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Towards a Predictive Model of Driver Acceptance of Active Collision Avoidance Systems

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Abstract

Drivers' acceptance of advanced-driver-assistance-systems (ADAS), such as pedestrian alert systems (PAS), is vital if the full benefits are to be realised. However, the adoption and continued use of such technology is not only contingent on the system's technical competence, but is also dependent upon drivers' attitudes towards the system, and the impact that it has on their driving behaviour and performance. Understanding and integrating the factors that affect and define acceptance in a driving context is therefore important, but complex. We present an in-depth literature review, enriched by a driving simulator study (both conducted as part of the EU-Horizon2020 PROSPECT project), that together begin to collate these factors and explore their interrelationship. A preliminary, descriptive model of driver acceptance is subsequently presented. Further work will enhance and validate the model, with the aim of creating a predictive model that can be used to inform the design of future in-vehicle technologies.

Keywords: driver acceptance; trust; false alarms; acceptance model; simulator study; literature review.

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1. Introduction

Drivers' acceptance of advanced-driver-assistance-systems (ADAS) is important if the full benefits are to be realised – poor acceptance may result in drivers ignoring such systems, finding creative workarounds, or deactivating the system completely. However, the factors that affect the acceptance of technology in a driving context are complex and interrelated. For example, automated in-car, pedestrian-alert-systems (PASs) have potential to assist drivers and mitigate the risk to pedestrians by providing warnings and/or taking control of their vehicle if a pedestrian is present within the vehicle's path and/or a collision is likely based on the current speeds/trajectories of both parties. However, the success of such technology is not only predicated on the system's technical proficiency (to accurately detect pedestrians and make a precise estimation of their current/future positions with respect to the moving vehicle), but is also dependent upon drivers' attitudes towards the system – providing warnings or taking action too soon may annoy drivers and erode trust in the system, whereas late notifications may invite low confidence in the system's ability to detect future hazards. Moreover, even if acceptance is measured and quantified, the data yielded by the methods used may not be in a form that is practically useful for informing system design. The aim of the current project is to use a human-centred approach to develop a predictive model of driver acceptance that can be used to inform the design of future in-vehicle technology.

The current research was conducted as part of the Proactive Safety for Pedestrians and Cyclists (PROSPECT) project. The PROSPECT project aims to significantly improve the effectiveness of active vulnerable road user (VRU) safety systems by expanding the scope of scenarios addressed, and improving overall system performance. This is achieved by providing a better understanding of relevant VRU scenarios by means of statistical accident studies and naturalistic urban observations, improving VRU sensing using enlarged VRU sensor coverage as well as improving sensor and situational analysis, and applying advanced HMI and vehicle control strategies, combining vehicle steering and braking, for collision avoidance. To ensure the success of such work, it is imperative that drivers accept the new system. The paper presents an in-depth literature review and summarises the findings from a preliminary simulator study exploring the relationship between false alarms and driver acceptance. A preliminary model of driver acceptance is presented.

2. Literature Review: Understanding Acceptance

In a driving context, acceptance has been described as "the degree to which an individual incorporates the system in his/her driving, or if the system is not available, intends to use it" (Adell, 2009). In fact, this definition covers both *acceptability* and *acceptance* – two terms which although seemingly different, are often used interchangeably. Strictly speaking, *acceptability* is defined as "the prospective judgement of measures to be introduced in the future" (Schade and Schlag, 2003), and represents an attitude of an individual (i.e. their likes or dislikes) towards a certain kind of technology (Jamson, 2010). Acceptability is thus an *a priori* measure of the extent to which a person thinks they will accept and use a particular system – typically based on very limited exposure – and will be available early in the product lifecycle. *Acceptance*, on the other hand, can only be determined after use, and is a measure of a person's satisfaction with the experience of interaction and use; it is not necessarily linked to a driver's *liking* of the system. Acceptance is not limited to the binary outputs of 'acceptance' or 'non-acceptance', but rather measured on a continuous scale (Adell, 2009). If a system is not seen as 'acceptable' by drivers, they will not buy it and even if they do, they may disable it out of frustration (disuse), or use it in a manner unintended by designers (abuse) (Parasuraman and Riley, 1997).

The determinants of drivers' acceptance are therefore complex and derive from various factors, including trust, the driver's experience of interaction with technology, their understanding of system limits, and the context in which it is implemented. Thus, factors, such as the number and frequency of false alarms, are likely to play a significant role in shaping drivers' trust and acceptance. Moreover, human behaviour is not primarily determined by objective factors, but also by subjective perceptions (Ghazizadeh et al. 2012). This means that acceptance is based on individual attitudes, expectations and experience as well as the subjective evaluation of expected benefits (Schade and Baum, 2007). It has even been suggested that the degree of technological innovation has a lesser effect on acceptance than personal experience (Ausserer and Risser, 2005). The user-centred design approach represents a product design philosophy where human factors are of central concern within the design process. This means that consideration of the factors which will influence user acceptance should be incorporated as early as possible into the design of a system and assessed/redesigned in an iterative process to increase market success (Adell, 2010).

2.1 Acceptance Models

Acceptance models can be used to understand how individuals might 'accept' a system by highlighting the factors which influence and stimulate acceptability/acceptance. There are a number of existing models which are relevant in the automated driving context. The Theory of Reasoned Action (TRA; Fishbein and Ajzen, 1980) suggests that a person's behaviour is determined by his/her intention to perform that behaviour and that this intention is, in turn, influenced by his/her attitudes and subjective norms towards the behaviour. The Technology Acceptance Model (TAM; Davis, 1989) extends TRA and suggests that behavioural intentions, attitudes, perceived usefulness of a system, and perceived ease of use of a system directly and indirectly influence the actual use of a system. The perceived usefulness and ease of use of a system are also mediated by the effects of external variables. The Theory of Planned Behaviour (TPB; Ajzen, 1991) is an extended version of TRA with the addition of perceived behavioural control (people's perception of their ability to perform a given behaviour) as one factor which affects intention and ultimately influences behaviour. Finally, the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) posits that there are four key factors that affect usage behaviour: performance expectancy, effort expectancy, social influence and facilitating conditions. The first three factors determine usage intention which ultimately affects usage behaviour; while the last factor directly influence usage behaviour. Gender, age, experience and voluntariness of use will also have an impact on the aforementioned factors.

While these acceptance models were originally developed in the domain of information technology to assess users' acceptance of information systems, they have also been adapted for other domains, such as driving. Unfortunately, only a few acceptance models incorporate trust within the driving context. One such example, proposed by Choi and Ji (2015) examined users' adoption aspects of autonomous vehicles, with the aim of identifying the factors that encourage people to trust an autonomous vehicle. An acceptance model, based on a survey of 552 drivers, was proposed. They found that 'perceived usefulness' and 'trust' were major determinants of their intention to use autonomous vehicles; in particular, trust had a negative effect on perceived risk. Furthermore, system transparency (the degree to which users can predict and understand the operating of autonomous vehicles), technical competence (the degree of user perception on the performance of the autonomous vehicles), and situation management (the user's belief that he or she can recover control in a situation whenever desired) were shown to have a positive effect on trust. Ghazizadeh et al. (2012) evaluated truck drivers' attitudes towards an on-board monitoring system (OBMS) and extended TAM (Davis, 1989) with trust. The results of their study demonstrated that 'perceived usefulness' played the most important role in determining drivers' intention to use the technology. Trust in the system was again highlighted as an important factor in determining a user's intent to use the system. However, perceived ease of use was shown to have little effect on the intention to use, when accounting for both perceived usefulness and trust.

2.2 Factors Affecting Perceptions of Automated Technologies

2.2.1 Perceived Risk

Perceived risk is defined as the perceived uncertainty in a given situation (Mayer et al. 1995) and is a key component of trust and acceptance models (Mayer et al. 1995). Pavlou (2003) found that, particularly with regard to the decision to use or not to use an automated device, perceived risk is a major factor linked to trust, whereby trust reduces the perceived risk. Other studies that have used the TAM constructs in assessing user adoption of driving assistance systems also showed that perceived risk strongly influences the intention to use a system (Adell, 2010). Perceived risk depends on the expected probability of a negative situation (Numan, 1998). If drivers are to trust in-vehicle automated technology, it must behave in the manner expected, reducing the perceived risk of a negative situation.

2.2.2 Reliability and Dependability

Reliability is defined as the ability of a device or system to perform a required function under stated conditions for a specified period (Morel et al. 2009), whereas dependability refers to the frequency of automation breakdowns or error messages (Merritt and Ilgen, 2008). A reliable and dependable system creates trust across different types of task such as control, cognitive, or perceptual tasks (e.g. Ho et al. 2005; Moray et al. 2000). Irrespective of initial levels, trust may reduce with decreasing reliability. There is some evidence suggesting that trust declines quite rapidly below a certain level of reliability and the absolute level of this drop-off seems to be highly system- and context-dependent, with estimates ranging from 90% (Moray et al. 2000) and 70% (Kantowitz et al. 1997) to 60% (Fox, 1996).

In general, accurate and reliable information enhances the trust of operators and users of automated systems (Spain and Bliss, 2008). However, errors are unavoidable in human-automation interaction. Errors are traditionally discussed in terms of both misses and false alarms (see Dixon and Wickens, 2006; Dixon et al. 2007). In the context of proactive safety systems (e.g. a pedestrian detection and warning system), false alarms occur when a system warns the driver about a predicted event but the event does not occur. A miss occurs when a system fails to warn the driver when an event does occur. The reduction of both of these types of error increases the reliability of the system and positively impacts trust development and subsequent acceptance (De Vries et al. 2003). Higher reliability is shown to lead to higher operator response frequency, and higher compliance and reliance on the automation (Spain and Bliss, 2008). Yamada and Kuchar (2006) found that amongst drivers, 'miss' rates led to the degradation of trust in a system and slower response times. However, it is also thought that the degree of difficulty of the task also appears to influence trust and acceptance – in a target identification task, Madhavan and Wiegmann (2007) found no significant difference between an 'easy miss' group and an 'easy false alarm' group. However, the 'difficult errors' group trusted the automation more than the 'easy errors' group. A similar finding was also reported by Master et al. (2005). This suggests that individuals are more willing to trust automation, despite errors, when the task is difficult. Research has also shown that automation errors that occur early in the course of an interaction have a greater negative impact on trust than errors occurring later (Manzey et al. 2012; Sanchez, 2006). For example, Riley (1994) reported that novice pilots are more likely to turn automated systems off when they fail, compared to experienced pilots. This finding indicates that first impressions with automation are important, and early errors can have a lasting impact on the trust formation process.

2.2.3 Predictability

In the context of interpersonal relationships, Rempel et al. (1985) argued that predictability, and the degree to which future behaviour can be anticipated, forms the basis of trust early in a relationship. In the context of automation, predictability is defined as how well the behaviour of the automation matches the operator's expectation of that behaviour. If users' experiences with a machine produces predictable outcomes, then they may start to trust the system, leading to increased acceptance (Cahour and Forzy, 2009; Muir, 1994). However, when they experience unanticipated reactions from the system, there is a rapid drop in trust that often leads to disuse or a disregard for future information provided by the system (Wiegmann et al. 2010). High predictability can, however, also be a problem in the event that a system error occurs, because this goes completely against a user's expectation. For example, de Waard et al. (1999) reported that 50% of drivers failed to regain control of the vehicle following a system malfunction in a driving simulator study. This was because they believed that the system would intervene despite being compromised. The effect of predictability on trust is also closely linked with the magnitude of automation fault. A minor fault with unpredictable results appears to affect trust more than a large fault of constant error (Moray et al. 2000; Muir and Moray, 1996). In other words, trust can still develop when a systematic fault occurs, provided users can develop a control strategy and have prior knowledge of the fault (Riley, 1994).

2.2.4 Individual and Demographics Factors

Overall, the results of previous research demonstrate the potential for individual factors to have an influence on trust and acceptance in automation, although the evidence is currently fairly sparse. Consistent gender differences with respect to trust in automation have not yet been confirmed through existing research. However, it has so far consistently shown that men have a higher interest in automated driving than women, more positive attitudes towards automated driving, and a higher willingness to use and buy the technology (Kyriakidis et al. 2014; Payre e al. 2014). Kyriakidis et al. (2014) also revealed that men were less worried about automation failures but were more concerned with liability issues.

Several studies have shown age to be a significant variable affecting trust in automation; cognitive changes, cohort effects, or some combination of both variables, may be the cause of age-related differences (Ho et al. 2005). Ho et al. (2005) found that older adults trust and rely on decision aids more than younger adults, but they do not calibrate their trust any differently following automation errors. Existing research also suggests that people of different ages may employ different strategies when analysing the trustworthiness of automated system (McCarley et al. 2003). However, the reported effect of age on user acceptance of automated driving is inconsistent (Nordhoff et al. 2016).

Biros et al. (2003) demonstrated that participants with greater dispositional trust in computers displayed more trust in information from an unmanned combat aerial vehicle. Meanwhile, Merritt and Ilgen (2008) found that trust propensity predicted participants' post-task trust – individuals with high levels of trust propensity were more likely to place greater trust in the automation aid when it performed well. Contrarily, when the automation aid performed poorly, individuals with low levels of trust propensity express greater trust in the aid than those with high trust propensity. Thus, individuals with high levels of dispositional trust in automation are more inclined to trust reliable systems, but their trust may decline more substantially following system errors.

2.3 Measuring Trust and Acceptance

Both primary task measures (e.g. performance data relating to driver-vehicle performance) and subjective measures (e.g. questionnaires and interviews) can be used to infer an individual's level of trust and acceptance in technology. Information obtained in relation to driver-vehicle performance can be used to assess how far the driver is using the system in the way that was originally intended by the systems designer, as well as how appropriate this behaviour is in relation to the actual capabilities of the system. Measures can be taken under laboratory conditions or using prototypes on a real road, however, the validity of results will be dependent on having access to prototypes which exhibit the same levels of predictability, reliability and dependability as real systems. Objective and subjective data relating to new or early prototype technology may be obtained from driving simulator studies, which offer a safe and controlled environment for testing a wide range of driving environments and scenarios. Experience can also be 'compressed' in a simulated testing environment, meaning that participants can be exposed to a wide range of conditions in a short space of time, which would be impossible to achieve on real roads. In automated driving research, however, compression of experience often results in participants being exposed to many automation activations, failures or 'false alarms' within a very short time period. This is a disadvantage because, in reality, drivers may never (or only extremely rarely) encounter a system malfunction, and in the case of some automated technology, such as crash avoidance systems, the system may never be called into action. Therefore, exposing study participants to many repeats of these types of actions greatly reduces the ecological validity of these studies and will likely have an impact on any results, particularly self-ratings of trust and acceptance. Questionnaires and interviews with users of automated driving systems can address some of these shortcomings, and have been used to capture more long-term personal experiences (e.g. Weyer et al., 2015), although there are always limitations with participants recalling experiential information accurately.

As the domain of trust and acceptance research within the driving context is still relatively new, robust measuring instruments are not extensive. They are either adopted or modified from existing questionnaires in the automation domain (e.g. Stanton and Young, 2005; Ma and Kaber, 2007) or created on an ad-hoc basis (e.g. Beller et al., 2013; Waytz et al., 2014). Most of these questionnaires have not (in general) benefited from the same rigor in development and validation that has characterized measures of interpersonal trust. The Empirically Derived (ED) scale developed by Jian et al. (2000) is a notable exception that has been subjected to a validation study (Spain et al. 2008) and used extensively (e.g. Verberne et al. 2012).

Subjective measures of acceptance tend to use a range of terminologies ('accept/acceptable', 'satisfying needs', 'willingness to use') and sub-factors (actual use, perceived system importance, reliability, human-machine interface (HMI) assessment) to assess the concept (Adell, 2009). In measuring acceptance, system familiarisation is incredibly important, as we learn through experience. Allowing participants to have familiarisation time with a technology, ideally in a longitudinal study design (repeated exposures over a number of days/weeks/months), will improve the validity of acceptance measures, although it is not always easy to achieve given restrictions in research budgets and timescales.

3. Simulator Study – Exploring Acceptance based on the Occurrence of False Alarms

It is clear that the factors affecting driver trust and acceptance are complex and interrelated. To begin to explore these within a safe and controlled environment, we conducted a simulator study that investigated the relationship between false alarms and driver acceptance of a PAS. Given the requirement to make a precise estimation of human behaviour, in addition to current limitations in detection technologies, false alarms are an unavoidable consequence of PASs, but can be one of the most significant contributing factors in the development of trust and acceptance: by *maximising* detection rates, drivers are likely to be flooded with false-alarm warnings, with the inevitable consequence that they may miss or ignore genuine alerts in safety-critical situations (i.e. the system 'cries wolf'). In contrast, systems designed to *minimise* false alarms may miss genuine safety-critical situations. Moreover, in the absence of false alarms, genuine alerts may be so rare as to be utterly unfamiliar and consequently drivers' reactions will be unpredictable. It has also been suggested that providing an 'appropriate level' of false alarms helps to ensure that drivers are able to calibrate their trust in the system (Lee and See, 2004).

Given the unpredictability of human behaviour, the likelihood of false alarms occurring for a PAS is closely aligned with the time-to-collision (TTC) at which the warning is presented – as the TTC increases, there is a corresponding increase in the occurrence and number of false positive detections (Keller and Gavrila, 2014). Using this approach during our study, false alarm rates were determined based on TTC. Full details of the study can be found in Large et al. (2017). A summary is provided below to provide context and background for the development of the preliminary model.

Twenty-four experienced drivers (15 male, 9 female, with ages ranging from 19 to 55 years; mean number of years with licence, 10.7) were asked to negotiate a single lane urban high-street (with pathways moderately populated with pedestrians) on multiple occasions using a medium-fidelity driving simulator (Figure 1). On five occasions during each drive (presented at random throughout the scenario), a pedestrian approached the roadside, as if intending to cross the road. Some of the pedestrians then continued to cross the road while others remained at the roadside – all five pedestrians were identified by the PAS system, thereby giving rise to 'false positive alarms' in the latter situation (i.e. the system accurately detected the presence of a pedestrian but falsely predicted their intention to enter the roadway). This scenario was chosen to correspond with current accident data which show that the most prominent crash types involving pedestrians occur in an urban setting where the pedestrian crosses a straight road (from either the nearside or off-side) outside of demarcated pedestrian crossings, is not obstructed from view, and the vehicle is travelling at speeds of 30-50km/h (PROSPECT, 2016).

PAS warnings were presented within the vehicle as a static visual alert icon and/auditory icon presented at 75dB (based on design guidelines (Campbell et al., 2007)). To add a further novel element, visual warnings were provided using a head-up display (HUD), and both visual and auditory warnings were spatially congruent (i.e. corresponded with the side of the road from which the pedestrian approached). A generic high-contrast alert icon was selected to aid ease of recognition and saliency to visual attention (Figure 1). The icon was presented for a period of 4.0-seconds, based on design recommendations (Campbell et al., 2007). Warnings were presented at different times-to-collision (TTCs), with the number of *accurately* detected pedestrians (i.e. those who continued to cross the road) decreasing with increasing TTC, thus simulating the increasing false alarm rate associated with the provision of earlier warnings (Keller and Gavrila, 2014). The approach therefore assumes that the technology performed correctly – in so far as it accurately detected pedestrians (and predicted that they were at risk based on their current speed/trajectory), in all situations, i.e. there were no 'false negative' alarms whereby the system mistakenly detects a pedestrian that is not actually present. Consequently, any false alarms were due to changes in the behaviour of pedestrians (which might be reasonably expected in a real-world system, particularly at elevated TTCs), rather than any technical limitations of the system. The aim of the study was therefore to explore the isolated effects of 'false positive' interventions only, i.e. situations when the system falsely predicts a pedestrian's intention to enter the host vehicle's trajectory.

After each scenario (corresponding to a different warning type and TTC), participants rated their attitudes towards the PAS using bespoke Likert-type scales (from 1 to 10, where 1 = 'not at all' and 10 = 'completely'). Scales explored the constructs of trust, confidence, annoyance, desirability (all thought to influence acceptance), and were constructed based on previous usability assessment recommendations (Reader, 1999). For example, 'confidence' was determined by inviting responses to the question: *"How confident are you that the system will be able to cope with all situations in the future?"*, and 'desirability' with the question *"How likely would you be to use the system if it was available in your own car?"* In addition, driving performance data were captured from the simulator software. These were analysed to extract the headway distance to the pedestrian when drivers responded to the warning/hazard, i.e. when they lifted their foot from the accelerator, began braking (applied foot to brake) and brought the car to a stop (or reached minimum speed).

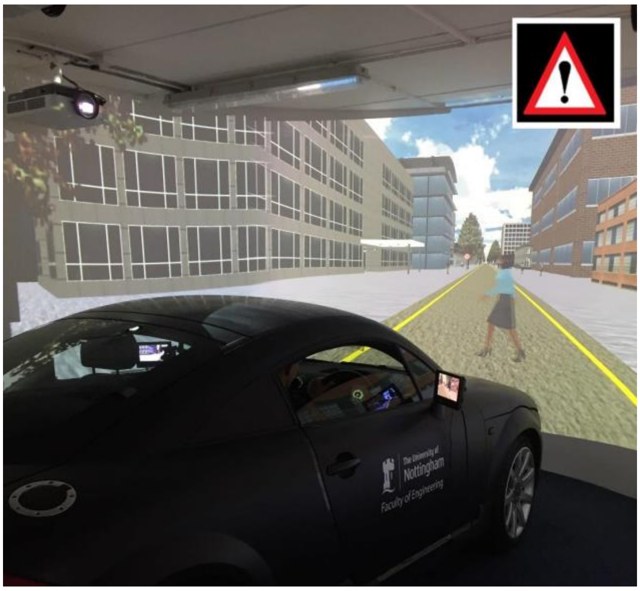

Fig. 1 Driving simulator showing urban high-street scenario and pedestrian crossing road ahead, with visual alert icon that was presented on the HUD (inset).

3.1 Results

For full results and analysis, please refer to Large et al. (2017). In summary, it was evident that participants placed the highest level of trust and confidence in the system when warnings were presented at intermediate TTCs (3.0 and 4.0 seconds). These corresponded to false alarm rates of 40% and 60%, respectively, suggesting that drivers were apparently willing to accept relatively high false alarm rates without affecting their trust or confidence in the system. It is noteworthy that ratings of trust and confidence reduced significantly with both increasing *and* decreasing TTC, with the lowest levels evident at the shortest TTC of 2.0 seconds. This is likely to be because drivers felt that these warnings were provided too late for comfort rather than due to concerns about the technical capability of the system. Participants also indicated that they were most likely to use the system (revealed through the construct of 'Desirability') based on their experiences of 3.0 and 4.0 second warnings. There were few differences highlighted specifically associated with ratings of Annoyance, although drivers tended to rate warnings delivered at the longest TTCs as most annoying. At this distance, it is possible that drivers were unaware of the potential threat posed by the pedestrian – indeed, earlier alerts can often be interpreted as 'false positives' (Abe and Richardson, 2006). Alternatively, drivers may have felt that they had sufficient time to respond without the assistance of a PAS. Overall, the results of the study suggest that, although drivers are likely to stop sooner and apply more gradual braking force, if warnings are provided earlier – thereby providing a greater safety margin between vehicle and pedestrian – warnings that are provided too early (or indeed, too late) are likely to annoy drivers and inspire lower levels of confidence in the technology, and reduced acceptance. This can lead to drivers disregarding the advice and relying on their own judgement, especially at longer TTCs.

4. A Preliminary Model of Driver Acceptance

Based upon the findings of the simulator studies, a preliminary model of driver trust and acceptance in relation to three interconnected features (time to collision, false alarm rate, driver's time to respond) of a proactive safety system is proposed (Figure 2). The model shows how these characteristics of a PAS influence trust and acceptance. These factors are intrinsically linked and the relationship was the basis of differentiating the conditions used in the false alarms study (Section 3). At longer TTCs, the false alarm rate will be high as many VRUs which are identified by the system as potential risks (therefore triggering an alarm), will alter their behaviour in the time between warning and possible collision, and no longer present a risk. In addtion, drivers will have more time to respond to warnings at longer TTCs, and subsequently change their behaviour. At the opposite end of the scale, at low TTC, drivers will have less time to respond but the false alarm rate will be lower as VRUs detected at this stage as a risk are less likely to alter their behaviour. The study in Section 3 assessed drivers' perceptions of trust, confidence, annoyance and desirability based on their experiences of using the system at different TTCs. The model illustrates that false alarm rate / TTC / driver response time can be both too high and too low to encourage driver acceptance of a system, but the perceptual factors underlying acceptance are subtly different at the two extremes of the scale. The importance of the perceptual factors was judged based on the results of the false alarms study according to relative scores between the different TTCs and on previous findings in the literature. In the model, the relative importance of each perceptual factor to acceptance at each end of the scale is indicated by font size and was based on subjective estimates by the researchers. The model is designed to demonstrate that there is a margin between high and low TTC / false alarm rate / driver response time which promotes the highest levels of driver acceptance of a PAS, but this is not clearly defined and will likely also vary between individuals (illustrated by grey shading in the diagram, rather than solid lines).

As discussed in the study description, we are assuming a linear relationship between TTC and false alarm rate; of course, this is likely to be an oversimplification. There will also be many other factors which influence acceptance and would affect the bounds of the 'margin of acceptance' in the model. According to the acceptance models reviewed in Section 2.1, additional perceptual factors include perceived usefulness (Choi and Ji, 2015, Ghazizadeh et al., 2012, Nordhoff et al., 2016), perceived ease of use (Choi and Ji, 2015, Ghazizadeh et al., 2012), perceived risk (Choi and Ji, 2015), satisfaction, efficiency, effectiveness, and pleasure (Nordhoff et al., 2016). These all relate to the user's perceptions of a system based on their interaction with it. Additionally, there are many other factors which affect individuals' perceptions of themselves and will also influence acceptance on an individual basis. We can suggest possible ways in which these factors might influence the margin of acceptance in the current model. For example, perceived ease of use could relate to the ease with which warnings from a PAS can be interpreted by drivers: this factor might therefore be rated lower with a low TTC system as drivers will be less familiar with warnings as they happen infrequently and therefore will find it more difficult to immediately recognise their meaning. This is a problem with many proactive safety systems as their purpose is to warn of events which are very infrequent in normal driving (i.e. the possible collision with a pedestrian) and therefore drivers can never build up any familiarity with system feedback. Perceived usefulness will be strongly linked to false alarm rates, with a very high rate being perceived as not useful as drivers will not be able to distinguish when a real risk is present. It is also likely to be an influencing factor at low false alarm levels too, as a system which fails to warn will be seen as pointless. The perceived risk of using a system will be higher with lower TTC as drivers will feel that the system cannot be relied upon to warn appropriately and with enough time to respond successfully. High TTC warnings may be seen as low risk in terms of collisions with pedestrians, but may create other risky situations if the driver is regularly reacting to false alarms (e.g. high incidence of sudden unnecessary braking could increase risk of collisions with vehicles travelling behind). We can infer many of these effects from the existing models (Choi and Ji, 2015, Ghazizadeh et al., 2012, Nordhoff et al., 2016) but it will also be important to study how these factors influence acceptance of a PAS specifically.

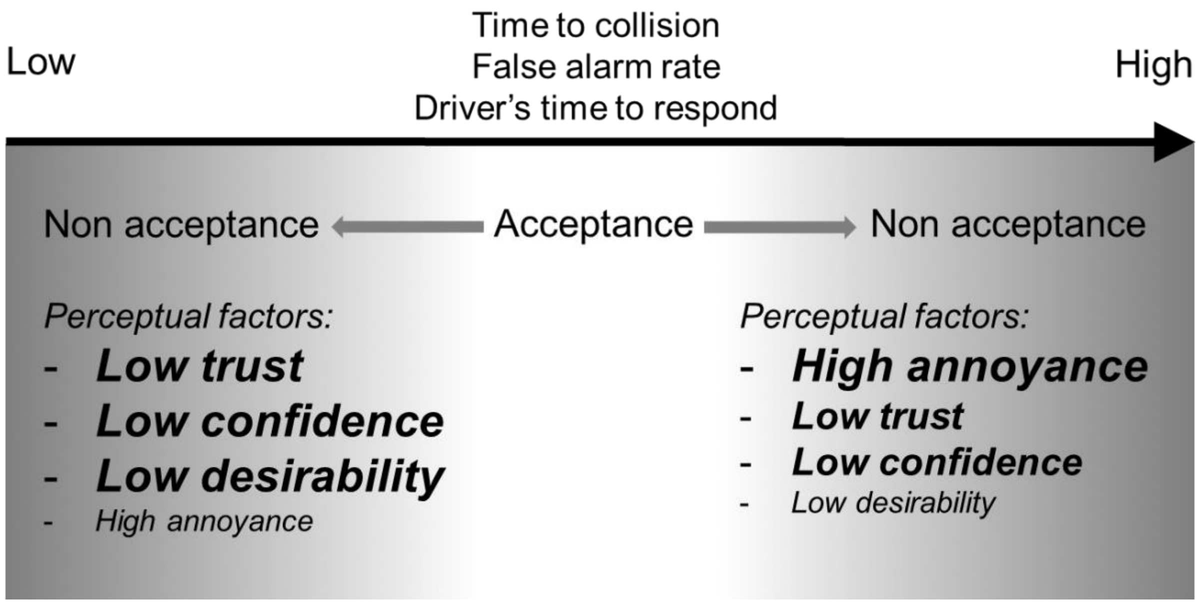

Fig. 2 Preliminary model of the relationship between driver acceptance of a PAS and TTC of warning

5. Conclusions

The paper presented an in-depth literature review that introduced and discussed the factors that are likely to influence driver acceptance of in-vehicle collision avoidance technology. This is enriched by a driving simulator study that investigated the effect of false alarms on trust and acceptance. A preliminary, descriptive model of driver acceptance is subsequently proposed, indicating that the highest levels of driver acceptance of a PAS system are likely to be achieved when warnings are presented at intermediate TTCs. If warnings are provided too late (or indeed, too early), they are likely to annoy drivers and inspire lower levels of desirability and confidence in the technology; in practice, this can lead to drivers disregarding the advice and relying on their own judgement. However, it is recognised that during the simulator study, participants were exposed to a high number of warnings over a short period of time. In reality, such warnings are likely to be seldom experienced. In addition, as we highlighted at the outset and throughout, the factors that affect the acceptance of technology in a driving context are complex and interrelated. Further empirical work is therefore required to enhance and validate our model, and incorporate further factors, before a predictive model of driver acceptance can be proposed.

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