasjon om og samtykker til behandlingen

formålsbegrensning (art. 5.1 b), ved at personopplysninger samles inn for spesifikke, uttrykkelig angitte og berettigede formål, og ikke behandles til nye, uforenlige formål

dataminimering (art. 5.1 c), ved at det kun behandles opplysninger som er adekvate, relevante og nødvendige for formålet med prosjektet

lagringsbegrensning (art. 5.1 e), ved at personopplysningene ikke lagres lengre enn nødvendig for å oppfylle formålet

DE REGISTRERTES RETTIGHETER
Så lenge de registrerte kan identifiseres i datamaterialet vil de ha følgende rettigheter: innsyn (art. 15), retting (art. 16), sletting (art. 17), begrensning (art. 18), og dataportabilitet (art. 20).

Personverntjenester vurderer at informasjonen om behandlingen som de registrerte vil motta oppfyller lovens krav til form og innhold, jf. art. 12.1 og art. 13.

Vi minner om at hvis en registrert tar kontakt om sine rettigheter, har behandlingsansvarlig institusjon plikt til å svare innen en måned.

FØLG DIN INSTITUSJONS RETNINGSLINJER
Personverntjenester legger til grunn at behandlingen oppfyller kravene i personvernforordningen om riktighet (art. 5.1 d), integritet og konfidensialitet (art. 5.1. f) og sikkerhet (art. 32).

Ved bruk av databehandler (spørreskjemaleverandør, skylagring eller videosamtale) må behandlingen oppfylle kravene til bruk av databehandler, jf. art 28 og 29. Bruk leverandører som din institusjon har avtale med.

For å forsikre dere om at kravene oppfylles, må dere følge interne retningslinjer og/eller rådføre dere med behandlingsansvarlig institusjon.

MELD VESENTLIGE ENDRINGER
Dersom det skjer vesentlige endringer i behandlingen av personopplysninger, kan det være nødvendig å melde dette til oss ved å oppdatere meldeskjemaet. Før du melder inn en endring, oppfordrer vi deg til å lese om hvilke type endringer det er nødvendig å melde: https://www.nsd.no/personverntjenester/fylle-ut-meldeskjema-for-personopplysninger/melde-endringer-i-meldeskjema

Du må vente på svar fra oss før endringen gjennomføres.

OPPFØLGING AV PROSJEKTET
Personverntjenester vil følge opp ved planlagt avslutning for å avklare om behandlingen av personopplysningene er avsluttet.

Lykke til med prosjektet!

UiO University of Oslo
Faculty of Social Sciences – Departement of Psychology

Sander Vassanyi
Ole Aasvik

Ref.number: **23261657**
Date: 26 October 2022

Ethical evaluation of research project

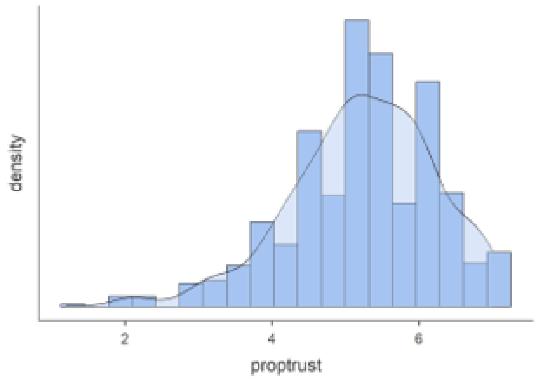
Your project, "Examining Trust in Autonomous Vehicle Acceptance Trough Dynamic Norms" has been ethically evaluated by the Department of Psychology's internal research ethics committee.

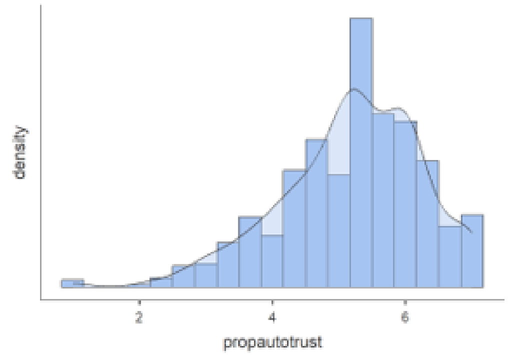
After the evaluation The Department of Psychology's internal research ethics committee recommend the project.

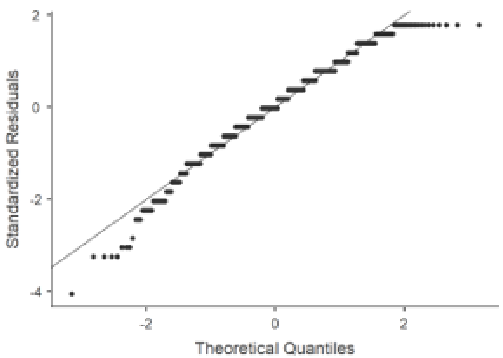
Sincerely yours, on behalf of the Committee,

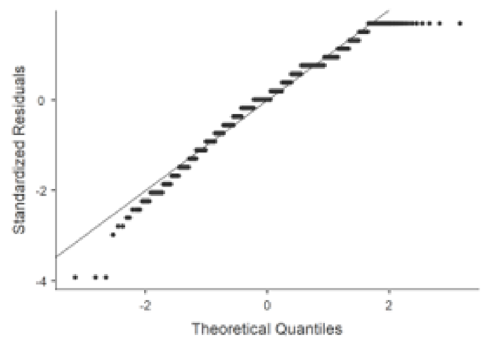
Professor Silje Endresen Reme, Head of Committee
Members of the Department of Psychology's Research Ethics Committee
https://www.uio.no/for-ansatte/enhetssider/sv/psi/psi-eng/internal-ethics-committee/index.html

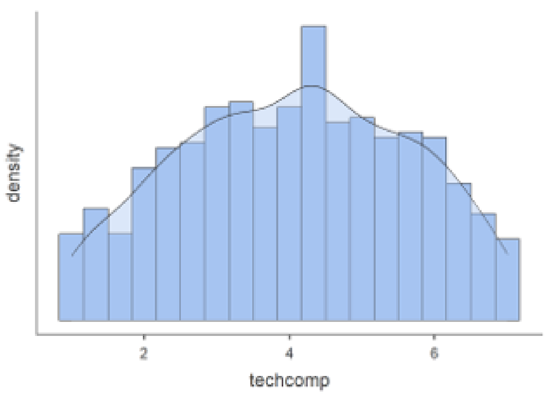
Appendix E – QQ Plots and Complete Descriptives of the Scales

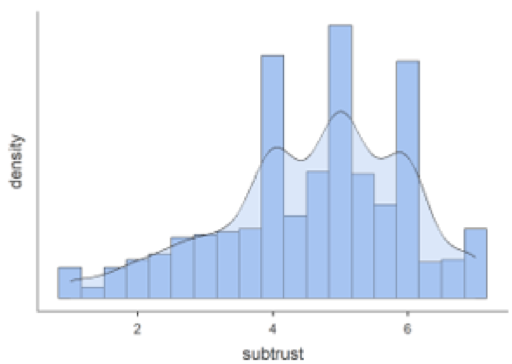


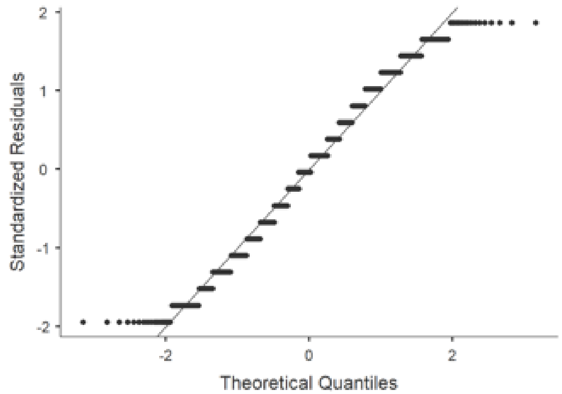








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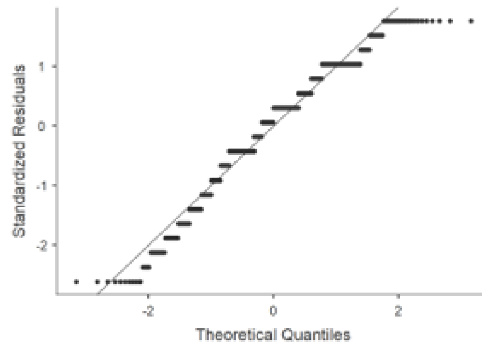
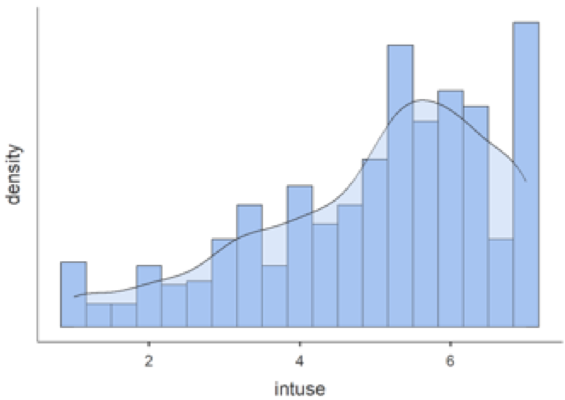
2
1
0
-1
-2
-2
0
2
Theoretical Quantiles


Standardized Residuals
1
0
-1
-2
-2
0
2
Theoretical Quantiles


density
2
4
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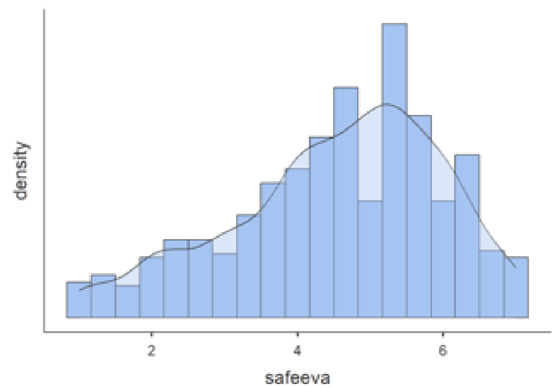
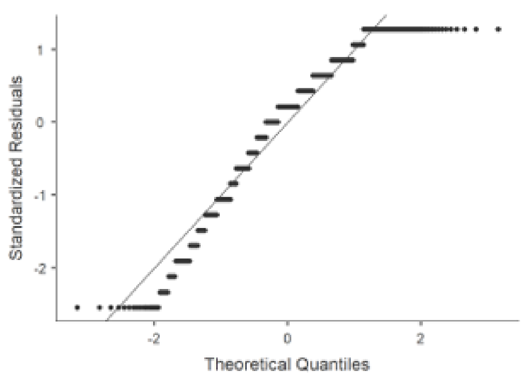
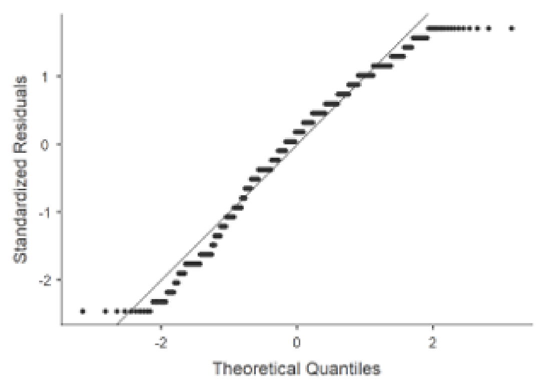
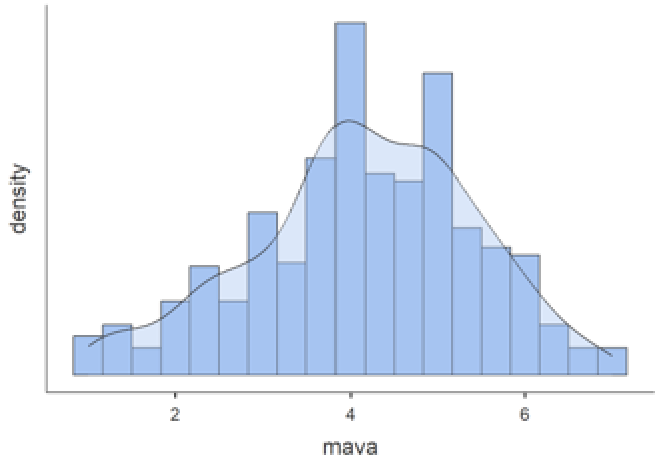
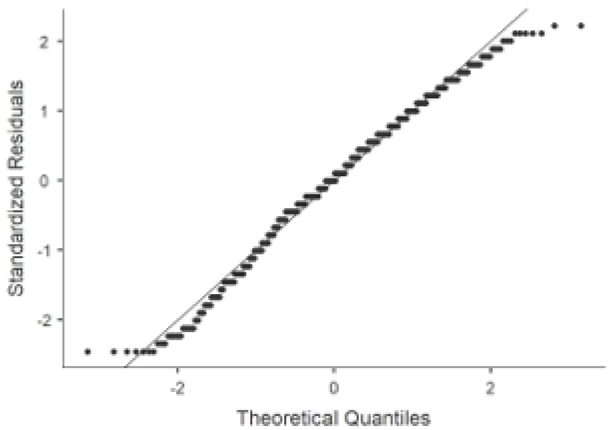
intuse


density
2
4
6
safeeva


Standardized Residuals
1
0
-1
-2
-2
0
2
Theoretical Quantiles


Standardized Residuals
1
0
-1
-2
-2
0
2
Theoretical Quantiles


density
2
4
6
mava


Standardized Residuals
2
1
0
-1
-2
-2
0
2
Theoretical Quantiles

Appendix F – Full Correlational Matrix

Table 11

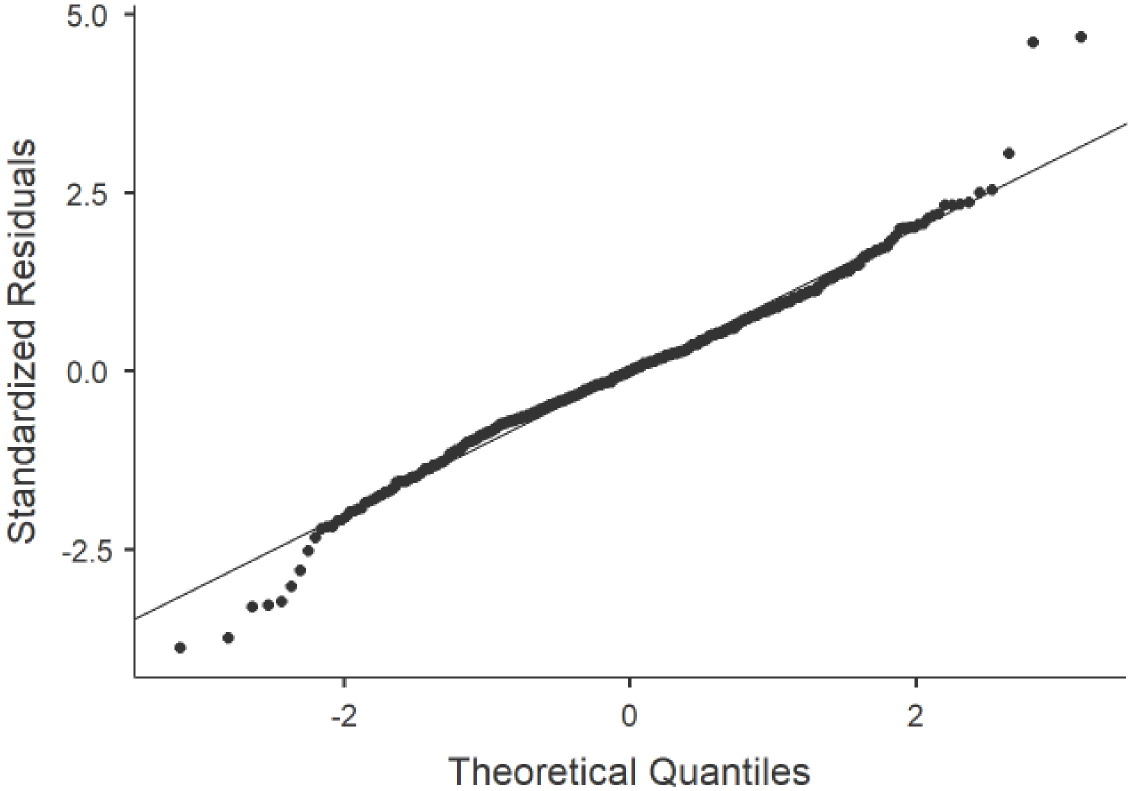
Means and Correlations with Confidence Intervals

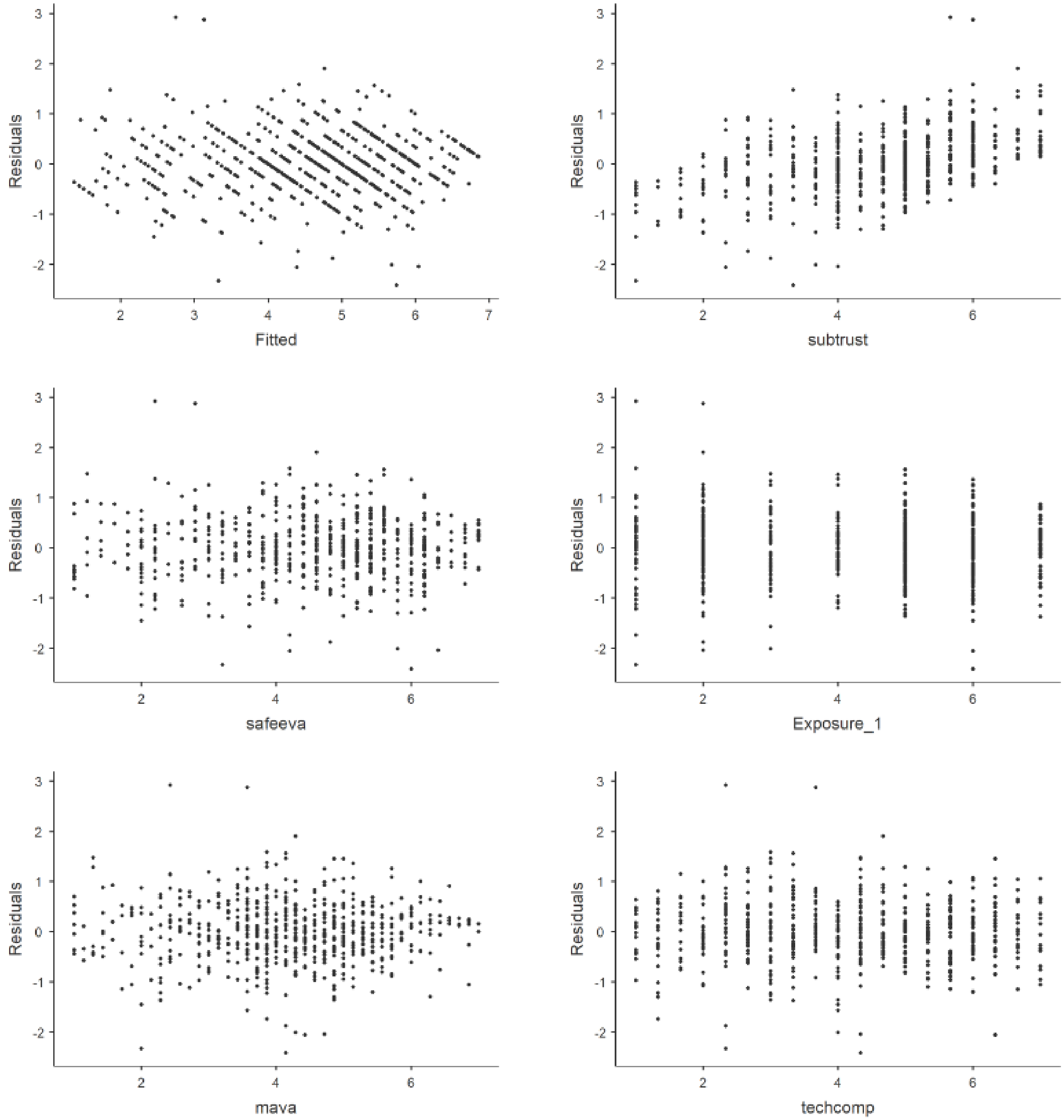
Variable	*M*	1	2	3	4	5	6
1. Propensity to trust	5.23						
2. Technical competence	4.06	-.01					
		[-.07, .06]					
3. Propensity to trust automation	5.18	.29**	.29**				
		[.23, .34]	[.23, .34]				
4. Subjective trust in shared autonomous shuttles	4.59	.26**	.25**	.51**			
		[.20, .32]	[.19, .31]	[.46, .55]			
5. Intention to use SASs	4.99	.22**	.30**	.47**	.82**		
		[.16, .28]	[.24, .36]	[.42, .52]	[.80, .84]		
6. Safety evaluation	4.54	.26**	.26**	.48**	.88**	.87**	
		[.20, .32]	[.20, .32]	[.43, .53]	[.86, .89]	[.85, .89]	
7. MAVA	4.15	.26**	.34**	.42**	.75**	.81**	.82**
		[.20, .32]	[.28, .40]	[.37, .47]	[.72, .78]	[.79, .83]	[.80, .84]

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$. ** indicates $p < .01$.

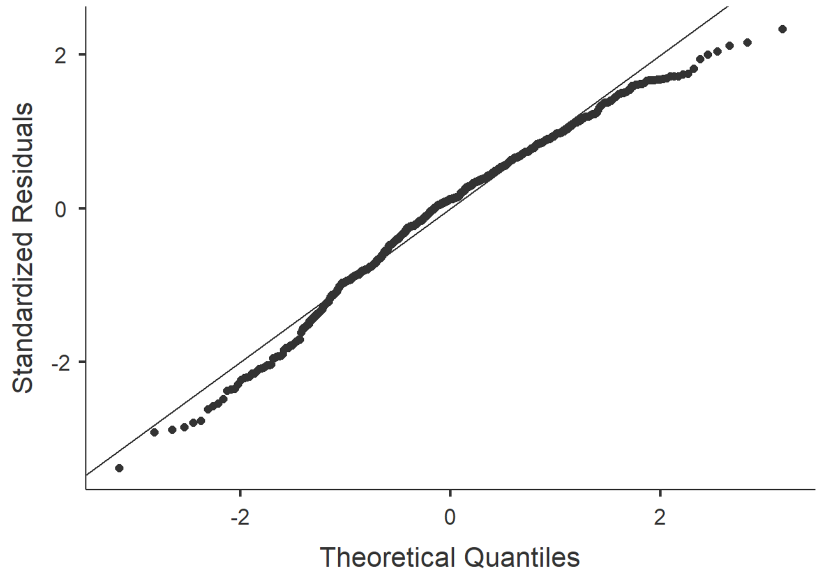
Appendix G – QQ and Residual Plots for Multivariate Regression Models

Model 1




Residuals
Fitted
Residuals
subtrust
Residuals
safeeva
Residuals
Exposure_1
Residuals
mava
Residuals
techcomp

Model 2


Standardized Residuals
Theoretical Quantiles
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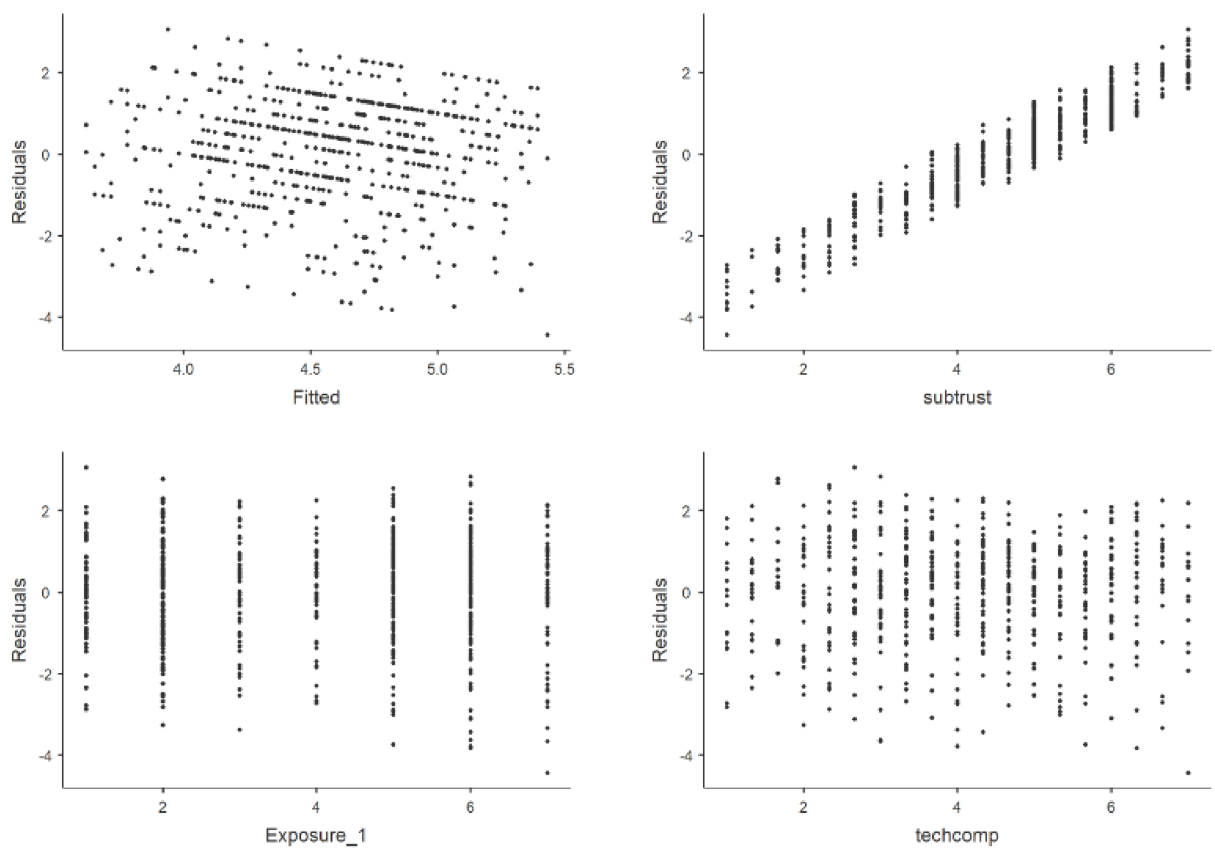
0
-2
-2
0
2


Residuals
Fitted
4.0
4.5
5.0
5.5
subtrust
Exposure_1
techcomp
2
0
-2
-4
2
4
6