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# Transport safety and human factors in the era of automation: What can transport modes learn from each other?

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## ABSTRACT

One of the main aims of introducing automation in transport is to improve safety by reducing or eliminating human errors; it is often argued however that this may induce new types of errors. There is different level of maturity with automation in different transport modes (road, aviation, maritime and rail), however no systematic research has been conducted on the lessons learned in different sectors, so that they can be exploited for the design of safer automated systems. The aim of this paper is to review the impact of key human factors on the safety of automated transport systems, with focus on relevant experiences from different transport sectors. A systematic literature review is carried out on the following topics: the level of trust in automation – in particular the impact of mis-aligned trust, i.e. mistrust vs overreliance, the resulting impact on operator situation awareness (SA), the implications for takeover control from machine to human, and the role of experience and training on using automated transport systems. The results revealed several areas where experiences from the aviation and road domain can be transferable to other sectors. Experiences from maritime and rail transport, although limited, tend to confirm the general patterns. Remarkably, in the road sector where higher levels of automation are only recently introduced, there are clearer and more quantitative approaches to human factors, while other sectors focus only on mental modes. Other sectors could use similar approaches to define their own context-specific metrics. The paper makes a synthesis of key messages on automation safety in different transport sectors, and presents an assessment of their transferability.

## 1. Introduction

### 1.1. Background

Transport accidents have high socioeconomic impacts. In the rail, aviation and maritime sectors, there are between 0.05 and 0.35 fatalities per billion passenger-kilometres of travel (EU Agency for Railways, 2016), in a relatively low number of accidents but with many fatalities per accident, attracting thus the public interest. On the other hand, road traffic fatality risk is more than 20 times higher than that of other transport modes, estimated at 5.8 per billion vehicle-kilometres of travel (ETSC, 2016), with ~70 fatalities occurring on European Union's (EU) roads every day. There are different accident contributory factors and safety issues in different transport modes, however human factors are persistently among the major causes of accidents. In particular, human factors are known to be responsible for more than 90 % of road accidents (due to e.g. speeding, distraction, driving under the influence

of alcohol, inexperience etc.). In aviation, 80 % of accident causes are attributed to human causes, a share that has been increasing over time with the deployment of automation (Nagel, 1988). Moreover, recent research demonstrated that while investigating maritime accidents due to automation failure, 60 % of these accidents were still caused by human errors (Pazouki et al., 2018).

Overall, the goals of automation are to increase safety and efficiency (Harris, 2011). In road transport, one of the main purposes of developing autonomous vehicles (AVs) is to 'eliminate' the impact of human error on road safety. Automation is rapidly emerging in the road and maritime sectors, while there are already considerable experiences from automation in the aviation and rail sectors. Nevertheless, transport automation cannot yet handle all situations. When the system's boundary of automation capability is reached, a human operator must reclaim manual control (van der Kleij et al., 2018). In the road sector, six levels of automation are defined, ranging from levels 0 & 1 (no automation or simple driver assistance), to levels 2 & 3 (conditional or

partial automation), to levels 4 & 5 (high or full automation) – the latter being the ones in which the driver is not required to be ready to take control of the vehicle at all times (SAE, 2018).

One of the requirements for successful implementation of automation is trust (Hoff and Bashir, 2014). Trust can be defined as "the attitude that an agent will help achieve an individual's goal in a situation characterized by uncertainty and vulnerability" (Lee and See, 2004). Trust is not only important for implementing new technology, but also for the correct use of new technology. On the one hand, when trust is low or absent, the automated system might not be used. On the other hand, excessive trust in automation could lead to misuse of the automated system. It may instil complacency and complete lack of monitoring (Lee and See, 2004; Bailey and Scerbo, 2007). Misaligned levels of trust in automation have been related with accidents involving different modes of transport (Hoff and Bashir, 2014), e.g. the Scandinavian Airlines Flight 901 incident (NTSB, 1984), the disaster of the cruise ship Costa Concordia in 2012, and the Tesla fatal road crash with a semi-trailer in Florida in May 2016 (NTSB, 2017). It is found that 77 % of incidents in the NASA's Aviation Safety Reporting System (ASRS) database are related to overreliance on automation (Molloy and Parasuraman, 1996; Mosier et al., 2013).

Furthermore, in high levels of automation the human's tasks switch from manually operating to passively monitoring whether the automated system functions correctly and intervening where necessary. Given that humans are not good at monitoring systems (Wiener and Curry, 1980; Bainbridge, 1983), the so-called "out-of-the-loop" (OOTL) performance problem can lead to new accident mechanisms (Endsley and Kirris, 1995). The OOTL problem is largely due to loss of situation awareness (SA). SA is defined as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future". When SA is lost, humans cannot intervene effectively, since they first need to recover awareness of the system state before taking over control (Endsley, 2017; Gartenberg et al., 2014). This requires time, which might be unavailable, possibly leading to errors or accidents and decreasing safety (Biondi et al., 2019). Higher levels of automation create lower workload for humans and higher human-system performance under normal circumstances, but decrease operator SA (Onnasch et al., 2014; SAE, 2018). Several aviation and maritime accidents were linked to a loss of SA due to misunderstanding of or over-trust in the automation, e.g. American Airlines flight AA903, TAROM flight ROT381 (Martins, 2016), Air France flight 447 (Salmon et al., 2016) and the Royal Majesty vessel grounding (Lützhöft and Dekker, 2002).

Within the deployment of automated transport systems, the transition from the automated system to manual driving labelled as takeover control is given strong emphasis in the recent literature However, the experiences from other transport modes on takeover control failures with respect to SA and OOTL performance problems, and the possibilities for transfer of knowledge, have not been adequately examined.

Moreover, research in different transport modes has demonstrated that automation safety is strongly associated with experience with and training on the use of automation, especially with respect to skills critical for the safe interaction between human and machine, i.e. SA, performing tasks simultaneously, automation complacency (McBride et al., 2014). The extent to which this knowledge could be transferred to the context of safe operation of AVs has not been examined in existing studies.

Overall, there is a 'silos' effect in transport automation and safety research: most literature focuses exclusively onto one transport sector (aviation, maritime, rail, or road), with only few authors comparing different transport modes (e.g. Trösterer et al., 2017). Yet, there may be considerable opportunities for transfer of knowledge and lessons to be learnt in this field. On the one hand there are decades of experience with aviation operators' training and response to increasingly high levels of automation, and on the other hand there is a rapidly emerging trend towards higher automation in the other transport sectors, that

could benefit from that experience. The similarities between transport modes in terms of purpose (mobility & transport), physical and mental modes of operation (e.g. steering, monitoring) and relevant societal risks leads to assume – despite their differences - that the comparison between them would be more relevant than with other non-transport related sectors, and the potential for transferability will be higher.

*1.2. Objectives*

This paper aims to review existing research in different transport domains (road, aviation, maritime and rail) regarding the conditions for safe automation with respect to key human factors affecting driver/operator performance, in order to identify lessons learnt in different modes and their transferability to other modes. The topics reviewed include: the level of trust in automation – in particular the impact of mis-aligned level of trust, the resulting impact on driver/operator situation awareness, the implications for takeover performance from machine to human, and the role of experience and training on using automated transport systems. While these topics are reviewed separately here, in reality the concepts may overlap.

The paper is structured as follows: Section 2 presents the methods for conducting a systematic literature review on the examined topics, the selection and prioritization criteria for studies. Section 3 includes the results of the review, summarized per key human factor and per transport mode. Section 4 includes a discussion of the results with focus on the identification of key areas for transfer of knowledge between transport modes, as well as an assessment of the transferability conditions. Section 5 presents conclusions and areas for further research in this field.

## 2. Methodology

A systematic review of existing literature was conducted through key databases including Scopus, Web of Science, and TRID. The search strategy was based on a combination of search terms in a structured and iterative manner on the basis of the following general rule: < automation > AND < safety > AND < transport mode > AND < human factor > ; the search was carried out separately for each transport mode (road, rail, aviation, maritime) and human factor (trust, situation awareness, transition of control, experience and training). The keywords used per concept are summarized in Table 1. The search was limited to papers in English.

The number of 'hits' (i.e. the results of the initial search) for each human factor was quite high e.g. 410 articles for trust, 399 for SA (190 results for aviation, 28 for maritime, 18 for rail and 163 for road). In each case, articles were filtered first by their titles to eliminate results obviously irrelevant for this research. Later, the process of filtering was continued by screening the abstracts of the remaining results. For the relevant literature, full body text was examined. Lastly, references present in the finally selected literature were reviewed and included ('backwards snowballing').

The criteria for article selection can be outlined as follows:

**Table 1**
Research topics and search terms used.

| Research topics | Keywords |
|---|---|
| Automation | Automation, autonomous, driverless, autopilot |
| Safety | Safety, risk, collision, crash, accident, incident |
| Transport mode | Road, driver, vehicle, aviation, flight, pilot, crew, maritime, marine, vessel, rail, train, operator |
| Trust | Trust, complacency, over-trust, overreliance, mistrust, distrust, lack of trust, under-reliance |
| Situation awareness | Situation* awareness, SA, out-of-the-loop, OOTL |
| Transition of control | Transition of control, take overs, takeover control |
| Experience / Training | Experience, expertise, skills, training, practice |

(i) All included articles should focus on the impact of the respective human factor on automation safety. Articles that did not focus on transport automation were excluded (e.g. health automation). Studies focusing on military transport were excluded, since the military operates under different conditions. Articles had to focus on the impact on the human operator, thus impacts on other humans in the transport field (e.g. traffic controllers) were excluded.

(ii) Articles that focus on high levels of automation that require a low (but non-zero) human involvement (i.e. an equivalence of SAE driving automation levels 3 or 4) were considered more relevant for this study.

(iii) To ensure quality, selected articles should have a clear and transparent description of the research method used. Moreover, in case of many articles, those reporting quantitative results were prioritized over qualitative studies, as quantitative results typically include information on confidence intervals and statistical significance of the identified effects, enhancing thus their reliability. In certain cases, more recent articles were prioritized over outdated ones. For instance, articles published after 1990 for the aviation sector and after 2000 for the rail and maritime sectors were prioritized.

In case of trust, SA, experience and training, all eligible studies as per the above criteria were included. In the case of transition of control, the initial search yielded a very high number of potentially relevant studies; in this case, an additional criterion of prioritization of existing reviews and meta-analyses was added; these were then complemented with studies published only after the publication date of the review/ meta-analysis

Fig. 1 shows the included eligible studies per human factor and transport sector. In total, 15 studies on trust, 35 on SA, 10 on transition of control and 14 on experience and training were included. 41 of these focus on the road domain, 21 on aviation, 9 on maritime and 3 on rail. Three meta-analyses on transition of control and SA in the road sector were found and included. No meta-analyses for other study areas were found.

## 3. Results

### 3.1. Mis-aligned trust in automation

Fig. 2 illustrates the relationship between trust and automation capability. As mentioned previously, on the one hand, when trust is low or absent, the automated system might not be used. On the other hand, excessive trust – over-trust – in automation could lead to the wrong use of the automated system. Therefore, the critical question is that of properly aligned level of trust.

### 3.1.1. Road sector

Studies from the road transport sector are mostly based on driving simulator research. Payre et al. (2016) executed a simulator study with 69 participants aimed at investigating the effects of trust, among others, when using fully automated driving. They found a positive correlation

between level of trust and manual control recovery time in emergency circumstances.

Another simulator study (Xiong et al., 2012) researched the use patterns of adaptive cruise control (ACC) among early adopters. It was suggested that three clusters of ACC use exist: risky, moderate risky and conservative. Drivers with risky driving behaviour had relatively high trust in the ACC (potentially "misaligned trust") and took more time to respond to critical events.

The simulator study by Johns et al. (2018) tested the outcome of support systems and driver alerts on driving performance. They conclude that over-trust in automation has indirect effects on the user who will become more vulnerable to unanticipated external influences on steering, such as in case of a pothole, a banked road, and wind forces.

In Miller et al. (2016), the use of steering wheel mounted buttons enabling or disabling the automated driving system was tested. Alternatively, drivers could put a hand on the steering wheel equipped with captive touch-sensitive technology. The automated control could be reversed by the throttle and brake pedals, which resulted in a variation of behaviours in different events. Driver's behaviour varied, some of them did not trust in the automated driving. The researchers conclude that it is dangerous to over-trust the systems in situations that tend to be strange, unpredictable, and hazardous.

Victor et al. (2018) examined how to secure driver conflict intervention and monitoring commitment while using high, but not fully reliable automation. A test vehicle followed a lead vehicle, and the experiment was setup to present a conflict. 28 % of participants had a crash event, mainly due to their high levels of trust in the automated car. In a study that analysed data from autonomous vehicles testing in California (Dixit et al., 2016), a positive correlation was found between distance travelled and reaction time, thereby suggesting that trust in the autonomous vehicle increases over time. They also show evidence that drivers who lack trust will take manual control of the vehicle and reduce reaction time.

Yet another study researched to what extend different human factors influenced latent hazard detection in highly automated vehicles (Vlakveld et al., 2018). Results showed that the trust in the reliability of the automated system was not a significant predictor for the number of gazes at latent hazards.

### 3.1.2. Aviation sector

Relevant examples from flight simulator research (Bailey and Scerbo, 2007) found a correlation between high levels of trust of the pilot and low levels of monitoring. This research was based on two studies which evaluated the impact of monitoring complexity, system reliability, operator trust and system experience on automation-induced complacency.

Another study (Wickens et al., 1999) used a simulator to represent air-to ground targeting missions of 3 min, expecting guidance from a navigation system on a forward view. There was no cue on the 33 % of the simulation trials. On the 67 % of the cuing, 40 % were wrong. Pilots got directions to say 'target' and to focus their simulated aircraft boresight on the main objective and restraint the trigger when their purpose was right. They also got instructions to say 'abort' if they did
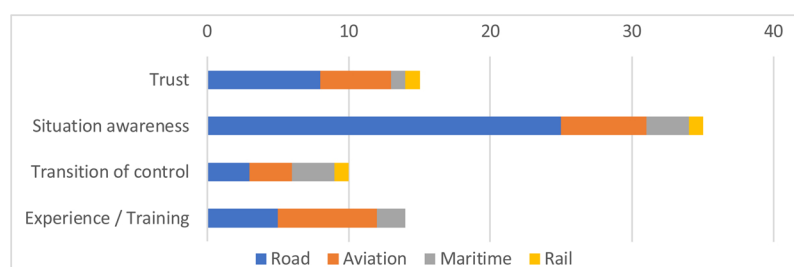


**Fig. 1.** Number of included articles per human factor and transport domain.
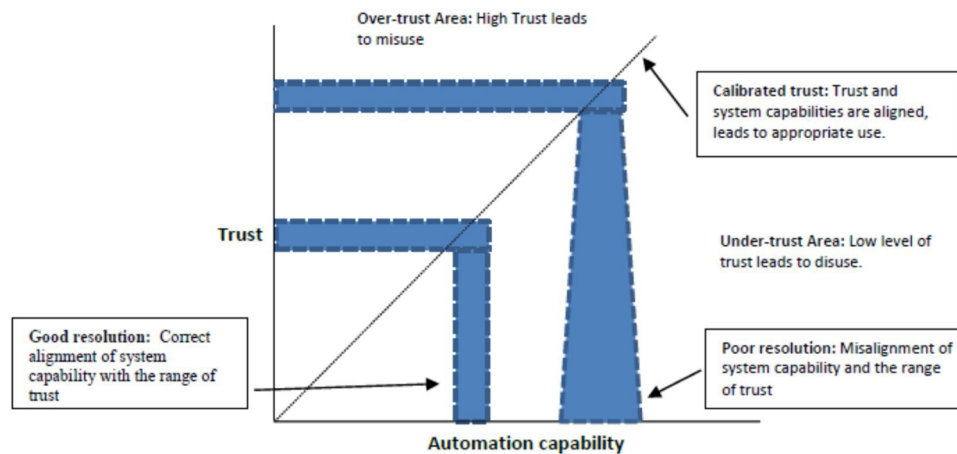
**Fig. 2.** Relationship among trust levels and automation capability. Adapted from Lee and See (2004).

not trust that the objective was in scene. After each trial, pilots were requested to express their decision confidence on a 4-point scale. The results were unexpected and demonstrated the risks of over-trust especially when automation supports difficult tasks for the user.

Dorneich et al. (2017) did an empirical investigation which appraised key human factors issues associated with automation visibility and information quality. One test examined the interaction between automation visibility and information quality in the context of a decision-aiding automation. In this investigation, over-trust in the automation's recommendations led to failure to annul insignificant diversion aid instructions. Confidence did not change despite the different conditions. However, it had a negative result on the performance when information quality was low. Pilots spent less time checking for missing information due to their high trust in automation.

Based on reports from the Aviation Safety Reporting System (ASRS), the variety of situation awareness errors in aviation was studied (Jones and Endsley, 1996). 143 episodes were studied, such as elements related to the failure of overseeing data by pilots and controllers, comprising overreliance on automation (2.77 % of the situation awareness errors). A greater number of the dependence on automation errors aroused from the expectation of the flight crew from the autopilot or the flight management system to perform significant tasks.

### 3.1.3. Maritime sector
In the maritime sector, a study (Pazouki et al., 2018) evaluated the consciousness of deck officer cadets identifying an emergency circumstance due to the defeat of the autopilot in a vessel simulator. The research did not show a correlation between recognition time of an autopilot failure with the level of trust in automation. On the contrary, the shortest recognition time was from the subject with highest trust.

### 3.1.4. Rail sector
For the rail sector, a study about use, disuse and abuse of railway automation (Parasuraman and Riley, 1997) reports the case of the Conrail train accident near Baltimore in 1987. The investigation suggested that drivers ignored visual and auditory warning signals in the train cab, therefore, were not alert of the speed violation. The researchers relate this with under-reliance on automation.

### 3.1.5. Summary
The findings about the effect of inappropriate levels of trust in automation are summarized in Table 2. Most literature found that the level of trust impacted safety. In case of overreliance on automation, reaction time increases, SA decreases, and the likelihood of an accident increases. A lack of trust reduces reaction time, because the operator does not rely on the system and therefore remains alert. But that lack of trust can also lead to accidents when the operator decides to ignore

indications of the system. Yet other studies found that the level of trust had no influence on the recognition time of an autopilot failure (aviation) or the number of spotted latent hazards (road).

In general, limited research on the impact of trust was found in the maritime and rail domain. Furthermore, only few studies investigated the impact of under-reliance, while most articles focused on over-reliance.

### 3.2. Situation awareness in automated driving

This section places focus on the causes and impacts on SA with automated systems in different transport sectors. Research into the effect of automation on SA in aviation is conducted since the 1990s (Wickens, 2008). In recent years many researchers are studying the effect of (semi) automation on SA of car drivers; these are meta-analysed in de Winter et al. (2014). The present paper summarizes their findings and adds additional literature.

### 3.2.1. Road sector
In general, in the road sector SA may be measured by a variety of metrics:

- Eye-movements based: % of time looking at the road center / in the side mirror (e.g. in Barnard and Lai, 2010; Carsten et. Al, 2012; Vogelpohl et al., 2018)
- Object detection and comprehension-based: spot sudden appearance of objects, % of latent hazards detected (e.g. in Barnard and Lai, 2010; Vlakveld et al., 2018)
- Voluntary uptake of non-driving related tasks (NDT) (e.g. in Omae et al., 2005; Levitan & Bloomfield, 1996)
- Response to critical events: reaction time / brake response time, takeover time at disengagement of automation, rear-end collision avoidance, lane changing ability (e.g. Merat and Jamson, 2009; Strand et al., 2014; Schermers et al., 2004)

More specifically, several studies found that drivers distracted by a non-driving related task (NDT) looked less at the road center during highly automated (HAD) than manual driving, both in simulator (Barnard & Lei, 2010; Carsten et al., 2012) and in test-track studies (Llaneras et al., 2013). Vogelpohl et al. (2018) found that, while break reaction times for distracted drivers are the same as for manual drivers, distracted drivers were slower in securing their driving environment by looking in the side-mirror than drivers without an NDT or manual drivers. It has been found that, the less lead time inexperienced NDT-distracted HAD-drivers have, the less latent hazards they look at (Samuel et al., 2017). The recognition rates are the same as during manual driving, indicating drivers need 8 s to build up SA after

**Table 2**
Impacts of mis-aligned trust in automation in different transport modes.

| Source | Transport mode | | | | Method | | | Level of trust | | Impact of mis-aligned trust |
|---|---|---|---|---|---|---|---|---|---|---|
| | Road | Aviation | Maritime | Rail | Simulator | Investigation report | Other | Overreliance | Underreliance | |
| Payre et al., 2016 | • | | | | • | | | • | | Increased manual control recovery time |
| Xiong et al., 2012 | • | | | | • | | | • | | Riskier driving behavior |
| Victor et al., 2018 | • | | | | • | | | • | | Drivers could not handle conflict |
| Dixit et al., 2016 | • | | | | | | • | • | • | Higher reliance increased reaction times; under reliance increased likelihood to manually takeover control |
| Johns et al., 2018 | • | | | | • | | | • | | Indirect effects. Driver more vulnerable to unanticipated influences on steering |
| Miller et al., 2016 | • | | | | • | | | • | | Over-trust is dangerous in emergency situations |
| Vlakveld et al., 2018 | • | | | | • | | | • | • | The level of trust had no impact on the number of spotted latent hazards |
| NTSB, 2017 | • | | | | | • | | • | | Lack of responsiveness can lead to fatal accidents |
| Bailey and Scerbo, 2007 | | • | | | | | | • | | Reduced ability to monitor complex systems |
| Dorneich et al., 2017 | | • | | | | • | | • | | Low quality information with high trust lead to failure to check for missing information and recognise important information. |
| Jones & Endsley 1995 | | • | | | | | | • | | Overreliance on automation represented 2.77 % of the SA errors |
| Wickens et al., 1999 | | • | | | • | | | • | | Over-trust is especially risky when automation is used in difficult task |
| NTSB, 1984 | | • | | | | • | | • | | Overreliance on autothrottle led to accident |
| Pazouki et al., 2018 | | | • | | • | | • | • | • | No impact of trust on recognition time of an autopilot failure |
| Parasuraman and Riley, 1997 | | | | • | | | | | • | Underreliance on warning systems led to fatal accident? |

takeover. During follow-up studies (Wright et al., 2017; Vlakveld et al., 2018), researchers found that more experienced middle-aged drivers only needed $4-6$ sec to gaze at latent hazards and build up SA, compared to young drivers. Additionally, age, driving experience, sensation seeking, trust in the reliability of automation and the extent of NDT-involvement were no significant predictors of number of gazes at hazards.

Several simulator studies show that drivers that were OOTL reacted more slowly to critical events and performed worse after regaining vehicle control than manual drivers, i.e. had slower or fewer break responses (de Waard et al., 1999; Merat and Jamson, 2009), slower reaction times (Damböck et al., 2013), more collisions with lead vehicles (Strand et al., 2014), a decreased ability to keep the vehicle on the road (Flemisch et al., 2008), or a reduced likelihood to change lanes (Schermers et al., 2004). Furthermore, van den Beukel et al. (2013) found that, the shorter the time between takeover request (TOR) and collision, the more likely an accident will happen. Another simulator study showed that lower degrees of visual information (e.g. fog) increased takeover time (TOT) (Louw et al., 2017). These studies provide evidence that being OOTL while driving leads to worse driving performance and higher accident risk.

Other studies however provide evidence that HAD leads to similar responses to critical events as manual driving. Researchers found HAD drivers and manual drivers had comparable reaction behaviours and times to unexpected breaking of lead vehicles (Martens et al., 2008; Lank et al., 2011; Louw et al., 2017), as well as comparable reactions to unexpected required lane changes (Merat et al., 2012). Additionally, if the automation failed unexpectedly without warning signal, drivers were able to take over control when needed and were able to avoid accidents (Kircher et al., 2013). Gold et al. (2013) found that distracted HAD drivers were able to avoid obstacles with lead times of $5-7$ sec, even though their responses were more abrupt. A simulator study (van den Beukel et al., 2013) found that, the less time HAD drivers had between takeover and collision, the lower they rated their SA score using the SART (Situation Awareness Rating Technique) method, showing that time criticality and SA are significantly correlated. Additionally, drivers rated their SA higher if they did not have an accident, implying higher SA-levels lead to less collisions.

In a study by Lu et al. (2017), participants watched videos of traffic situations on highways lasting between $1-12$ s. Afterwards they had to reproduce the positions, distances and speeds of the other cars. Results showed the number of correctly positioned vehicles and the total distance error improves up to 7 s and 12 s respectively, and then plateaus. The estimation of other vehicles' speeds showed no saturation affect, implying SA is still being gained even 20 s later.

### 3.2.2. Aviation sector

Several studies on SA and automation exist from the aviation sector. Jones and Endsley (1996) identified 143 airplane incidents that were caused by SA errors. 22.9 % of these incidents were found to be associated with errors caused by workload and task distraction. Many of these were due to dealing with automation, but it is unclear how many exactly.

In a semi-structured interview study (Trösterer et al., 2017), pilots emphasized the importance of understanding the different automation modes to understand what is happening and to decide if it is working correctly. The primary flight display and flight mode annunciators, which show important system information on one screen and is easily monitored, help pilots to keep a better overview and improve their SA.

A pen-and-paper-based scenario study with 62 professional pilots concluded that the level of automation impacts SA. Only automation systems requiring several input steps were judged to impair SA (Mosier et al., 2013).

Field et al. (2016) showed in a simulator study that higher-performing crews (measured by means of a desirable flight crew performance list) had better SA than low-performing crews when dealing with

unlikely events, particularly during high workload segments. They concluded that these crews use their skills (knowledge, teamwork, problem solving, decision-making) better, helping them maintain better SA.

### 3.2.3. Maritime sector

In the maritime sector, a study (Øvergård et al., 2015) interviewed operators involved in near-accidents due to automation failures where operators successfully took-over manual control. Even with low SA levels, most operators were able to understand there was a problem and avoid accidents by using pre-defined procedures. A simulator study (Pazouki et al., 2018) found that 5/6 deck officers without prior training failed to recognize a subtle failure of the autopilot due to being distracted by a questionnaire, while 5/6 officers with training recognized the failure. The untrained officers had lower SA levels than trained ones.

Another simulator study (van der Kleij et al., 2018) tested a change support tool that helps monitoring by showing if parameters changed excessively over time. Participants had to monitor values and decide on the correct response. In half the scenarios participants were distracted by a second task. No differences in performance and SA for the cases no support/no distraction, support/no distraction and support/distraction were found. Performance and SA were significantly worse for no support/distraction. This shows the support system can help distracted monitors reach the same SA levels and performance as non-distracted monitors, however they also found action response times were lower than without distraction.

### 3.2.4. Rail sector

In the railway sector, a simulator study (Suter and Stoller, 2014) showed that time pressure negatively impacts SA performance as observed in train drivers for difficult sections. However, time pressure had no effect on train driver's own perception of SA (measured by SART).

### 3.2.5. Summary

Research shows human operators are not good at taking over manual control after having been OOTL, and that low SA negatively affects takeover performance and safety. Lower SA levels led to a lower ability to take correct decisions, a lower likelihood to spot sudden appearances of objects and a lower likelihood to avoid collisions. The evidence for whether low SA levels negatively impacts reaction times to critical events (with or without TOR) is unclear: some studies supported this, others did not. The consequences of lower SA levels are summarized in Table 3a.

With regards to causes of SA levels, various human, technological and environmental factors were identified. Specifically, automation overreliance, not understanding automation, task distraction, time pressure and higher levels of automation negatively impacted SA. However, training, experience, supporting tools, planning trips ahead and more lead time can significantly improve SA. The results of SA causes are summarized in Table 3b.

When comparing the different transport modes, it was observed that research in aviation and maritime mostly focused on causes of low SA, while research on road driving focuses on both causes and consequences. However, in both the maritime and rail sectors, research into SA is very limited.

## 3.3. Transition of control between human and machine

### 3.3.1. Road sector

The transition of control from automated to manual driving became an increasingly debated topic within the road transport sector. The takeover time budget (TTB) is often defined as: "the sum of time from the takeover request and the time to the collision" (Clark and Feng, 2017). Zhang et al. (2019) define the time budget more generally as the 'time available until the system limit of the automation is reached',

including cases of an upcoming collision or operational limits of the automated system (e.g., due to faded road markings). The takeover time (TOT) is the time until the first signs of steering corrections or braking behaviour are diagnosed after automation is switched off, and includes a perception time, a cognitive processing time, and a time to assume motor readiness (e.g. place hands on the wheel, foot on the brake etc.). Fig. 3 shows a graphical depiction of the takeover procedure from automated driving to manual driving.

An extensive literature review on factors that influence takeover control in AVs based on 83 empirical studies was published recently (McDonald et al., 2019), as well as an extensive meta-analysis on takeover control (Zhang et al., 2019). The influential factors on takeover control in the road sector described in these reviews are the takeover time budget (TTB), secondary/NDT tasks, the modality of the takeover request, the manner of the takeover, the driving environment, the level of automation and driver factors. The impact of these influential factors on takeover control are described below.

The transition can either be an emergency takeover or a non-emergency takeover. In a non-emergency takeover automation is switched off on a system-based regular level while in an emergency takeover automation is switched off by an unexpected event. Generally, it was found that the takeover time (TOT) of both transitions was almost similar (McDonald et al., 2019). However, via a driving simulation study, whereby drivers completed three experimental drives, it was demonstrated that non-emergency transitions exhibited a better takeover quality (TQ), expressed by better lateral control and more steering corrections within the same TOT (Merat et al., 2014). It is noted that takeover quality (TQ) is a broad term used to reflect the transition by means of a variety of metrics, ranging from longitudinal and lateral control metrics to driver hazard perception and state awareness aspects.

The results of the examined studies portray that a longer TTB increases the total TOT while shorter TTB results in a poor TQ. Additionally, a secondary NDT influences takeover control. The extent of the impact depends on the type of secondary task, but generally, TOT increases and TQ decreases. Furthermore, takeover modality entails the type of indication that is given to the driver when automation is switched off e.g. auditory, visual or vibrotactile indications. Generally, auditory and vibrotactile modalities improve the TOT compared to visual. Studies show that the driving environment e.g. weather conditions, road elements, and traffic situations also impact takeover control. For example, adverse weather and dense traffic increase TOT and decrease TQ. Moreover, studies demonstrated that a higher automation level increases TOT and decreases TQ. Finally, driver factors such as low situation awareness and mis-aligned trust in automation usually negatively impact takeover performance.

### 3.3.2. Aviation sector

In the aviation sector, empirical evidence has shown that mode errors and automation surprises had led to several aviation incidents due to pilot-automation breakdowns providing a need for manual control (Sarter, 2008). Most studies concern flight simulators testing scenarios and address mental modes affecting the transition rather than factors related to the takeover request like takeover modality. An important factor that impacts the ability to recognize automation failure and the need for manual control, thereby, impacting the takeover performance of pilots is automation complacency (Parasuraman et al., 1993).

Moreover, combining a degraded SA, with overreliance on automation and automation complacency can lead to a poor takeover performance (Advisory Group for Aerospace Research and Development, 1995; Jarvis et al., 2014). In Hancock (2017) thirty-two experienced pilots participated in the transition from automated back to a multi-task manual environment. It examined four different ways of invoking automation: system-initiated automation; pilot command by negation; pilot command by initiation; and pilot-initiated automation. Additionally, the takeover request modalities concerned: visual, auditory

**Table 3**
Impacts of highly-automated systems on SA in different transport modes.

**(a) Impacts on SA**

Factors that influence SA (Causes): Higher (factor) leads to higher SA (+), lower SA (-), or has no effect on SA (o)

| Source | Transport mode | | | | Method | | Other | Impacts on SA (Causes of SA) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Road | Aviation | Maritime | Rail | Simulator / Test track | Interview | | Automation over-reliance | Not understanding automation | Task distraction | Planning trip ahead and comparing the autopilot's actions to the plan |
| Jones and Endsley (1996) | | • | | | | | •[1] | - | - | | |
| Pazouki et al. (2018) | | | • | | • | | | | | - | |
| van der Kleij et al. (2018) | | | • | | • | | •[2] | | | - | |
| de Winter et al. (2014) | • | | | | • | | | o | | - | |
| Vlakveld et al. (2018) | • | | | | • | | | | | | |
| Trösterer, et al. (2017) | | • | | | • | | | | | | + |
| Field et al. (2016) | | • | | | | • | | | | | |
| Wright et al. (2017) | • | | | | • | | •[3] | | | | |
| Mosier, et al. (2013) | | • | | | • | | | | | | |
| Samuel et al. (2017) | • | | | | • | | | | | | |
| Lu et al. (2017) | • | | | | •[4] | | | | | | |
| van den Beukel and van der Voort (2013) | • | | | | • | | | | | | |
| Suter and Stoller (2014) | | | | • | • | | | | | | |
| Louw, et al. (2017) | | | | | • | | | | | | |
| Øvergård et al. (2015) | • | | • | | | • | | | | | |

**(a) Impacts on SA**

Factors that influence SA (Causes): Higher (factor) leads to higher SA (+), lower SA (-), or has no effect on SA (o)

| Source | Impacts on SA (Causes of SA) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Decision-making skills | Experience | Training | Level of automation | Lead time | Informative tools | Time-pressure | Visual information | Predefined procedures |
| Jones and Endsley (1996) | | | | | | | | | |
| Pazouki et al. (2018) | | | + | | | | | | |
| van der Kleij et al. (2018) | | | | | | + | | | |
| de Winter et al. (2014) | | | | - | | | | | |
| Vlakveld et al. (2018) | | | | | + | + | | | |
| Trösterer, et al. (2017) | | | | | | | | | |
| Field et al. (2016) | + | | | | | | | | |
| Wright et al. (2017) | | + | | - | + | | | | |
| Mosier, et al. (2013) | | + | | | | | | | |
| Samuel et al. (2017) | | | | | + | | | | |
| Lu et al. (2017) | | | | | + | | | | |
| van den Beukel and van der Voort (2013) | | | | | + | | | | |
| Suter and Stoller (2014) | | | | | | | - | | |
| Louw, et al. (2017) | | | | | | | | + | |
| Øvergård et al. (2015) | | | | | | | | | + |

**Table 3** (*continued*)

(b) Impacts of SA

Factors influenced by SA (Consequences): Lower levels of SA lead to increase of factor (+), a decrease of factor (-) or has no effect on factor (o)

| Source | Transport mode | | | | Method | | | Impacts of SA (Consequences) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Road | Aviation | Maritime | Rail | Simulator / Test track | Case study | Video-based | Ability to take the correct decision | Likelihood to spot sudden appearances of objects | Likelihood to avoid collisions | Reaction times to critical events | Reaction times to critical events without TOR |
| Salmon et al. (2016) | | • | | | | • | | - | | | | |
| van der Kleij et al. (2018) | | | • | | • | | | - | | | | |
| Lu et al. (2017) | • | | | | • | | | - | | | | |
| Field et al. (2016) | | • | | | • | | • | - | | | | |
| Barnard and Lai (2010) | • | | | | • | | | | - | | | |
| Vlakveld et al. (2018) | • | | | | • | | | | - | | | |
| Samuel et al. (2017) | • | | | | • | | | | - | | | |
| Wright et al. (2017) | • | | | | • | | | | | | | |
| Strand et al. (2014) | • | | | | • | | | | | - | | |
| Gold et al. (2013) | • | | | | • | | | | | - | | |
| van den Beukel and van der Voort (2013) | • | | | | • | | | | | - | | |
| Damböck et al. (2013) | • | | | | • | | | | | | - | |
| Merat and Jamson (2009) | • | | | | • | | | | | | - | |
| Omae et al. (2005) | • | | | | • | | | | | | - | |
| Schermers et al. (2004) | • | | | | • | | | | | | - | |
| de Waard et al. (1999) | • | | | | • | | | | | | - | |
| Merat et al. (2012) | • | | | | • | | | | | | o | |
| Lank et al. (2011) | • | | | | • | | | | | | o | |
| Martens et al. (2008) | • | | | | • | | | | | | o | |
| Louw, et al. (2017) | • | | | | • | | | | | | o | |
| Kircher et al. (2013) | • | | | | • | | | | | | | o |
| Young (2000) | • | | | | • | | | | | | | o |

[1] accident investigation.
[2] review.
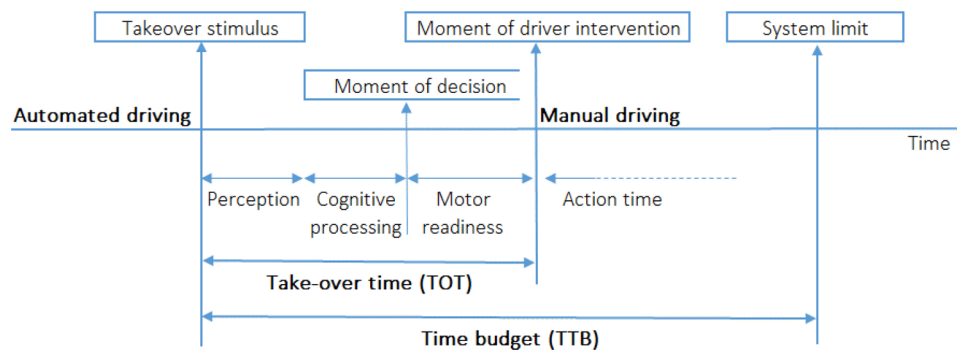[3] survey.
[4] video experiment.

**Fig. 3.** Takeover procedure from automated to manual driving (Adapted from: Zhang et al., 2019).

or combined. The display was either small or big and placed in a central or tangential location. Results showed that takeover performance depended on a combination of the above-mentioned factors and that each factor influenced different tasks. For instance, system-initiated automation had a significantly different impact on tracking performance, and was also associated with increased pilot fatigue; visual warning was found to be more mentally demanding than auditory or combined; the display location affected specific subtasks. Overall, there was a significant three-way interaction between invocation, display and warning modalities, however both performance and subjective perception of multitask demand were increased in system-initiated automation.

### 3.3.3. Maritime sector

In the maritime sector, it is found that automation changes the tasks of operators, thereby, creating room for other possible human mistakes (Cavalleri, 2008; Ding et al., 2013). However, no papers are published that solely focus on the transition of control from automation to manual and, correspondingly, no metrics like TOT or TQ for takeover performance exist. In one of the few relevant studies (Pazouki et al., 2018), only 50 % of the deck officers were able to recognize automation failure and successfully retrieved control. In the analysis of the grounding of the Royal Majesty (Lützhöft and Dekker, 2002) it was highlighted that the main factor that influenced the interaction between ship operators and shipboard automation was the lack of feedback, which enhances miscommunication between human and machine and is a crucial factor in not identifying the need for manual control, resulting in a poor takeover performance.

### 3.3.4. Rail sector

No studies were found that solely focused on the transition of control from automated driving to manual driving in the railway sector. Due to the high penetration of automatic train protection systems, the role of the driver in emergency situations has been minimized – at least in equipped networks. One study (Karvonen et al., 2011) did identify how current metro/train drivers contribute to the safety and performance of the railway system and how a transition to a fully automated system will influence this, based on a case study of the Helsinki metro. One of the challenges mentioned that a higher automated system might cause operators to become separated from practical tasks and become too passive (e.g. OOTL), possibly creating unsafe situations if automation fails and a manual transition is required.

### 3.3.5. Summary

Factors that influence takeover performance significantly differ per sector. The methods applied to determine these influential factors are, however, similar. Most studies use virtual simulators to examine the influential factors on takeover performance and their impact. In general, very limited research in the maritime and rail domains focused on the transition of control.

Only the road sector has established clear metrics to measure the performance of operators during the transition of control, namely

takeover time (TOT) and takeover quality (TQ). In the road sector, factors that influence takeover performance include mental modes (e.g. situation awareness, automation complacency), but most research focused on physical factors related to the takeover request (e.g. TOR modality, type of manual invocation). Other sectors mostly mention mental modes (e.g. SA, automation complacency, automation bias) as crucial factors in takeover control. Results are summarized in Table 4.

### 3.4. The role of experience and training

The value of experience has been widely researched in the general transportation domain without having necessarily focused on automated modes. For training, research has emphasized on new approaches with the goal of improving operator performance in regular or anomalous situations (Strauch, 2017). In this review, the role of experience and training focuses on skills critical for safe interaction with automation, namely multi-tasking and SA.

### 3.4.1. Road sector

In the road transport sector, a study (Koustanaï et al., 2012) explored the role of training with forward collision warning (FCW) using a car driving simulator and a group of 28 experienced drivers split into three sub-groups: a group that had not any contact with the FCW, a group with lack of knowledge about the system that read a written description of the FCW, and a familiarized group that also read the written description and, in addition, used the system. The drivers who used the system did not experience any collision, whereas a 20 % of the drivers who read about the FCW and a 40 % of the unfamiliarised drivers did. The authors suggest that simulator familiarization has a positive effect on driver-system interactions. The simulator study of Payre et al. (2016) showed that more pertinent training may alleviate the negative impacts of over-trust in automation on reaction time.

### 3.4.2. Aviation sector

A similar research from the aviation sector (Masalonis, 2003) investigated how trust on automation and its consequent performance decrement could be varied by deliberate airplane piloting training. It was demonstrated that trained individuals were more skilled to address conflicts, probably due to the fact they were more cautious knowing that automation had variable reliability. Regarding the capability of performing tasks simultaneously, Seamster et al. (1993) examined the ways in which different airline operators resolved unwanted situations. The results demonstrated that expert operators were able to switch their attention to assess non-critical factors of the situations, whereas trainees continuously went from one issue to another. Wiggins and O'Hare (1995) investigated the detection of weather-related hazards on inexperienced, intermediate and experienced airplane pilots and concluded that 'the inexperienced group took significantly longer than the experienced group to examine the information screens.

In Doane et al. (2004), experienced and unexperienced pilots conducted an experiment of three trials to determine if the consequences of

**Table 4**
Factors affecting takeover control performance in different transport modes.

| Source | Transport mode | | | | Method | | | | | Influential factors on takeover performance and their impact | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Road | Aviation | Maritime | Rail | Review | Simulator | Real-life | Investigation | Other | Manual invocation | Take over time budget |
| Merat et al., 2014 | • | | | | | • | | | | TOT(+/-) TQ(+/-) | |
| McDonald et al., 2019 | • | | | | • | • | | | | TOT(+/-) | TOT(+) TQ(-) |
| Zhang et al., 2019 | • | | | | • | • | • | | | | TOT(+) |
| Parasuraman et al., 1993 | | • | | | | • | | | | | |
| AGARD, 1995 | | • | | | | | | | • | | |
| Hancock, 2017 | | • | | | | | • | | | (+/-) | |
| Pazouki et al., 2018 | | | • | | | | • | | | | |
| Ding et al., 2013 | | | • | | | | • | • | | | |
| Lützhöft and Dekker, 2002 | | | • | | | | | | • | | |
| Karvonen et al., 2011 | | | | • | | | | | • | | |

| Source | Secondary tasks | The modality of takeover request | Environmental conditions | Level of ↑ automation | Driver factors | Degraded SA | Automation complacency | Automation bias | Passive observers | No or different feedback | Display location |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Merat et al., 2014 | TOT(+/-) TQ(+/-) | | | | TOT(+)TQ(-) | | | | | | |
| McDonald et al., 2019 | TOT(+/-) | TOT(+/-) TQ(+/-) TOT(+/-) | TOT(+/-) TQ(+/-) TOT(+/-) | TOT(+)TQ(-) | | | | | | | |
| Zhang et al., 2019 | | | | TOT(+) | | | | | | | |
| Parasuraman et al., 1993 | | | | (-) | | | (-) | | | | |
| AGARD, 1995 | (+/-) | | | | | (-) | | | | | |
| Hancock, 2017 | | | | | | | | | | | (+/-) |
| Pazouki et al., 2018 | | | | | | (-) | (-) | (-) | | | |
| Ding et al., 2013 | | | | | | (-) | (-) | | (-) | (-) | |
| Lützhöft and Dekker, 2002 | | | | | | | | | (-) | (-) | |
| Karvonen et al., 2011 | | | | (-) | | | | | (-) | | |

specific actions would match their expectations. Here again, the results showed a better accuracy from the experienced pilots.

A few studies explored the effects of training on the response to automation-related errors against different types of abnormal events (McKinney and Davis, 2003; Casner et al., 2013). In these studies, pilots were faced with events under the circumstances they were used to bear during their trainings, and also under unpredictable circumstances as they would probably happen during real flight conditions. The results of both researches showed that pilots provided suitable and convenient responses when presented with the circumstances seen during past trainings. On the other hand, when the abnormal events occurred in a new and unexpected manner, the responses were improper and disproportionate. Finally, a simulator study (Manzey et al., 2006) investigated automation complacency and the effect of training on it. The results showed a clear evidence that exposing the pilots to automation failures during training decreased complacency.

### 3.4.3. Maritime and rail sector

Little or no dedicated studies from the maritime or railway sectors examining the role of experience and training on automation were found. One study (Pazouki et al., 2018) showed the importance of training for situation awareness in maritime operations, namely the recognition of emergency situations due to failing of automation.

### 3.4.4. Summary

In the aviation and road domain, both training and experience were mostly found to positively impact transport automation safety. More experienced operators could more accurately anticipate consequences of actions, manage workload better and identify hazards faster and more accurately. More training was found to reduce complacency, reduce the likelihood of accidents, increase the likelihood to identify automation failures and positively impact decision-making in situations similar to those in training scenarios. However, since many other factors also impact safety, these correlations can sometimes be weak. No or few results were found for the maritime and rail sectors. Results are summarized in Table 5.

## 4. Discussion

### 4.1. Transfer of knowledge

The results of the present research reveal several common challenges and opportunities for transfer of knowledge between transport modes regarding automation and safety. In order to examine these opportunities, the differences between transport modes should be kept in mind. The time window for reaction time is usually bigger in aviation and maritime modes, while rail and road have less time. Moreover, in aviation and maritime there is a team of operators, while on road and rail there is an individual driver. The number of concurrent users on the same road is usually high, while for the other three modes it is low, except in vicinity of a terminal or a port. Furthermore, the dimensions of movement are also different. The quantity and quality of training required for operators also differs – plane, vessel and train operators are rigorously and continuously trained and evaluated, while car drivers are usually not.

Despite these differences, it is hypothesized that certain findings can be transferred to other sectors. This section summarizes the main transferrable findings for the discussed human factors – trust, situation awareness, transition of control to manual, experience and training – and their effects on automation safety. Since these factors are related to each other, this section aims to integrate the concepts. An overview of some key transferrable messages can be found in Fig. 4.

Transferability is assessed by three levels: 'transferable', 'potentially transferable' or 'not transferable'. The criteria for assessing transferability can be outlined as follows:

(i) Transferable between modes are considered those results in which a topic has been researched in at least two transport modes with similar results; or when a topic has been widely researched in one (or more) transport modes and there is no obvious reason to assume that the differences between transport modes would significantly affect the transferability.

(ii) Potentially transferable are considered those results in which a topic has been researched in at least two transport modes but with some contradictory results; or when a topic has been widely researched in one (or more) transport modes and there are reasons to assume that the differences between transport modes may compromise transferability.

(iii) Not transferable are considered those results in which a topic has been researched to a small extent and/or in only one transport mode; or there are substantial differences between modes (i.e. the time needed to build up situation awareness is far more critical in road transport); or results are not at all relevant (e.g. the effect of teamwork on SA is not relevant in road or rail transport).

Nevertheless, this should be considered a preliminary assessment, and dedicated research should be carried out to validate or adjust the applicability of each experience to another sector.

The effects of mistrust in and low reliance on automation have been investigated in the road and maritime domain, but the results are mixed. One study identified underreliance as a source of a fatal rail accident, due to ignoring warnings. Two papers found no impact of the level of trust on safety, specifically on the number of spotted latent hazards (Vlakveld et al., 2018) and the recognition time of an autopilot failure (Pazouki et al., 2018). Another paper found that people who rely less on automation were more likely to take back manual control and had faster reaction times in takeovers (Dixit et al., 2016). In how far mistrust of automation thus impacts safety remains under researched, thus no lessons learned can be transferred yet. Nevertheless, mistrust of automation can lead to using it less (see Dixit et al., 2016). Yet, the purpose of automation is partly to reduce human factors as a cause of accidents, which is not possible if automation is not used. Overall, more research on mistrust/underreliance on automation is needed, as well as how to avoid disuse.

The problem of overreliance on automation has been widely researched in the road and aviation sector. Research results mostly agree that overreliance on automation can impair SA (Jones and Endsley, 1996; Bailey and Scerbo, 2007), increase takeover time (Payre et al., 2016), lead to slower reaction times (Dixit et al., 2016), riskier driving behaviour (Xiong et al., 2012) and generally negatively impact safety (Victor et al., 2018; Johns et al., 2018; Miller et al., 2016; NTSB, 2017, 1984); these general patterns are considered transferable to other sectors. In aviation, over-trust was more likely when automation supports difficult tasks (Wickens et al., 1999), a finding that may be relevant to higher levels of automation in cars. Moreover, Dorneich et al. (2017) suggest that visibility of automation may assist in the proper alignment of trust, an individual finding that seems relevant for other transport modes.

From these results it can be concluded that especially when high levels of trust in automation are combined with not understanding how automation works, dangerous situations can arise (e.g. unexpected behaviours, not recognizing automation failure, too slow responses to automation failure). These results are transferrable to all domains.

Regarding causes of lower levels of SA, while many conclusions are only supported by research into one or two modes, whenever different modes researched the same factor, they (broadly) came to the same conclusions. For instance, both the aviation and road domains find higher levels of automation lead to less SA (de Winter et al., 2014; Mosier et al., 2013). One explanation for this is that higher levels of automation leave room for humans to do other tasks (Onnasch et al., 2014). Research in the aviation, maritime and road sector all conclude that task distraction negatively impacts SA. Moreover, one study found

**Table 5**
Impact of experience and training on safe automation in different transport modes.

| Source | Transport mode | | | | Method | | | | Implication | | Skill(s) | Results |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Road | Aviation | Maritime | Rail | Video-based | Simulator | Real-life | Other | Experience | Training | | |
| Doane et al. (2004) | | • | | | • | | | | • | | Anticipation of consequences of actions. | Experts are more accurate than novices. |
| Seamster et al. (1993) | | • | | | | | | •* | • | | Workload management | Experts better at time sharing tasks and at managing workload. |
| Wiggins and O'Hare (1995) | | • | | | • | | | | • | | Detection of weather-related hazards | Inexperienced group took significantly longer than the experienced group to examine the information screens. |
| Mourant and Rockwell (1972) | • | | | | | | • | | • | | Visual and control performance | Expert drivers make better use of peripheral vision, with improved detection of hazardous situations than novice drivers. |
| Sagberg and Bjørnskau (2006) | • | | | | • | | | | • | | Hazard perception & workload management | Average reaction times decrease with experience & novice drivers had longer reaction times with secondary tasks. |
| Smith et al. (2009) | • | | | | • | | | | • | | Hazard perception | Hazard perception skills of more experienced drivers unnafected by sleepiness, while inexperienced drivers were significantly slowed. |
| Casner et al. (2013) | | • | | | | • | | | | • | Reaction to abnormal in-flight events. | Pilots provided suitable responses when presented with the circumstances seen during past trainings. |
| Manzey et al. (2006) | | • | | | | • | | | | • | Automation complacency. | Exposing the pilots to automation failures during training decreases complacency. |
| Masalonis (2003) | | • | | | | • | | | | • | Trust in automation. | Trained individuals are more skilled to address conflicts. |
| Mckinney and Davis (2003) | | • | | | | | • | | | • | Decision-making in once-in-a-career crisis decision scenarios. | Deliberate practice can prepare pilots for accurate decision-making. |
| Payre et al. (2016) | • | | | | | • | | | | • | Manual control recovery time. | Correlation between trust in automation and reaction time following a simple practice; correlation not found following an elaborated practice. |
| Koustanaï et al. (2012) | • | | | | | • | | | | • | Understanding of forward collision warning. | Drivers who previously used the system did not experience any collision; 20 % of the drivers who read about it and 40 % of the unfamiliarized drivers did. |
| Pazouki et al. (2018) | | | • | | | • | | | | • | Recognition of emergency situations due to the fail of automation. | Trained deck officers recognized the introduced major fault; without training officers were not able to recognize it. |
| SURPASS Project (2012) | | | • | | | | | •** | | • | Responding to automation failures. | Better education and training is one of the solutions to potentially reduce maritime automated-related accidents. |

\* paper-based.
\*\* Investigation reports.

| Key messages ✓✓✓ | From sector(s) | | | | Transferability | To Sector(s) | | | |
|---|---|---|---|---|---|---|---|---|---|
| Over-trust leads to slower reaction times, ignoring warnings and higher risk | road | aviation | | | Transferable | | | maritime | rail |
| Over-trust is more likely when automation supports difficult tasks | | aviation | | | Potentially transferable | road | | | |
| Over-trust to automation reduces takeover performance | road | | | | Transferable | | | maritime | rail |
| Mis-trust may lead operators to ignore warnings or disuse the automation completely | road | | maritime | rail | Not transferable | | aviation | | |
| Visibility of automation assists in proper alignment of trust | | aviation | | | Potentially transferable | road | aviation | | rail |
| Higher level of automation induces OOTL problems and leads to loss of SA, which impairs the ability to react properly | road | aviation | | | Transferable | | | maritime | rail |
| Loss of SA leads to slower reaction times, increased accident risk (in specific scenarios) | road | | | | Not transferable | | | | |
| Automation leads the operator to other tasks, creating room for new types of errors | road | aviation | maritime | | Transferable | | | | rail |
| Automation 'mode annunciators' improve SA | | aviation | | | Potentially transferable | road | | maritime | rail |
| Planning trips ahead and comparing the actions of the automated system against the prepared route helps to identify automation failures. | | aviation | | | Transferable | | | maritime | rail |
| SA is regained at 4-8 sec, but may build up to 20s for some elements | road | | | | Potentially transferable | | aviation | maritime | rail |
| Complexity and many input steps of automation reduces SA | | aviation | | | Potentially transferable | | | maritime | rail |
| Time pressure decreases SA performance | | | | rail | Potentially transferable | | aviation | maritime | |
| Experience and training improve trust, SA and operator response | road | aviation | maritime | | Transferable | | | | rail |
| Training on handling distraction improves SA and divided attention with automation | | aviation | maritime | | Transferable | road | | | |
| Exposing automation failures during taining reduces complacency | | aviation | | | Transferable | | | maritime | rail |
| Extreme & unexpected situiations should be included in training | | aviation | | | Transferable | | | maritime | rail |
| Group skills and teamwork improve SA and decision-making | | aviation | | | Potentially transferable | | | maritime | |
| Lack of feedback/alert on automation failures results in poor recognition | | | maritime | | Transferable | road | | | rail |
| Quantitative metrics of takeover performance allow for objective assessment | road | | | | Transferable | | aviation | maritime | rail |
| Non-emergency takeovers have better TQ within the same TOT | road | | | | Potentially transferable | | aviation | maritime | rail |
| Auditory and vibrotactile modalities improve the TOT compared to visual ones | road | | | | Potentially transferable | | aviation | maritime | rail |

**Fig. 4.** Key messages from different transport modes and assessment of transferability to other transport modes.

that higher complexity of automation and more input steps significantly decrease SA-levels (Mosier et al., 2013). This is potentially transferable to maritime and rail contexts where automation inputs may be more extensive that in cars. For all modes this implies designers must be aware that operators of highly automated systems will likely be OOTL, thus systems that get operators aware quicker when takeovers are needed.

Indeed, supporting tools showing or annunciating (changes in) system parameters and the mode of automation were already found to positively influence SA and the recognition rate of automation failures in the aviation and maritime domain (van der Kleij et al., 2018; Trösterer et al., 2017). Similar tools are likely to be useful in the rail and road domain as well.

Another approach to mitigate the loss of SA during monitoring is used in aviation: pilots plan the trip before flying and map alternative routes for emergencies (Trösterer, et al., 2017). Planning ahead enables

pilots to compare the actions of the autopilot against their planned trip. Particularly the maritime and rail domains could apply this practice. This is less applicable for car drivers, due to the higher number and variability of trips; moreover, road drivers are not expected to plan trips in a systematic way.

Another conclusion is that time likely has a large impact on SA. In the rail domain, time-pressure was shown to negatively impact SA (Suter and Stoller, 2014); this seems more relevant for professional operators (aviation and maritime).

Furthermore, in the road domain it was found that higher lead times led to higher levels of SA (e.g. van den Beukel and van den Voort, 2013). While in some studies the level of SA plateaued after $4-8$ s passed (Samuel et al., 2017; Wright et al., 2017; Vlakveld et al., 2018), other studies did not find such a saturation effect even after over 20 s (Lu et al., 2017). These differences in results partly depend on the SA measurement method applied (see e.g. de Winter et al., 2014), but it

could also mean that awareness about different factors (e.g. recognition of imminent collision vs latent hazards), is build up at different rates. These results are potentially transferrable to the aviation, maritime and rail domain, but they would need to be adjusted to the relevant time available in their respective operations.

Research on the consequences of loss of SA is mainly conducted for the road domain. However, this research is very domain-specific (e.g. obstacle detection, specific traffic situations). Since every mode has different critical events and possible actions, results cannot be transferred. However, evidence that a loss of SA impairs the ability to react appropriately to the situation was found for the aviation, road and maritime domain, and likely applies at a general level to the rail domain as well.

The literature showed that car and aviation operators with experience with operating the system and the autopilot exhibit a better workload management (Seamster et al., 1993; Sagberg & Bjørnskau, 2006) that allows them to perform tasks simultaneously. This, together with the experiments that demonstrate that experience positively affects SA (Field et al., 2016; Wright et al., 2017), confirm that experience is one of the determinant factors to improve safety of automated transport systems. Furthermore, it has been demonstrated that training with autonomous cars, airplanes and vessels reduces automation complacency, and can improve SA (Pazouki et al., 2018) and the ability of operators to recognize and respond to unusual and unexpected circumstances (Casner et al., 2013; Manzey et al., 2006; McKinney and Davis, 2003; Koustanaï et al., 2012; Pazouki et al., 2018). These results are consistent across the three domains and are hypothesized to hold for the rail domain as well. It can be concluded that training improves safety.

Nevertheless, even though training is a regular activity conducted by pilots in the aviation sector, automation-related errors continue to happen. These incidents suggest that training practices have not completely removed human errors in using automation systems. Casner et al. (2013) and McKinney and Davis (2003) suggest that trainings scenarios were too predictable. In addition, a cause of this inefficient training may also be that the needed automation-related expertise had not been well established in the first place. In other words, operators may have been contemplated as qualified or unqualified in general transportation operations, without necessarily being experts in automation operations. Automation-related errors will therefore still happen until the standards for the needed skills to operate automated transportation modes at an expert level are clearly defined; in this context, the aviation sector is well ahead and the road sector, with the rapid development of autonomous vehicles could benefit.

Indeed, more variety in scenarios that allow pilots to familiarize themselves with the capability boundaries of the automation system are needed, especially situations that expose pilots to unexpected automation failures. Since the rail and maritime domains are similar with regard to the need for trained professionals, these results likely transfer to these domains as well. However, due to time and cost reasons it is uncertain whether it would be feasible to expose car drivers to this same level of training.

Another interesting aspect here is that of group training. In the aviation domain, group skills and effective teamwork were shown to improve SA and decision-making (Field et al., 2016). Designers of training procedures in the aviation and maritime domains could take advantage of this by incorporating teamwork skills in automation training. Since only one person operates a car or train, this suggestion does not seem to transfer to the road and rail domains.

Literature on transition of control from automated to manual operation mostly focused on the road domain. Clear metrics for takeover performance were established, which is essential in the road sector because a fast and adequate takeover is the key to avoiding accidents. In contrast, in the maritime, rail and aviation sectors no performance measures were established. This is especially surprising for the aviation sector because automation has long been introduced in planes, and

research would have been expected to have identified better defined metrics and more explicit influential factors. It is suggested that maritime, rail and aviation research also define their own context-specific metrics for takeover performance, in order to assess takeover performance in a quantitative and more objective way - especially in emergency conditions, in which it can be safety critical.

Some specific finding from the road sector, such as the better TQ of drivers within the same TOT (Merat et al., 2014) and the positive impact of auditory and vibrotactile modalities on TOT (Zhang et al., 2019) are potentially transferable to other transport modes.

### 4.2. Limitations

The present research has certain limitations. The inclusion of additional search terms in the literature search, other languages or books, might have led to additional results. Especially regarding trust and SA, some controversy in the definitions and metrics used in the literature may have limited the exhaustiveness of the results. The prioritization of recent papers in some cases, may have limited the extent of the results, e.g. by excluding earlier studies on automation in aviation; on the other hand, it might be questionable whether these earlier studies would still be applicable to the modern context.

The findings are limited by the fact that most studies are using simulators. Studies are carried out under very specific scenarios and modelling assumptions, which may not necessarily reflect real life. Additionally, many of these studies had small sample sizes, thus results might not generalize well. Although quality criteria were included in the selection of the studies (see section 2), no systematic assessment of their quality was done. In general, there is currently insufficient empirical data from field-studies, especially in the road sector. Lastly, particularly in the rail and maritime domains research on the impact of human factors is lacking, thus allowing for less cross comparison between modes. Overall, the results must be evaluated while keeping these limitations in mind.

### 5. Conclusions and Future Research

The present research aimed to review key human factors related to the safe deployment of automated systems in different transport modes, in order to identify common challenges and opportunities for transfer of knowledge between transport modes. The results revealed several areas where experiences from aviation and road can be transferable to other modes, namely regarding the training of operators, the conditions for which trust in automation can be properly aligned, the conditions that determine SA and the conditions for the timely transitions from machine to human. The limited experiences from other transport modes tend to confirm these general patterns.

The scope of this research was to conduct a broad and exploratory review of knowledge in different transport sectors. A formal meta-analysis was out of the scope of the present research, however each one of the topics tackled would warrant one (e.g. there are two recent existing meta-analyses of takeover performance on the road). In particular, it would be interesting to meta-analyse the safety impact for each human factor within each transport mode and obtain quantitative weighted mean effects of these impacts. This would also allow a more formal and conclusive assessment of the transferability of knowledge between different sectors.

During the review, various literature gaps and opportunities for future research were found. In general, research into the effect of human factors on automation safety in the rail and maritime domain were limited. This paper suggested opportunities to transfer knowledge from other modes, but future research is needed to confirm these hypotheses. Additionally, future research should emphasize field-testing of human factors affecting the safety of automated transport systems. Specifically, in the road domain, where reaction times are the most critical, more on-road testing is needed.

Regarding the impact of trust, specifically the impact of under-trust remains unclear. Research is needed that focuses on the causes of under trust in automation, in order to suggest how to alleviate disuse.

For research on SA, it is suggested to study what amount of SA is build up at which rate. Evidence for the road domain suggests that certain types of SA build up within a few seconds (e.g. recognition of hazards), while other constructs take longer to build up (e.g. estimation of positions and speed of other vehicles). Additionally, since no such quantitative studies exist in aviation, rail and maritime domains, similar research here could provide important safety implications.

Furthermore, most studies in aviation do not explicitly discuss how different automation levels impact SA. Instead, automation is taken as given. It is suggested to conduct explicit research on how different automation modes impact SA and safety. Related to this, additional research is needed on how different automation systems in the cockpit work together, since too many systems could lead to an overflow of information overflow, which was shown to negatively impact SA (Martins, 2016). Similar research would also gain important insights for other modes.

Regarding takeover performance, literature mainly focused on road transport. No clear metrics to determine takeover quality exist for the aviation, rail and maritime domain, yet the metrics could be important to assess the impact of influential factors on takeover.

The review on training showed that in aviation, needed automation-related expertise has not been well established. A lack of standards for needed automation skills could cause pilots to not be trained in every relevant automation failure scenario. Establishing training standards with regards to automation could be useful in the aviation, rail and maritime domain.

## Declaration of Competing Interest

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

## CRediT authorship contribution statement

**Eleonora Papadimitriou:** Conceptualization, Methodology, Writing - review & editing, Supervision. **Chantal Schneider:** Investigation, Writing - original draft, Writing - review & editing. **Juan Aguinaga Tello:** Investigation, Writing - original draft. **Wouter Damen:** Investigation, Writing - original draft. **Max Lomba Vrouenraets:** Investigation, Writing - original draft. **Annebel ten Broeke:** Investigation, Writing - original draft.

## Appendix 1

| | |
|---|---|
| ACC | Adaptive Cruise Control |
| AV | Automated/autonomous vehicles |
| FCW | Forward collision warning |
| HAD | Highly automated driving |
| NDT | Non-driving related tasks |
| OOTL | Out of the loop |
| SA | Situation Awareness |
| SART | Situation Awareness Rating Technique |
| TOR | Takeover request |
| TOT | Takeover time |
| TQ | Takeover quality |
| TTB | Takeover time budget |

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