Final Report: The Development and Performance Testing of a LAARMA—Large Animal Activated Roadside Monitoring and Alert System

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Executive Summary

Animal–Vehicle Collisions (AVCs) present a significant threat to wildlife conservation and human safety, particularly in wildlife-rich areas like regional Australia. Conventional mitigation measures, such as wildlife crossings and fencing, are often limited by geographical and financial constraints. While driver awareness campaigns may raise awareness about the general risk of AVCs, they are not and cannot be targeted to context- or time-specific instances where a motorist must take action because an animal is on or near the road. Thus, there is a critical need for real-time interventions that inform motorists of an impending hazard in terms of an animal having been detected on or near the road.

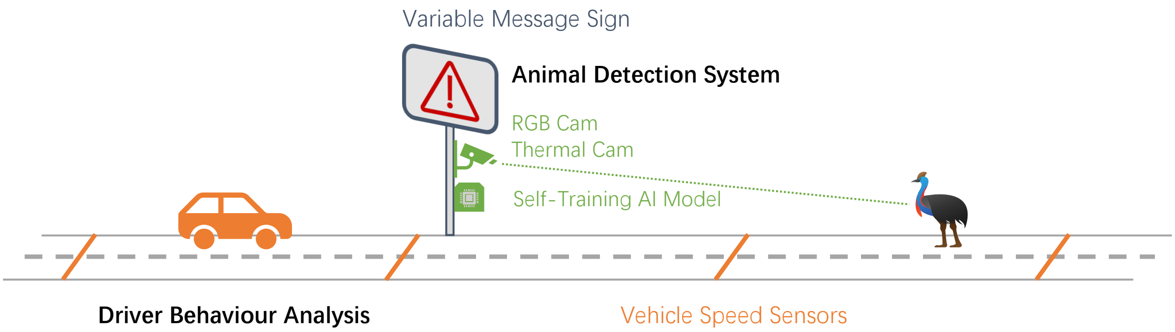


Figure 1.: An overview of the developed LAARMA system.

This collaborative study, conducted by The University of Sydney, Queensland University of Technology, and the Queensland Government's Department of Transport and Main Roads, developed a novel Large Animal Activated Roadside Monitoring and Alert (LAARMA) system, as presented in Figure 1. The LAARMA system integrates several advanced technologies, including a multi-sensor detection suite, a machine learning-based animal detection algorithm, and purpose-devised Variable Message Sign (VMS) messaging. Specifically, the system monitors roadside large animals, in particular, cassowaries, at distances of up to 200 metres via a relatively cost-effective suite of perception sensors in various weather conditions. Upon detecting a cassowary on or near the road, the system immediately triggers a warning message to be displayed on a roadside VMS. The messaging was purposefully devised and sought to ensure drivers' awareness of the alert as a real-time hazard. An innovative feature of the animal detection in the LAARMA system was its self-supervised learning pipeline, which enabled the system to automatically label real-world animal data collected during field operations, continually improving its accuracy and reliability without extensive human supervision. This approach has shown effectiveness in addressing the challenge of data scarcity, particularly in cases where insufficient training data existed for specific animal species.

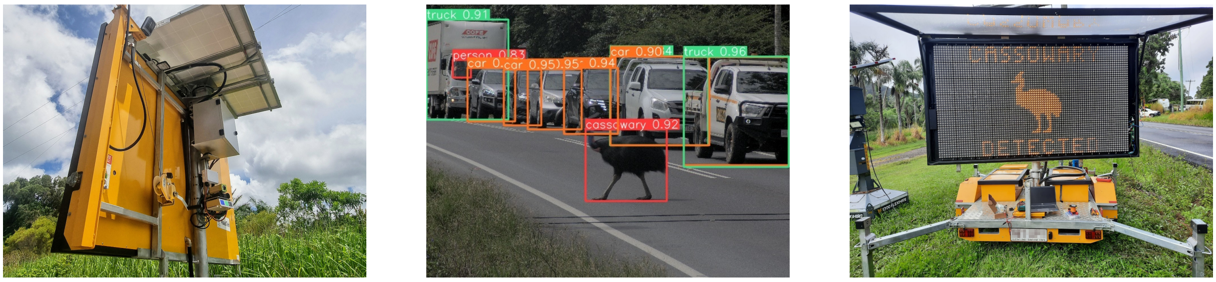
Prior to the conduct of an on-road trial of the LAARMA technology, a series of messaging concepts were developed, then concept-tested via qualitative focus groups (Study 1), and finally evaluated via a large-scale online survey of drivers' responses to messaging (Study 2). Such aspects were underpinned by robust conceptual and methodological approaches to message design and evaluation; namely, the Step approach to Message Design and Testing (SatMDT). From an initial 20 messages at concept-testing (conducted with N = 36 licensed drivers/riders across eight focus groups), four messages were selected for further evaluation in the online survey (with N = 557 licensed drivers/riders who were allocated to either a message condition to see one of the four messages being tested or a control, no-message condition to enable comparisons between groups and relative to a baseline). Overall, all four messages evaluated in Study 2 performed consistently well across all measures of effectiveness, which suggests that the implementation of any of these messages would likely have the intended effects on driving behaviours. However, there were instances where some messages appeared to outperform others on specific measures and suggests that there is scope to selectively apply messages according to the parameters that are considered of highest priority. Noting the VMS was to display a message across 2 screens, for screen 1 of the message, a greater portion of participants across both Study 1 and 2 reported that it would be more effective to identify the type of animal on the signage compared to participants who reported that the animal should not be identified. For screen 2, there were no significant differences in how useful participants perceived the four driving strategies that were tested; however, participants across both studies commented that the slowing down strategy should be presented before the scanning strategy as it made sense the first important response to encourage was to have motorists slow down. Participants across both studies emphasised the importance of motorists understanding that the message was a real-time warning, and expressed concerns that motorists might become complacent if the sign were to remain activated and/or they did not come across any animals while driving. This provided support for leaving the sign blank and only flashing a message when an animal had been detected.

The first of the behavioural monitoring studies in this program of research comprised a driving simulator study. Two messages (from Study 2), as shown in Figure 2, were selected

Figure 2.: Visuals for the VMS. The display for the first message alternated the images (a) and (c), while the display for the second message alternated the images (b) and (c).

for testing in this simulator study. The simulator study comprised 51 participants (all of whom were required to be licensed drivers/riders) who each undertook a 40-minute simulated drive. During the drive, participants were shown one of the messages and in relation to scenarios where a cassowary was either crossing the road or walking alongside the road. Results were also considered in relation to two key analysis windows: the approach window and the event window. The approach window commenced 5 seconds before reaching the VMS and ended exactly where the VMS was situated. The event window essentially captures behaviour in the cassowary detection zone and corresponded to the point where the Time-To-Collision (TTC) equalled zero. Overall, the results from the simulator study provided support for the effectiveness of the messaging in significantly reducing participants' speeds in the approach zone; however, no such significant reduction was found for speeds in the event zone. In other words, participants' initial response on sighting a message on the VMS was to significantly reduce one's speed. The results also highlighted that while both messages were associated with positive behavioural effects in terms of speed reductions, there were some differences in the relative effectiveness of the two messages that were tested depending on whether the scenario was a cassowary crossing the road or appearing alongside the road. The latter finding highlighted that consideration should be given to the specific intent of a message to ensure selection of the optimal message for a given purpose.

The final study within the program of research comprised a five-month field trial of the technology and messaging at a site in Far North Queensland (FNQ) where it was known that cassowaries frequented. After the system's installation in late January 2024, it underwent three months of data collection for model training, followed by a two-month on-road trial during which the designed VMS message was displayed to alert motorists to cassowary detection events, as illustrated in Figure 3. A total of 287 manually-verified cassowary sightings were recorded from 8 March to 30 June 2024, providing valuable insights into cassowary activities from month to month, and serving as ground truth for evaluating detection per-



(a) (b) (c)

Figure 3.: Installation of the animal detection system onto the VMS trailer and its deployment in the field are shown. (a) shows the VMS in the field with the detection system installed. (b) shows an example of cassowary detection using the trained model. (c) shows the message displayed on the VMS for notifying motorists the real-time cassowary detection event.

formance. Despite some technical challenges, the system effectively triggered VMS alerts for motorists upon detecting a cassowary on or near the road during the on-road trial from 30 April to 30 June 2024. The on-road trial results validated the LAARMA system's ability to detect cassowaries under real-world conditions, achieving a recall rate of 0.97. This means the system accurately triggered for 97% of the events where cassowaries were present. The exceptionally high recall demonstrates the system's high sensitivity in detecting cassowaries crossing or near the road, a critical aspect for road safety-related use cases. Notably, the self-training machine learning pipeline proved to be a robust method for continuous model improvement. There are in total 10 models trained during the data collection and on-road trial periods, using data available up to different dates. Quantitative evaluation results showed a clear trend of improved model performance over time. For instance, for detecting cassowaries within a 100-metre range, the mean True Positive Rate (TPR) increased significantly from 4.2% for the first trained model, to 78.5% for the last trained model. A significant increase in mean TPR was also observed for detecting cassowaries between 100 and 200 meters. Overall, the field trial demonstrated that using synthetic data for initial training and auto labelling with a Vision-Language Model (VLM) was effective in overcoming the data scarcity problem and improving model performance. In addition, the field data analysis results discussed the strengths and limitations of different sensor modalities for detecting cassowaries at different ranges, providing a general guideline for choosing the suitable sensor configuration when deploying the system at new animal crossing sites.

In addition to the animal detection results, the driver behaviour analysis across four vehicle monitoring sites in the field trial, as illustrated in Figure 4, provided support for the positive effects of the LAARMA system and the messaging it triggers on motorists' behaviour. Specifically, the field traffic data analysis revealed significant reductions in vehicle speeds in the event zone, with decreases of 6.30 km/h and 5.06 km/h at two sites, respectively, when

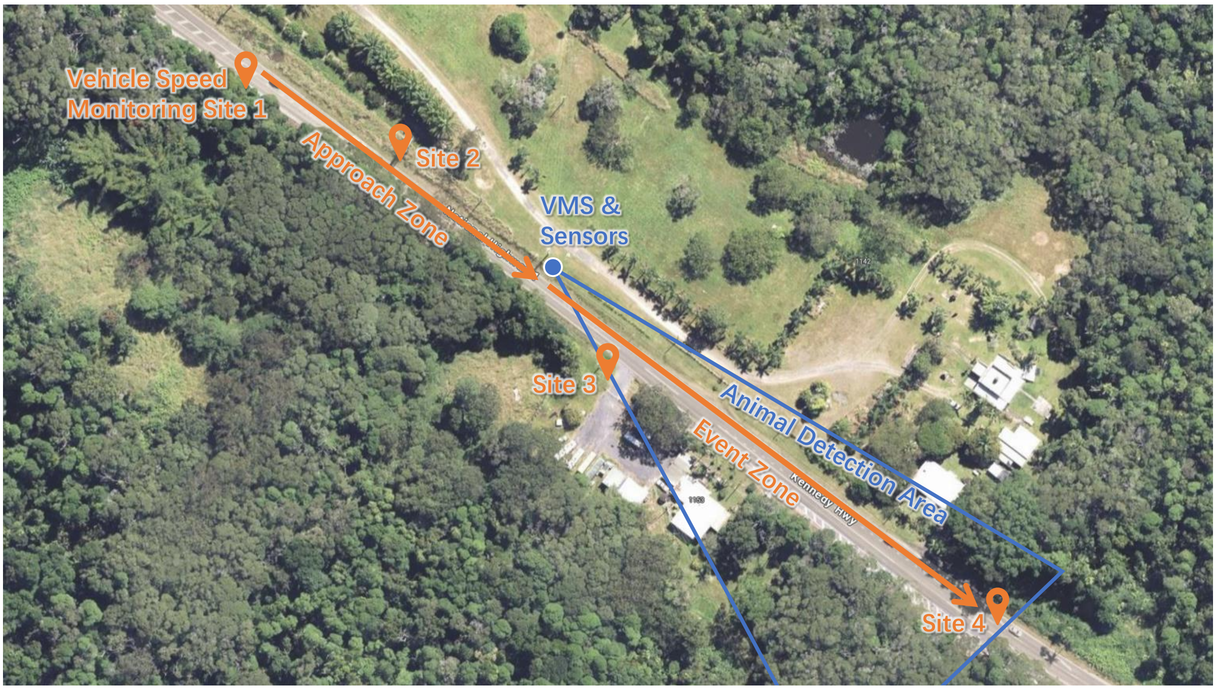


Figure 4.: Map of the four vehicle speed monitoring sites corresponding to the approach zone (i.e., Sites 1 and 2) and the event zone (i.e., Sites 3 and 4).

messaging was displayed on the VMS (as triggered by the LAARMA system). These speed reductions correspond to approximately 10% of the posted speed limit of 60 km/h in the trial area. In the approach zone, while the VMS still played a significant role in reducing speeds, the decrease was slightly less pronounced, with reductions of 4.26 km/h and 3.44 km/h at two sites, respectively. The crash reduction analysis further supported this, showing that LAARMA's impact is more pronounced in the event zone, where significant reductions in fatal and serious injuries were observed using the Nilsson power model. Overall, the analysis results provided support for the road safety benefits of the system and efforts to mitigate potential AVCs.

In conclusion, the study highlights the effectiveness of combining advanced machine learning-based detection technologies with purpose-devised messaging displayed on roadside VMS. Together, these elements comprising the LAARMA system resulted in positive effects on influencing motorists' behaviour, as demonstrated in a driving simulator as well as in an on-road field trial. The comprehensive program of research offers valuable and practical insights for similar deployments of such technology for detecting animals on or near the road in other regions.

Acknowledgement

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Acronyms

ACFR Australian Centre for Robotics

AVC Animal–Vehicle Collision

CARRS-Q Centre for Accident Research and Road Safety - Queensland

CNN Convolutional Neural Network

FNQ Far North Queensland

FoV Field-of-View

FPR False Positive Rate

GPS Global Positioning System

LAARMA Large Animal Activated Roadside Monitoring and Alert

LiDAR Light Detection and Ranging

OVD Open-Vocabulary Object Detection

OWL Web Ontology Language

QUT Queensland University of Technology

RADS Roadside Animal Detection System

RGB Red Green Blue

SAM Segment Anything Model

SatMDT Step approach to Message Design and Testing

TMR Queensland Government's Department of Transport and Main Roads

TPR True Positive Rate

TTC Time-To-Collision

USYD The University of Sydney

VLM Vision-Language Model

VMS Variable Message Sign

Contents

References

Appendices

1

Introduction

This technical report provides a comprehensive summary of the outcomes for the Queensland Government's Department of Transport and Main Roads (TMR) project titled "The Development and Performance Testing of a LAARMA—Large Animal Activated Roadside Monitoring and Alert System".

This one-year project started on 1 September 2023 and finished on 31 August 2024, and was conducted by the joint team of Australian Centre for Robotics (ACFR) at The University of Sydney (USYD) and Centre for Accident Research and Road Safety - Queensland (CARRS-Q) at the Queensland University of Technology (QUT).

1.1. Background

Roadkill resulting from Animal–Vehicle Collisions (AVCs) is not just a tragic loss of wildlife but also poses a significant safety hazard to humans. In regions like Australia, where diverse fauna often intersects with human infrastructure, the issue is particularly pronounced. The presence of large animals on roads and roadsides present road safety risks due to:

- Vehicle strikes of large animals;
- Erratic driver responses to being startled by animals on the roadside and taking evasive action to avoid striking the animal.

Conventional mitigation measures, such as wildlife crossings and fencing, are often limited by geographical and financial constraints. Addressing this, there has been a surge in both research endeavours and commercial products focusing on Roadside Animal Detection Systems (RADSs) and analogous systems. These initiatives aim to bridge the gap between the natural habitats of animals and the ever-expanding road networks. Deployed in both controlled laboratory settings and real-world environments, these systems are engineered to detect animals in proximity to roads. By doing so, they serve a dual purpose: alerting motorists to enhance their vigilance and providing guidance on safely navigating interactions with the detected wildlife. However, challenges still exist in these existing solutions, for instance:

- Some RADSs introduce artificial stimuli (e.g., lights and sounds) that may disrupt natural animal behaviours and habitats.
- Many systems are associated with high installation and maintenance costs, which pose barriers to widespread adoption.
- Questions remain about how well these technologies can be scaled and integrated into different geographic and climatic regions, as well as their adaptability to Australia-specific conditions.
- Innovative machine-learning-based approaches have emerged as promising solutions for animal detection; however, these approaches face challenges in detecting species where there is insufficient existing data for model training.
- There is a significant lack of specific quantifiable outcomes and statistical analyses reflecting the reduction in AVCs and enhancement of road safety.
- There is a need for more research on the effectiveness of specific variable warning messaging content in reducing AVCs.

1.2. Project Objectives

The intent of this project was to develop and field test a system for detecting large animals on the roadside and prompting an alert to motorists to provide advanced warning of the hazard. The project has two overarching aims which are to:

- Accurately and reliably detect and identify large animals on the road and roadside at distances up to 200 metres under various weather conditions, including daytime, nighttime, rain, and dry conditions.

- System shall utilise machine learning to "train" itself in accurate detection and identification of large animals,
- Create open-source software for the detection and identification of animals on the roadside.

• Evaluate changes in driver behaviour (road safety) in response to animals on roadside when drivers are provided advanced message of real-time hazard. Specifically:

- Detect change characteristics in driver behaviour (braking, speed profile change, lane departure),
- Measure magnitude of change in driver behaviour,
- Measure duration of the change in driver behaviour (from installation of warning system), and
- Evaluate which message wording is more effective.

1.3. Developed System Overview

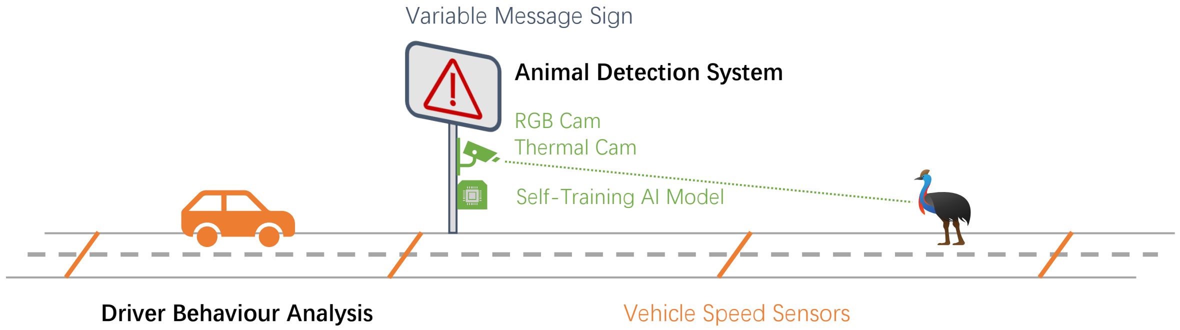


Figure 1.1.: An overview of the developed LAARMA system.

To achieve the project objectives outlined in Section 1.2, the joint team carried out research and development work on subsystems including the perception sensor suite for roadside animal detection, the associated software for artificial intelligence (AI) inference running on the edge computer, the message design for the Variable Message Sign (VMS), and driver behaviour monitoring for road safety analysis. An overview of the proposed system is presented in Figure 1.1. Figure 1.2 provides a diagrammatic representation of the overall project.

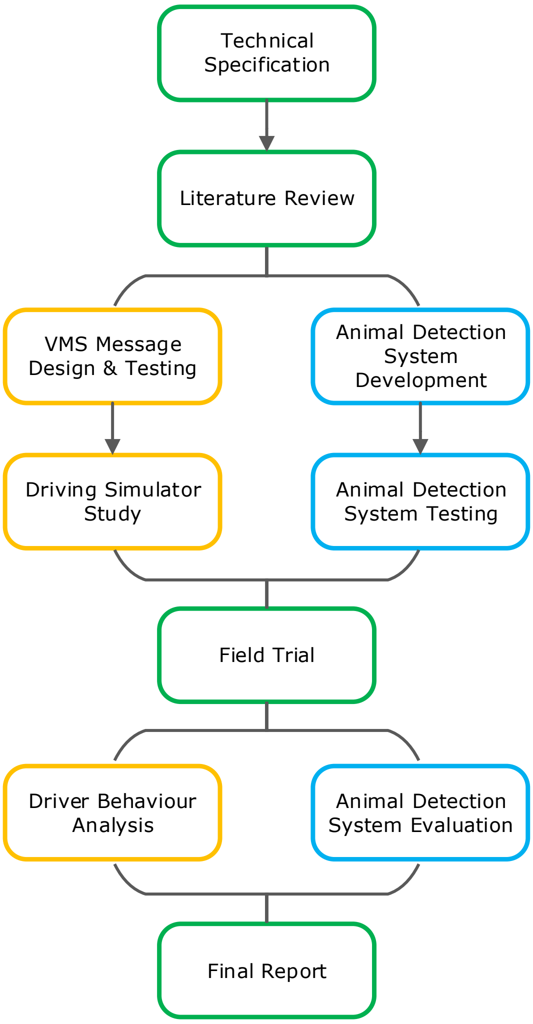


Figure 1.2.: A diagrammatic representation of the research and development components and studies within the overall LAARMA system project. From top to bottom, the figure clearly illustrates the sequence of these components and studies, with some being conducted concurrently by the USYD team (in blue) and the QUT team (in yellow), while the rest (in green) are conducted jointly by both teams.

Field trial results obtained from Far North Queensland (FNQ) have shown the effectiveness of the developed system in detecting cassowaries and improving road safety outcomes. As noted, particular focus in this project was upon the detection of cassowaries although the system was designed and developed with the capability to extend its application to large animals more broadly.

1.4. Roles and Responsibilities

The USYD and QUT teams have collaborated closely to share the project work and deliver the project outcomes jointly. Each team is the lead institute for different components of the project, as illustrated in Figure 1.2 and also listed in Table 1.1.

Project Work		**Lead Institute**
Literature Review		USYD & QUT
R&D	Animal detection system development & testing	USYD
	VMS message design & testing	QUT
Driving Simulator Study		QUT
Field Trial		USYD
Data Analysis	Detection system evaluation	USYD
	Driver behaviour evaluation	QUT
Reporting		USYD & QUT

Table 1.1.: Project scope and work distribution.

1.5. Open-Source Code

The project source code is available for free access through the following two GitHub repositories:

https://github.com/acfr/CassDetect.git

https://github.com/acfr/laarma.git

2

Literature Review

2.1. Animal–Vehicle Collisions and Road Safety (QUT)

2.1.1 Introduction

This review was prepared by Ms Nyree Gordon and Ms Amy Schramm together with Prof Ioni Lewis. It includes information on the scope and nature of AVCs in Australia and around the world. Interventions and their effectiveness in reducing AVCs are also reviewed; however, given the nature of the proposed intervention involving technology-based solutions to deliver real-time warnings via portable roadside messaging in this project, particular focus within this review was upon the development of messaging content as well as the means by which to evaluate the effectiveness of such messaging in helping to reduce AVCs. This focus includes an overview of the conceptual framework underpinning the design and evaluation of messaging strategies, the Step approach to Message Design and Testing (SatMDT [1]). This framework also underpins this program of research with respect to the development, testing, and evaluation of messaging content to be delivered by an innovative, real-time responsive technological solution advising motorists when an animal has been detected on or nearby the road.

To identify relevant literature, including government reports and academic papers, the following databases were searched:

- SpringerLink
- ScienceDirect
- Google Scholar
- Web of Science

To capture the broad scope of information required and variable descriptors within its research, the following search terms were used:

- Animal-vehicle crash (AND intervention OR evaluation)
- Wildlife-vehicle crash (AND intervention OR evaluation)
- Road safety (AND messaging OR intervention OR evaluation)
- Health messaging

2.1.2 Background

2.1.2.A. Animal–Vehicle Collisions

Animal-vehicle collisions, or AVCs, are referred to using different terms in the literature, including not only AVCs but terms such as deer-vehicle collisions, and wildlife-vehicle collisions (WVCs). For the purposes of this review, the term AVCs is adopted.

AVCs are associated with substantial costs to individuals, communities, and the environment each year. In 2004, over a billion dollars of vehicle damage was reported annually in the United States due to crashes involving animals [2]. The human and societal costs of injury, rehabilitation and death cannot be quantified, nor can the effects of AVCs on conservation efforts. Analysis of crash data in the US between 1965 and 2017 found that there was a four-fold increase in animal fatalities resulting from AVCs in that time [3]. Unfortunately, in countries such as Australia, a large number of native and protected species are particularly vulnerable [2] making it a substantial threat to those ecologies.

The main cause of human injury and/or vehicle damage related to AVCs is not in terms of actual impact with the animal but more often the result of impact-avoidance measures, such as extreme braking and swerving [4–7]. These manoeuvres can lead to loss of vehicle control, rollovers or impact with secondary objects, exacerbating the damage and, thus, cost and severity of the incident.

The occurrence of AVCs is influenced by various factors relating to motorists, animals, and the environment (e.g., road infrastructure and time of day as well as ecological factors pertaining to animals' mating seasons and climatic conditions). The subsequent sections of this review highlight studies which have provided insight into one or more of these factors, but first an overview of this project and the animals to be of focus within it, is provided.

The southern cassowary (Casuarius casuarius johnsonii) is a large flightless bird, endemic to north-east Queensland where it is found in pristine rainforest as well as urbanised areas. It is listed as an endangered species by both the Australian Commonwealth and Queensland State Governments, with motor vehicle strikes posing a significant threat to the species' subsistence. The Queensland Government's TMR [8] reports that 174 cassowary deaths were attributed to vehicle strikes between 1996 and 2018. In most cases, AVCs in which a cassowary is fatally wounded also evoke considerable distress to the local community who may often be able to readily identify and affectionately 'name' particular birds who reside in their area.

At heights of up to two metres and weights up to 85 kg [9], the cassowary qualifies as a large animal. Collisions related to these animals can lead to significant damage to property, injury and loss of life. Despite its size, the chances of a cassowary surviving a vehicle strike are low, according to Rigby [10]. The cassowary makes a valuable contribution to the regeneration and shaping of our rainforests through seed dispersal [11]. Lower numbers of cassowary will lead to a disruption in rainforest ecology which will then have flow-on effects, such as loss of flora species which, in turn, effects fauna etcetera. Lastly, as an iconic and culturally significant animal, the cassowary holds tourism value for its area. The ongoing success of the species is of benefit to everyone.

A range of measures have been trialed to reduce vehicle strikes of cassowaries and other large animals. These measures have included reduction in speeds through areas of known habitat, warning signs and infrastructure solutions (e.g., bridges and fencing). However, with the evolution of technology, comes opportunity for innovative and potentially impactful ways, in terms of influencing motorists' preparedness (to encounter such animals) and behaviour (to reduce speeds and monitor the environment) to be devised and implemented. The current program of research will devise and evaluate the effectiveness of real-time messaging delivered as part of an innovative technological solution. The technology, based upon machine learning to identify cassowaries when on or near roads, will trigger a message to motorists to warn of the potential hazard.

2.1.2.B. Factors Influencing Animal–Vehicle Collisions

Overall, limited research has been conducted in Australia regarding factors influencing AVCs. Almost two decades ago, the Rural and Remote Road Safety Study, conducted by the CARRS-Q and the Rural Health Research Unit (RHRU) at James Cook University, aimed to identify the human, vehicular, and environmental factors that contributed to serious road casualties in rural and remote North Queensland [2]. From March 2004 to June 2007, interviews were conducted with 383 patients who were hospitalised due to a crash (298 male). Information gathered included demographic details, attitudes to road safety and enforcement, alcohol and drug consumption. Patients were also asked to describe the crash in their own words. In this study, animal-related crashes accounted for 5.5% of all on-road serious casualties with night-time travel being a prominent risk factor for such a crash. Animal-motorcycle crashes were of the highest rate (51.7%) of any of the on-road crashes investigated in this study. A significant proportion of swerve and avoid crashes were also reported. Several patients reported having no warning with animals appearing at close range moments before impact. Elevated crash counts in higher speed zones suggested that drivers/riders need to be particularly vigilant

Figure 2.1.: An example of some traditional roadside advisory signs used in the past in Queensland regarding areas of potential road crossing by wild animals.

in these areas, especially at the high-risk times of dawn, dusk, and darkness when animals may be more likely to be moving about. The high proportion of kangaroos and wallabies involved in these crashes (44.8%) highlighted the need for interventions to address AVCs which were specific to the Australian driving context and addressing large(r) animals. Figure 2.1 provides an example of signs used in the past in Queensland to advise of road crossings of wild animals. The official meaning of these signs, as was explained by the Queensland Government [12], was that "the road ahead is an area where wild animals are known to cross, or be on, the road and can be a hazard". This information is relatively generic and vague which can contribute to habituation and, ultimately, have a limited effect on driver behaviour. The Rowden et al. [2] study also highlighted that there was likely underreporting of AVCs in that only those resulting in serious injury (to a human) were likely to be reported.

To understand more about AVCs, there have been studies which have examined the person-, animal-, and environment-related aspects that are associated with such incidents. The subsequent section also presents some evidence based on statistical modelling procedures that have been used in the attempt to highlight at-risk locations for AVCs.

Person-Related Factors

A recent large-scale survey in Hungary explored the habits and attitudes of 1942 drivers regarding AVCs [5]. The researchers found that drivers who had less experience with, and fear of, AVCs drove with more confidence, at higher speeds and less vigilance than those who had experienced and/or who were fearful of being involved in AVCs. They also found that with more years of driving experience, there was also an increase in one's perceived ability to handle unexpected driving situations, such as an animal encounter. Perhaps unsurprisingly, it was also found that drivers who reported a higher regard for the importance of nature

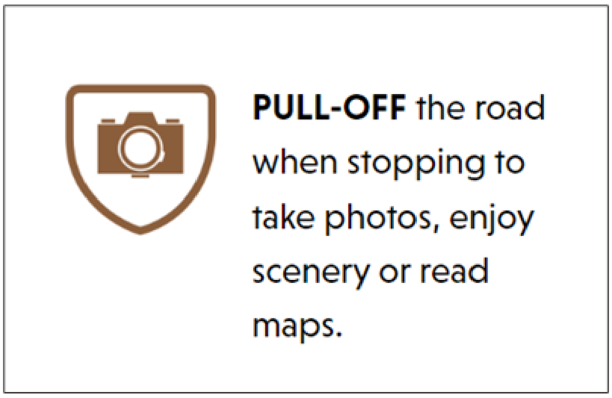


Figure 2.2.: Example of road safety sign (Road Safety Advisory Council, Tasmania [13]).

conservation and/or traffic safety in relation to preventing AVCs self-reported driving with more care and attention [5].

Other evidence relating to person-related factors has found that a lack of knowledge about the appropriate or correct course of action in the event of an animal encounter also influences potential AVCs [2, 4, 5]. The nature of AVCs avoidance manoeuvres that a driver or rider may need to implement such as swerving to avoid an animal can also increase the likelihood of a serious injury crash [4]. While research has shown that the safest solution for a motorist is to actually slow down and (unfortunately) hit the animal, in a study of crash mechanisms involved in 366 AVCs in Australia, Wilson et al. [7] reported that 58.5% of AVCs involved the motorist swerving to avoid impact with the animal. Unfortunately, however, swerving can often result in collision with adjacent objects, such as other vehicles, trees, poles and guardrails thus increasing the severity and costs of the crash [2, 7].

Additional considerations of this project are road safety issues related to motorists' (and potentially more so for motorists who are tourists to the area) behaviours around wanting to sight cassowaries when advised of their presence. The distraction of trying to sight a cassowary in the wild while operating a vehicle poses a significant risk to all road users. In areas known as popular tourist areas, some jurisdictions have opted to erect signage advising motorists of safety requirements when wanting to observe surrounding attractions. For instance, the sign shown in Figure 2.2 is an example from the Road Safety Advisory Council in Tasmania [13] to encourage motorists to pull off the road whenever stopping to take photographs or enjoy the scenery. Related to messaging of this nature and especially pertinent to this project is that it will be important to check for any unintended behaviours of motorists such as their braking suddenly and pulling up in a carriageway in response to messaging about cassowaries being in the vicinity in the hope of seeing one.

A further consideration is non-English speaking tourists. Limited work has examined the use of bilingual messaging on road signs. Research from Finland examined the visual demand associated with the display of alternating bilingual messages on VMS. An experimental driving study was conducted in Finland with a VMS displaying a "LOOSE GRAVEL" message either as a bilingual message or alternating between Swedish and Finnish for 2 seconds per frame [14]. No significant difference in eye fixations between the three sign configurations, although the authors note that more complicated signs may illicit different driver responses [14]. While no significant difference due to age was found, older drivers' gaze durations and longest fixation duration trended higher when compared with younger drivers [14].

Animal-Related Factors

Animal factors influencing AVCs occurrence range from the physicality of particular species to their social behaviours. Borza et al. [5] and Hill, et al. [3] reported that animals larger in size accounted for the highest number of AVCs (which could also be due to the reporting bias that AVCs associated with larger animals are more likely to be severe and thus reported). Bil [4] reported that while less than 5% of AVCs occurring in Canada resulted in injury to a human, the risk of injury is related to the size of the animal involved. AVCs involving large animals (e.g., moose or camel) are more likely to result in a vehicle occupant sustaining serious or fatal injury. It is noted that, as a large animal, cassowary-vehicle crashes fall into the category of posing higher risk of severe outcomes. A large-scale study conducted by Cook and Blumstein [15] aimed at explaining variations in vulnerability to AVCs based on a number of different animal species. They found that omnivorous mammals (that eat both plants and animals) have the highest rate of being killed in AVCs while carnivorous mammals (that feed on other animals) have the lowest. Their results also suggested that mammals and birds that are known to be more social (e.g., wolves, emus) seem to be less vulnerable to being killed in AVCs than solitary animals (e.g., moose, koalas). They also reported that diet is an influential contributor to that vulnerability. That is, nocturnal animals are more vulnerable to AVCs with the majority occurring between sunset and sunrise when such animals are on the search for food [7, 16–18]; while seasonal factors such as drought and mating cycles are also significant factors contributing to AVCs [19]. Higher levels of movement have been noted in times of drought as animals search for food and water for survival and, likewise, activity and movement of animals increases during mating seasons.

In Australia, research has been conducted that examined the risk of wildlife collisions for six terrestrial native species in Victoria. Two kangaroo species (Eastern Grey and Black Wallaby), two possum species (Common Ringtail and Common Brushtail), as well as wombat and koala collisions were included in the study [20]. The study demonstrated that species-specific environmental and anthropogenic variables influenced the risk of AVCs. More specifically, the most suitable habitat for a species, prevalence (occurrence rate) of the species and traffic speeds influenced AVCs risk such that vehicles travelling at higher speeds were less likely to avoid a crash whether with the animal or as a result of swerving [20]. It was also noted that some species (such as reptiles who like to sun themselves on bitumen) are attracted to roads, therefore increasing their risk of AVCs involvement. Kangaroos are the most common animal involved in AVCs in Australia [7]. By their nature, kangaroos are fast moving and thus can appear suddenly giving motorists little time to respond. Wilson, et al. [7] reviewed 366 cases of patients (278 male, median age = 40) admitted to a tertiary trauma centre as a result of kangaroo-related crashes between 2000 and 2020. Swerving was found to be the most common cause of crashes and to be more common at night, possibly further impacted due to the motorist having diminished visibility. Time of year was not found to influence the occurrence of AVCs in this study (which was somewhat unusual and may be influenced by species); however, sunrise was identified as the most common time for crashes. Based on these findings, the authors recommended driving with extra caution around dawn and to follow "current Australian government advice that discourages swerving" [7].

Environment-Related Factors

The preceding section highlighted environmental factors such as drought and the mating cycles of animals that may influence occurrence of AVCs. Weather and time of year are also notable factors found in most research [16, 18, 21, 22], with an exception noted in the case of [7]. For example, hibernation patterns dictate prevalence of certain animals around roadways at different times of the year while rain and wet conditions are known to be preferred for amphibian migration [23].

Studies in Australia, Europe and the USA also note an increased risk for AVCs in rural landscapes and urban-rural border areas [2, 16, 24]. Single lane or 2-lane rural roads, high animal density, and thick vegetation found in rural areas and national parks are all factors that increase the risk of AVCs [25, 26]. Unfortunately, as cities grow and encroach on rural landscapes, animals must alter their patterns and activity to survive. Naidenko et al., [27] describe the white-tailed deer as a significant threat to road safety in the USA, partly due to its adaptability to urban landscapes while Madgwick [28] explains that the cassowary has become more of an urban dweller by default, as development encroaches into its natural habitat. The unpredictability of how animals will adapt to changing landscapes presents an ongoing risk for AVCs.

Regarding the environment in terms of the road context and infrastructure, however, transport infrastructure affects wildlife in four major ways. This includes fragmenting populations, disturbing natural behaviours, direct mortality (collisions) and indirect mortality [21, 29, 30]. Influential factors on AVCs along a major highway in northern Zimbabwe were assessed by Gandiwa, et al. [31]. This study's findings revealed that roadside water sources, such as dams, and denser vegetation found adjacent to roads were a major attraction for wild animals including mammals, reptiles, birds and amphibians and which increased the risk of AVCs, while road design such as curves and hills limiting forward vision was also a factor. Diaz-Varela, et al. [32] analysed data from 377 collision points on a 1426-kilometre road network in Lugo, Northwest Spain, between 2006 and 2007. They found that road type and quality of road influence the probability of AVCs occurrence such that 60% of the crashes in their database occurred on basic primary roads with limited infrastructure.

The broad range of influences and possible combinations of person-, animal-, and environment-related factors contributing to AVCs require an equally diverse and comprehensive range of countermeasures to address such factors. The subsequent section overviews some evidence based on statistical modelling approaches. This evidence is presented to the extent that it highlights the efforts undertaken to understand more about factors contributing to AVCs and how at-risk locations may be identified.

Statistical Modelling To Understand More About Animal–Vehicle Collisions

Statistical modelling approaches have been implemented to further understand and predict AVCs. Modelling may also support decision-making where data may be limited (e.g., underreporting of AVCs). A study conducted in Maine in the US found that underreporting of wildlife-vehicle collisions did not influence predictive model accuracy to detect AVCs hotspots, providing that that 30% or more of AVCs were reported [33].

Various modelling approaches have been used to identify AVCs hotspots. Of particular interest to this project is the use of Poisson CAR GLM to identify vehicle strike hotspots of cassowaries in the area surrounding Mission Beach, Queensland [34]. Poisson models assess risk while considering other elements, such as geographical design [35]. This study used information from a local database of cassowary sightings between 1999 and 2012 and statistically modelled which areas, time frames and life stages were related to elevated vehicle strike frequency. The understanding of influences on wildlife vehicle strike clustering obtained from this process is transferrable to a wide range of species and is particularly useful in developing appropriate mitigation methods for a geographic area. Closely related to Poisson is Niche-based ecological modelling that Ha and Shilling [36] explain, can accurately predict high-risk AVCs locations using environmental variables combined with human population density data.

Bayesian modelling is commonly used to identify trends in data. Bayesian spatiotemporal models were applied to AVCs data from Minnesota in the US by Ashraf and Dey [37]. These authors sought to identify specific area trends and locations where AVCs were increasing or decreasing. The authors developed five models; one parametric spatiotemporal model and four spatiotemporal models with a variety of interactions. The performance of these models was evaluated by analysing data on deer-vehicle collisions in Minnesota between 2015 and 2019. Results showed that the parametric spatiotemporal model and spatiotemporal interaction model with type 1 interaction (between unstructured spatial and temporal effect) were the most successful for model diagnostics and goodness of fit measures, making them most suitable for future modelling of this type. Critical data, such as number of animal crossings, is often not available and for large sections of roadway networks have low AVCs counts. Gurumurthy et al. [38] implemented Bayesian hierarchical models to account for seasonality issues across a large road network. This approach was validated with large datasets, with the model accurately providing monthly seasonality variations in predicted AVCs counts. Other modelling approaches, such as point pattern network models have also demonstrated capacity to develop driving routes that mitigate AVCs risk. Researchers used point patterns network structures to identify optimisation path selection [22]. This model considers the optimal path selection to determine the safest path between point pairs. More recently, researchers have explored the potential of using artificial intelligence (AI) and advance camera technology (multispectral imagery) to predict AVCs hotspots. The research has demonstrated that AI-developed models were more accurate than current mathematical modelling approaches [39].

While most research has used modelling to identify locations at risk of AVCs, some research has examined the use of modelling to predict AVCs injury severity and collision costs. Random parameters binary logit models have been employed to determine the likelihood of observing deer on a road and vehicles striking a deer. A correlated random parameters ordered logit model was then used to estimate the risk of injury severity resulting from the AVCs [40]. Researchers in Sweden use population dynamics models and econometric methods to predict how species involvement in AVCs and the future costs of AVCs is likely to change [41]. Further to this, modelling can be used for determining the optimal location for intervention (such as VMS) placement. Austroads [42] provide an example of this as the Australian National Risk Assessment Model (ANRAM) to calculate cost benefits of proposed sites. When historical crash records are not available the risk assessment and predictions of crash numbers are applied along with crash reduction factors to determine crash savings. This allows for comparison of predicted site outcomes to be considered when choosing placement of items such as VMSs.

These findings demonstrate the modelling approaches that have been used to determine factors contributing to AVCs as well as at-risk locations. Such knowledge is critical to the extent it helps with the identification of potential countermeasures. With this in mind, the next section of this review discusses interventions aimed at addressing AVCs.

2.1.2.C. Interventions Aimed at Addressing Animal–Vehicle Collisions

A range of measures have been developed and implemented to reduce AVCs, with varying degrees of success. Interventions have included signs, physical structures such as fences, crossing structures that are useful for climbing animals such as possums and squirrels and tunnels that are popular in Europe for amphibians and medium sized mammals. Road reflectors on roadside posts are used in Australia as a deterrent for animals as the reflectors glow from vehicle headlights at nighttime and create a perceptual barrier [2]. These treatments are also recommended by Austroads [43] as a countermeasure for motorcycle riding hazards. Odour repellents have been used in the Czech Republic as an alternative to fencing by applying them at regular heights (i.e., 80cm) on poles and it being placed there or used at regular intervals [44]. Of particular relevance to the current project, technological solutions, such as dynamic warning signs (or VMSs), are becoming more popular across the world. Other measures mentioned by Borza, et al. [5] relate to improvements in road engineering and maintenance, game management and driver education. Given the intent to develop and evaluate dynamic real-time roadside messaging as part of the overall current project, focus herein is upon warning signs and messaging as an intervention to reduce AVCs.

Warning Signs About Animal–Vehicle Collisions

Static warning signs represent a traditional intervention approach used to alert drivers to risks they may encounter in the road environment. In the following reviews some researchers have questioned the efficacy of these static signs in reducing AVCs, while others have suggested that their versatility and cost-effectiveness mean they are a viable option in helping to reduce AVCs.

Tryjanowski, et al. [45] reviewed evidence relating to the use and effectiveness of static road warning signs and concluded that the main response elicited by a motorist to these types of warning signs is merely recognition as opposed to motivating behaviour change. In an interview with ABC news, Professor Darryl Jones from Griffith University stated that “They make absolutely no difference to anything” [46]. Tryjanowski, et al. [45] suggest that further research is required to enhance the effectiveness of such signage to extend beyond mere recognition to ensure action is taken – whether that is to slow down or to monitor the road environment more diligently. The SatMDT [1] which is employed in this project and described in Section 4 of this review directly addresses this behaviour change aspect with respect to the development of targeted message content.

Tryjanowksi et al. [45] also noted that the effectiveness of these static warning signs can be increased when a speed limit (reduction) is also set to accompany the warning. Crash data show that AVCs are of increased severity at higher speeds [7]. Druta and Alden [47] found that even a driver prepared for the prospect of an animal on road, may still hit an animal if they are driving too fast. Quite simply, at a slower speed, drivers are more able to both detect and avoid animals even within a relatively short detection distance. In his research into reducing collisions with marine life, Dr Mark Boulet has found that as well as raising awareness, signs must give clear instruction on what related action people should take [46]. In the case of reducing AVCs the action should be to drive more slowly [5, 7, 45]. Thus, it seems gauging effectiveness of signage in reducing AVCs should take into account the extent to which it promotes or encourages motorists to reduce their speed.

While static roadside signs may have a place as an intervention in helping to reduce AVCs and have the benefit of being a relatively low-cost option, there have been recent calls to implement more effective strategies to reduce AVCs (see [48]). Tryjanowski, et al. [45] suggest that there had been a societal shift from a focus on protecting road users from AVCs to more of an emphasis on protecting animals and especially the latter when the animals are rare or native. It appears that this view is shared by administrative bodies and the public [45]. This shift is important to the extent that it provides some insight into potential messaging content—that a focus more on welfare and protecting animals may be appropriate. We revisit this latter aspect in Section 2.1.3.A of this review when discussing messaging content design. In the next section, however, we review some of the evidence available regarding the role of technology and messaging in reducing AVCs.

Technology and Warning Messaging About Animal–Vehicle Collisions

The variety of technological messaging options is constantly growing [49–51]. VMSs, which are electronic signs that can be programmed to display different messages, can now be integrated with other technology to cater to a range of situations as is the case with the current project. Specifically, technology now enables VMSs to be connected to a detection device (to detect presence of animals) and thus relay real time hazard warnings to a motorist. Detection devices can now also send warnings and information to in-vehicle advanced driver assistance systems that work on GPS.

Extending into the future and drawing upon the likes of connected vehicle technologies, there is exploration of next generation (NG) RADSs. These systems would aim to identify animals and assess threat levels for potential AVCs. It is proposed that these systems would

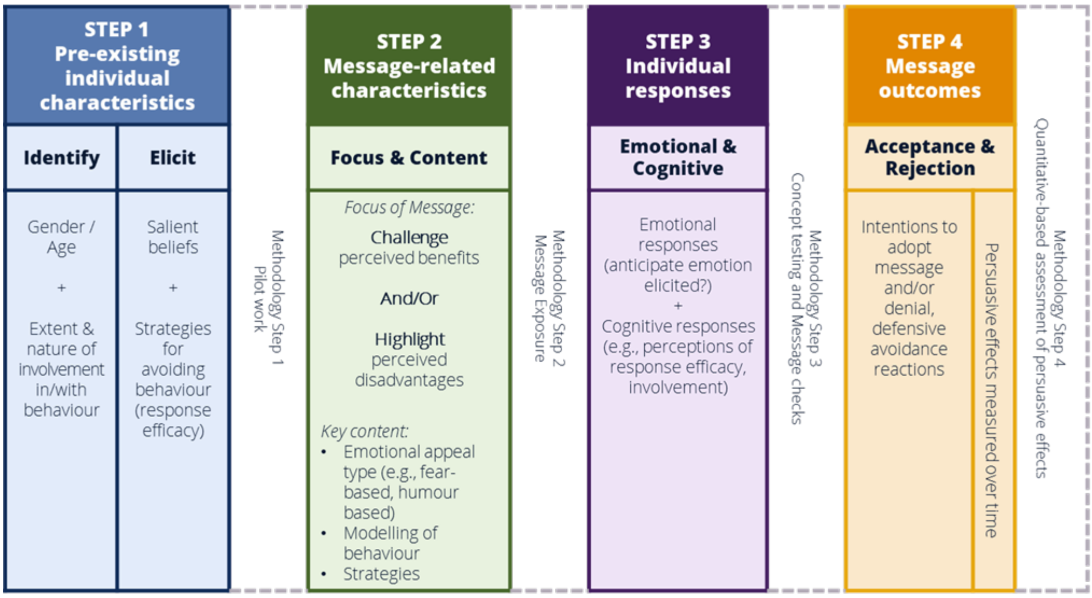


Figure 2.3.: The Step approach to Message Design and Testing (SatMDT [1]).

provide the ability to display various warning levels to motorists rather than a uniform or more general advice of there being a possible threat of AVCs [52]. The NG RADSs may also use vehicle-to-infrastructure (V2I) communication to directly control vehicle speeds [52].

2.1.3 Messaging Design

This program of research will be underpinned by one of the most contemporary frameworks in road safety messaging design and evaluation, the SatMDT [1], which is shown in Figure 2.3.

The SatMDT framework incorporates principles derived from social psychological theories of behaviour prediction, attitude-behaviour relations, and persuasion. As Figure 2.3 shows, the SatMDT comprises four steps: (1) getting to know the audience, (2) development of message content, (3) concept testing, and (4) final message evaluation. The theoretical models that inform the SatMDT include the Theory of Planned Behaviour (TPB [53]), The Elaboration Likelihood Model [54], the Extended Parallel Process Model (EPPM [55]), and Social Learning Theory [56]. Now well-established as a robust theoretical framework, the SatMDT has underpinned the development and/or evaluation of an array of messaging relating to various road user behaviours (e.g., speeding and child pedestrian safety) and other road safety issues including raising public awareness of connected vehicle technology [57]. The framework has also shown its versatility in terms of informing the development of messaging to be delivered via various media types (see [58] for a review of the SatMDT's application). Of relevance to the current project, the framework has informed messages displayed on VMSs including highway VMSs [59] as well as portable roadside VMS trailers (e.g., [60]), with the portable VMS trailer option to be the signage used in the current study.

Researchers have examined how to design signs to proactively improve visitor safety in Australian national parks [61]. This study is noted to the extent that animal encounters could be expected to be a part of visitor safety at national parks and, thus, insights garnered from this study may assist roadside messaging design for messaging regarding animals on or near the road. Consistent with the SatMDT, Saunders et al. [61] noted that it is important to first understand the target audience, including an awareness of existing knowledge and expectations. In addition, to understand individuals' familiarity with potential risks, including their perceptions of how likely and severe the risks could be, is important. Saunders et al. [61] noted that graphical symbols within messages can positively influence individuals' comprehension of warning signs. Moreover, they concluded that to ensure signs adequately warn park users, the signage needed to be noticeable, easily encoded (absorbed and understood quickly), located near the hazard, be credible, and describe the desired or expected behaviour.

The subsequent section of this review focuses more on the content of roadside messaging.

2.1.3.A. Content Design for Road Warning Signs and Variable Message Signs

Currently, no international standard exists regarding road sign design where such signs seek to prevent AVCs. It appears many countries take different approaches, such as referring to their own local, perhaps more charismatic species on warning signs [45]. While design guidelines exist, such guidelines are for road signs more broadly. Aspects relating to these guidelines are reviewed to the extent they may provide some insights pertinent to the development of messaging content for the current project.

Traffic Signs

There are universal design considerations in the development of traffic signs worldwide. For instance, it is important that images are legible from the specified distance and do not distract drivers with unnecessary detail [62]. The size of the images used is equally important. Small images may be more difficult to decipher from a distance while use of images that are too large increases the reading difficulty of older drivers due to issues with text blurring, particularly at night. Contrast of colour and brightness between the message components and sign background should also be considered for optimising readability. Dewar and Pronin [62] suggest that the use of consistent sign models (i.e., the use of colours and shape for warning or mandatory signs) is important to facilitate driver comprehension. It is also important to consider whether the hazard or the consequence of an action should be included on the sign, or if drivers should be told what they must or must not do, with consideration always given to prioritising the simplification of signage content [61, 62].

A laboratory study, examining driver eye movement behaviours when encountering various road traffic signs conducted in Croatia, found that signs must be clear and not require significant mental load to efficiently derive meaning [63]. Research has been conducted in Turkey regarding static traffic sign comprehension. This research examined local knowledge of European Union signs to be installed as part of the European Union harmonisation process [64]. As was highlighted in Babic, et al. [63]'s findings that driver understanding of traffic signs improved with familiarity, Kirmizioglu and Tuydes-Yaman [64] found that signs similar in design to existing signs are well known with high levels of understanding of sign meaning. However, signs not widely recognised will require increased education to improve awareness as a proportion of road users attributed an opposite meaning to the signs' intended meaning. As Kirmizioglu and Tuydes-Yaman [64] state, this could pose a significant risk, especially in circumstances such as where a "No Overtaking" sign was installed, and some road users understood it as "Overtaking Encouraged" so drove accordingly.

To understand how drivers comprehend traffic signs, a laboratory study was undertaken in Spain by Mazón et al. [65]. Participants were presented with static signs and more dynamic VMSs which provided information on road conditions and routing options. The study was conducted in two parts; comprehension and response times were assessed via recall of time-limited displays, followed by a reading span test that assessed working memory. Signs containing specific location details were more accurately recalled than those displaying generic information. Signs which identified the distance between incidents and the driver demonstrated lower cognitive demand in participants. A reason for this, hypothesised by Mazón, et al. [65], was that the structure and elements of the message promoted efficient extraction of its meaning. The authors concluded that ensuring design consistency, and providing adequate but not too much information, is essential in relaying information to drivers without impeding their cognitive load.

Also in Spain, researchers used a driving simulator to examine if the current understanding of reading capabilities (familiar and/or short words being read more quickly with less cognitive load) apply to signage within the road environment [66]. Results showed the advantages of short words compared to long words, in terms of reading speed and reduced cognitive load, were more pronounced when participants were reading road signs within the driving simulator. Such findings indicate that not only do those established understandings of cognitive load and word type and length apply but may in fact be further emphasised when travelling in the road environment.

Regarding dynamic VMSs, a field study conducted in Ohio, USA, examined how instantaneous feedback on driver behaviour in terms of compliance with pedestrian crossing yielding requirements, influenced drivers' behaviour. For this study, pedestrians using a pedestrian crossing were provided with a sign (green "thank you for stopping") to hold up if drivers stopped while, if drivers did not stop, a pedestrian further down the road held up a pink "please stop next time" sign. Researchers observed driver behaviour at the intervention site as well as a downstream location [67]. When compared with baseline data, compliance at pedestrian crossings increased significantly both at the treatment site and the downstream site. Such findings suggest that feedback by other road users and simple targeted messaging encourages drivers to improve compliance with road rules at pedestrian crossings. While not involving instantaneous feedback, Kirmizioglu and Tuydes-Yaman [64]'s results support Nasar [67]'s in terms of message framing. Just as the green and pink signs improved driver compliance, participants in Kirmizioglu and Tuydes-Yaman [64]'s survey, reported higher recall for positively framed than negatively framed messages. The results also found that most participants who self-reported behaviour change also reported higher recall of the positively framed messages despite believing that the negative messages would have a greater impact on their behaviour. There is ongoing debate around the choice to display warning messages constantly or only when directly applicable to a real-time hazard. The research in this review demonstrates that current views and practice vary. The Queensland Government's policy [68] on the display of information on VMSs allows for both philosophies, discretionary to individual situations and requirements. As pointed out by Glendon and Lewis [60], human factor principles necessitate only messages that require immediate behaviour change (e.g., speed choice) be displayed to minimise distraction and habituation. On the converse, the Queensland Government policy also acknowledges the necessity to assure drivers that such technology is not faulty and/or wasting tax payer money. The policy makes it clear that the specific factors (e.g., geometry, congestion) for each VMS site must be considered in this decision, with road user safety being the preliminary concern. Given the need for drivers to be aware of the real-time nature of the warnings when a warning is to be displayed in this current trial, there is evidence to suggest that messages triggered only when required do assist in conveying the real-time nature of that message (see [59] whereby drivers only received a message regarding speeding or tailgating when they were detected as engaging in one of these behaviours; otherwise, the VMS signage displayed on highway gantries was left blank).

Of integral consequence to the effectiveness of warning signs is the physical placement of the sign in proximity to the hazard, in relation to allowing time/space for adequate behavioural response. As explained by Glendon and Lewis [60], the stages of detection, reading, comprehension and response to a VMS require time and distance which must be allowed for when choosing a location. As an example, according to the Learn Drive Survive Team, Australia [69], when travelling at 80 km per hour, a driver's reaction distance is at least 33 metres. When combined with braking distance (in dry conditions) the total distance covered from detection to a complete stop can be anything up from 69 metres. Factors such as road geometry and the objectives of a particular research project combine in influencing decisions regarding the optimum placement of VMSs. Schramm, et al. [59] conducted a field study in South-East Queensland to evaluate the effect of VMS messages, displayed on highway gantries, on driver behaviour change recorded not only at each of the individual VMS sites (of which there were six; three northbound and three southbound on a 'Blackspot section' or high crash section, of the Bruce Highway) as well as overall in terms of vehicles travelling through the on-road study site. The VMSs were positioned at 10-kilometre intervals, with speed monitoring devices (pneumatic tubes or induction loops) posited at 500 metres prior to the sign (to determine baseline, non-message exposure behaviour of motorists) as well as 500 metres upstream from a sign, to determine longer term impacts of the messaging on driver behaviour within a 90 km/h speed zoned road. These measurement distances before and after the signs provided the means to determine the effects of the messaging in accordance with the study's research objectives which were to reduce travel speeds and increase headway of the vehicles travelling through the test area. The signs were only activated and thus displayed either a speeding or tailgating message if a motorist was detected engaging in one of these behaviours. The aim was that if a motorist saw a message, ideally the effect would then continue for some distance on the highway and not just at the sign; and hence why the 500-metre follow-up of behaviour. Overall, the results confirmed a positive effect of these VMS messaging in reducing travel speeds of vehicles travelling in their study site as well as increases in vehicle headways (consistent with the purpose-devised messaging targeting speeding and tailgating which were developed by project investigator [on this project also], Lewis).

In another relatively recent project, three anti-speeding messages, were field tested for their effects on speed behaviour using a roadside VMS trailer located on a suburban road in Queensland [60]. The location was chosen based on Queensland Government crash data listing sites of at least one serious (fatality or hospitalisation) speed-related crash within the previous five years and suitability for installing the trailer-mounted VMSs and pneumatic speed detection tubes on the road. Driver behaviour was recorded using pneumatic tubes at three locations including before (120 metres prior) and after the VMS (of which, after was assessed at both 80 metres after, and then again at 310 metres after the VMS). As noted earlier, the placement of the VMS and associated subsequent behavioural measures (pneumatic tubes) in this study was intended to assess motorists' baseline behaviour just prior to being able to see the sign and then to compare that with what occurred at the sign (after having some time to see and respond to the sign to reduce speeds if they were indeed intending to slow down) and then again further down the road to see how long any changes in behaviour were retained for. The design and thus distances of tube placement was intentional and aligned with the research questions of this specific study. Unlike the current project, this earlier project with roadside VMS was focused on the impact of the VMS messaging on driver behaviour and of the messaging itself. In the current project, as well as the VMS and the message it shows, there is also the added aspect of the messaging being a real-time message about the recent detection of an animal (cassowary) near or on the road in that study site. Thus, in the current project, the aspects influencing motorists' behaviour may not be just the VMS and its messaging but also the prospect of seeing and actually seeing an animal (cassowary) on or near the roadside.

In addition, in the Glendon and Lewis [60] portable VMS study (on impact of messaging on motorists' speeding behaviour) motorists coming from the opposite direction also had their behaviour (speeds and headways) measured via bidirectional tubes. Thus, these oncoming vehicles, not seeing the VMS message (rather just the back of a VMS trailer on the opposite side of the road) functioned as a control group whereby baseline measures of this latter group could be assessed throughout the test site and thus compared with those of the intervention group travelling on the carriageway of the side on which the message was purposefully situated to target. This aspect could be incorporated into the current project as well; however, it must be kept in mind that the control group could have potentially also see the animal (cassowary) that the sign is warning motorists about. Thus, any reductions in the control group in the current study would need to take into account not just the fact that they are not the intended recipients of the message on the VMS but also the possibility that they may have already seen and responded to seeing an animal on or near the road. This aspect must be borne in mind and highlights that in this study, the value of additional measures such as on-road camera may be required beyond just pneumatic tubes as any reductions in speeds of the motorists travelling in either direction could signal the sighting of an animal on or near the road, the impact of the signage, or in some cases both these aspects (in the case of those travelling in the direction in which the signage is positioned).

The NSW Government's Road Transport Authority guidelines [70] to VMS placement contain relevant information to the current study, that being the placement of signage (permanent and portable) in regional areas that alerts motorists to a hazard. According to these guidelines, the recommended minimum distance between a VMS and a hazard, within an 80 – 90 km/h speed zone where road geometry is considered "ideal" is 120 – 180 metres with approximately an extra 4 metres needed in rural areas. Further to this, factors such as road shoulders, clear zones and even slight curves must be considered in the placement of portable VMS systems. At installation, angled placement must be implemented to maximise oncoming motorists' visibility and minimise potential glare. These aspects are all pertinent considerations for this project.

The development of traffic signs is a complex endeavour involving consideration of a range of aspects. Design features, including size, colour, contrast, legibility and placement combine with message development considerations such as word structure and psychological framing to achieve optimal effectiveness. While no one formula can be successful in all situations, the preceding evidence has highlighted common themes of the need for uniformity/familiarity in signage, the benefit of positively framed massaging, and keeping messaging simple.

Variable Message Sign Messaging Content Preferences and Understanding

Early work on VMS content design was conducted in the UK. A stated preference study was conducted to understand drivers' responses to VMS messaging [71]. Younger drivers and female drivers reported being less likely to take alternate routes as advised by VMS. Also, prior experience with alternate routes influenced the likelihood of detouring, with alternate route use increasing as experience increased. VMSs displaying travel delay times rather than total travel time were preferred by drivers. Drivers described the provision of vague information (e.g., "long delays" or "delays likely") as ambiguous and as estimates of what such terms may mean, generated a varied array of time delay times. These estimations can be further involved when additional information regarding the cause of the delay is provided (e.g., crash, congestion, no additional information). As also reported in Section 2.1.3.B, VMS messages containing tangible details of required or preferred behavioural options are more likely to elicit more favourable responses from drivers. This evidence is consistent with the construct in messaging design of response efficacy which essentially relates to the extent that a message provides concrete or tangible strategies for a motorist to engage in. The importance of this construct has been supported both theoretically with its inclusion in the Extended Parallel Process Model (EPPM [55]) and, subsequently, the SatMDT framework (see [1]) as well as empirically where studies have shown that response efficacy both enhances rates that individuals are likely to accept a message as well as reducing the extent to which they may reject it [72].

Further to this, a simulator study, with data supplemented by eye tracking recordings, was used to investigate the effects of driver age and message layout on visual perception and understanding of VMS messaging. The message design factors considered were the use of all capitalised letters, only initial letters capitalised, as well as the use of familiar, unfamiliar pictograms or no pictograms [73]. The results revealed that lettering format, as uppercase or lowercase, did not impact on driver reading times. Cognition times were higher when unfamiliar pictograms were presented, indicating that it was critical for pictograms to be familiar to optimise understanding and minimise cognitive load [73]. The study also found that older drivers had more difficulty perceiving the VMS messaging than younger drivers [73]. Choices in colour use also played a significant role in drivers' perceptions of the VMS messages and reiterate the need to concept-test such options prior to use on-road (see [1]).

A field study conducted in France with an early VMS examined legibility and contrast characteristics and found that VMS point size did not influence message legibility [74]. During daylight, sign contrast was most critical to sign legibility. The authors found that increasing contrast, until the calculated contrast value reached 8, increased recognition. Luminance was most critical for night-time conditions. Excessive luminance has been found to be uncomfortable to the eyes, however such discomfort was found not to interfere with participants' ability to comprehend the VMS messaging. Study results were unable to determine a narrow range when comfort and accuracy were optimised, with the authors recommending a luminance range of $30 < L < 23cd/m^2$ [74].

To examine the aspect of optimising drivers' understanding of VMS messaging, research was conducted in Iran to determine appropriate content in the case of tunnel emergency notifications requiring drivers to evacuate the tunnel. A stated preference survey was used to evaluate the use of text and pictograms and message presentation [75]. All messages contained the words "STOP ENGINE; LEAVE TUNNEL" and these words were presented alone or with an image and with or without flashing wigwags. The image included on the VMS was one of the following: a standard green emergency exit symbol, the emergency exit symbol in white, a yellow triangle with an exclamation mark, a standard no entry symbol (red circle with a white bar in the centre). The signs either had the image positioned to the left or above the text. The study revealed respondent preference was for the text combined with the green exit symbol without wigwags [75]. The authors concluded that symbol familiarity may assist driver understanding and preference and suggests, once again, the importance of keeping messages simple.

Glendon and Lewis [60] completed an on-road field trial to evaluate motorists' responses to anti-speeding messaging displayed on portable roadside VMSs. The messages had been theoretically informed and thoroughly concept-tested prior to their use on-road. The results in terms of demonstrated reductions in motorists' speeds in response to some of the messaging provided support for the value of theory in informing messaging content and the importance of concept-testing messaging prior to on-road use. Further details of this study, as an on-road evaluation study of messaging effectiveness, are described in Section 2.1.3.B.

The preceding review of evidence demonstrates that messaging displayed on VMSs should include tangible and useful information and strategies as well as for such content to be clear, succinct and, if feasible and relevant to do so, to implement familiar symbols to facilitate efficient understanding. The importance of theory in developing content as well as the need to ensure thorough piloting prior to use was highlighted.

Use of Text or Pictograms

Pictograms are becoming increasingly popular in road messaging content. Graphical representations can be more universal than text for foreign-speaking visitors to a country and for those with reading impairments. As the focus of the current program of research will involve an on-road field test of the messaging and this on-road component is occurring in a location (North Queensland) which is a popular destination for international tourists, this aspect may likely be of particular significance.

Grace et al. [76] used a driving simulator to examine the effectiveness of word-based versus image-based messages displayed on a warning sign that alerted drivers to the presence of large animals near a road in Florida, USA. The sign was connected to an RADS similar to that being investigated for the current project. The effect of the RADS on collision rate, driver speed and latency to brake was also investigated. N = 90 licenced drivers were randomly assigned to a control group, word-based RADS or image-based RADS condition. Participants were not informed of the study's true purpose to avoid anticipatory behaviour (expecting an animal to appear on the road). Results showed that drivers in both RADSs conditions reduced their speed, braked earlier in response to the animal and were involved in less AVCs. Of particular interest was the finding of a significant speed reduction at twilight, when animal activity is known to increase. A mean speed reduction from 97 km/h in the control group to 89.5 km/h in the image-based group (7.5 km/h difference) was slightly larger than the text-based condition and indicated optimum safety benefits for the image-based RADS condition [76]. Image-based signs were associated with slightly better results than word-based signs but the reductions in speed and other behaviours did not differ significantly. Overall, the data collected indicates that the use of RADSs can reduce crash probability, driver speed, and reaction time to brake, with image-based signage providing the optimum results albeit not significantly different to the text-based RADS option. To determine the most appropriate images to display on VMSs, a study conducted by Er-hui et al. [77] in China compared possible pictograms for five roads conditions (i.e., rain, fog, crosswind, snow, road closure) that previously had not used any pictograms. Driver reported preferences were observed for pictograms for messaging relating to all road conditions. While no differences were found for sign preferences across age and gender, some differences were observed between categories of years of driving experience [77].

Also in China, a driving simulator study explored drivers' information threshold of graphical VMSs based on visual perception characteristics of drivers. Participants were presented text-only signs, simplified graphical signs, and graphical signs with text [51]. Unsurprisingly, legibility distance decreased as sign information volume increased. Legibility speed and subjective difficulty ratings also increased as sign complexity increased [51]. These results indicate that easily identifiable pictograms may be the best type of traffic message for efficient comprehension.

While the effects of roadside sign size, familiarity and format on driver performance in the USA found that target identification was more accurate when less information was presented on a sign (6 items versus 9 items) [78], research has also found that drivers were more accurate when identifying text-based targets as opposed to pictogram targets. Within each age group (young, middle-aged and elderly), driver performance did not significantly differ based on the amount of information provided (6 or 9 panels), logo familiarity or sign format (text or pictogram. However, Zahabi, et al. [78] note that elderly drivers were found to have worse detection performance of both text and pictograms on signs than both other groups.

Another consideration when designing message content is the influence of various individual differences beyond just aspects such as age and gender. In a driving simulator study in Spain, Roca et al. [79] examined via two studies both how reading impairments such as dyslexia may affect drivers' capacity to comprehend VMS messages and if words or pictograms were more easily understood by drivers with a reading impairment. Both studies found that drivers with dyslexia allocated more gazes at the traffic signs whether words or pictograms appeared, and which resulted in a reduction in speed control (higher speed variability). Results for individuals' comprehension of graphical VMS messages were also duplicated in both studies with no difference identified between reading impaired and unimpaired drivers. Roca, et al. [79] reported that drivers with reading impairments required more cognitive effort and longer reading times when messages were presented in text format while Roca, et al. [80] found that drivers with reading impairments demonstrated shorter legibility distances compared with unimpaired driver, but reading accuracy was not affected. The similarities of these results suggest that pictograms may well be the best and safest option for VMS content which is sensitive to motorists with some reading impairments.

2.1.3.B. Message Evaluation—Effect of Road Signs and Advanced Messaging Systems on Motorists' Perceptions and Behaviour

Multiple approaches, including self-report surveys, simulators, and field studies, have been used to examine motorists' responses to messaging approaches and, thus, to evaluate the effects of such messaging-based interventions (see [1] and [60]). Of particular interest to this review, given the initiative to be devised and evaluated within the overall project, was examining the extent to which studies have shown that VMSs may influence motorists' behaviour and, in particular, in terms of reducing travelling speeds and increasing monitoring or vigilance of the road environment.

Driver Response to Signs (Perceptual and/or Behavioural)

As a road safety countermeasure, seminal work by Elliott [81] via the first ever meta-analysis of road safety advertising campaigns, identified that road safety advertising and messaging may seek to achieve increases in individuals' awareness, motivate changes in attitudes or future intentions, and/or ultimately change behaviours.

Regarding the study by Glendon and Lewis [60] cited earlier in this review (see Section 2.1.3.A) in which three anti-speeding messages were designed and then field tested for their effects on speed behaviour using a roadside VMS trailer located on a suburban road in Queensland, the results indicated that the proportion of road users exceeding the posted speed limit were consistently lower when the anti-speeding VMSs were displayed. There was also a residual effect, with a reduction in mean speeds and proportion of drivers exceeding the speed limit observed for the week following the removal of the VMS. None of the three messages reduced vehicle mean speeds at night when compared to the control period during. The effectiveness differed between the three messages and across time. Message 1 (SPEEDING? / PENALTIES APPLY!!) and 2 (KEEP OUR STREETS SAFE / STAY WITHIN THE LIMIT) had the greatest effect during school hours, followed by Message 1 and 3 (REDUCE YOUR SPEED / KEEP YOUR FAMILY SAFE) during the day. While VMS anti-speeding messages may not dramatically reduce speed selection of drivers, small reductions in speed and speed variability can improve safety [60].

Recent work by Mohammadi, et al. [50] investigated motorists' beliefs about the effectiveness of static AVCs warning signs in Iran. Results of a self-report survey revealed what was considered a somewhat self-perpetuating cycle in respondents' beliefs and behaviours. A general lack of trust in the effectiveness of warning signs was reportedly due to the behavioural habits of a cohort of motorists who speed in the absence of cameras. When conditions allow high-speed driving with no speed cameras, these motorists' awareness of warning signs seems to diminish. Roads that do not accompany warning signs see an increased effect. Consequently, as these behaviours are increasingly observed, more drivers lose faith in the perceived effectiveness of warning signs and the more they too, may also ignore them. The authors also reported, however, that although static warning signs have been shown to be ineffective in decreasing driver speed, enhanced warning signs, or VMSs, have shown some promising effects in reducing drivers' speeds. Increasing the effectiveness of warning signs can reduce the speed of vehicles and subsequent speed-related crashes. For instance, a recent Canadian study reported reductions in deer-vehicle collisions as motorists' reduced speeds in response to the implementation of temporary VMSs rather than static signs [50].

The colour of a VMS sign and message lines can also influence individuals' responses. This effect was examined in a laboratory study conducted in Taiwan by Lai [82]. Participants were shown a video of a drive within a static driving simulator, where four VMS messages requiring a set behaviour (press brake pedal, press accelerator pedal, turn the steering wheel to the left or turn it to the right) were edited into the video. Response times were significantly impacted by sign colour schemes and the amount of information presented. Signs with two colours, rather than one or three colours, had the faster response times and had higher preference scores. The researchers posit that the drivers' responses, and stated preferences, were related to the use of colours to chunk information, where one colour was used to provide information about the road situation and the second colour was used to provide information on how to respond. Two linked VMSs with matched colour chunking messages resulted in faster driver responses and higher levels of driver approval than a single line message VMS. The increased response time for single line messages may be explained by the longer message line (requiring longer scanning), while the increased response time for three-line messages may be explained by the need for drivers to conduct chunking of text [82].

A Polish investigation into driver response times in real-world driving conditions [83] found that their research group of 15 participants of a range of ages and genders displayed an average total reaction time of 0.68 seconds, with a standard deviation of 0.15 seconds. The study consisted of free driving in a research area, performing any manoeuvres in any chosen route to allow for focus on driving. The task of reacting to a red signal by shifting feet from the accelerator pedal to the brake pedal, braking the vehicle and then continuing to drive was tested under a range of conditions. The authors emphasised that although this study examined real-world driving conditions, no universal standard guide can be assigned to such a concept due to the wide range of variables present in every driving/accident scenario.

Another important variable in eliciting an appropriate response to VMSs is message duration. Its effect on drivers' understanding of VMS was explored by Dutta, et al. [84] in the USA. The effect of two sign message duration levels were investigated, ranging from 2 seconds to 4 seconds, as well as message repetition on drivers' route choice. Drivers who received the VMS twice (one repetition) demonstrated lower message miss rates (i.e., incorrect route choice) and merged earlier than drivers who only viewed the message once. Dutta, et al. [84] reported that drivers were observed pre-empting the information provided on the second screen of a bi-phasic VMS, and concluded that, as well as being critical to ensure messaging consistency, it is imperative that the first screen is not displayed for too long. It is also important to ensure VMS content is simple and cannot be obstructed by roadside hazards (e.g., high vehicles) which aligns with findings by others [51, 60, 66, 79, 85].

Finally, together with the visual considerations related to VMSs, message content has a major effect on driver responses. For example, a field study conducted in France examined the effect of message framing (loss-based or gain-based) on drivers' subsequent actual speed behaviour. Four anti-speed messages were developed, with gain- and loss-based messages focusing on crash and fuel economy impacts of speed compliance behaviours ("respected speed limit = less crashes"; "speed limit respected = less fuel consumption"; "exceeded speed limit = more crashes"; and "exceeded speed limit = more fuel consumption") [86]. A control group sample was achieved by a message which simply displayed the time of day on the VMS. Speed reductions were observed in all sign conditions, with the greatest speed reductions observed for the gain-framed messages. As stated by Kirmizioglu and Tuydes-Yaman [64], positively-framed messages elicit higher recall and behaviour change than negative messages.

Speed was also a dependent variable in a driving simulator study in Italy that assessed VMS comprehension, and the subsequent effect on driver behaviour. The research found that when drivers do not understand the VMS information, vehicle speed is 5% slower compared to when a driver understands the sign [87]. The study also examined driver accelerator pressure. When drivers understood the sign, the pressure on the accelerator decreases when approaching the sign and then increases once the driver has passed the sign. If the VMS is not understood, the pressure on the pedal decreases on approach to the sign and continues to decrease after the driver has passed the sign. Several authors reviewed in this paper have mentioned the safety issue of unstable speed control. In this case, the disparity in speed control between drivers who do and do not understand displayed messages is the safety concern as it may result in traffic flow disruption and crashes.

The subsequent studies relate to VMSs and impacts on motorists' speeds in response in relation to some specific contexts. These studies are reviewed to the extent that they still relate to the use of VMSs on-road and with a specific intent to motivate perceptual and/or behavioural change among motorists.

First, regarding VMSs displaying route guidance or delay notification information. Early research conducted in the Netherlands examined how radio broadcasts and VMS information influenced driver route choice behaviour. The findings indicate that drivers were more likely to be influenced to make route modifications based on VMS information than radio broadcasts, with female drivers being less likely to be influenced by such traffic information to take a different route [88]. A field study conducted in Norway investigated the effects of VMS route guidance on driver behaviour, with data collected on speed, braking behaviour and route choice [89]. This study found that there was high compliance with the VMS messaging, in that every driver complied with the instruction to change route to avoid a closed highway section, with every fifth driver following the detour directions while the remainder made alternate route changes. This behaviour is likely influenced by local knowledge with regards the shortest detour, as demonstrated in the Emmerik et al. [88] study. The study also showed a significant reduction in speed as vehicles approached the VMS when the detour messaging was active. It was noted the heavy braking may result in an increase in risk of rear-end collisions [89]. Jing, et al. [90] also reported an increased risk of rear-end collisions relating to VMS complexity. VMSs requiring higher mental workload resulted in speed fluctuations that can be perceived as an increased safety risk.

Second, regarding VMS messaging implemented to advise motorists of upcoming road works. Researchers in Qatar examined the use of animations on VMSs at road work zones by monitoring participants in a driving simulator. Comparison of behaviour responses between static and animated VMS road signs indicating work zone speed limits or lane merging behaviours was recorded. Animated VMS signs resulted in a significant reduction in driver travel speeds and resulted in earlier merging behaviours. Drivers were also observed to be more likely to maintain larger headways [91]. Driver behaviours in response to remote stop-slow controls at regional roadworks zones were evaluated by researchers in Queensland. The field study collected driver behaviours and attitudes. Driving behaviours, including compliance, stopping behaviour, travel speed and deceleration profile, were assessed from pneumatic tubes and video recordings [92]. Attitudinal data was collected through an intercept survey. Three traffic lights (red-amber-green light combination, red-amber combination, and red-amber arrow combination) and one static sign combinations were trialled. Compliance rates were high for all four remote stop-slow devices however, drivers had higher approach speeds, increased approach speed variability and faster deceleration rates when compared to roadworker controlled stop-slow control. Survey findings indicated a lack of driver understanding of new light combinations (both red-amber combinations), with drivers unsure about the sign meaning, given that amber lights do not indicate to proceed after stopped at standard traffic lights as they were in this study [92].

Third, studies have been conducted to evaluate the effectiveness of VMSs when used to display messages about potential increased rear-end crash risk in a particular location. A field study was conducted in Iran to evaluate the effects of providing drivers with information regarding rear-end collision risk where such risk was advised as being of one of three levels—low, medium, or high [93]. The presentation of the three risk levels to drivers resulted in different driver responses, none of which found a relationship between speed and headway. The effect of messages indicating the risk of rear-end collision was low resulted in drivers in the middle and slow lane increasing driving speed at night, and never resulted in a reduction in mean speed [93]. A medium risk message also resulted in an increased mean speed, although not to the same extent as the "low" risk message. When drivers were presented with a "high" risk message, mean speeds were significantly lower for all time-of-day options as well as vehicle lane conditions except for the slow lane at night when there was no significant change [93]. Risk compensatory behaviours present a road safety problem, with this research suggesting there is a base level of risk drivers are willing to tolerate, and they will increase engagement in risky behaviours to ensure that is met.

Finally, VMSs have been used around the world to advise of inclement weather conditions to alert motorists of changing risks on-road. In a field study conducted in Finland, the effectiveness of VMS messaging displaying a warning about slippery roads was examined in terms of their influence on driver behaviour [94]. Mean reductions in traffic speed of 1-2 km/h were reported in response to the messaging. When drivers were presented with information regarding a recommended minimum headway, the number of short headways observed were reduced. An intercept survey was also conducted for drivers who were presented with the minimum headway sign. In addition to the observed behaviour modifications, the survey findings revealed a valuable road safety contribution attributable to the messaging. Specifically, drivers reported that the signs refocussed their attention to look for cues on the potential road condition hazard, resulting in them initiating road slipperiness testing, and engage in careful passing behaviours [94]. This attentional refocus and increased vigilance is also important for reducing AVCs and a goal of messaging in the current project.

Evaluations of Interventions Addressing AVCs

There are a range of interventions that may be implemented in efforts to address AVCs. To provide a holistic view of how AVCs can be addressed, a sample of these are reviewed in this section along with evidence relating to their effectiveness. However, given the focus on technology and messaging intervention being devised and tested in this project, we start with reviewing evidence about road side messaging used as a means to try and prevent AVCs.

Warning Signs

Warning signs demonstrate a traditional method of communicating expectations and hazards in the road environment. Early approaches were to install static warning signs. In FNQ, huge cassowary warning signs are located on the roadside as well as the road surface. As mentioned in Section 2.1.2.C, it has been found that static warning signs elicit barely more than recognition by many drivers and high levels of signage are known to lead to habituation which results in moderating their influence over drivers. In their guidelines for minimum signal sight distance, Mokkapati and Hawkins [95] explain that, to maximise effectiveness of warning signs, they should be placed close to the location where the warning applies, and drivers are required to initiate a behavioural response. This effect was demonstrated by Winnett and Wheeler [96] who conducted a large-scale study of the effectiveness of over 60 installations in a range of contexts across the UK and found that the largest speed reductions occurred close to signs. Research conducted in Utah investigated strategies to improve the performance of static animal crossing warning signs [48] also supports this guideline. The study found that a very small proportion (2%) of AVCs occurred within the recognition distance, of 300 feet (91.4m) in Utah, of these crossing signs. However, routes with high numbers of warning signs had a lower number of AVCs per mile indicating that repeated reminders raised drivers' awareness and vigilance in general. While static signs have a place in reducing AVCs as a low-cost mitigation measure, the authors recommended the implementation of more efficient and effective measures for a more significant reduction.

As technology has improved, and associated costs decrease, warning signs have become more proactive. Detection systems are used to support the direction of targeted warnings to drivers. Early research was conducted in North America. Initially, beam-break technologies were used to detect animals and provide driver warnings via VMSs. Data collected by the system, including vehicle speeds and traffic volume, was recorded in Northern California for 10 months. The system was designed to be active (with LED warning messages illuminated) only when an animal was detected [97]. This system was found to reduce mean vehicle speeds, when illuminated, by 5 km/h for the 7.5 months of the study, compared to the preceding 2.5 month control period. In southern Sweden, a study was carried out on a VMS located in close proximity to an at-grade fauna gate where animals cross the highway. These gates are 30 m wide openings in wildlife roadside fencing to focus animal crossing points while minimising population fragmentation. VMSs alert drivers when animals are detected and tracked (by a system that utilises three heat cameras, two radar cameras and two infrared cameras) within the at-grade fauna gate. During a 12-month period, 326 wildlife crossing events were recorded. While data was only collected from one location, an AVCs reduction of 66% was observed. This preliminary data suggests this is an effective approach for reducing collisions while maintaining habitat connectivity [98]. A different detection system, using radar (specifically targeting moose-involved AVCs), was used in Canada. This radar system, a 360°-radar scanning system, was installed on a highway segment in Alberta, Canada [99]. The system was demonstrated to reliably identify large animals, track their movements and activate a roadside beacon (specifically, flashing amber lights) to provide advanced warning to drivers. A preliminary review of driver behaviours found that when the warning beacon was activated, vehicle speeds reduced by approximately 15% during all times of day. This reflects an approximate 16 km/h reduction in speed. Further work was not completed to evaluate the effect on AVCs within the monitored road section. The similarity between the current study and this evaluation suggests that the findings of this study could supplement Mukherjee et al.'s work [99].

In a setting with comparisons to the current study, dynamic animal warning signs, that were installed to reduce panther-involved AVCs, were evaluated in Florida [100]. Placement of the signs was informed by roadkill data to maximise their impact. The proxy of vehicle speeds was used to determine the effectiveness of active warning signs on reducing AVCs. Traffic volumes vary significantly between tourist season and off-season, as does the roadside activity of large mammal species. During tourist season, where there is higher mammal activity, there was a significant reduction in vehicle speeds when the dynamic warning sign was active (i.e., messaging about an animal being detected in the road environment). The reduction in vehicle speed during tourist season is critical, given the higher vehicle speeds during this season, combined with greater traffic volumes and higher animal activity. This finding is promising for the current study due to the similar variables involved (i.e., tourist speed impact and animal activity.) Also of interest to the current study was the comparison of driving patterns between tourist and off-season when, it is assumed, traffic comprises mostly local residents. While significant speed reductions were noted in response to the flashing signs in tourist season, the overall mean speeds were lower in the off-season. The authors theorised the reason for this was that locals know to always drive more slowly due to possible animal collisions and therefore, do not need to reduce their speed to the same degree as tourists who are not conscious of the risk until warned. While further work is required to determine the flow-on impact on AVCs, successful speed reduction in such environments is a positive outcome.

Driver behavioural responses to road safety messages are now also being assessed in driving simulators. A computer-animated simulator study examined driver behavioural responses to a range of situations on a 90 km/h road in Sweden [101]. The situations assessed, by way of vehicle speed and deceleration metrics, in forest or open landscapes, with or without a wildlife fence were: 1) simulated moose encounter (by way of artistic impression and cut-out figures, 2) automatic speed camera, 3) wildlife warning sign, and 4) a radio message. Experiencing a moose through the simulated drive had the greatest speed reduction effect and the largest deceleration behaviour, with reductions occurring early in an open landscape and lowest passing velocity. Smaller decelerations were observed when the moose was observed on a road with a wildlife fence. Speed cameras resulted in increased relative speeds before and after being passed suggesting relatively no longer-term effects beyond having seen the camera. The authors hypothesised that these were due to the mandatory forewarning of a speed camera, via an E24 sign, applicable in Sweden and then the desire to recoup what was perceived as time lost while driving at a reduced speed past the camera. In contrast, the most effective countermeasures at reducing vehicle speeds were the more novel treatments of simulated moose encounters, followed by radio messages. Further examination is needed to understand the degree of influence their novelty had on these results and if time and habituation would decrease their relative effectiveness. In the meantime, Jägerbrand and Antonson [101] suggest that moose decoys or artwork observable by drivers may have a speed reducing effect on drivers.

In line with the objective of this project being the development of messaging intending to reduce and prevent AVCs, the preceding review focussed on communication of AVCs risk as an intervention. There are many more approaches used to minimise motorists' risk of AVCs. Studies have examined the effect of interventions on wildlife crossing behaviours and risk of wildlife mortality. Given that these approaches are designed to eliminate AVCs risk, limited work has been conducted to examine their effects on crash or human injury risk. Investigations have explored the impact of various interventions on a wide range of species, some of this evidence is reviewed in the subsequent section for the sake of completion and to highlight that interventions intended to reduce AVCs are varied and numerous.

Physical Interventions (e.g., fences, tunnels) Physical interventions separate fauna from road hazards, reducing the risk of AVCs. It is difficult to retain wildlife population connectivity when installing extensive roadside fencing, with an additional disadvantage of significant fin-

Figure 2.4.: Jumpout ramp, Highway 1010, San Luis Obispo County, California [102].

ancial costs to fully fencing roadways. In their Cassowary Conservation Management Plan, the Queensland TMR [8] describe best practice as using physical interventions to separate fauna from roads in conjunction with alternative crossings to prevent population fragmentation.

Researchers in Portugal used statistical modelling to assess the effectiveness of partial roadside fencing in reducing Martens' (small, weasle-like animals) involvement in AVCs [29]. Modelling demonstrated efficacy of fencing for mitigating the risk of AVCs, with higher reductions in roadkill compared with passages. Even partial fencing of roadways (between 25% and 7% of roadway length) was shown to reduce Marten's roadkill while delivering the additional advantage of reducing genetic differentiation (or genetic isolation) through population fragmentation. Field work conducted in the US found that the use of underpasses by large animals was not influenced by the presence or absence of fencing but primarily by crossing structure type (various widths and heights) and location (e.g., isolated from human activity or not, nearby habitat, wildlife population density) [25].

The effectiveness of AVCs mitigation structures (jumpout ramps as shown in Figure 2.4, overpass, underpass, fence) on AVCs was examined in a long-term study in Alberta, Canada [103]. Average annual daily traffic on the road segment increased between 1983 and 2018, and in the same period observations at mitigation structures found that large ungulate counts increased while small ungulate counts decreased (unrelated to local population observations). Mitigation structures were installed in 1999 and 2004, with a significant reduction in AVCs observed from 2004 onwards. One potential limitation of the study design was the reliance on official crash data, as this is likely to underreport collisions that are fatal for wildlife but result in minimal damage to vehicles or humans. As the authors note, an added advantage of employing appropriate mitigation measures for a given environment is the potential to further reduce AVCs and improve habitat connectivity.

Researchers in Brazil examined the use of unfenced highway underpasses by lowland tapirs and other medium and large mammals [104]. The study found that mammal species use of crossing structures (culverts and cattle boxes) differed by species type, with some species only using specific structures (river otters and water opossums only used culverts, and wild canids and felids were only recorded in cattle boxes while other species (e.g., ocelot, giant anteater, crag-eating racoon and lowland tapir) used both structures. Abra, et al. [104] pose that the costs associated at minimising the impact on the ecology are minimised by utilising structures that are already built, and maintained, to ensure mammal mobility and reducing population fragmentation. There are several large culverts installed around FNQ as the cassowary is considered a large animal. According to the TMR [8], bridges and viaducts are thought to be most suitable for facilitating cassowary movement due to their open and natural designs. Evaluation of their effectiveness has not been found in this literature review.

Other Interventions A range of alternative interventions have been trialled to reduce cassowary-vehicle collisions in FNQ including speed bumps and road surface markings. No information in terms of the effects of such interventions was able to be located for reporting in this review. Research has also examined the effectiveness of other novel interventions such as traffic calming interventions [105], odour repellants [44, 106], daylight savings time [107], acoustic warning systems [108, 109] and warning reflector systems [19]. As noted previously, these other interventions have been briefly noted herein for the sake of completion and to highlight the extent to which efforts have been varied and numerous in attempts to address and prevent AVCs.

2.1.4 Concluding Comments

AVCs are associated with substantial costs to individuals, communities, and the environment worldwide. In countries such as Australia, many native and protected animals, such as the southern cassowary, are particularly vulnerable [2]. Despite the implementation of a variety of countermeasures to minimise cassowary-vehicle collisions, fatalities from these collisions continue to factor into the threat of the species' subsistence as well as road safety for all travelling in areas where cassowaries reside.

This review of current research highlights that vehicle speed is the primary factor of influence that countermeasures must address to reduce AVCs. With increased speed comes decreased ability to monitor the roadside environment and handle unexpected driving situations (i.e., think and respond in a timely manner for the safest outcome) [2, 4, 5, 7, 27, 45]. Speed reduction warnings have traditionally been communicated through static signage and road markings [105] which carry the risk of habituation and loss of effectiveness on drivers. VMSs are a novel way to communicate targeted messages to drivers and have been shown to yield more favourable results in achieving driver compliance than previous methods [50, 97, 101].

The overall objective of this project was to develop, and field test a system for detecting large animals (namely cassowaries) on the roadside that prompts a VMS alert to motorists providing advanced warning of the animal being on or near the road and, thus, warning of a potential hazard. Consequently, the focus of this review has been particularly upon the development and evaluation of messaging strategies and, in particular, messaging displayed on roadside VMSs. Development of the messaging in this project will be underpinned by the SatMDT [1], which incorporates principles derived from social psychological theories of behaviour prediction, attitude-behaviour relations, and persuasion. The intent of messaging developed for use in the trial areas (and thus evaluated in this project) is to encourage motorists to slow down and increase their vigilance in monitoring for animals on and around the roads. Checking for inadvertent effects such as immediate stopping on the roadway also need to be examined as such behaviours could negatively impact road safety.

Currently, no international standard exists regarding road sign design where such signs seek to prevent AVCs [45] and while Australia implements standards on signage and its use, government responsibilities for road safety vary across jurisdictions. Roads signs are regulated by each state's government but standardised overall [110]. Trends in the existing research indicate that such VMS messaging should be as concise as practical to expedite understanding, using a minimum number of colours, short, words and no unnecessary information [63, 65, 66]. Targeted and positively-framed messaging is shown to elicit higher behaviour change, while clear instructions as to what the alternative behaviour should be is imperative [46, 64, 67]. In some cases, the use of images shows some beneficial effects relative to text-only but one study (relating to warnings about animals on or near road) found no significant benefit in use of images relative to text-only messages [76]. Familiar and identifiable images have achieved higher comprehension efficiency [51, 64, 79, 80]. There are recommended guides for the placement of VMSs based on factors such as distance from hazard, historic data of crashes, animal activity and roadkill, road geometry and facilities. The distance of tools to measure motorist behaviour show similar considerations and also identify the important role played by research questions in influencing placement of such measures as pneumatic tubes and induction loops (see [59, 60]). Appreciably, given such aspects can vary across studies, among some of the more consistent aspects to consider are human reaction time to factor in time it takes to see, comprehend, and react to a message.

This research will address a gap in the literature addressing AVCs with large, flightless birds (particularly cassowaries) and related countermeasures. While these reviews indicate that the use of an RADS such as proposed for this project can reduce crash probability, driver speed, and latency to brake [76] in a range of settings, this research will provide data for Australia-specific conditions and unique species to enrich overall knowledge.

2.2. Roadside Animal Detection Systems (USYD)

2.2.1 Introduction

In response to the rising incidents of AVCs, recent years have seen a significant increase in research efforts and development of commercial solutions to mitigate AVCs. The focus has primarily been on RADSs and other systems with similar functions. These tools are not just for detecting animals; they play an crucial role in alerting drivers in real-time, allowing them to adjust their driving and avoid potential collisions. By doing so, they contribute significantly to road safety and the preservation of wildlife.

To understand the landscape of existing solutions, we explored research papers, case studies, and existing products to understand their strengths, limitations, and areas of application. Our focus is particularly on systems that have shown effectiveness in challenging conditions, such as during nighttime or in rainy weather.

The rest of this section is organised as follows. Section 2.2.2 provides a comprehensive review of existing RADSs in the research and commercial spaces. Section 2.2.3 compares different sensor modalities, and Section 2.2.4 provides details on machine learning approaches that are often considered for animal detection. Section 2.2.5 presents a review of current and past field trials. Lastly, the conclusions are drawn in Section 2.2.6.

2.2.2 Existing Systems

As human infrastructure and wildlife habitats become increasingly intertwined, the need for advanced animal detection systems on roadsides has become more important. These systems aim not only to protect the diverse fauna but also to ensure the safety of motorists. In this section, we provide detail on existing RADSs that have made progress in this domain.

2.2.2.A. CVEDIA-RT

CVEDIA-RT [111] is an AI inference engine designed for developers and integrators, using synthetic data for training its animal detection algorithms. Instead of relying on traditional methods of data collection, CVEDIA-RT generates data with 3D models. This technique, similar to animation processes, allows for faster and more flexible data generation/collection. The 3D models provide intricate details about objects, allowing for a more nuanced understanding and visualisation by computers. While the benefits of synthetic data, such as speed and flexibility, are evident, there is a broader conversation in the scientific community about its potential impact on AI bias, privacy, and overall accuracy compared to real-world data.

2.2.2.B. Roadside Animal Detection System on U.S. 41

The RADS situated on U.S. 41 [112] exemplifies the fusion of technological innovation with ecological consciousness. Harnessing solar energy, it employs sensors to swiftly notify drivers when large fauna approach the roadway. When such wildlife is identified, the system triggers intense, blinking LED lights on several cautionary signs, guiding drivers to proceed with vigilance. Structurally, the system incorporates two infrared sensor arrays, positioned in parallel on both sides of the road, cumulatively spanning 2.1 km. Positioned 45 cm above the ground, these sensors are fine-tuned to recognise a wide variety of species. Including animals such as the Florida panther and the bobcat, the system offers comprehensive detection capabilities. Its primary aim is to reduce vehicular collisions with animals, safeguarding the area's diverse wildlife. This not only contribute to road safety but also plays a pivotal role in conserving the region's biodiversity. However, while the system's advantages are clear in terms of safety and conservation, potential challenges might include maintenance of the vast sensor network, ensuring consistent solar power supply, and the system's effectiveness during adverse weather conditions.

2.2.2.C. ClearWay

ClearWay [113] is a leader in radar-based RADS. When an animal, particularly those larger than a small dog, ventures close to the road, ClearWay activates the electric roadside signs. This immediate response ensures that drivers are not only alerted to the potential threat but also remain consistently vigilant. One of ClearWay's standout features is its ability to track the direction in which an animal is moving, offering drivers a clearer picture of the potential hazard. Moreover, by assessing the potential threat level of the detected wildlife, ClearWay provides a more nuanced alert system, ensuring that drivers are adequately informed and can respond appropriately. However, while the system boasts several advantages, potential challenges include its ability to differentiate between varying animal sizes accurately, its effectiveness in different weather conditions, and the maintenance of the radar system.

2.2.2.D. The PATH Animal Warning System (PAWS)

In 2009, Caltrans, backed by the US Department of Transportation, initiated the Partners for Advanced Transportation Technology (PATH) Animal Warning System (PAWS) on a stretch of State Route 3 near Fort Jones in the Scott Valley area of Siskiyou County [114]. This particular site was selected due to its infamy as a hotspot for black-tailed deer accidents, making it one of the state's most perilous zones for such incidents. The innovative PAWS system utilises microwave beams as its primary detection mechanism. When a large animal, such as a deer, intersects these beams, the system is triggered, sending a prompt signal that activates illuminated warning signs positioned on both sides of the highway. This immediate visual alert serves to warn drivers of the impending danger, allowing them to adjust their speed or be more vigilant. The advantages of the PAWS system are manifold. Its use of microwave beams ensures a high degree of accuracy in animal detection, reducing the chances of false alarms. The immediate activation of warning signs provides real-time alerts, which can be crucial in preventing accidents. Furthermore, by focusing on areas with a high incidence of AVCs, the system addresses the problem at its most critical points. However, there are potential challenges to consider. The system's reliance on microwave beams might make it susceptible to interference or malfunctions in adverse weather conditions. Additionally, the installation and maintenance of such advanced technology could entail higher costs. Lastly, while the system is adept at detecting large animals, smaller animals that might still pose a risk to drivers might not be detected as efficiently.

2.2.2.E. The Thermographic Wildlife Detection System

A recent research paper presented an innovative method for detecting wildlife near roads at night using thermographic imagery [115]. This approach is especially effective in bolstering vehicle safety during the dark hours. The study introduced a smart detection system that seamlessly integrates the Histogram of Oriented Gradients (HOG) technique with a Convolutional Neural Network (CNN). To assess its performance, the system was benchmarked against multiple CNN architectures, including the basic CNN and the VGG16-based CNN, as well as several machine learning algorithms such as support vector machines (SVMs), random forest (RF), decision tree (DT), linear regression (LR), and Gaussian naïve Bayes (GNB). The system was evaluated using real-world thermal images of wild deer from San Antonio, TX, USA. Encouragingly, the HOG-CNN blend achieved a commendable detection accuracy rate of around 91% for wild deer near roads, outperforming other algorithms in the test. However, the system does have its constraints, notably its exclusive operation during nighttime and the limited datasets used for training (854 images) and testing (214 images) the deep learning model [116] [117].

2.2.2.F. Virtual Fencing

The Virtual Fencing system is an innovative roadside solution designed to prevent animal-related accidents [118, 119]. Activated by the headlights of approaching vehicles, it emits a combination of sound and flashing blue and yellow LED lights [118, 119]. This dual alert mechanism aims to warn and deter animals from the road, reducing their startling effect. Strategically placed at 25-metre intervals on alternating sides of the road, these devices create a sequential "virtual fence" as vehicles pass. A prominent device produced by iPTE Traffic Solutions Ltd. [119] in Austria is solar-powered and crafted to establish a virtual fence alongside roads. It functions from evening until morning, focusing on crepuscular and nocturnal creatures. This device features an inbuilt light sensor that senses an oncoming vehicle's headlight intensity at a benchmark of 150 lux, initiating both visual and auditory alerts. According to the manufacturer, the emitted sound captures the animals' focus, and the flashing illumination causes discomfort, prompting them to move away from the road area. However, there are some limitations. The system's reliance on vehicle headlights might pose challenges in certain conditions. The effectiveness during extreme weather remains uncertain, and the fixed 25-metre spacing may not be optimal for all scenarios. Lastly, its primary utility is during nighttime, potentially leaving daytime incidents less addressed.

2.2.2.G. The Buried Cable Roadside Animal Detection System

The Buried Cable RADS [120] represents a recent approach to mitigating roadkill incidents involving large and medium-sized animals. Embedded beneath the road's surface, this system employs a 300-m-long dual-cable sensor that actively monitors animal movements. When animals cross over or near these cables, their presence perturbs an invisible electromagnetic detection field generated around them. This disturbance prompts the system's central processor unit to sound an alarm, simultaneously pinpointing the exact location of the intrusion. The detection process is nuanced, relying on criteria such as the animal's conductivity, size, and movement patterns. The system can discern multiple animals crossing at once, ensuring a comprehensive monitoring scope. Its efficacy was put to the test on the Virginia Smart Road, a location frequented by large wild animals like deer and bear, and the results were promising. The system is further fine-tuned in their more recent work [121] by modifying the processor's configuration settings. A detection threshold of 70 dB was set for the entire cable length, considering the traffic volume of the selected road section.

The Buried Cable RADS offers several notable advantages. Its high precision ensures accurate location tracking of detected animals, providing a reliable means to anticipate potential roadkill incidents. The system's ability to detect multiple animals crossing simultaneously enhances its efficiency, ensuring a broad monitoring scope. Furthermore, its underground placement means it's unobtrusive, preserving the natural landscape and avoiding visual disturbances. However, there are accompanying challenges. The installation process can be complex, potentially requiring extensive roadwork that could disrupt traffic and the environment. Maintenance might also pose difficulties due to the system's buried nature, complicating routine checks and repairs. Additionally, its specificity in detecting larger animals based on conductivity could mean smaller animals or those with minimal conductivity might go undetected, leaving some roadkill risks unmitigated.

2.2.2.H. Remarks

It is important to acknowledge that there is limited data available for evaluating the road safety benefits achieved from these systems. Specific quantifiable outcomes and statistical analyses reflecting the reduction in AVCs and enhancement of road safety are not extensively documented in the available literature. Furthermore, there is a lack of commentary on the broader adoption of these RADSs beyond the initial trials. The scalability and integration of these technologies into widespread use, their adaptability to varied geographic and climatic conditions, and their effectiveness over extended periods warrant further exploration.

We recognise that the unavailability of this information could be attributed to several factors, including the nascent stage of these technologies, constraints in data collection, or limited scope of the initial studies and trials. Future research in this domain could benefit from longitudinal studies that not only assess the immediate impact of these detection systems but also evaluate their long-term efficacy, sustainability, and adaptability. Comprehensive analyses that include varied metrics such as the reduction in collision rates, wildlife preservation statistics, and cost-effectiveness will contribute to a more holistic understanding of these systems' value and potential for broader implementation.

2.2.3 Sensors

The challenge of detecting large animals near or on roads is complex, and no single sensor can address all scenarios effectively. Different environments, animal behaviours, and road conditions demand different detection methodologies. For instance, while some sensors excel in dense forests, others might be more suited for open terrain. The size, speed, and habits of the animals to detect also play a key role in determining the most effective detection method. As a result, a diverse range of sensor technologies has been developed and deployed to tackle this issue. Each sensor type, from Global Positioning System (GPS) collars to infrared cameras, offers unique advantages and is tailored to specific detection challenges, ensuring that large animals are detected promptly and accurately to prevent potential AVCs.

2.2.3.A. GPS Collars

GPS collars are wearable devices that transmit real-time location data, primarily used to track animals' migration patterns and habitat preferences [122–124]. They offer a detailed insight into animal movements, proving invaluable for conservation efforts, especially when monitoring endangered species. Additionally, these collars can be integrated with other sensors, providing a holistic view of animal behaviour and movements. However, they come with their set of challenges. The bulkiness of some collars can interfere with the animal's natural behaviour. Moreover, they often have a limited battery life, which can restrict long-term monitoring. In our case, it is very expensive to equip wild large animals with GPS collars. This financial aspect makes deploying them on a large scale particularly challenging and demands significant resources.

2.2.3.B. RFID

RFID tags, or Radio Frequency Identification tags, are primarily used in livestock management, offering a unique identification for each animal [125, 126]. These tags are durable and require minimal maintenance, making them ideal for long-term animal studies and efficient herd management. Their ability to store individual health, vaccination, and breeding details is a significant advantage. However, their range is limited. For data collection, animals need to be in proximity to scanners, which means they don't offer real-time location or behaviour tracking like some other sensors. Similar to GPS collars, in our case, it is very expensive to place RFID tags on every wild large animal. This cost factor can be a significant constraint when considering large-scale deployments.

2.2.3.C. Near-Infrared Cameras

Near-Infrared (NIR) cameras are designed to capture light in the near-infrared spectrum, which ranges from about 700 to 2500 nanometers, just beyond what the human eye can see. These cameras are especially valuable in low-light or nighttime conditions [127, 128], but there is often not enough naturally occurring infrared light to generate a clear image. This is where illuminators, essentially NIR LED lights are required. When these illuminators emit near-infrared light, it reflects off objects and returns to the camera, enabling it to produce images even in complete darkness. One of the significant advantages of using NIR light is its invisibility to the human eye, making it ideal for discreet surveillance. The area under observation is bathed in light that's imperceptible to humans, yet the camera can capture detailed images. Furthermore, in fluctuating lighting conditions, the amount of natural infrared light can vary. Illuminators ensure that NIR cameras maintain consistent image quality regardless of these changes in ambient light. Additionally, in advanced systems like facial recognition, NIR illuminators can provide depth information, enhancing accuracy and detail in models or recognition processes. In essence, while NIR cameras are adept at detecting near-infrared light, illuminators are often essential to ensure clarity and consistency in their imaging.

2.2.3.D. RGB Cameras

RGB cameras, commonly referred to as colour cameras, capture images using red, green, and blue channels, mirroring the human eye's perception of colour. In the endeavour to prevent roadkill, these cameras can play a pivotal role [129–131]. Their ability to provide clear, high-resolution, and colour-rich images makes them adept at detecting large animals during daylight hours. The colour data can be instrumental in distinguishing animals from the background, especially in diverse environments where the animal's colouration contrasts with its surroundings. Advanced image processing algorithms can further enhance their detection capabilities, identifying animal shapes and movements. However, RGB cameras have inherent limitations. Their performance can be significantly hampered during nighttime or in low-light conditions, unlike sensors that detect heat or use infrared. Shadows, glare, or direct sunlight can also impact the clarity of the captured images, potentially leading to false detections or missed animals. Furthermore, in conditions like dense vegetation or fog, the visibility and effectiveness of RGB cameras can be compromised. While they are generally more affordable than some advanced sensors, they might require sophisticated algorithms and continuous calibration to maintain accuracy in diverse scenarios.

2.2.3.E. LiDAR

LiDAR is a remote sensing technology that uses pulsed laser light to measure distances to objects, creating detailed three-dimensional representations of the environment. In the realm of preventing roadkill, LiDAR sensors offer a promising solution. Its high-resolution data can precisely detect and differentiate large animals from other obstacles [132, 133], reducing false alarms. Operating both day and night, LiDAR does not rely on ambient light, making it effective in various lighting conditions. Furthermore, its ability to penetrate light fog or vegetation offers a clearer view of potential hazards. However, there are challenges to consider. While LiDAR provides shape and distance data, it doesn't offer colour information, which can be useful in some detection scenarios. Dense vegetation or heavy rain can impact its effectiveness, scattering the laser pulses. Long-range and high-resolution LiDAR systems can be expensive, and interpreting the data requires specialised software and expertise. Despite these challenges, its potential in large animal detection systems remains significant.

2.2.3.F. Radar

Radar, an acronym for Radio Detection and Ranging, is a sensing system that emits radio waves and analyses the reflections to determine the distance, angle, and velocity of objects. In the context of preventing roadkill, radar can be a potent tool. Its primary advantage lies in its ability to detect large animals in various conditions [99, 134, 135], including darkness, fog, rain, or snow, where visual systems might fail. By detecting moving animals from a distance, radar provides ample time for vehicles to receive alerts and react, enhancing road safety. Furthermore, it is less affected by light conditions, ensuring consistent performance regardless of the time of day. However, challenges exist. While radar is adopted for detecting animal movement, it often struggles to differentiate between animals and other moving objects without sophisticated data processing. Dense vegetation or certain terrains might also impact radar waves, affecting detection accuracy. Additionally, high-end radar systems can be costly, and their integration into a comprehensive RADS might require specialised expertise.

2.2.3.G. Thermal Cameras

Thermal cameras are advanced imaging devices that capture pictures based on the heat emitted by objects. Unlike traditional cameras that rely on visible light, thermal cameras visualise temperature differences, making them particularly adept at detecting warm-blooded animals against cooler backgrounds [136–138]. In the context of preventing roadkill, these cameras can have a significant impact. Large animals, due to their size and metabolic activity, emit a distinct heat signature that stands out, especially during nighttime or in low-visibility conditions. This makes thermal cameras exceptionally effective for identifying the presence of animals near roadways, even in complete darkness. Their ability to operate independently of ambient light ensures consistent performance, reducing the risk of AVCs. Furthermore, they can function effectively in various environmental conditions, such as fog or dense vegetation, where other sensors might struggle. However, there are challenges to consider. In environments with minimal temperature differences, like during hot days, the effectiveness of thermal cameras can be compromised. They might also struggle to detect animals that are well-insulated or have fur that traps heat effectively. High-quality thermal cameras can be a significant investment, and interpreting the captured data might require specialised software and expertise, adding to the system's complexity.

2.2.3.H. IR Beam Sensors

IR beam sensors, often referred to as infrared break-beam sensors, operate based on a straightforward principle: they emit infrared beams that, when interrupted, signal the presence of an object. In the context of preventing roadkill, these sensors can be strategically placed alongside roads to detect large animals that might pose a collision risk [112, 139]. As described in a study on U.S. 41, a system was implemented using such sensors arranged in arrays, effectively covering stretches of road to detect local wildlife. The advantages of IR beam interrupt sensors are notable. They can operate day and night, are relatively unaffected by ambient light conditions, and can provide real-time alerts, making them invaluable for timely warnings. Furthermore, their design can be tailored to detect only larger animals, reducing false alarms from smaller creatures. However, there are challenges to consider. Environmental factors like fog or heavy rain might affect the sensor's effectiveness. The system requires regular maintenance to ensure the beams remain unobstructed. Additionally, while they can detect an animal's presence, they don't provide detailed information about the animal's type or behaviour. Despite these challenges, their potential in RADSs remains significant.

2.2.3.I. Intrusion Buried Cable Detection Sensor

The intrusion buried cable detection sensor [120, 121] utilises a 300-m-long dual-cable sensor embedded beneath the road surface to monitor animal movements. When animals approach or cross these cables, they disturb an invisible electromagnetic detection field generated around the cables. This system's detection mechanism is intricate, taking into account factors such as the animal's conductivity, size, and movement patterns. Notably, it can identify multiple animals crossing simultaneously. The system's central processor unit is alerted by any disturbance, and it can precisely pinpoint the location of the intrusion. To optimise detection, the processor's settings are adjustable, with a detection threshold set at 70 dB across the entire cable length, factoring in the traffic volume of the specific road segment.

2.2.4 Machine Learning Approaches

In recent years, research has increasingly focused on leveraging machine learning technologies in the development of RADSs. Deep learning, a specialised subset of machine learning, has emerged as a promising solution for animal detection. These models excel in processing complex visual data captured by sensors such as RGB, NIR, or thermal cameras, thereby offering the potential to significantly improve detection rates and enhance safety measures for both humans and animals. However, the deployment of deep learning models faces challenges, particularly the labour-intensive and costly task of data labelling. In this regard, self-supervised learning offers a breakthrough as it allows for the automatic labelling of datasets, which not only expedites the training process but also reduces the potential for human-induced labelling errors. This approach could be pivotal in making deep learning models more scalable and efficient for large animal detection. Another critical consideration is the practical environment in which these detection systems are usually deployed. Given that many such systems are intended for use in rural or remote areas where computational resources are limited, there is a need for real-time data processing capabilities. Edge computing serves as a solution to this challenge by facilitating data storage and computation closer to the source, thus enabling real-time decision-making and reducing latency. This is particularly relevant in rural settings where intelligent transportation systems require immediate data processing for optimal functioning.

Therefore, this section will examine the following five interconnected topics:

1. Machine learning approaches in large animal detection
2. Few-shot and zero-shot learning for rare species
3. Label efficient learning for object detection
4. The role of edge computing in enabling real-time, resource-efficient deployments

5. Machine learning models on field robots and edge devices

It provides a comprehensive understanding of the machine learning approaches currently shaping the future of large animal detection systems.

2.2.4.A. Machine Learning in Large Animal Detection

Machine Learning is a subset of artificial intelligence that enables systems to learn from data, identify patterns, and make decisions without explicit human intervention [140, 141]. Algorithms in machine learning are diverse, ranging from supervised learning methods like RF and SVMs to unsupervised methods like clustering and Neural Networks. The applications are wide-ranging and have penetrated various fields, including healthcare, finance, and natural sciences. In the context of large animal detection, machine learning models are increasingly adopted to improve the accuracy and effectiveness of detection systems [142–144]. These models can process large sets of sensor data to predict the likelihood of animal presence, thereby aiding in the prevention of AVCs. The adaptability and self-improving nature of machine learning algorithms make them well-suited for dynamic environments where animal behaviour and movement patterns can be unpredictable.

Machine learning is revolutionising roadside transportation facilities, especially in mitigating AVCs. Traditional roadside systems, such as fencing and underpasses, have been limited in their effectiveness due to the unpredictability of animal movements. However, with machine learning, intelligent detection mechanisms are being integrated into these facilities. These mechanisms, equipped with sensors and cameras, can predict and alert about animal presence in real-time. For instance, smart wildlife crossings, which use machine learning algorithms, can adaptively control warning signs based on the detected animal activity, ensuring drivers are alerted promptly. Machine learning models, particularly CNNs, are employed to differentiate between animal species, tailoring the alert's urgency. This specificity in detection aids in providing contextual information to drivers, ensuring they react appropriately. As more data is collected, these machine-learning-integrated facilities refine their predictions, enhancing their effectiveness. Furthermore, the fusion of machine learning with geographic information systems in these facilities has enabled the creation of dynamic risk maps, which can be displayed on digital roadside billboards, offering real-time updates on potential crossing zones. Continuous advancements in machine learning promise a future where roadside transportation facilities are not only reactive but also proactive in ensuring road safety for both vehicles and wildlife.

Various types of sensors can feed data into machine learning algorithms for animal detection. RGB sensors capture standard visual data, while thermal sensors can detect heat signatures [129–131]. LiDAR [132, 133] and Radar [99, 134, 135] are also commonly used, especially in conditions of low visibility or for capturing data in three dimensions. These sensors collectively provide a rich set of data that machine learning algorithms can analyse for predictive modelling.

The main advantage of machine learning algorithms in animal detection lies in their ability to continually improve their predictive models as more data is gathered [142–146]. This is particularly crucial for adapting to seasonal or environmental changes that may affect animal behaviour. Machine learning algorithms can also handle multi-sensor data, thereby providing a more comprehensive understanding of animal movement patterns. This multi-sensory approach is often more effective than traditional methods which may rely on a single type of sensor.

Despite their potential, current machine learning models for animal detection face notable challenges. A primary limitation is their reliance on human-labelled datasets for training. Firstly, there's a scarcity of existing datasets specifically tailored for animal detection, and this paucity becomes even more pronounced when detecting uncommon species. This lack of comprehensive datasets restricts the model's ability to recognise a diverse range of animals. Secondly, the process of manual annotation of these datasets is labour-intensive. This not only consumes a significant amount of time but also introduces the risk of human error or bias into the model [147]. Furthermore, many advanced machine learning algorithms demand considerable computational resources [148, 149], posing challenges for their direct implementation into field devices, which typically have restricted processing capabilities.

2.2.4.B. Few-Shot and Zero-Shot Learning for Rare Species Detection

In the field of wildlife conservation and research, it is crucial to detect and identify both common and rare species. Traditional machine learning models, which have shown success in various domains, face a hurdle when it comes to uncommon species. They rely on extensive labelled datasets to train effectively. However, for uncommon species, such datasets are either minimal or non-existent.

Few-shot and zero-shot learning [150–152] are two advanced techniques that hold the potential to revolutionise the detection of these elusive species. Few-shot learning, as the name suggests, is designed to recognise new categories based on a very limited set of labelled examples. This is particularly beneficial when dealing with species for which only a handful of images or videos might be available [153, 154]. Instead of requiring thousands of images to train, few-shot learning models can generalise from just a few, making them invaluable tools for ecologists and conservationists.

Zero-shot learning, on the other hand, takes this a step further. It leverages semantic relationships between known and unknown species, enabling models to detect and classify animals they've never seen during training [155]. Imagine a scenario where a model, trained on various bird species, encounters a rare bird it hasn't seen before. Using attributes of birds it already knows, the zero-shot model can make an educated guess about this new species. This ability to infer characteristics of an unseen species based on known attributes is what makes zero-shot learning so powerful.

2.2.4.C. Label Efficient Learning for Object Detection

The process of manually labelling vast datasets is not only tedious but also error-prone, potentially introducing biases that can adversely affect the model's performance. Furthermore, acquiring ground truth labels for niche tasks, such as rare animal detection, can be impractical and costly. Given the rapid expansion of data in today's digital era, there is a pressing need for automating the data labelling process. To address this, various machine learning paradigms have been proposed to train models with limited supervision, including self-supervised learning (SSL), semi-supervised learning object detection (SSOD), and weakly supervised learning object detection (WSOD), reducing human intervention and thereby ensuring more consistent, objective, and scalable labelling.

SSL is a relatively new subset of machine learning where the model is trained to solve auxiliary tasks using information extracted solely from the input data, without relying on explicitly labelled examples. Essentially, it leverages the structure within the data to generate its own supervisory signal [148, 149]. This methodology bridges the gap between supervised learning, which demands extensive labelled data, and unsupervised learning, which often lacks direction and specificity [147, 156].

Among the approaches developed for SSOD, self-supervised sample mining (SSM) [157] incorporates high-confidence patches from unlabelled images as pseudo labels to enhance training. [158] focuses on improving data consistency and eliminating background distractions, while the STAC [159], which stands for self-training (via pseudo label) and the augmentation driven consistency regularisation, leverages extensive data augmentation techniques on unlabelled images to enrich model robustness. Additionally, [160] implements a teacher-student framework that utilises knowledge distillation to improve the learning process in SSOD. Similarly, [161] adopts a mean teacher strategy, wherein a more stable and consistent model guides the learning of the primary model. These methods aim to optimise limited labelled data and maximise learning from unlabelled datasets. However, they still face challenges, such as the requirement for noise-free annotations and a balanced split of labelled and unlabelled data, which are not always achievable in practical scenarios. Furthermore, the use of rich feature representations generated by emergent vision foundation models like self-distillation with no labels (DINO) [162, 163], contrastive language-image pre-training (CLIP) [164], Segment Anything Model (SAM) [165], and Web Ontology Language (OWL) [166] can significantly reduce or eliminate the need for manual data annotation in existing training protocols.

In the realm of animal detection, accurate and rapid identification is crucial, be it for conservation efforts, traffic safety, or ecological studies. Traditional machine learning models for animal detection usually demand labelled data, often curated manually by experts. By applying these self-, semi-, or weakly-supervised learning methods, models can use unlabelled videos and images to discern patterns, such as animal movements or distinctive features, effectively training themselves [167, 168]. For instance, a self-supervised model might be tasked with predicting the next frame in a video, thereby learning about animal motion patterns. As it progresses, the model becomes better equipped to detect and identify animals from novel inputs.

2.2.4.D. Resource-Efficient Edge Computing in Detection Systems

Edge computing has emerged as a paradigm that brings computation closer to the data source, such as Internet of things (IoT) devices, sensors, and other endpoints. This approach is designed to reduce latency, save bandwidth, and provide efficient processing [169, 170]. Traditional cloud computing models often require data to be sent to centralised servers for processing, which can introduce latency and consume significant bandwidth. Edge computing, on the other hand, processes data at or near its source, making it particularly suitable for resource-limited settings. This local processing can lead to faster response times and reduced network congestion [171, 172]. In the context of intelligent transportation, edge computing can enhance vehicular services through computation offloading. For instance, mobile edge computing has been applied to vehicular networks to optimise resource allocation and reduce computation overhead [173, 174].

Implementing edge computing requires both hardware and software considerations. On the hardware side, energy-efficient architectures are crucial to ensure sustainability, especially in resource-constrained environments [175, 176]. Software-wise, efficient algorithms for task offloading, resource allocation, and data processing are essential to maximise the benefits of edge computing [177, 178]. Several case studies and experiments have demonstrated the potential of edge computing in various applications. For instance, a study on video processing in multimedia IoT systems highlighted the effectiveness of self-supervised models in discerning patterns from unlabelled videos and images [168]. Another experiment showcased the benefits of a hybrid approach, combining edge computing with cloud resources, to optimise task segmentation and resource allocation in IoT-enabled mobile edge clouds [179].

2.2.4.E. Machine Learning Models on Field Robots and Edge Devices

Field robots and edge devices often lack sufficient computational resources for training machine learning models, making self-training on these platforms using unlabelled data particularly challenging. Self-training methods [180–182] typically involve training a model on the device with labelled data and then making predictions on unlabelled data. If the top prediction score for an unlabelled input exceeds a threshold, the input is pseudo-labelled and used in further training iterations. While this approach can enhance performance, it also slows down training and can lead to instability depending on the threshold. Additionally, many edge devices and field robots do not have access to labelled data or may have noisy labels for initial model training, significantly hindering the effectiveness of self-training using top prediction scores.

Another approach involves adapting and fine-tuning pre-trained machine learning models directly at the edge, eliminating the need for complete retraining. Various studies [183–187] propose transfer learning for edge learning, allowing models on edge devices to adapt and fine-tune with minimal computational resources. Online adaptive learning methods generate immediate predictions and incrementally update the model upon detecting concept drift, such as using covariance matrices or least-square SVMs. However, they often sacrifice performance for efficiency. The MobileDA [188] addresses domain adaptation for edge devices by distilling knowledge from a teacher network on a server to a student network on the edge device, achieving domain-invariance and state-of-the-art performance in real-world scenarios like IoT-based WiFi gesture recognition. However, the effectiveness of MobileDA assumes that the teacher network has performed well on field data, which is challenging in practice because field data is usually unlabelled and difficult to obtain. Relying exclusively on teacher models trained with web-sourced data can lead to deficiencies in the student model's capacity to collect data and self-improve. If the knowledge embedded in the teacher model does not align with the student model's operational environment, the student may face difficulties in gathering and learning from relevant real-world data. This misalignment can impede the student model's ability to adapt and evolve over time, thereby compromising its effectiveness and overall utility.

Distributed and collaborative techniques are widely used for edge-device machine learning models. These techniques leverage the computational capabilities of multiple edge devices, aggregating their results instead of relying on a single resource-constrained device. Federated learning [189–192] offers a transformative approach to decentralised model training. In the context of edge learning, where data is distributed across numerous edge devices, FL enables collaborative training without centralising sensitive data. While FL can help reduce computation needs for model training, addressing data shift and self-training for edge devices remains challenging.

2.2.5 Field Trials

The growing issue of roadkill involving a diverse range of animal species highlights the urgent need for effective RADSs. Field trials serve as a pivotal phase in the development and assessment of these technologies, though the emphasis has traditionally been more on conservation than road safety. In the real-world testing environments, the effectiveness, limitations, and logistical considerations of different systems need to be comprehensively evaluated. The trials yield essential data on detection accuracy and the impact on animal behaviour, significantly informing the scientific community and policy-makers. The rigour of the methodologies employed, involving various blocks and monitoring periods, ensures the collected data is robust and reliable.

2.2.5.A. The Virtual Fencing System in Tasmania

The Virtual Fencing system, developed by iPTE Traffic Solutions Ltd. in Austria [119], is an innovative roadside solution designed to mitigate roadkill and enhance road safety. Installed along a 4.5-km stretch of Tasmania's Huon Highway in April 2018, the system operates from dusk to dawn, targeting nocturnal and crepuscular animals [118]. It employs solar-powered devices placed at 25-meter intervals on both sides of the road.

For the Tasmanian trial, the 4.5-km stretch was divided into six equal segments with 750-meter buffer zones at both ends, totalling eight monitored segments. These segments were divided into two blocks, and the system was activated in phases across these blocks. The study spanned 126 days of roadkill monitoring. However, despite prior studies indicating reductions in roadkill up to 90% in Austria and over 50% [119], the Tasmanian field trial [118] shows that the system did not produce significant results. A total of 174 roadkill incidents were monitored, mainly involving Bennett's wallabies, Tasmanian pademelons, and common brush-tail possums, and no substantial reduction was observed.

The system requires low maintenance and offers high reliability, but it has limitations, including unproven effectiveness in extreme weather and a reliance on vehicle headlights, which mainly address nighttime incidents. Its impact on wildlife habits and routines raises concerns, as it introduces artificial stimuli that could disrupt natural behaviours and stress levels, necessitating long-term studies to understand its ecological impact fully.

In summary, the Virtual Fencing system offers a promising yet inconclusive approach to reducing roadkill. While it claims a number of advantages, the results from the Tasmanian study point to the need for further research, system modifications, and perhaps a more thorough ecological impact assessment to establish its overall effectiveness.

2.2.5.B. The Buried Cable Roadside Animal Detection System in Virginia

The Virginia Department of Transportation (VDOT), in collaboration with the Virginia Tech Transportation Institute (VTTI), undertook a 10-month field trial to assess an RADS aimed at reducing AVCs [120, 121]. The system utilises modular ranging buried coaxial cables and SC2 technology to create an electromagnetic field that detects large animals. Preliminary site surveys were conducted by VTTI researchers to address installation requirements and potential obstacles. The trial period even accounted for seasonal variances, including winter months.

While the trial data suggested over 95% detection reliability and the ability to function under different environmental conditions, such as snow, there are two major concerns that need to be addressed. First, the actual detection accuracy in real-world settings could be lower than the study suggests. Factors like animal behaviour, size, and speed could affect the system's efficacy, raising questions about its operational reliability. False positives or inconsistent detection rates could undermine road safety, potentially leading to distractions for drivers or less effective animal deterrence. The financial constraints associated with this system cannot be overlooked. The installation process involves not just the sensor cables but also complex site surveys and potential road infrastructure modifications. Moreover, these specialised cables require periodic calibration and maintenance, all of which contribute to the system's overall costs. Without a detailed cost-benefit analysis, it remains uncertain whether the initial and ongoing financial investments would be justified by the system's efficacy in reducing roadkill and enhancing driver safety.

While the technology appears promising and the methodology of the field trial was robust, these points highlight that the RADS still requires significant improvements in both detection accuracy and cost-effectiveness before it can be considered for broader implementation.

2.2.5.C. The Roadside Animal Detection System in Florida

The RADS in Florida is an innovative project to reduce the risk of AVCs along a 1.3-mile section of US 41 [193]. Initiated through a multi-agency collaboration, the system became operational in January 2012. It aims to protect large animals such as panthers by alerting motorists with bright LED lights, activated by solar-powered sensors that identify wildlife approaching the roadway. The system sensors are daisy-chained infrared sensors, specifically engineered to detect large animals. They are strategically placed 153 meters apart, just beyond the road shoulders, creating a 2.1 km detection beam that runs parallel to the road. The system is designed to ignore smaller animals by setting the infrared beam at a height of 46 cm above the ground. The project underwent rigorous evaluation using a driving simulator to measure its efficacy, eliminating external variables such as weather and equipment malfunctions. The study included 90 participants, ranging from 18 to 45+ years old, divided evenly into three age groups to consider age's impact on driver behaviour.

The study focused on two main objectives: evaluating the system's impact on driver speed, reaction time, and the likelihood of collisions, and comparing the effectiveness of word-based versus picture-based warning signs. Results were promising: drivers responded positively to the system warnings, reducing speed and improving reaction times. The picture-based signs were found to be particularly effective during twilight hours, reinforcing prior research advocating for their use. Though the difference in collision rates between word-based and picture-based signs was not statistically significant, researchers suggest that a larger sample size could yield more conclusive results. An additional key insight was that even a small reduction in speed could result in a significant decrease in the likelihood of a collision. The simulator study found that a speed decrease from 97 km/h to 89.5 km/h could significantly reduce crash rates. The study also reinforced the importance of driver age as a factor, with younger drivers displaying more risk-prone behaviour, emphasising the need for targeted educational programs.

Another significant finding pertained to the system's effectiveness at different times of day. Data suggested that the lower nighttime speed limit in Big Cypress National Preserve could be highly effective in reducing AVCs, an implication that could inform future policy decisions. Brake reaction times, a crucial factor in preventing collisions, were notably better among the youngest and oldest age groups when exposed to picture-based the system's signs, suggesting that these may be more effective in priming drivers to expect an animal on the road.

In summary, the Florida RADS project presents a well-researched, multi-faceted approach to the complex issue of AVCs. While the results indicate that the system has the potential to make meaningful improvements in driver behaviour, they also open up avenues for further research, including the comparative effectiveness of different types of warning signs and the need for age-specific interventions.

2.2.5.D. The PATH Animal Warning System in California

The project was a collaboration between Caltrans and the California PATH Program, with the Western Transportation Institute of Montana State University as a subcontractor [114]. The focus was on the PAWS and the reliability of RADSs. AVCs are a growing concern as urban development encroaches on wildlife habitats. Solutions like fencing, overpasses, and dynamic flashing systems have been explored. The project aimed to: (1) assess animal warning systems' effectiveness, and (2) gauge driver reactions to these warnings. A site near Fort Jones in Northern California was selected for the study. An RADS using a microwave system was chosen to work with PAWS. The PAWS Monitoring System allowed researchers to monitor system functionality and detect recent events. The PAWS data acquisition system (DAS) combined data from animal detectors and vehicular radars to measure driver responses. Phase Two began with repairing the system after a 9-month hiatus due to contractual delays. Challenges included repairing damage from a vehicle collision at the test site. The study used two experimental designs to understand the influence of warning signs on drivers.

The research team believes the project effectively measured the detection system's reliability. However, they recommend further reliability research post-system modifications. The project's duration was deemed insufficient to assess the system's impact on large mammal-vehicle collisions. The team suggests monitoring for 3-5 more years and re-analysing the data. Defining success parameters and threshold values for such projects is crucial. While public opinion is valuable for system location and design, long-term decisions on RADSs should be based on a strategic plan. This plan should consider systems in various regions, ensuring design and reliability issues are addressed, and include a comprehensive public communication strategy.

2.2.5.E. Remarks

Road Safety and System Reliability: The implications of RADS technologies on road safety are paramount, which require a thorough examination of their reliability and effectiveness in preventing accidents. A critical analysis of how these systems respond to failures is essential for ensuring that they consistently contribute to improved driver awareness and overall road safety.

Optimising for Ecological Preservation and Human Safety: Adaptations and adjustments made during field trials should not only focus on technological refinement but also prioritise optimising the systems for ecological preservation and human safety. This requires a multidisciplinary approach, bringing together expertise from technology, ecology, transportation, and other relevant fields.

Adapting to the Australian Context: Australia's distinctive wildlife and challenging road conditions necessitate a specialised approach to RADSs. The continent is renowned for its diverse array of unique and rare species, many of which exhibit distinct appearances, behaviours, and life cycles that are not found in other parts of the world. This uniqueness presents specific challenges for the implementation of RADS, requiring technologies that are finely tuned to the local fauna's specific habits. Ensuring that these systems are sensitive to the particular characteristics of Australian wildlife is crucial, as the goal is to reduce roadkill incidents without disrupting the animals' natural activities or habitats.

Field trials conducted within Australia must aim for holistic solutions, enhancing road safety for both humans and animals while preserving the ecological balance. Unlike some RADS implementations in other regions, which may not fully consider the impact on animal behaviour and habitat, the Australian context demands a more nuanced and considerate approach. By taking into account the distinctiveness of Australia's wildlife and their habitats, RADSs in Australia have the potential to set new standards in mitigating roadkill incidents, ensuring safer roads, and fostering a thriving ecological system.

Building a Robust and Reliable Solution: Drawing lessons from past experiences and system failures is crucial to developing a robust and reliable RADS solution for Australia. This requires a dedicated effort to test and adapt these systems, ensuring that they are fit for purpose and capable of contributing to wildlife preservation, enhancing driver safety, and mitigating roadkill incidents.

2.2.6 Conclusions

The increasing issue of roadkill, driven by the expansion of human infrastructure into wildlife areas, requires innovative strategies to protect both wildlife and humans. In this context, RADSs, enhanced by deep learning models and validated through comprehensive field trials, emerge as a cornerstone in the strategic approach to curb AVCs.

Advanced Sensory Technologies: RADSs are distinguished by their incorporation of cutting-edge sensory technologies. The systems are not limited to traditional sensors but are enhanced with the integration of technologies like LiDAR, radar, and thermal cameras. These advanced sensors are proficient in capturing intricate environmental data, offering a comprehensive insight into animal movements in real-time. Their capability to function effectively in low light conditions amplifies the operational efficiency of RADSs, ensuring a 24/7 active animal detection mechanism.

Deep Learning Model for Animal Detection: The efficacy of RADSs is amplified by the integration of deep learning models, which are pivotal in transforming raw, complex data into actionable insights. These models are engineered to identify intricate patterns, enabling precise animal detection. Innovations in self-supervised learning and edge computing have emerged as solutions to the challenges of efficient data labelling and real-time processing, respectively. These advancements are instrumental in enhancing the adaptability and effectiveness of RADSs.

Automatic Data Labelling: In the realm of data analysis, the advent of self-supervised, few-shot, and zero-shot learning has revolutionised the process of data labelling. These innovative techniques facilitate automatic labelling of extensive and complex datasets. Their integration ensures enhanced accuracy in animal detection and augments the adaptability of RADSs to identify a wide variety of species, including the rare and less documented ones, effectively addressing the data insufficiency challenge.

Evaluation of Safety Outcomes: The theoretical assertions of the effectiveness of RADSs are substantiated through field trials. These trials, conducted in diverse real-world settings, provide critical feedback essential for the continuous refinement of the systems. However, there exists a gap in knowledge about whether the performance of these trials has led to the broader deployment of the systems in various regions or settings.

Broader Deployment Potential of Field Trials: Furthermore, understanding the broader deployment implications can offer a more comprehensive view of RADSs' potential impact on larger scales. The overarching objective remains the significant contribution of RADSs to enhancing safety outcomes, diminishing roadkill incidents, and promoting a balanced coexistence between human and wildlife populations. Recognising and addressing this knowledge gap can further solidify the system's potential for widespread adoption.

In this evolving landscape, the integration of advanced sensor technologies, sophisticated deep learning models, and empirical insights from field trials is pivotal. It plays a key role in moving towards a future where the safety and preservation of both human and animal lives are not just a possibility but a tangible reality. Yet, further studies and assessments are essential to bridge the knowledge gap regarding the scalability and broader application of these systems following their promising initial trial results.

3

Animal Detection System Development and Testing (USYD)

3.1. Introduction

This chapter details the development and testing of a large animal detection system and its associated machine learning approach for classification. It employs advanced technologies to address the challenges associated with real-time animal detection in varying environmental conditions. Additionally, the system is designed to be low-cost and easy to deploy, requiring minimal infrastructure support in the field.

To thoroughly evaluate the performance of the developed system, particularly focusing on its effectiveness in edge deployment and its detection range, we have conducted a series of comprehensive testing experiments. These experiments are designed to rigorously assess the system's capability to accurately detect objects at varying distances and under different operational conditions. This evaluation process is crucial for ensuring that the system not only meets the expected specifications in controlled settings but also performs reliably in real-world scenarios, where factors such as environmental variability and hardware limitations can significantly impact effectiveness.

The chapter begins with the hardware design of the developed system in Section 3.2.1, detailing the sensor suite, networking, and edge computing. This is followed by the software structure in Section 3.2.2, which addresses key elements such as image processing pipelines, event-triggering pipeline, data logging, and remote access capabilities. These system features are vital for ensuring that the system is not only functional but also manageable and accessible for practical applications. Section 3.2.3 covers the methodology, auto-labelling, and experimental results of the novel machine learning pipeline developed to enable the self-training of the animal detection model. This approach ensures the system's capability to detect objects beyond pre-defined categories, thereby enhancing its adaptability to large animal detection. Central to our pipeline is an optimised object detection model, tailored for edge deployment. This model strikes a balance between real-time processing speed and detection accuracy, which is essential for immediate responses in dynamic road environments.

The chapter also covers the system testing after the development phase. Section 3.3.1 presents tests conducted in outdoor and lab environments to validate various system functions developed. Section 3.3.2 presents the evaluation results of the fine-tuned detection model.

Lastly, the conclusions are presented in Section 3.4.

3.2. System Development

3.2.1 Hardware Design

3.2.1.A. Sensor Suite

The sensor suite primarily consists of two RGB cameras, one thermal camera, and one solid-state LiDAR, as illustrated in Figure 3.1. Among these sensors, the cameras are specifically designed for large animal detection, utilising a vision-based machine learning approach effective under both day and night lighting conditions. While the cameras serve as the primary sensor type for animal detection, the LiDAR sensor is included in this project to provide an alternative sensory modality for monitoring vehicle-animal interactions.

Figure 3.1.: The sensor head developed for animal detection. Its components, from top to bottom, include: a black cap housing WiFi, GPS, and 4G antennas for communication; a white electrical junction box; an aluminium enclosure for the thermal camera; two RGB cameras (the left being the medium-angle camera and the right, the telephoto camera); and the solid-state LiDAR. In the picture, the sensor head is shown temporarily mounted on a tripod for outdoor testing.

RGB Cameras

The RGB camera model employed is the Lucid Vision Labs TDR054S-CC, featuring 5.4 MP, 2880 x 1860 pixel resolution, and 120 dB high dynamic range (HDR) imaging. HDR cameras are essential for accurate and robust animal monitoring in Queensland's outdoor environments, as they are designed to capture a wide range of lighting conditions—from bright sunlight to dark shadows—in a single image. This capability makes them well-suited for capturing detailed and accurate images of animals in outdoor scenes, where lighting can be unpredictable and challenging for standard non-HDR cameras to balance.

Additionally, the two RGB cameras complement each other, being paired with different optical lenses to cover near and far scenes. The medium-angle optical lens employed is the Edmund Optics 12 mm, with a 41.4° horizontal Field-of-View (FoV), while the telephoto lens used for the other camera is the Edmund Optics 50 mm, with a 10° horizontal FoV. Digital zooming is also utilised for images from the medium-angle camera to cover mid-range scenes. It should be noted that image cropping and resizing techniques are applied to each camera to achieve a higher frame rate and lower data storage requirements for logging while ensuring the animal detection performance remains unaffected. These details will be elaborated on in later sections.

The camera bodies are factory IP67-rated, and both lenses are housed in IP67-rated lens tubes, enabling the entire RGB camera systems to operate under all weather conditions. Therefore, no additional enclosure is required for the cameras.

Thermal Camera

The lack of a lighting source poses a significant challenge for animal detection using RGB cameras during nighttime. To overcome this limitation, the system employs a thermal imaging camera, the FLIR A68, which has a resolution of 640×480 pixels. All objects, including animals, emit infrared radiation, which is invisible to the human eye. Thermal imaging cameras can detect this radiation and create a visual representation of the heat signatures emitted by animals, even in complete darkness. This capability makes them an effective tool for identifying and tracking animals at night or in dense foliage. The thermal camera is equipped with a factory lens that has a 24° horizontal FoV.

The thermal camera is housed in an autoVimation Salamander enclosure with a Germanium front window, as illustrated in Figure 3.1, to make it weatherproof in outdoor environments.

LiDAR

The LiDAR sensor used in the system is the Neuvition Titan M1-R solid-state LiDAR, featuring a working distance of up to 300 metres for objects with 20% reflectivity. This LiDAR has a 15° horizontal FoV and an 8° vertical FoV, and it provides dense point clouds at a rate of 10 frames per second. These point clouds are useful for reconstructing vehicle and animal trajectories in post-analysis. The LiDAR sensor has a factory IP67 rating.

3.2.1.B. Networking and Edge Computing

The network equipment and edge computing components are presented in Figure 3.2. The system features an NVIDIA Orin 64GB Dev Kit, serving as the main computing unit for sensory data processing, image inference, data logging, and triggering animal detection events. A QNAP QSW-2104-2T network switch is employed to connect all sensors and the Orin, using 1Gbps and 10Gbps Ethernet connections, respectively. The network is managed by a Teltonika RUTX11 industrial router, which also provides dual-band WiFi and 4G LTE cellular connectivity.

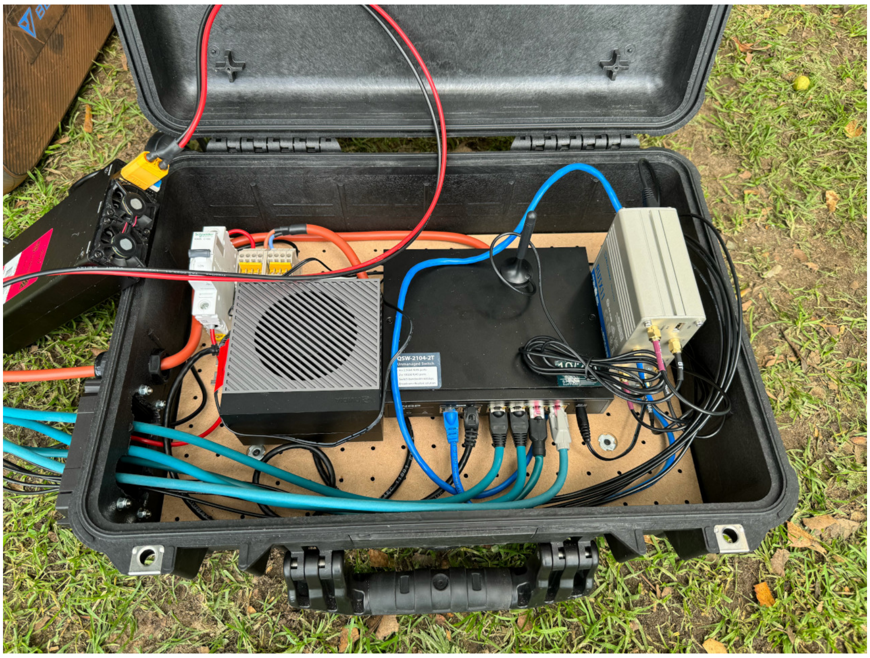


Figure 3.2.: The networking and edge computing for the developed system. From left to right: a white electrical circuit breaker; the NVIDIA Orin computing unit; the QNAP network switch; and the Teltonika router. These devices were temporarily housed in a Pelican protector case for outdoor testing, as shown in the picture.

An overview of the system's Ethernet connection can be found in Figure 3.3. The entire system operates on 12V DC power, with an average power consumption of 96W and a peak of 140W. Since the LiDAR sensor is not used for animal detection in the project, removing it from the system can significantly reduce power consumption.

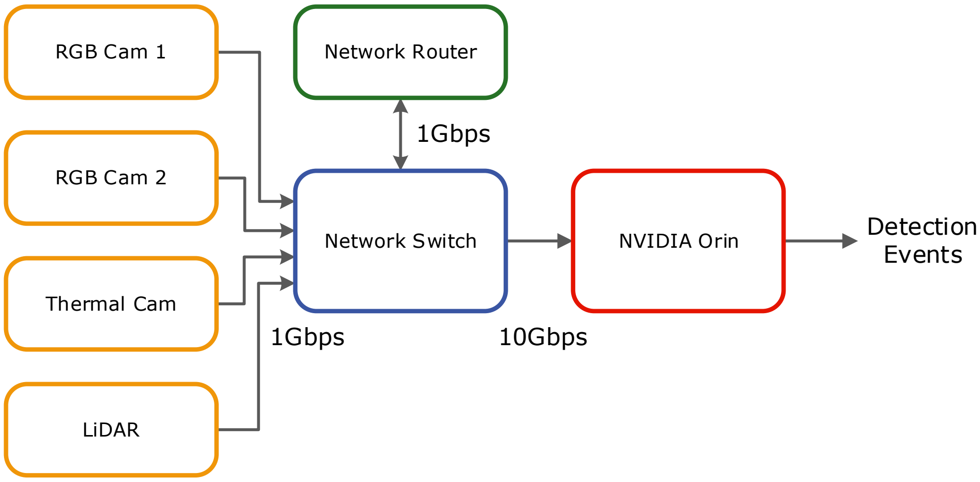


Figure 3.3.: The system Ethernet connection.

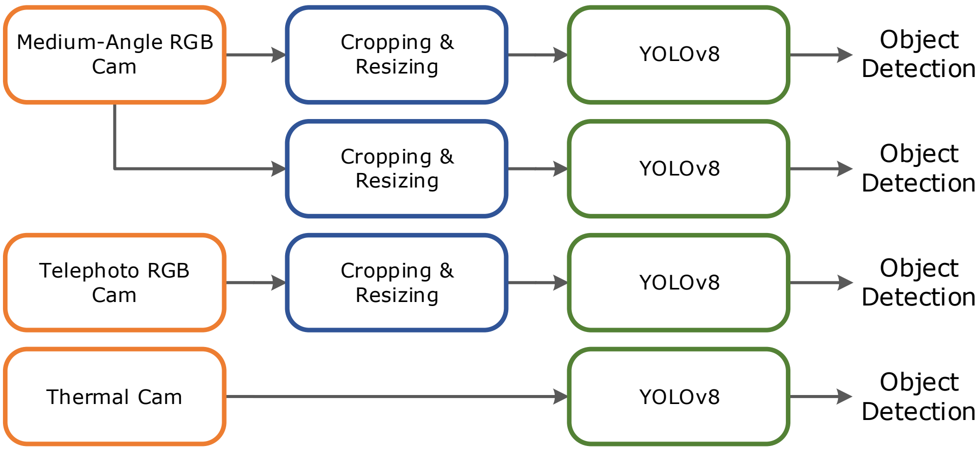


Figure 3.4.: The image processing pipelines for the cameras.

3.2.2 Software Structure

3.2.2.A. Image Processing Pipelines

There are four image processing pipelines running in parallel in the software, as shown in Figure 3.4. Each pipeline captures images from a camera as input and performs basic image manipulation techniques, including cropping and resizing, before feeding them into the YOLOv8 object detector to generate detection results. It is important to note that these four pipelines process images from three cameras, with the first and second pipelines in Figure 3.4 sharing images from the same medium-angle RGB camera, but using different cropping settings. The second pipeline processes a smaller region of the images from the camera, creating a digital zoom-in effect. All pipelines for the RGB cameras resize the original images to match the input resolution for YOLOv8 and to conserve data logging space. Since the thermal camera produces VGA resolution images, no image resizing is required. The object detection results from the four pipelines are then fed into the event-triggering pipeline for further processing.

3.2.2.B. Event-Triggering Pipeline

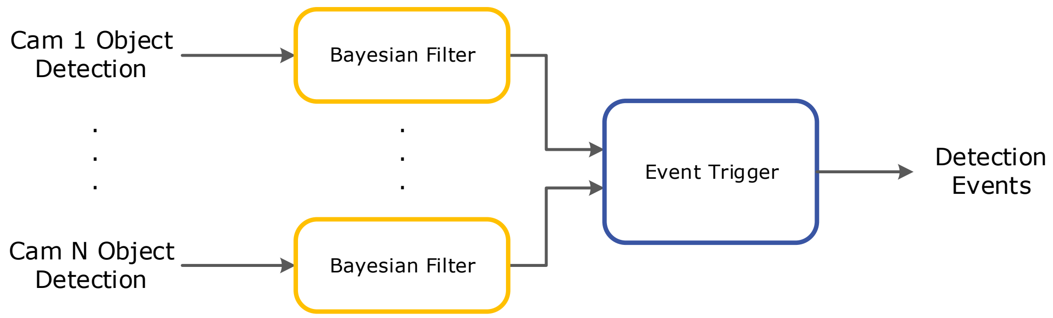


Figure 3.5.: The event-triggering pipeline for the cameras.

The event-triggering pipeline takes the YOLOv8 detection results as input, performs signal filtering, and aggregates the outcomes to trigger the final detection events, as shown in Figure 3.5. The raw YOLOv8 output contains the detection of a list of object classes supported by the trained detection model. However, the system only needs to check for the detection of one or multiple animal classes that it is designed for, such as "cassowary", defined here as the class(es) of interest (CoI). Despite the detection model's performance, the raw detection results are often noisy, containing missed detections and false positives, which necessitate proper signal filtering. In this pipeline, independent Bayesian filters are employed for each object detection input channel. Eventually, the filtered signals are fused to trigger a detection event, which is then connected to the event-triggered data logging and the roadside message display.

3.2.2.C. Data Logging

The data logging feature developed for the system can be divided into two parts: continuous data logging and event-triggered data logging. The continuous logging operates 24/7, providing essential field data for training the initial detection model and for subsequent iterative model improvements throughout the system's life cycle. In contrast, the event-triggered logging only records data just before and after the animal detection events occur, primarily for post-analysis and event playback. Data logged in either scheme can also be used for evaluating the system's performance in animal detection. The edge computing unit has a 2TB solid-state disk for storing the logged data.

Continuous Data Logging

The system logs a continuous stream of raw sensory data, including image frames, LiDAR point clouds, and other essential detection and system information. Due to limited data storage on the edge computing unit, the logging is managed with a few control strategies:

1. Log sensory data at lower frame rates, e.g., one-tenth of the original rates
2. Use data compression, e.g., JPEG compression for images and lossless compression for LiDAR point clouds
3. Manage the logged files against an allocated data budget on the local file system

Furthermore, the system generates lightweight H.265 encoded videos of camera images for conveniently previewing scenes of interest in the field without needing to extract the complete set of logged files from the system, thus saving on 4G data usage and transmission time.

Event-Triggered Data Logging

The system also features event-triggered data logging, which logs data for x seconds before and y seconds after a detection event. The purpose of this logging scheme is to capture sensory data at the original frame rates around the events, which are essential for playback, investigation of the events, post-analysis of data, and evaluation of system performance.

3.2.2.D. Remote Access

The system provides remote access for various purposes, including status monitoring, system maintenance, troubleshooting, and data retrieval. It offers two methods for remote login: through a virtual private network (VPN) or using its public domain name `amraal.duckdns.org`. To enhance its security against cybersecurity threats, the system only accepts SSH logins using public/private ED25519 key pairs from authorised remote hosts. Software tools have been developed to extract H.265 preview videos and logged data files from the system remotely.

Finally, the system also provides a real-time streaming protocol (RTSP) stream of the camera images for quick live previews. This feature is accessible only through a WiFi connection and VPN for security reasons.

3.2.3 Self-Training Machine Learning Pipeline

The LAARMA system requires the training of an effective machine learning model for roadside large animal detection, along with the subsequent deployment of the trained model on an edge device, which presents several unique challenges:

Data Acquisition and Labelling: A fundamental challenge in training machine learning models, especially for animal detection, is the need for a substantial amount of accurately labelled data. In the context of cassowary detection, this means obtaining a considerable volume of well-labelled images or videos of cassowaries in various road scenarios. The key challenge is how to efficiently and cost-effectively label such a dataset for training deep learning models without compromising the quality and diversity of the data.

Resource Constraints in Deployment Environments: Roadside units, often deployed in remote areas, face constraints such as scarce electricity and computing power. These limitations pose significant challenges for deploying an efficient and reliable detection system. Innovative solutions are needed to optimise the system's performance within these resource limitations, including considerations for low-power operation, efficient data processing, and model optimisation suitable for edge computing environments.

Data Sampling and Model Improvement Post-Deployment: After deployment, the system must efficiently sample and process the data collected from its operational environment. This involves deciding which data to log, how to obtain necessary data from the edge computer, and how to use it to refine the machine learning model. Additionally, periodic updates to the model are needed to accommodate changes in environmental conditions, cassowary behaviour, or traffic patterns. The challenge lies in developing a streamlined process for regular model updates that can be implemented remotely, ensuring the system remains accurate and effective over time.

Our system effectively addresses these challenges through an innovative self-training machine learning pipeline that integrates cloud and edge computing technologies. The details of the pipeline are presented in the following sections.

3.2.3.A. Methodology

This section outlines the methodology behind our self-training framework for detecting large animals on roads and roadsides. The pipeline leverages a combination of cloud and edge computing technologies to create a scalable system adaptable to environmental conditions and different animal species.

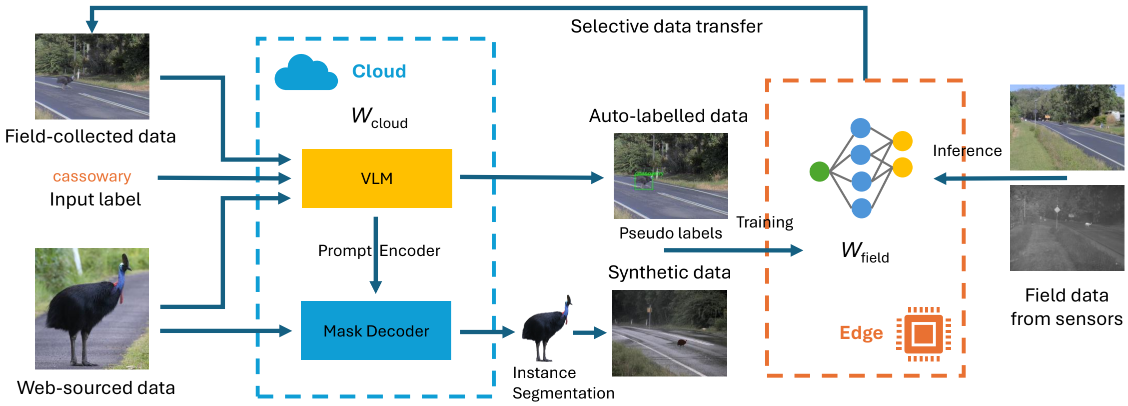


Figure 3.6.: Workflow of our self-training machine learning pipeline. Initially, a VLM running on a cloud server synthesises images of cassowaries and generates the pseudo-labels using the web-sourced cassowary images and field background images. These images are used to train the initial animal detection model that operates on the edge device. In the field, this edge model processes images captured and selects relevant data to send back to the cloud server. The VLM then automatically processes the received field data, generating pseudo-labels, which are used to fine-tune the edge model. This iterative cycle progressively refines and improves the detection performance of the edge model.

Figure 3.6 illustrates the workflow of the self-training machine learning pipeline, showcasing the integration of cloud and edge processes that underpin our innovative approach to roadside animal detection.

The core of our methodology revolves around the use of a VLM for Open-Vocabulary Object Detection (OVD) [166], which operates on a cloud server. This VLM is first tasked with synthesising realistic images of cassowaries, serving as the initial dataset for training a closed-vocabulary animal detection model to be deployed in the field. These synthesised images are important as they allow us to train the animal detection model without the need for extensive, costly field data collection and labelling, addressing a significant hurdle in machine learning for field applications.

Once trained, the closed-vocabulary animal detection model is deployed on an edge device in field locations where cassowaries are likely to appear. For convenience, this closed-vocabulary model is also referred to as the edge model for the remainder of the section.

The edge device can operate under constraints of limited power supply, computing capacity, and intermittent connectivity. In field operation, this edge device continuously processes environmental data, selecting only the most relevant data to send back to the cloud server. This selective data transmission is important to maintain efficiency, particularly in remote or resource-limited settings.

In the cloud, the VLM takes over again, processing the incoming field data to generate pseudo-labels. These labels are not only used to refine the training of the edge model but also enhance its ability to adapt to new and changing data patterns. This dynamic updating mechanism ensures that the model evolves in response to new information, thereby maintaining its accuracy and reliability over time.

Overall, the pipeline is designed with generality and scalability in mind, making it applicable for detecting various large animal species beyond cassowaries. Next, this section details each component of the pipeline, from initial data synthesis to the continuous learning on deployed edge devices, complemented by experimental results that highlight the efficacy of our approach.

3.2.3.B. Efficient Animal Detection Model for Edge Deployment

An efficient animal detection model, optimised for the constraints of edge computing, is essential in the real-time operation of the developed LAARMA system. This model is designed to balance the trade-off between detection accuracy and computational efficiency. It utilises state-of-the-art algorithms capable of processing images or video feeds in real time, even with limited computing resources. The model is streamlined to reduce the computational load while maintaining high accuracy in detecting large animals under various environmental conditions. This efficiency is critical for ensuring the system's reliability and responsiveness in real-world deployment scenarios.

In this project, we have chosen YOLOv8 [194] as the edge model for our animal detection task, owing to its remarkable computational efficiency and real-time processing capabilities. This model stands out as a suitable choice for applications where real-time detection is crucial, such as in wildlife monitoring and traffic management systems. An example of using YOLOv8 in a traffic scene is presented in Figure 3.7. The choice of YOLOv8 is particularly advantageous in scenarios where quick decision-making is essential, as it allows for immediate identification and response to potential hazards on the road. Also, the model's streamlined architecture reduces the computational burden, making its deployment feasible on roadside units with restricted processing capabilities.

Figure 3.7.: Testing the detection capabilities of YOLOv8 in a crowded road scenario. This showcases the YOLOv8's robustness and precision in detecting various classes of objects even in densely populated scenes.

Furthermore, the resolution of raw images from cameras is often higher than what is sufficient for a YOLOv8 detector. This motivates the use of digital zooming to further improve the object detection range without additional hardware costs. Figure 3.8 demonstrates the detector's effectiveness in accurately identifying objects from a considerable distance using digital zooming.

3.2.3.C. Synthesising Data for Initial Training Phase

Training machine learning models to accurately detect objects requires a substantial volume of high-quality data. For our project, this involves gathering numerous labelled images of cassowaries directly from their natural habitats. However, the acquisition of field data on cassowaries is challenging due to hardware limitations and stringent data transfer constraints. Besides, the brief visibility of cassowaries, typically ranging from 20 to 50 seconds, further complicates the collection of sufficient data for effective training.

To overcome these challenges, we adopted a strategy of using synthetic data to initialise the self-training machine learning pipeline. This process involves running a VLM (in our case, a variant based on OWL) and SAM to detect and segment cassowary instances in web-sourced images, respectively. These segmented cassowary instances are then digitally inserted into

(a) (b)

Figure 3.8.: Using the YOLOv8 detector for detecting distant objects. The digital zooming technique is adopted in the system to enhance the detection range by cropping a smaller patch from the original image and processing it through the detector. (a) shows the detection on the original image. (b) illustrates that the detector effectively identifies traffic participants approximately 200 metres away after applying the digital zooming to the original image.

Figure 3.9.: Results of synthesised cassowary visuals, where instances of cassowaries, obtained from public sources, are seamlessly integrated into field backgrounds.

various field backgrounds. To enhance the realism of the synthetic data, we apply a Gaussian blur to seamlessly blend the cassowaries with their backgrounds. Two examples are presented in Figure 3.9. This method helps create a diverse dataset and simulates different lighting conditions and cassowary poses, which are essential for enhancing the model's robustness.

At the end of the initial phase, we deployed a YOLOv8 model trained using the synthetic data in the field to systematically gather real-world images of cassowaries directly from their natural environment. This approach not only facilitated the collection of valuable field data but also enabled us to evaluate the performance of the first YOLOv8 model under real-world conditions. As a result, this helped us refine the model's detection capabilities and adapt it to the field scenarios.

3.2.3.D. Auto-Labelling and Iterative Field Model Improvements

OVD marks a significant departure from traditional closed-vocabulary methods in object detection. Unlike closed-vocabulary object detection, which relies on a fixed set of categories learned during training, OVD models are capable of detecting objects based on their appearance descriptions. This allows for the recognition of a broader range of objects that may not be present in the initial training dataset. These models are trained using contrastive learning, which utilises pairs of text and images. This approach enables the model to form associations between textual descriptions and visual representations, thereby enhancing its capability to detect and describe objects beyond pre-defined categories. However, OVD models are often large in size and require extensive computing resources, posing challenges for deployment on edge devices with limited computational resources. Moreover, while they offer the advantage of detecting a wide range of objects, their performance may not always match that of closed-vocabulary systems in detecting objects that are part of their training dataset. This trade-off between versatility and specialised efficiency is a crucial aspect to consider in the application of OVD models.

Figure 3.10.: Results of applying OVD to RGB images. The cassowaries in the images are accurately detected and localised, showcasing the effectiveness of OVD in identifying and pinpointing specific species within images.

In the developed LAARMA system, we used a VLM as a OVD method to automate the labelling of field data collected using the deployed field model, i.e., YOLOv8. The VLM used here is the same one applied during the initial training phase. Figure 3.10 presents an example of using the VLM to auto-label cassowaries in RGB images. Subsequently, we utilise the data labelled by the OVD system to fine-tune the field model. By repeating the above two steps, the field model's performance is iteratively improved during the field operation. The iterative

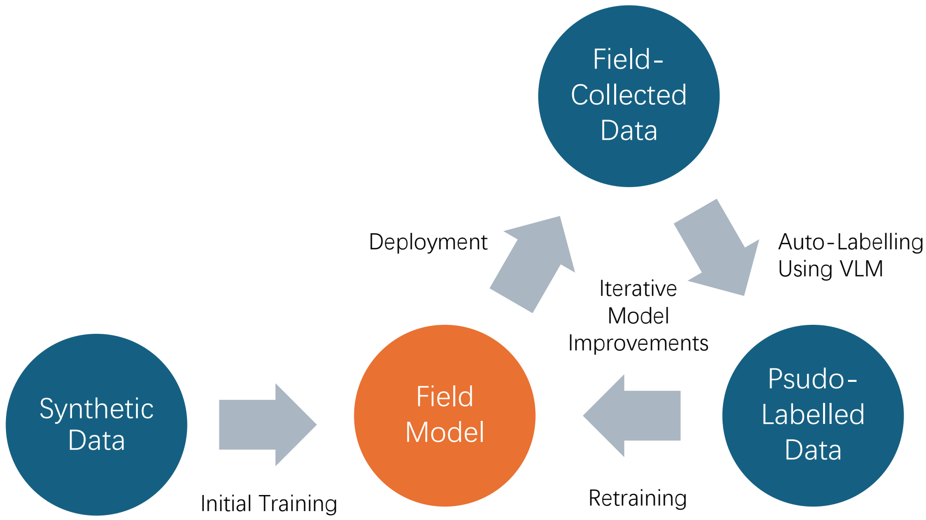


Figure 3.11.: The initial training phase for the field model using the synthetic data and the subsequent iterative model improvements using the auto-labelled field-collected data.

process is presented in Figure 3.11. Additionally, the VLM has shown impressive capability across different sensor domains, such as thermal imagery, as demonstrated in Figure 3.12.

This second phase leverages the specificity and efficiency of a closed-vocabulary system, fine-tuning it with the diverse and accurately labelled dataset generated by the OVD model. This hybrid approach aims to combine the comprehensive detection capabilities of OVD models with the focused efficiency of closed-vocabulary systems, creating a robust and effective tool for wildlife detection in varying environments.

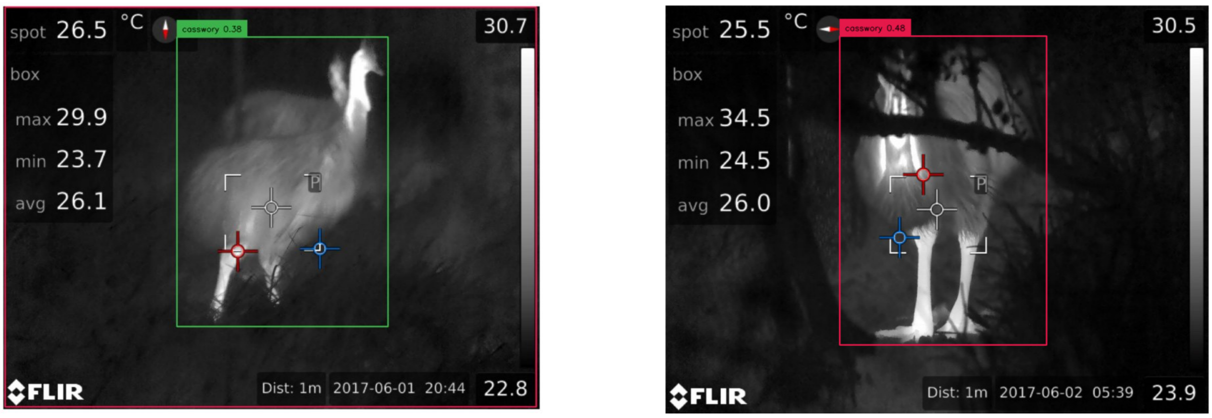


Figure 3.12.: Results of applying OVD to thermal images. It is shown that cassowaries are accurately detected and localised within these thermal images.

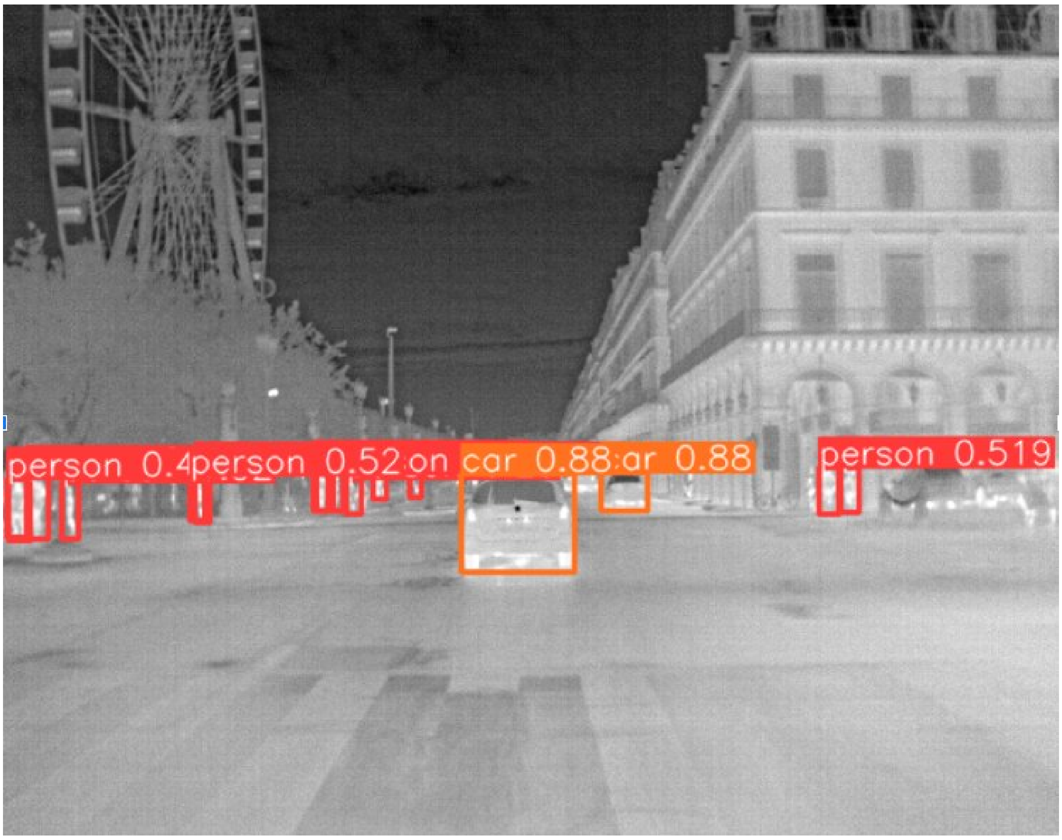


Figure 3.13.: Results of applying domain adaptation to thermal images. By employing transfer learning, the detection model is fine-tuned to operate effectively within the thermal image domain.

3.2.3.E. Model Fine-Tuning and Domain Adaptation

To ensure the field model's effectiveness in different environments and over time, fine-tuning and domain adaptation are integral parts of the LAARMA system's development. Fine-tuning involves adjusting the model based on initial deployment feedback, optimising it for the specific characteristics of the areas where the system is installed. Domain adaptation, on the other hand, focuses on modifying the model to maintain high performance despite changes in environmental conditions, such as weather variations, different lighting conditions, or seasonal changes in animal behaviour. Domain adaptation is also required when the machine learning approach is applied in different sensor domains. This process involves continuous learning from new data collected by the deployed units, enabling the field model to adapt and evolve, thus maintaining its accuracy and reliability in the long term. For the LAARMA system, one of the challenges is using YOLOv8 for detecting target objects in thermal images. Figure 3.13 shows that domain adaptation is a promising solution to this challenge.

For roadside animal detection, we can exploit transfer learning to adapt a pre-trained detection model, originally developed for different datasets, to a new specific detection task.

Transfer learning is valuable in scenarios like ours where data specific to the target animal species is limited. By employing this method, we leverage a model that has already been trained on a large and diverse dataset to recognise general patterns and features, then fine-tune this model for detecting large animals, such as cassowaries. This approach allows us to utilise the knowledge the model has already acquired, significantly reducing the need for a large amount of animal-specific training data.

For the transfer learning in our project, we used a technique that involves freezing some parameters of the pre-trained model during the training phase for animal detection. This means we keep certain layers of the neural network, typically the early layers responsible for identifying basic, universal features like edges and textures, unchanged. Meanwhile, the later, more task-specific layers are fine-tuned using our field-collected animal dataset. This strategy not only reduces the computational load and the amount of required training data but also helps prevent overfitting, especially given the relatively small size of our animal-specific dataset.

Moreover, to further enhance the model's performance in animal detection, we implemented data augmentation techniques in our image processing pipeline. Data augmentation involves modifying existing images in the dataset through transformations, such as rotations, flipping, scaling, cropping, and changing lighting conditions. These alterations create a more diverse training dataset, helping the model to become more robust and less prone to overfitting. Training the model on this augmented dataset allows it to learn to recognise the specific animal species under a variety of different conditions and perspectives, thereby improving its ability to generalise and perform effectively in the real-world scenarios we aim to address.

3.3. System Testing

3.3.1 System Functions Tests

To validate the various features developed for the large animal detection system, we conducted a series of outdoor and laboratory tests under different conditions. The primary objective of these tests is to assess the system's effectiveness in real-world environments and to ensure its reliability across different scenarios.

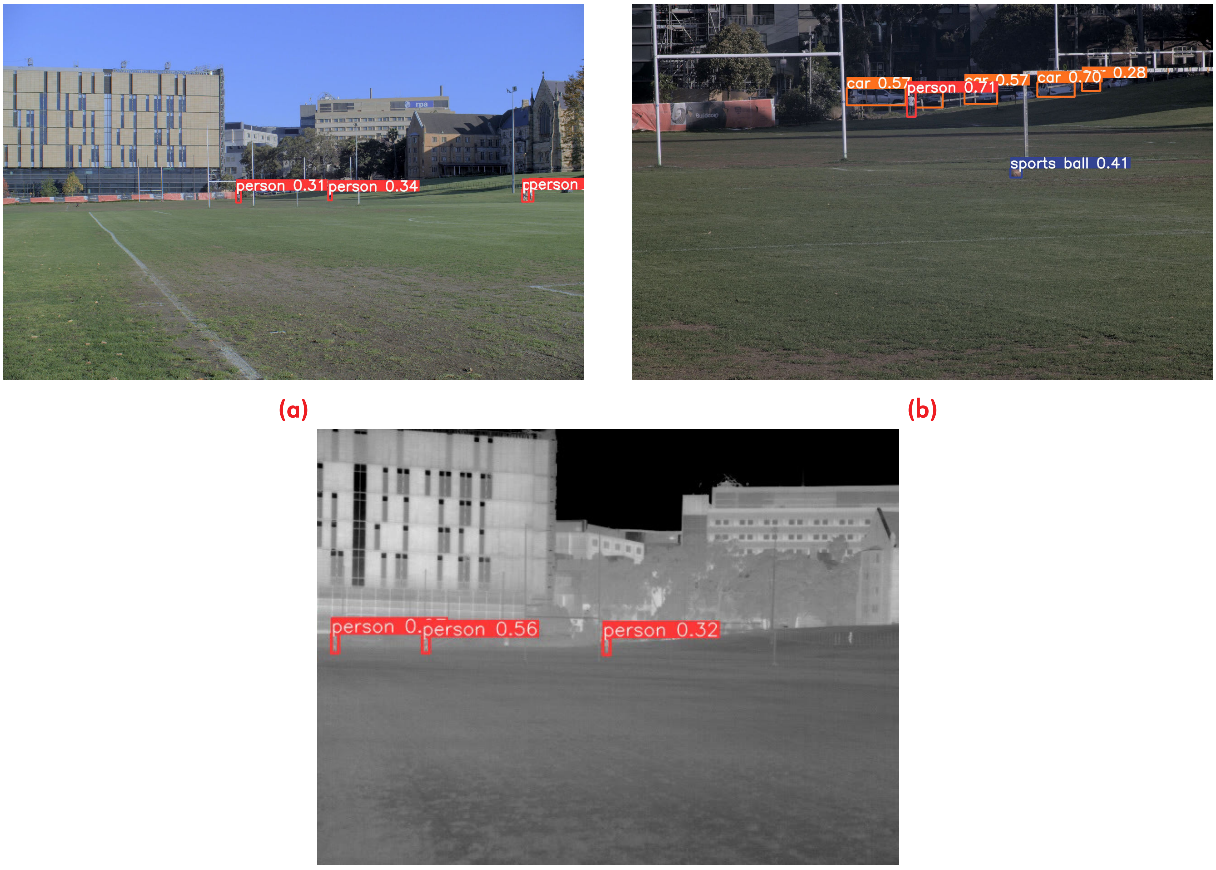
Figure 3.14.: The St John's Oval in USYD campus used for outdoor tests. The developed system was set up at the location marked by the blue circle, and the sensors were pointing in the south-east direction, as indicated by the orange arrow. The testing field stretches more than 230 metres long, from the system's location to the St John's College car park in the south.

3.3.1.A. Outdoor Test Location

For our outdoor tests, we selected a sports field that extends over 230 metres within USYD campus, as illustrated in Figure 3.14. This expansive space provides us with a suitable environment to rigorously test the working range of the sensor suite. During these tests, we successfully demonstrated that the developed system is capable of identifying objects at distances exceeding 200 metres. This long-range detection capability is crucial for early warning and timely response in real-world applications, especially in scenarios involving fast-moving traffic or wildlife.

3.3.1.B. Preliminary Test for Sensor Detection Range

A preliminary outdoor test was carried out on 5 October 2023, which was at the early stage of the system development, to gain a better understanding of the effective working range of the main detection sensors under their designated operational conditions. The tested sensors included the RGB cameras and the thermal camera.



(a) (b) (c)

Figure 3.15.: The camera images from the preliminary outdoor test. (a), (b), and (c) show images from the medium-angle RGB camera, the telephoto RGB camera, and the thermal camera, respectively. The camera images were processed by the pre-trained YOLOv8 model, with the detection results overlaid on the images.

Some example images in the test are presented in Figure 3.15. Since the pre-trained YOLOv8 model does not support the detection of cassowaries, the CoI in the test was selected as "person". Figure 3.15a and Figure 3.15b clearly demonstrate the capability of detecting the CoI more than 100 metres and 200 metres away, respectively, during day time using the RGB cameras.

Further testing was conducted to reveal the preliminary detection range of the thermal camera at night. The pre-trained YOLOv8 model was trained using RGB images from COCO dataset, which does not contain thermal images. The main challenge in the nighttime test is that the YOLOv8 model was used in a sensor domain different from the domain it was trained in. This domain gap usually causes a significant performance drop for most machine learning models. However, as Figure 3.15c reveals, the pre-trained YOLOv8 demonstrates exceptional detection performance when working with thermal images, managing to detect the CoI more than 150 metres away in the given testing scenario. There is still potential for a range boost using a smaller FoV lens, a fine-tuned detection model for thermal images, and other image processing techniques.

Overall, the preliminary test has shown the potential of the selected sensor suite and YOLOv8 detectors to be adopted as an effective roadside animal detection solution.

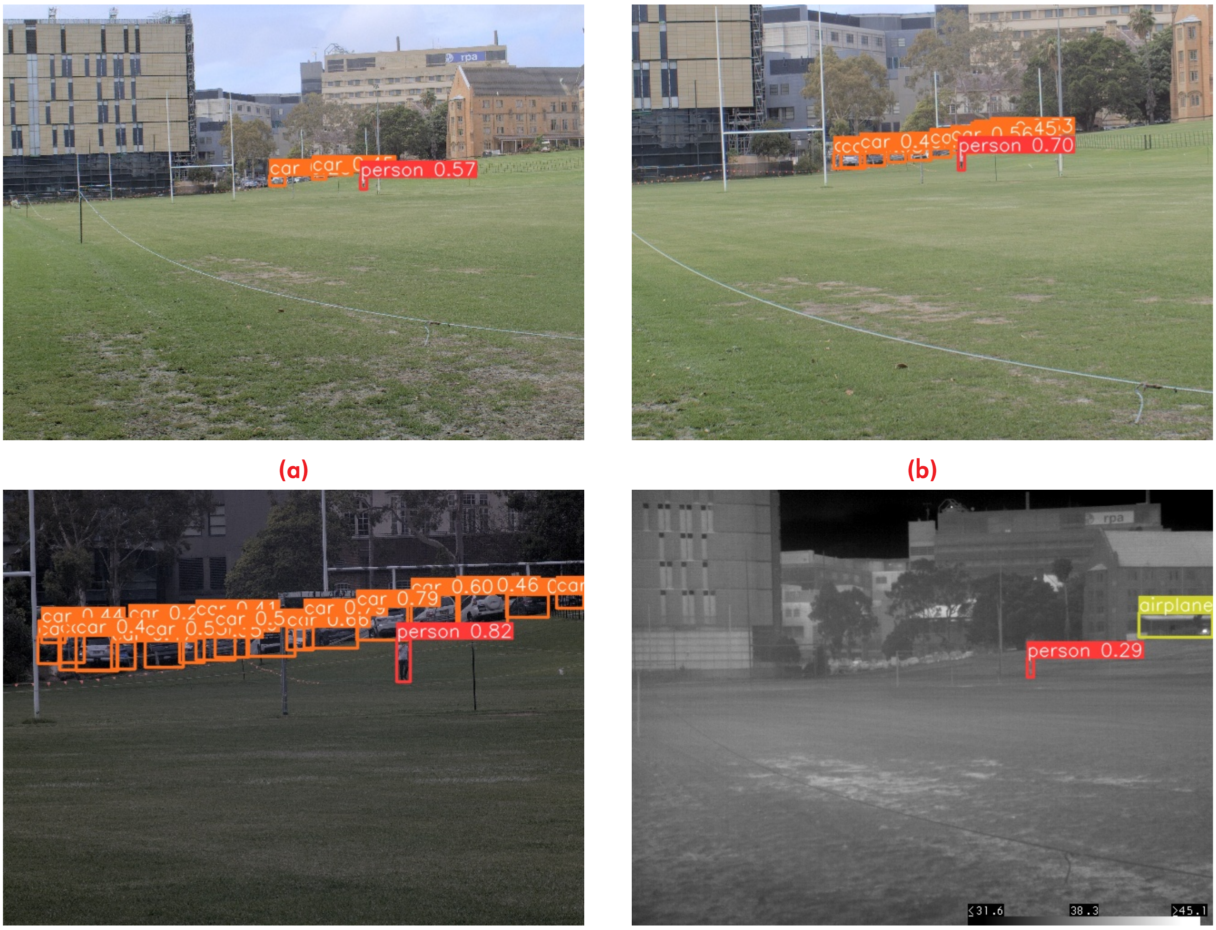
3.3.1.C. Comprehensive System Test

A more comprehensive system outdoor test was conducted on 23 November 2023, to validate various system features that had been developed up to that point. The tested sensors included the RGB cameras, the thermal camera, and the LiDAR. The main system features tested were:

1. Image processing pipelines
2. Real-time YOLOv8 detection for each camera pipeline
3. Continuous data logging

Figure 3.16 depicts the image frames from the cameras and the YOLOv8 detection results. As in the previous outdoor test, the object class "person" was selected as the CoI in the test. The detection results from this test are similar to those in Figure 3.15, due to the use of the same cameras and pre-trained YOLOv8 model in both tests. The main difference is that the YOLOv8 detectors had been deployed onto the edge computing unit, and all the image processing pipelines were running in real time in this test.

The outdoor test also served as an opportunity to test the continuous data logging feature. The preview video and the associated data files were then retrieved from the system for playback and analysis, as demonstrated in Figure 3.17.



(a) (b) (c) (d)

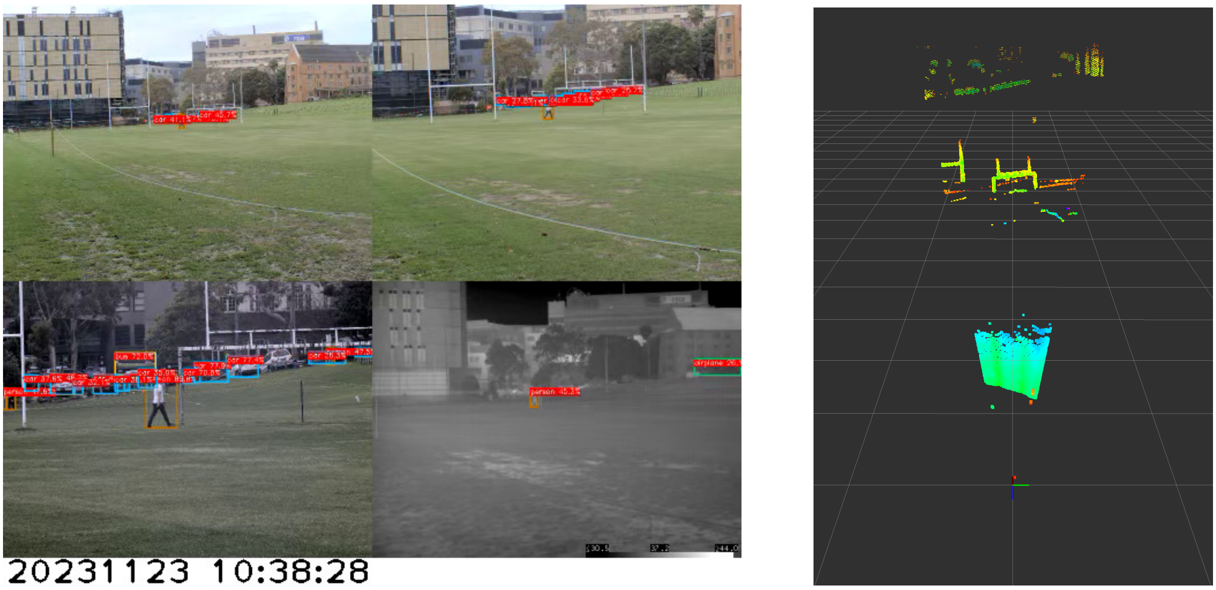
Figure 3.16.: The camera images and object detection results in the comprehensive outdoor test. (a)-(d) show an image from the medium-angle RGB camera, its digital-zoomed image, an image from the telephoto RGB camera, and a thermal image, respectively.

3.3.1.D. Testing the Event-Triggering Pipeline

Follow-up testing was conducted when the system development was closer to completion. The following system features were tested in a laboratory environment:

1. Event-triggering pipeline
2. Event-triggered data logging

At the time of conducting the lab test, the YOLOv8 model had not been trained to support the detection of cassowaries. Yet, the event-triggering functionality could still be well tested using a different CoI. In this lab test, “tennis racquet” was set as the CoI, which means the system triggers a detection event whenever it detects a tennis or badminton racquet within its sensor FoV. The results are presented in Figure 3.18, showcasing the successful detection



(a) (b)

Figure 3.17.: Playback of data logged in the comprehensive outdoor test. (a) shows a snapshot of the 2-by-2 image collage video recorded during the test, with the timestamp printed at the bottom-left corner of the video. In (b), a screenshot visualises the recorded dense point cloud from the solid-state LiDAR. It is clearly visible in the point cloud that structural features in the field, such as the rugby goal posts around 100 metres away, the car park, and surrounding buildings more than 200 metres away, can be distinguished. The size of each grid in (b) is 10 metres.

of a badminton racquet being waved in front of the sensors and how the event-triggering pipeline managed to pick up this event. The positive detection event then triggered the data logging as expected. The signal will also trigger the roadside message display when the system is deployed in the field. The testing results are visualised in Figure 3.18 through the playback of the first logged data file for this particular event.

3.3.2 Fine-Tuned Detection Model Evaluation

Initially, our YOLOv8 model was pre-trained using the COCO dataset, renowned for its comprehensive scope in object detection, segmentation, key-point detection, and captioning. This dataset contains approximately 328,000 images.

Subsequently, we employed transfer learning techniques to adapt the model for the cassowary dataset. This dataset features synthetic images and field-collected images that are automatically labelled by the VLM. Transfer learning can potentially affect the performance of the model initially trained on the COCO dataset. To assess this impact, we conducted a comparative analysis between the pre-trained and fine-tuned models.

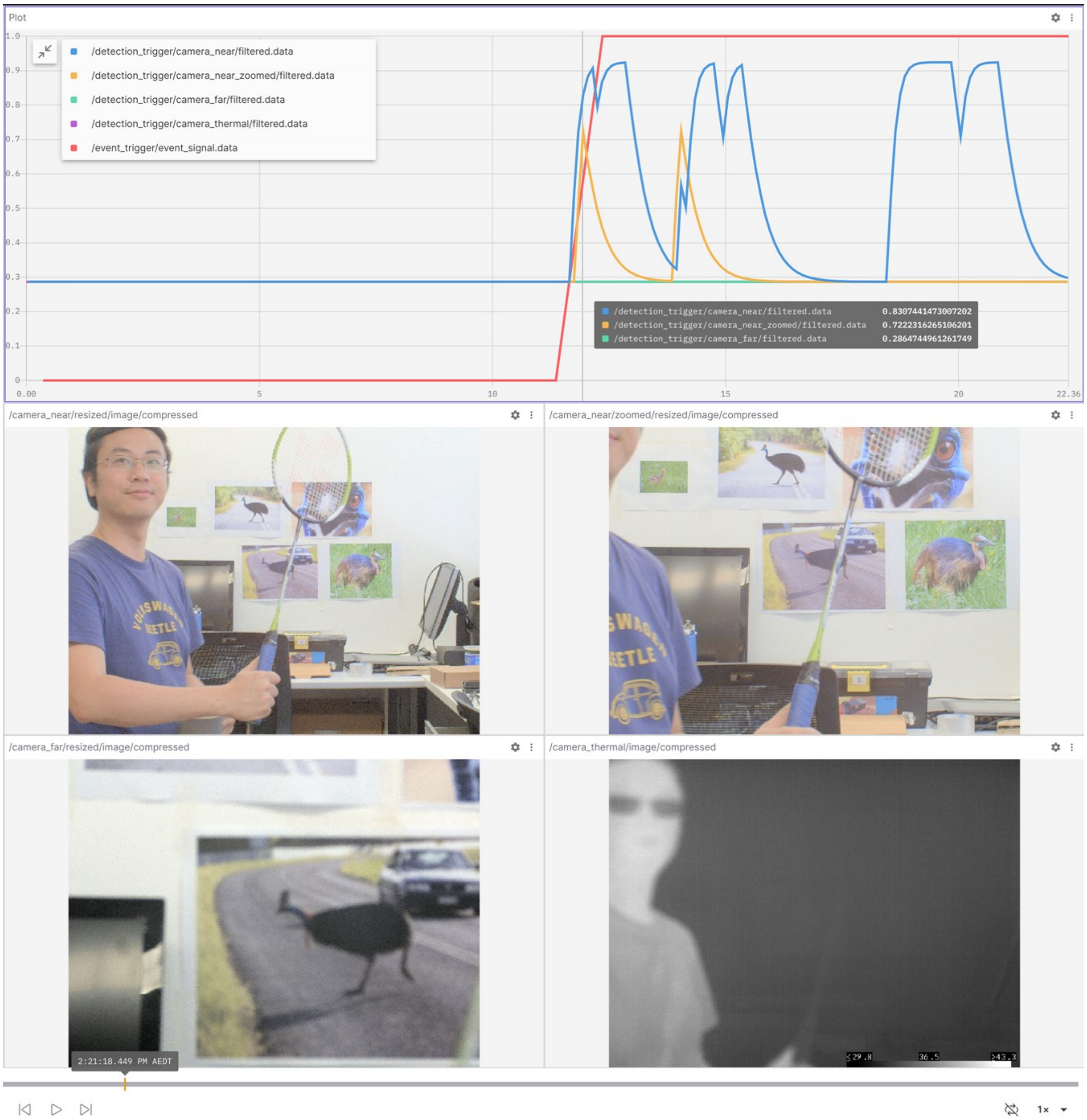


Figure 3.18.: Testing the event-triggering pipeline in the lab. It involved the system triggering a detection event when it detected a CoI object, which in this test was a tennis/badminton racquet, using its sensors. The top chart shows the Bayesian filtering results from the multiple image processing pipelines. The curves indicate the probability of detecting the presence of the racquet within their sensor FoVs. In this example, both the medium-angle camera image (blue line) and its digitally zoomed image (yellow line) picked up the racquet in the scene, producing high probabilities of positive detection. Meanwhile, the fused event detection outcome, represented by the red line, switched from false (zero in the chart) to true (one). This positive event then triggered the data logging for the event itself.

3.3.2.A. Model Definitions

Pre-trained model: This refers to the original model trained exclusively on the COCO dataset. **Fine-tuned model:** This model represents the adaptation of the pre-trained model, where the majority of parameters are frozen, and the model is retrained on the cassowary dataset.

3.3.2.B. Evaluation Metrics

In our experimental evaluations, the primary measure used to assess the model performance is the Mean Average Precision (mAP). The mAP metric is standard in the field of object detection, offering a comprehensive assessment by averaging the Average Precision (AP) scores across all recall levels, which range between 0 and 1.

- **Box(P) - Precision:** This metric quantifies the accuracy of the bounding box predictions, where higher values suggest a higher ratio of true positive detections to the total number of positive predictions made by the model

- **Box(R) - Recall:** This metric measures the ability of the model to correctly identify all available instances of objects, with higher values indicating a higher ratio of true positive detections to the actual number of objects present in the dataset

- **mAP50:** This represents the Mean Average Precision calculated at an Intersection over Union (IoU) threshold of 0.5, offering a balance between precision and recall for a binary interpretation of object presence

- **mAP50-95:** This is an average of the Mean Average Precision values calculated at IoU thresholds spanning from 0.5 to 0.95, in increments of 0.05. It is a more rigorous metric that takes into account the precision of the bounding box alignment with the ground-truth across a range of IoU thresholds, thus providing a more granular evaluation of model performance

These metrics collectively offer a comprehensive view of model efficacy, accounting for both the presence and precise localisation of objects within the images.

3.3.2.C. Preliminary Experiment Results

Utilising transfer learning, the fine-tuned model demonstrates consistency in performance across all previously established detection categories, as shown in Table 3.1 and Table 3.2.

Class	Images	Instances	Box(P)	Box(R)	mAP50	mAP50-95
all	260	474	0.755	0.511	0.632	0.479
ambulance	260	64	0.917	0.844	0.904	0.752
bus	260	46	0.659	0.696	0.792	0.641
car	260	238	0.773	0.387	0.55	0.377
motorcycle	260	46	0.609	0.478	0.508	0.327
truck	260	60	0.703	0.333	0.525	0.387
cassowary	260	20	0.867	0.326	0.513	0.39

Table 3.1.: Performance metrics for object detection across various classes.

Class	Images	Instances	Box(P)	Box(R)	mAP50	mAP50-95
person	1144	2701	0.659	0.6	0.618	0.373
car	1144	5728	0.642	0.427	0.648	0.392
bike	1144	95	0.472	0.558	0.488	0.267
motor	1144	322	0.731	0.835	0.699	0.523
airplane	1144	66	0.654	0.409	0.477	0.386
bus	1144	18	0.371	0.198	0.164	0.119

Table 3.2.: Summary of object detection model performance on thermal image datasets.

This consistency is maintained while successfully integrating the detection of a new class, namely, cassowary. This integration did not compromise the model's effectiveness in identifying and segmenting previously learnt classes, indicating a robust adaptation of the model to new data without losing its proficiency in original tasks.

The performance metrics, particularly the mAP, remained stable or showed minimal variance, suggesting that the transfer learning process effectively preserved the model's original capabilities. Additionally, the model's ability to detect the cassowary with high precision and recall highlights the effectiveness of our fine-tuning approach in expanding the model's detection repertoire without detracting from its existing strengths. Note that these preliminary results achieved for cassowaries in Table 3.1 are based on only 20 cassowary instances. More comprehensive and real-world evaluation results after the model was trained with field-collected data are presented in Section 7.2.2.

3.4. Conclusions

In this chapter, we have addressed the development of a state-of-the-art system designed to detect roadside large animals, enhancing road safety and wildlife preservation. The development of this system encompasses several key challenges, including the need for efficient processing and adaptability to different scenarios. Our approach integrates cutting-edge hardware with a powerful machine learning-based animal detection approach, making it both cost-effective and efficient for real-time applications. Utilising a suite of advanced detection sensors, the system is designed to operate in various environmental conditions, from daylight to nighttime settings.

The core strength of this system lies in its innovative use of the self-training machine learning pipeline, enabling it to learn and identify any large animal species. Data plays a crucial role in the effectiveness of any machine learning system. Our approach includes an auto-labelling feature based on OVD, thereby enriching the training dataset with minimal human inputs. The model undergoes further enhancement through fine-tuning and domain adaptation. These processes are critical in ensuring the model's effectiveness across different environments and conditions. The application of the field model, i.e., YOLOv8, ensures rapid and accurate detection, essential for timely responses in dynamic road situations.

The extensive testing and evaluation of the developed large animal detection system have demonstrated its capability and reliability across various scenarios, highlighting its potential as an effective solution for roadside animal detection. Outdoor and lab tests have validated the system's ability to accurately identify objects at long distances, a critical feature for providing early warning and response in real-world situations. A key aspect to the system development is the integration of the YOLOv8 model, which, although initially trained on standard RGB images, showed promising performance in detecting objects in thermal images during nighttime tests. The comprehensive system test further validated the functionality of image processing pipelines, real-time object detection, and continuous/event-triggered data logging, all running effectively on an edge computing platform. The fine-tuning of the detection model using transfer learning techniques allowed for the successful addition of a new detection class, "cassowary", without compromising the model's existing detection abilities. This indicates a robust model adaptation to new data while maintaining proficiency in original tasks. The stability of performance metrics, particularly the mAP, across various detection categories, have shown the effectiveness of our approach in expanding the model's detection capabilities. These results show that combining advanced sensing technology with machine learning creates an efficient and reliable system that can enhance both road safety and wildlife conservation.

4

Message Design and Testing (QUT)

4.1. Introduction

4.1.1 Background

AVCs are associated with substantial costs to individuals, communities, and the environment each year. In 2004, it was reported that crashes involving animals caused over $1 billion in vehicle damage annually in the United States [2]. The human and societal costs of injury, rehabilitation and death cannot be quantified, nor can the effects of AVCs on conservation efforts. Analysis of crash data in the US between 1965 and 2017 found that there was a four-fold increase in animal fatalities resulting from AVCs in that time [3]. In countries such as Australia, many native and protected species are particularly vulnerable [2].

The attitudes of motorists and their knowledge of how best to respond when an animal in is on the road has been identified as a contributing factor to AVCs occurrence. For example, a recent large-scale survey in Hungary explored the habits and attitudes of 1942 drivers regarding AVCs [5]. The results showed that drivers with less experience and fear of AVCs drove with more confidence, at higher speeds and less vigilance. Additionally, results showed that as years of driving experience increased, there was an the perceived ability to handle unexpected driving situations (such as an animal encounter) also increased. Perhaps unsurprisingly, it was also found that drivers who reported a higher regard for the importance of nature conservation or traffic safety in relation to preventing AVCs reported driving with more care and attention [5]. Other research has suggested that a lack of knowledge about the appropriate or correct course of action in the event of an animal encounter also influences potential AVCs [2, 4, 5]. The nature of AVCs avoidance manoeuvres that a driver or rider may need to implement, such as swerving to avoid an animal, can also increase the likelihood of a serious injury crash [4]. While research has shown that the safest solution for motorists is to simply slow down and (unfortunately) hit the animal, in a study of crash mechanisms involved in 366 AVCs in Australia, Wilson et al. [7] reported that 58.5% of AVCs involved the motorist swerving to avoid impact with the animal. Swerving can often result in loss of control, rollovers and/or colliding with other objects, such as trees, poles, and guardrails [2, 7].

Road signage is a commonly implemented measure to alert drivers to risks they may encounter in the road environment. While static road signage has been shown to have some effect in mitigation the risk of AVCs (e.g., [48]), a recent review investigating the effectiveness of road warning signage by Tryjanowski et al. [45] suggests that principally, the main response elicited by a motorist to a warning sign is merely recognition as opposed to motivating behaviour change and suggest that further research is required to enhance the effectiveness of such signage to extend beyond mere recognition to ensure action is taken. VMS may provide a more effective means to alert drivers to the presence of animals and encourage safer driving behaviours due to the ability to display a series of changing messages across a single LED screen. Currently, research examining the effectiveness of VMS in influencing driver behaviour is limited. However, a recent Australian study investigating the effects of roadside VMSs displaying dual-screened messaging aimed to encourage motorists to stay within the speed limit showed that the proportion of road users exceeding the posted speed limit was consistently lower when the anti-speeding VMS were displayed [60]. The results also showed a residual effect, whereby a reduction in mean speeds and lower proportion of drivers exceeding the speed limit continued to be observed for the week following the removal of the VMS [60]. These findings, while not related to AVCs suggest that roadside VMSs which not only alert motorists to the presence of a potential road hazard (such as nearby animal), but also offer driving strategies (such as slowing down) to navigate the situation safely, may reduce the risk of road collisions.

The current program of research, insofar as the messaging component of the project, consisted of two studies with the purpose of developing and evaluating messages that sought to, (i) alerts motorists that an animal, specifically a cassowary, had been detected in the road environment, and (ii) encourage motorists to slow down and scan the road environment. This project applied the SatMDT [1], see Figure 4.1, to develop and evaluate the messaging. As shown in Figure 4.1, the SatMDT includes four steps: Step 1: getting to know the audience, Step 2: development of the message content, Step 3: testing the message content, and Step 4: evaluating the message content. Study 1 drew upon Step 3 of the framework, while Study 2 drew upon Step 4. The SatMDT has been successfully applied in previous research to develop and evaluate anti-speeding messages [195], messages designed to reduce smartphone use among young drivers (e.g., [196, 197]), and messages promoting intentions to use connected vehicle technologies [57] to name but just a few applications (see [58] for more examples).

4.1.2 Method

Study 1 comprised eight focus groups with 36 drivers (Mean age = 42.72 years; 19 females) and explored their perceptions towards a series of message concepts designed to appear on roadside VMSs. The findings from the focus groups were used to develop four message concepts to be tested in Study 2. Study 2 was a between-groups design and comprised 557 drivers (Mean age = 50.29 years; 350 females) who completed an online survey. Participants were randomly allocated to one of five conditions (i.e., to view one of the four message

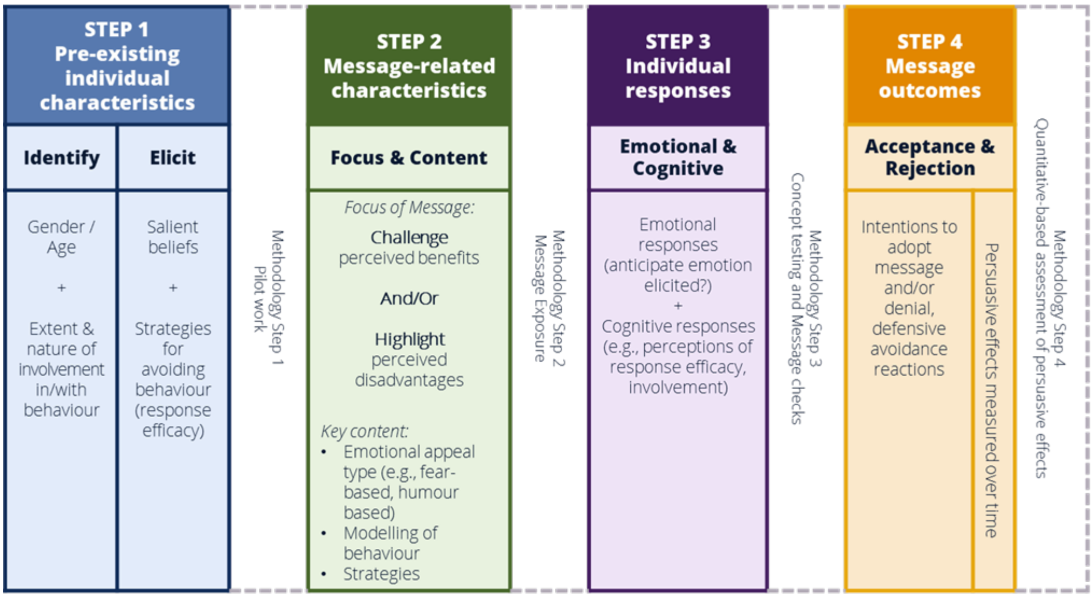


Figure 4.1.: The Step approach to Message Design and Testing [1].

concepts or the control, no message condition). Participants allocated to the four message conditions were asked about their perceptions towards the message content, responded to items relating to message acceptance (i.e., relating to how directly and indirectly effective the messages were), and asked about their preferences regarding the driving strategies offered as part of the message. The study was led by Prof Ioni Lewis, with assistance from Ms Nyree Gordon and Ms Melinda McDonald.

4.1.3 Key Findings

Overall, all four message concepts evaluated in Study 2 performed consistently well across all direct and indirect measures of effectiveness, which suggests that the implementation of any of these concepts would likely have the intended effects on driving behaviours. However, there were instances where some concepts appeared to outperform others on specific measures and suggests that there is scope to selectively apply messages according to the parameters that are considered of highest priority. For screen 1 of the message, a greater portion of participants across both studies reported that it would be more effective to identify the type of animal on the signage compared to participants who reported that the animal should not be identified. In Study 1 (where participants were able to compare multiple message concepts), most participants preferred the combination of both text and image to specify the type of animal. For screen 2, there were no significant differences in how useful participants perceived the four driving strategies to be; however, participants across both studies commented that the slowing down strategy should be presented before the scanning strategy. Participants across both studies emphasised that it was important that motorists understood that the message was a real-time warning and expressed concerns that motorists might become complacent if the sign were to remain activated and/or they did not come across any animals while driving. This provided support for leaving the sign blank and only 'flashing' a message when an animal had been detected. The findings also supported the potential value of future use of this technology being promoted through use of public education campaigns so that motorists could understand what it is and how it works.

4.1.4 Chapter Structure

Section 4.2 outlines the findings from Study 1 which consisted of eight in-person focus groups to test a series of 20 message concepts (see Appendix A for the message concepts). The findings from Study 1 were used to inform the develop of four message concepts to be evaluated in Study 2. Section 4.3 outlines the findings from Study 2, which involved evaluating the four message concepts in terms of their effectiveness via an online survey with a larger sample of motorists. Section 4.4 presents the overall conclusions emerging from this program of research as well as practical consideration for implementing the messaging in the forthcoming driving simulator study and the on-road field trial in North Queensland, both studies within the subsequent research to be conducted in the overarching LAARMA project.

4.2. Study 1

4.2.1 Overview

Study 1 explored participants' responses to 20 message concepts designed to be displayed on a VMS to inform motorists that an animal (specifically a cassowary in the context of this research) has been detected on or near the road (Step 3 of the SatMDT). This step of the conceptual framework focuses on ensuring that members of the intended target audience respond to the messaging as anticipated. The message concepts were developed based on broader literature regarding the use of roadside messaging alerting road users to the presence of animals and drew upon key constructs (i.e., emotional appeal and modelling of behaviour strategies as outlined in Step 2 of the SatMDT) that have been demonstrated to enhance message effectiveness (e.g., [60]). The message concepts developed by Prof

Ioni Lewis [IL] for Study 1 were designed to alert passing motorists that an animal had been detected in the vicinity and to encourage motorists to engage in two key driving behaviours—(1) slow down, and (2) scan the road environment. In line with Step 3 of the SatMDT, the purpose of Study 1 was to test whether the message concepts elicited the intended response by the target demographic (i.e., Australian motorists). Specifically, the concept testing sought to determine whether the messages were (a) effective in informing motorists that the message was a real-time warning that an animal was in the immediate road vicinity, and (b) whether the driving strategies offered as part of the message would motivate motorists to slow down and scan the road environment as directed. The message concepts tested in Study 1 are presented in Appendix A.

4.2.2 Method

4.2.2.A. Participants

Participants were recruited by Farron Research, an Australian market recruitment company. Participants were required to be aged 18 years or older, reside in Australia, hold a valid motor vehicle, or motorcycle licence, and drive/ride for at least one hour per week. Thirty-six drivers were recruited in November 2023 to participate in one of eight in-person focus group sessions to discuss the message concepts. Participants were aged between 23-77 years (Mean age = 42.72 years, SD = 16.31). All participants, resided in Queensland, held an open driver licence, and reported holding a licence between 6 and 60 years (M = 23.83, SD = 14.90). Participants drove for an average of 11.22 hours per week (SD = 10.29) with most participants reporting driving between 5 to 12 hours (55.6%, n = 20). All participants received a gift voucher for AUD 80 for participating in Study 1.

Demographic Survey

The brief demographic survey (see Appendix B) collected information about participants' gender, age, state of residence, postcode, type of driver licence, and how long they have held their licence. On average, participants completed the questionnaire in 5 minutes.

Focus Group

Eight in-person focus groups were conducted at the QUT, Kelvin Grove campus between 20 and 23 November 2023. The focus groups were guided by a semi-structured interview schedule (see Appendix C) which comprised questions consistent with well-established materials and procedures used when undertaking concept-testing in accordance with the SatMDT [1]. The purpose of these focus groups was to concept-test a series of, predominantly dual-screened, message concepts to be displayed on VMSs. Each focus group was audio recorded and facilitated by two researchers (Melinda McDonald [MM] and Nyree Gordon [NG]). The focus groups consisted of between 3 to 5 participants and, on average, group discussions lasted 1 hour. Salient elements of the focus group discussions and quotes offered by participants were noted excluding any personally identifying information by NG during the discussion.

4.2.2.B. Procedure

The university's Human Research Ethics Committee approved the study prior to its commencement (QUT Reference Number: 7663). Consent was obtained by participants on arrival by completing and signing a consent form before the focus group commenced. Participants were first asked to complete the demographic questionnaire prior to participating in the group discussions. In the group discussions, the message concepts were presented to participants visually, as a VMS-style mock-up, via a power-point presentation projected on a large screen. To investigate the legibility of the messages in the VMS format, the group facilitators refrained from reading the messages out loud unless required. The message concepts were presented in three sections: (1) Text Only, (2) Image and Text, and (3) Image Only. After presentation of a message concept, participants were invited to share their perspectives towards the message and to offer suggestions to improve the message content. The same process was repeated for a total of eight Text Only message concepts, six Image and Text message concepts, and eight Image Only message concepts. All message concepts that were tested have been included in Appendix A.

4.2.3 Results

4.2.3.A. Focus Group

The following section presents the findings from the focus group discussions. Specifically, it will detail participants' perceptions about each of the VMS messages concepts that were explored. Guided by questions in the interview schedule, thematic analysis was undertaken based on post-focus group discussions amongst the project team and aspects considered unclear and/or requiring further justification were identified and resolved in the following focus groups. The findings presented herein include de-identified quotes, as noted by NG during the group discussions, as supporting evidence of themes. Quotes are attributed to participants in a way to protect their confidentiality (i.e., only reported in relation to a participant's gender and their approximate age).

Comparison of Responses Between Participants

Overall, most messages were associated with relatively consistent responses from the study participants irrespective of their age and gender. Message C of the Image and Text concepts appeared to elicit some mixed responses across age groups, with older participants tending to react negatively to the Screen 2 message ('Reduce your speed. Be alert.'), while younger participants tending to be more in favour of the message. However, as the reasons offered for these reactions were not consistent within age-similar groups, this discrepancy is likely due to individual preferences rather than a broader age-related effect. Moreover, the most frequent negative commentary about this message across all participants was that there were too many words, which suggests that shortening the message may prompt more positive responses. In addition, younger participants tended to respond favourably to Alternative Text Message C1 ('Hazard ahead'), while most older participants were indifferent to the message or likened it to a road works sign. However, as there was an overarching preference for other message concepts that were tested, it was deemed unnecessary to investigate these differences regarding this one particular message any further. Hence, the following summary of key findings pertains to the overall sample. In addition, as there were no dual-screen message concepts (i.e., a Screen 1 and Screen 2 combination) that were preferred as a set in and of themselves, the findings for the messaging presented on Screen 1 and Screen 2 have been considered separately in each section.

Text Only Message Concepts

Screen 1

There were five different Text Only message options for Screen 1: Cassowary About (Messages A-D), Help Protect Our Cassowaries (Message E), Please Protect Our Native Fauna (Message F), Cassowaries About (Alternative Text 1), and Cassowary Recent Sighting (Alternative Text 2). The Text Only messages shown during the focus groups can be found in Appendix A (Figure 8.1 and Figure 8.2). For Messages A-D and Alternative Text 1, the consensus amongst participants was that 'cassowary' (singular) was easier to read and understand than 'cassowaries' (plural), although a small number of participants reported that 'cassowaries' denoted more of a hazard. All participants also agreed that the word 'about' was ineffective, citing that the term was "vague", relied on the drivers understanding Australian vernacular, and did not imply the presence of a real-time hazard. Participants frequently offered 'ahead', 'detected', or 'seen' as alternatives to better relay the immediacy of the message. Messages

E (Help Protect Our Cassowaries) and F (Please Protect Our Native Fauna) also consistently elicited negative responses, with participants stating that the messages were more like conservation campaigns, rather than an active warning that an animal had been detected on or near the road. Additionally, participants reported that the number of words used made the sign look busy and difficult to read. Most participants also agreed that the Alternative Text 2 message (Cassowary Recent Sighting) was vague, and that the term 'recent sighting' could be interpreted to mean different time frames (e.g., hours, days, weeks etc).

"I'm waiting for the next screen to tell me where I can donate money to." (Male, mid-40s)

"Looks more like a 24/7 campaign sign." (Female, mid-30s)

Screen 2

There were five different Text Only message options for Screen 2: Slow Down. Look Around. (Message A), Slow down. Monitor ahead (Message B), Scan. Check. Slow Down (Messages C/E) and Look Out and Slow Down (Messages D/F). Of these messages, most participants indicated a preference for Message D/F, citing that it was concise and offered clear instructions using plain English. Many participants also suggested that the 'and' be removed and to reverse the order of the statements so that 'Slow down' was presented first. Most participants reported disliking Message A (Slow Down. Look Around). The 'Look Around' component raised concerns that the direction could be interpreted as an invitation for drivers to look for the animal as if it were an attraction, rather than a driving hazard. Message B (Slow down. Monitor ahead) received mixed responses, with some participants reporting that the term 'Monitor ahead' provided clearer direction than 'Look Around' (Message A). However, most did not like the word 'monitor' for reasons including that it might not be easily understood by those who do not speak English as their first language, it implied that the driver's behaviour was being monitored, and that it may cause confusion due to the word having multiple meanings (e.g., monitor lizard). Most participants reported liking Message C/E (Scan. Check. Slow Down) more than A and B because it was short and simple; however, they also reported that 'scan' and 'check' meant the same thing and it was redundant to include both. Of the two words, 'scan' was preferred.

In addition, there were six Alternative Text message options offered at the end of the section: (A) Hazard ahead, (B) Watch out for animals on roads, (C) Slow down. Wildlife on road, (D) Be alert. Wildlife on road, (E) Be alert. Wildlife detected, and (F) Wildlife on road. Proceed with Caution. Of these alternative wordings, messages A, E, and F generated the most discussion. As previously noted, Message A (Hazard ahead) was generally preferred by younger participants. Those in favour of the message (regardless of age group) stated that the message made it clear that the animal (whose presence was noted on Screen 1) posed a potential driving threat. However, most participants preferred Message E (Wildlife detected), specifically the word 'detected' as it was seen to clearly indicate that the animal was in the immediate vicinity. Many participants went on to suggest that 'detected' ought to replace 'about' in the Screen 1 messages. Several participants also liked Message F (Wildlife on road. Proceed with Caution) as the 'wildlife on road' component made in clear that the message was not a general warning about animals inhabiting the area, and the 'proceed with caution' component gave drivers the freedom to adjust their driving behaviour according to what they believed would be the safest way to approach the situation.

"E gives a real sense of immediacy. It's effective." (Female, younger driver)

Image and Text Message Concepts

Screen 1

There were four message options shown for Screen 1 in the Image and Text section: An image of a cassowary with no text (Message A), an image of a smaller cassowary with the text 'Cassowary About' (Message B/D), the same cassowary image with the text 'Cassowaries About' (Message C/E), and an image of a cassowary with the text 'Help Keep Them Safe' (Message F). The Image and Text messages shown during the focus groups can be found in Figure 8.3 of Appendix A. Message A received mixed responses. Some participants preferred the image citing that it was attention-grabbing and could be "processed more quickly than words". While others reported that the image alone lacked urgency and did not make it clear that the animal has been detected and could be interpreted as "more sight-seeing advice". For Messages B-E, it was unanimously agreed that the smaller cassowary did not look like (or depict the scale of) the animal and might lead to confusion for motorists. Like the responses offered in the Text Only section, participants reported the same preference for the singular 'cassowary' as opposed to 'cassowaries' and concerns about the word 'about'. However, most participants indicated that having an image and text on Screen 1 would be useful for drivers to understand what animal to expect in the area, with many participants suggesting similar responses that were offered in the previous section (e.g., 'Cassowary detected'). All participants reported disliking the (single-screen concept) Message F, stating that it was reminiscent of a "activist" or "Greenie" sign.

Screen 2

Participants were shown five options for Screen 2. Messages A, B, D, and E were the same as messages offered in the previous Text Only section. Participants did not report any changes in preferences for these messages when paired with the new Screen 1 image or image/text message. Message C read 'Reduce Your Speed. Be Alert'. As reported in the previous section "Comparison of Responses Between Participants", this message received mixed reactions. Those in favour of the message found it to be "compelling", "clean" and "tangible", and that it would encourage them to "take more notice" of the signage. Whereas those who disliked the message considered it to be "vague", "not enforceable", and too similar to road works signage. However, it was commonly mentioned (from both the participants who liked the message and those who did not) that the message had too many words, with some participants suggesting that 'your' could be removed.

"The picture is processed more quickly than words and makes me more likely to read the next message. And we always remember the last thing we read." (Female, mid-20s)

Image Only Message Concepts

The Image Only section consisted of eight single-screened messages featuring a cassowary pictogram on each, four of which were monochromatic (amber, as used for the messages in the previous sections) and the other four incorporated additional colours (see Appendix A, Figure 8.4). Of the monochromatic images, most participants preferred Message A3 stating that the larger cassowary would be useful to "visualise" the size of the animal, and that the exaggerated crest made it look "scarier" and "dangerous". One participant preferred Message A2 stating that it was a more accurate depiction of a cassowary, and no participants preferred Message A1 or A4. Of the coloured images, most participants preferred Message B1, with some participants suggesting that Message B1 could be improved by having Message B2's larger crest. Specifically, participants liked the larger scale of the cassowary and commented that the use of blue and red on the neck would help drivers identify the animal. Many participants also reported liking Message B1, stating that the cassowary's white body would be eye-catching. However, others expressed concerns that the additional bright colours looked "touristy" (as opposed to the mostly amber Message B1 which looked more like a "warning"), and that the white body might cause confusion given that cassowaries do not have white plumage. No participants preferred Message B3 or B4. All participants agreed that an Image Only message would not be as effective as a text plus image message, having an image alone does not suggest that there is a potential hazard or danger ahead and may be seen as an invitation to drivers to search from the cassowary out of interest.

"The colours in B1 and B2 are better for identifying, if people don't know what a cassowary looks like." (Female, mid-50s)

General Comments

In addition to discussing the specific message concepts shown during the focus groups, participants were also invited to share their suggestions to improve the messages and express any other ideas that may be of interest to the research. Three themes were identified from these discussions—(1) whether the message should refer to a specific animal, (2) ensuring public awareness of the animal detection technology, and (3) suggested improvements for the design of the VMS. These themes are discussed below.

Reference to a Specific Animal

Some participants questioned whether it was necessary for the signage to indicate the presence of a specific animal (i.e., cassowary), and suggested that using a broader term such as 'animal', 'large animal', or 'wildlife' might be more effective. Specifically, these participants expressed the following concerns: (1) that some drivers might try to search for the animal (and in the process, potentially pose a road hazard for other drivers by slowing excessively or stopping), (2) the technology responsible for detecting the cassowary may fail to recognise other nearby animals (which may also create a road hazard), and, consequently, (3) drivers may become so focused on avoiding a cassowary that they fail to notice other driving obstacles and hazards. However, other participants reported that by displaying the specific animal on the sign, it would enable drivers to "know what to look for", where to look for it (e.g., looking closer to the ground for smaller animals), and to adjust their driving behaviour according to their understanding of the behaviours of the specified animal. All participants, regardless of their preference for a specific or generic term for the animal, agreed that it was important that the message implied the real-time presence of the animal and the potential danger it posed.

Public Awareness of Animal Detection Technology

Most participants commented that raising public awareness of the animal detection technology would be "necessary" to accompany the implementation of the signage to ensure drivers were aware of the real-time nature of the message. Some participants indicated that the public awareness campaign should be delivered via digital media (e.g., television, social media), while others suggested that static road signage in nearby areas (e.g., billboards) may be useful. One participant suggested information leaflets could be distributed to individuals hiring rental cars in relevant areas to alert tourists to the technology and associated messaging. In lieu of a public awareness campaign, some participants suggested additions to the signage that would better indicate that real-time nature of the message. Suggestions included showing the time that the animal was last seen, a counter showing the number of times the animal had been detected in a specified time frame (e.g., 1 hour, 24 hours), or a colour coding system that indicated how close the animal is from the signage. However, the addition of such aspects would need to be done so carefully as a consistent finding was the desire for succinct, easy-to-read and understand message concepts so any additional details may compromise the simplicity and effectiveness of the messaging.

Improvements to VMS Design

While evaluating the message content, participants often suggested improvements to the VMS design. Of the design elements, the colour scheme was most frequently commented upon. Most participants expressed a preference for incorporating colours other than amber for "emphasis", and to combat "sign fatigue" by differentiating these signs from roadworks and other common road signage. Many participants suggested making key words (e.g., detected, slow down) red to promote urgency, while a small number of participants suggested green due to its association with existing wildlife signage. However, some participants expressed concerns that additional colours/specific colours could affect readability for some drivers (e.g., older drivers, individuals who experience colour-blindness). Participants also often commented on the legibility of the text, noting that minimal words and thicker lines were preferred to enhance readability. Overall, participants did not frequently comment on the use of uppercase versus title case lettering, and the comments that were offered were mixed. Some participants reported disliking uppercase noting that it was "too much" and seemed "rude", while others considered uppercase easier to read and denoted the need for action. Title case was generally well received, especially for the Screen 2 "informative" messages. A small number of participants also commented that the use of full stops in the signage was "weird" and "unnecessary", and if any punctuation were to be included, it ought to be an exclamation mark following key statements (e.g., Slow down!).

4.2.4 Summary of Study 1

Study 1 involved concept-testing, conducted in accordance with the SatMDT, of 20 message concepts designed to be displayed on a VMS. The concepts were designed to inform motorists that an animal (specifically a cassowary in the context of this research) has been detected on or near the road. The following points highlight the main findings from Study 1:

- For Screen 1, most participants agreed that including text and an image of a cassowary would be most effective (relative to the text-only or image-only options). Most participants also reported disliking the term ‘about’ (e.g., ‘Cassowary About’), and offered alternatives such as ‘detected’, ‘ahead’ and ‘seen’ which were perceived to make to clearer than a cassowary was in the immediate vicinity. A small number of participants reported a preference for using a broader term (e.g., animal, wildlife) rather than identifying the specific animal (i.e., cassowary). However, most agreed that naming the animal would be more useful, and that the singular term “cassowary” was preferred to use of the plural “cassowaries” due to its brevity and legibility.

- For Screen 2, most participants agreed that the strategy ‘Look Out and Slow Down’ would be most effective, with the caveat that ‘and’ should be removed to make the statement more succinct. Participants offered mixed responses to the similar strategy ‘Reduce your Speed. Be alert.’, with some responding positively and others negatively. However, most participants agreed that regardless of the specific wording, the directive to slow down should be presented first (i.e., at the top of the screen) and emphasised that the language used should be short, sharp, and written in plain English. Regarding the cassowary images, participants unanimously reported a preference for the taller cassowary compared to the shorter cassowary, and most participants reported a preference for the cassowary to have a larger crest compared to the smaller crest. When comparing the monochromatic (amber only) images to the coloured images, most participants agreed that the use of colour was more attention-grabbing and, by highlighting the distinct colourings of the cassowary’s neck, would help motorists identify the animal.

- In terms of design elements, several participants suggested the use of different colours for the text to make the messages more “striking” and set them apart from commonly observed road signage (e.g., roadworks). However, it is difficult to determine which colours may be most suitable for this purpose. For that reason, retaining the amber font may be appropriate for the trial and future research could potentially investigate the effects of different font colours. Some participants noted a preference regarding the typography (e.g., uppercase versus title case); however, most participants were indifferent provided that the text was legible, and that the message was short, sharp, and simple. It appeared that a combination of font sizes may be best for the messaging in this trial – with uppercase on Screen 1 (to alert motorists to there being a cassowary detected) and the behavioural strategies on Screen 2 being presented in title case.

- Overall, regardless of their preferences for the message content (on either screen), most participants emphasised that it was important that the message must convey the real-time nature of the warning, and that the presence of the animal is understood to be a road hazard (rather than a local attraction). Most participants also suggested that the implementation of the signage should be accompanied by a public campaign which promotes the use of the animal detection technology to help drivers understand the specific purpose of this signage (acknowledging that this campaign still may not always reach all who may be driving in the area such as tourists).

4.3. Study 2

4.3.1 Overview

Study 2 evaluated the effectiveness of four message concepts (as per Step 4 of the SatMDT) that were developed according to the findings from the previous concept-testing study. This final step of the SatMDT is designed to measure both acceptance (via measures of attitudes, intentions, willingness, and message effectiveness) and rejection of messaging. An additional outcome measure includes the third-person effect (TPE). The TPE refers to the extent to which a participant perceives themselves and others (in this case, other motorists) to be influenced by a message. There are two types of TPEs: the classic TPE and the reverse TPE. The classic TPE refers to the extent to which an individual perceives that the message will have more impact on others rather than on themselves and the reverse TPE refers to the extent to which an individual perceives that the message will have more impact on themselves than on others [198, 199]. From a message effectiveness perspective, reverse TPEs are encouraging as they indicate greater perceived influence on oneself than others and evidence has shown such TPEs to be associated with increased reported intentions to adopt a message's recommendations [198].

The findings from Study 1 revealed that there was some concern regarding whether (a) drivers would understand that the message was a real-time warning (as opposed to a general or advisory message), and (b) that the message might inadvertently encourage risky behaviour through motorists changing their behaviour, such as stopping suddenly on the road in an effort to see the cassowary (as per the message). Thus, to further investigate these concerns, Study 2 also assessed some relatively unique outcome measures of message effectiveness relevant for this specific context and which were motorists' thoughts about the perceived immediacy of the message and the extent to which they thought they may adversely change their driving behaviour upon seeing message.

4.3.2 Method

4.3.2.A. Participants

A total of 557 participants aged between 19-89 years (Mean age = 50.29 years, SD = 13.96) were recruited by Farron Research, an Australian market research recruitment company. Participants completed the online survey between 7 December to 13 December 2023. As per the previous message concept-testing study (Study 1), participants were required to be aged 18 years or older, reside in Australia, hold a valid motor vehicle or motorcycle licence, and drive/ride for at least one hour per week. All participants received AUD15 for completing Study 2. Like the participant sample in Study 1, most participants held an open licence (96.4%). Participants in Study 2 reported holding their driver licence for between 1-73 years (M = 30.87 years, SD = 14.36) and reported driving an average of 9.04 hours per week (SD = 7.86). The socio-demographic characteristics of participants are reported in Table 4.1.

4.3.2.B. Design

Consistent with the methods and material recommendations of the SatMDT [1], a between-groups design was employed meaning that participants were randomly assigned to view only one of four message concepts (experimental condition) or were not shown a message (control condition). The intent behind exposing participants to one message only was to elicit responses based on the message they had seen, rather than offering comparative judgements regarding the effectiveness of different messages they had seen [1]. Mock designs of how the messages would appear as a roadside VMS, the intended display medium for the project's subsequent on-road trial, were created and used as the stimulus materials tested in the study. The four message concepts that were tested are presented in the section that follows (noting again that these were identified as a result of the findings from Study 1). Consistent with conceptual recommendations, the messages all contained information that a cassowary (or animal, in the case of Concept 3) had been detected to first raise attention of the issue at hand. Then, this information was followed by clear and tangible strategies (i.e., aligning with the concept of 'response efficacy' [55]) as to what a motorist could and should do in that situation. As Figures 4.2, 4.3, 4.4, and 4.5 show, in most instances, the messages

		n	%
Gender	Female	350	62.8
	Male	206	37.0
	Other	1	0.20
	Prefer not to say	0	0.00
Australian state or territory of residence	Queensland	98	17.6
	New South Wales	78	14.0
	Victoria	87	15.6
	Australian Capital Territory	78	14.0
	South Australia	80	14.4
	Tasmania	65	11.7
	Western Australia	41	7.4
	Northern Territory	30	5.4
Licence Type	Learner	3	0.5
	Provisional 1	6	1.1
	Provisional 2	6	1.1
	Open	540	96.4
	International	2	0.4

Table 4.1.: Socio-demographic characteristics of participants in Study 2.

involved text only with the exception to this being Concept 2 which also incorporated a figure of a cassowary accompanying the words “Cassowary Detected”.

As previously noted, participants were randomly allocated to one of the four experimental message conditions or the control (no message) condition. Table 4.2 lists the number of participants assigned to each message condition and the gender proportion and average age of participants in each condition. As shown in Table 4.2, the average age of participants in each condition ranged from 49 to 51 years, indicating that Study 2 captured the perspectives of an older cohort. However, based on the findings of the focus groups in Study 1 (see subsection “Comparison of Responses Between Participants” in Section 4.2.3.A), there was little evidence to suggest that participants’ age would influence their perspectives regarding message effectiveness, and thus the findings, of the current study to evaluate message effectiveness.

Figure 4.2.: Concept 1.

Figure 4.3.: Concept 2.

Figure 4.4.: Concept 3.

Figure 4.5.: Concept 4.

Condition	n	Mage (SD)	Gender (% females)
Message concept 1	111	50.79 (13.74)	68.5
Message concept 2	112	49.33 (14.16)	66.1
Message concept 3	107	51.00 (14.51)	67.3
Message concept 4	111	50.31 (13.75)	59.5
No message (control)	116	50.07 (13.83)	53.4

Table 4.2.: Number of participants in each condition.

4.3.2.C. Measures

The online survey consisted of five parts. All participants completed Part A: Demographics, and Part B: indirect measures of message effectiveness prior to being shown a message. As the terminology implies, indirect measures of effectiveness are those that relate to individuals' attitudes and intentions, and which are assessed without direct reference to or necessity to have viewed a message. In contrast, in Part C, the direct measures of message effectiveness, only participants in the experimental condition completed this section. Once again, as the terminology implies, direct measures of message effectiveness assess individuals' responses about messages directly and, thus, require a participant to have seen a message. Experimental condition participants then continued on to complete Part D of the survey which assessed the indirect measures of message effectiveness once again but this time, after they had seen a message. Participants in the experimental condition thus responded to these items both before viewing the message concept and again after they had viewed the image with the intent being to explore any changes to responses following exposure to the message. Participants in the control condition only responded to these items once. Finally, experimental condition participants completed Part E of the survey which assessed participants' preferred message strategies. A copy of the study survey is presented in Appendix D.

PART A: Demographics

Part A included demographic items examining participants' gender, age, state of residence, postcode, type of driver licence, how long they have held their licence, and how many hours they drive in an average week.

PART B: Indirect Measures of Message Effectiveness Prior to Seeing a Message

The indirect measures of message effectiveness comprised items examining participants' acceptance of messaging alerting them about an animal being on or near the road through three constructs (attitudes, intentions, and willingness) examined across two key behaviours; namely, slowing down and scanning the road environment. These two behaviours represented the behaviours that the messages were intended to encourage. Responses relating to these two behaviours were also assessed across two contexts, when driving during the day and when driving at night. The inclusion of both day and night contexts was to examine whether there were any differences in the effectiveness of the messaging based on visibility of the road context to which the messaging was alerting a motorist to.

Attitudes

Attitudes towards slowing down and scanning the road environment (during the day and during the night) were measured using three semantic differential scales (i.e., "To what extent would slowing down after seeing messaging about an animal being on or near the road be…" and "To what extent would scanning the road environment after seeing messaging about an animal being on or near the road be…"). Participants responded to items on 7-point scales ranging from (1) Unsafe to (7) Safe, (1) Bad to (7) Good, and (1) Unwise to (7) Wise. As displayed in Table 4.3, these items formed reliable scales for each behaviour (slowing down/scanning) across both times of day (day/night) in the experimental and the control conditions. Higher scores were associated with more favourable attitudes towards engaging in the specified driving behaviour and thus the desired behaviour.

Condition	**Slowing Down**		**Scanning**	
	Day α	**Night** α	**Day** α	**Night** α
Experimental	.90	.94	.93	.95
Control	.87	.91	.94	.95

Table 4.3.: Reliability of attitude scales (pre-message exposure).

Intentions

Intentions to slow down and to scan the road environment if messaging about an animal being on or near the road had been seen (during the day and during the night) were measured using four items (i.e., "I intend to slow down", "It is likely that I would slow down", "I intend to scan the road environment" and "It is likely that I would scan the road environment"). Participants responded to items on a 7-point Likert scale ranging from (1) *Strongly disagree* to (7) *Strongly agree*. These items formed reliable scales for each behaviour (slowing down/scanning) across both times of day (day/night) in the experimental and control condition (see Table 4.4). Higher scores were associated with greater intentions to adopt the specified driving behaviour.

Condition	Slowing Down		Scanning	
	Day r	Night r	Day r	Night r
Experimental	.77*	.87*	.83*	.89*
Control	.85*	.85*	.77*	.90*

*p < .001

Table 4.4.: Reliability of intention scales pre-message exposure.

Willingness

Willingness to slow down and to scan the road environment (during the day and during the night) were measured using two separate items (i.e., "How willing would you be to slow down after seeing messaging about there being an animal on or near the road?" and "How willing would you be to scan the road environment after seeing messaging about there being an animal on or near the road?"). Participants responded to the item on a 7-point scale ranging from (1) Not willing at all to (7) Very willing. Higher scores reflected greater willingness to perform each respective behaviour and thus indicative of greater willingness to perform the desired behaviour.

Likelihood of stopping suddenly

Several participants from the focus groups in Study 1 expressed concerns that the messages might encourage some drivers who are interested in seeing a cassowary to stop suddenly, potentially creating a road hazard. To measure the likelihood that participants would react in this way (while driving during the day and during night), a single item was included which asked "If you were driving along a regional road in an area you were unfamiliar with and saw messaging about there being an animal on or near the road, how likely do you think you would be to just stop suddenly in an attempt to see the animal?" Participants responded to the item on a 7-point Likert scale ranging from (1) Extremely unlikely to (7) Extremely likely. Higher scores reflected a higher likelihood of stopping suddenly after viewing the message and thus was indicative of the undesired response.

PART C: Direct Measure of Message Effectiveness

Message Effectiveness

Message effectiveness was measured by asking participants to indicate how "convincing" and "persuasive" they thought the message was (i.e., "How convincing do you think the message was?"; "How persuasive do you think the message was?") on two separate 7-point Likert scales ranging from (1) Not at all convincing/persuasive to (7) Very convincing/persuasive. These items formed a reliable scale (r (439) = .79, $p < .001$), with higher scores reflecting greater message effectiveness.

Third-Person Effect

The third-person effect (TPE) is a perceptual phenomenon based on a judgement that individuals tend to make regarding the perceived influence of a message on themselves personally relative to others (or third persons) [200]. The TPE represents a key outcome measure identified for evaluation of message effectiveness in accordance with the SatMDT [1]. The third-person differential perception score is calculated by subtracting perceived influence of a message on oneself mean score from the perceived influence on others mean score. When considering message influence, a reverse TPE is advantageous as it suggests that individuals consider a message as likely to influence them more than others (see [198]).

The TPE was measured through asking participants in the experimental conditions to rate the extent to which 1) themselves, 2) other motorists, and 3) other motorists of a similar age and gender, would be influenced by the message (i.e., "How much would you yourself/other motorists in general/other motorists of a similar age and gender to you, be influenced?). Participants responded to items on 7-point Likert scales ranging from (1) Not at all influenced to (7) Very influenced. Two third-person differential perception scores were created with negative mean scores indicating more influence on self than others and positive mean scores indicating more influence on others (i.e., other motorists in general, and other motorists of a similar age and gender) than self.

Message Rejection

Message rejection was measured using five items (i.e., "If you were driving along and saw this messaging, to what extent would you agree with the following statements?"), with participants in the experimental conditions providing responses to five behaviours: 1) Assume it was a general warning about animals in the area 2) Assume it was a real-time warning about an animal being on or near the road at that time, 3) Stop suddenly in your lane to try and see the animal, and 4) simply ignore the messaging. Participants answered these items through 7-point Likert scales ranging from (1) Strongly disagree to (7) Strongly agree, with higher scores indicating stronger agreeance with the statement. Given that these items reflected quite distinct measures, each item was analysed separately rather than combining items to form a scale.

PART D: Indirect Measures of Message Effectiveness After Message Exposure

Part D comprised the same items as Part B and was presented only to participants in the experimental condition (i.e., those who had been shown one of the four messages). Specifically, the items measured constructs including participants' attitudes towards slowing down/scanning the environment after seeing the message, their intentions and willingness to slow down/scan the environment after seeing the message. Like Part B, Part D asked participants to respond to each item twice – once while imagining that they were driving during the day, and again while imagining that they were driving at night. As reported in Table 4.5, the items formed reliable scales for attitudes towards slowing down (day/night) and scanning (day/night), and intention to slow down (day/night) and scan (day/night). As previously noted, willingness to perform each driving behaviour and the likelihood of stopping suddenly were measured using single items, thus it was not required to calculate reliability scores for these measures.

Construct	Number of Items	Slowing Down		Scanning	
		Day	Night	Day	Night
Attitudes	3	$\alpha = .92$	$\alpha = .96$	$\alpha = .95$	$\alpha = .97$
Intention	2	$r = .75^*$	$r = .89^*$	$r = .79^*$	$r = .90^*$

*p < .001

Table 4.5.: Reliability of attitude scales (Cronbach's α) and intention scales (Pearson's r) post-message exposure.

PART E: Preferred Driving Strategy for the Message

This section aimed to discern the specific wording that participants preferred for the driving strategies offered in the message. Participants were asked to rate the extent to which they perceived the following message strategies to be useful if that saw messaging indicating that there was a cassowary ahead or near the road on a 7-point Likert scale ranging from (1) *strongly disagree* to (7) *strongly agree*, along with a brief explanation of why they had provided these scores (in an open-ended response):

- Strategy 1: Slow down, look out.
- Strategy 2: Look out, slow down.
- Strategy 3: Reduce speed, be alert.
- Strategy 4: Be alert, reduce speed.

Additionally, participants were invited to provide other suggestions to improve the messages (with responses provided via free text).

4.3.2.D. Procedure

This study was approved by the QUT Human Research Ethics Committee (QUT approval number: 7663). The survey was hosted on the online survey platform, Qualtrics. Participants' consent was obtained via a question presented following the study's participant information sheet. After completing Parts A and B of the survey, participants were then randomly allocated to one of five conditions, namely, to receive one of four VMS message concepts (i.e., experimental condition), or no message concept (i.e., control condition). If participants were allocated to the control condition, they proceeded to the end of the survey. If allocated to the experimental condition, participants were asked to view the presented message before continuing onto Part C, D, and E, which assessed their responses to the message. Participation in the survey took approximately 30 minutes.

4.3.3 Results

4.3.3.A. Sample Checks

Statistical checks were conducted to test whether there were any demographic differences between the participants in each condition that may have potentially confounded statistical comparisons. A chi-square test confirmed that there were no significant differences in the gender mix between the five conditions, X2 (8,557) = 12.21, $p = .142$. A one-way analysis of variance confirmed that there were no significant differences in participants' age between the five conditions, $F(4, 550) = 0.24$, $p = .914$. Based on these results, the groups were considered demographically similar in their age and gender composition and thus any differences found between groups may be more likely attributed to the messaging type (or message versus no message condition).

4.3.3.B. Direct Measures of Effectiveness

The direct measures of effectiveness were asked after participants had viewed one of four message concepts. As noted previously, participants who were randomly allocated to the control (no message) condition did not respond to these items.

Message Effectiveness

A one-way analysis of variance was performed to determine whether there were any differences in the perceived effectiveness of the message concepts across the four experimental message concept conditions. The results showed that there was no significant difference in scores reported by participants, $F(3, 437) = 1.91$, $p = .127$, between message concept 1 ($M = 5.79$, $SD = 1.15$), message concept 2 ($M = 6.05$, $SD = 1.02$), message concept 3 ($M = 5.84$, $SD = 1.26$), and message concept 4 ($M = 5.84$, $SD = 1.18$). These findings revealed that on average, participants perceived all four message concepts to be effective (i.e., convincing and persuasive given the scale anchors of the 7-point scale for each of the two items which comprised the message effectiveness scale).

Third Person Effect

Table 4.6 displays the means and standard deviations of the third-person differential scores for each of the four experimental message concept conditions. The findings show that participants in all four message conditions considered the messages as being more influential on themselves compared to other motorists in general (i.e., a reverse TPE). This result is encouraging given that any indication that a message is influencing oneself more relative to others has been shown to be associated with greater attitudinal and intentional change (see [198]).

A one-way analysis of variance was performed to determine whether there were any significant differences in the degree to which the participants perceived the message to be more influential on themselves or other motorists in general across the four experimental message conditions. The results revealed that there was no significant differences in third-person differential scores reported by participants across the four experimental conditions, $F(3, 436) = 0.60$, $p = .617$.

A second one-way analysis of variance was conducted to assess the perceived influence of the message concept on self, compared to the perceived influence on other motorists of a similar age and gender. Table 4.7 displays the means and standard deviations of the third-person differential scores for each of the four experimental message concept conditions. Like the previous findings, the results showed that participants in all four experimental conditions

Condition	n	Third-person differential score M (SD)
1. Message Concept 1	110	-1.18 (1.16)
2. Message Concept 2	112	-1.06 (1.19)
3. Message Concept 3	106	-1.06 (1.21)
4. Message Concept 4	111	-1.23 (1.22)

Note: Third-person scores are derived from subtracting the scores on the perceived influence of a message on oneself item from perceived influence of the message on others (i.e., third persons) item. Each of these items was assessed on a 7-point scale with higher scores indicating greater influence. A negative mean third person differential score indicates perceived greater influence on self relative to others.

Table 4.6.: Third-person effect (TPE) of perceived influence of message concepts on self vs. other motorists in general.

considered the message to be more influential on themselves compared to on other motorists of a similar age and gender. The results of the one-way analysis of variance also revealed that there was no significant differences in third-person differential scores reported by participants across the four experimental conditions, $F(3, 436) = 0.21$, $p = .315$, indicating that all four message concepts had a similar level of perceived influence on participants, with greater perceived influence on self relative to others.

Message Rejection

A series of one-way analyses of variance were performed to determine whether there were any differences in the perceived likelihood that participants in each of the four message concept conditions would 1) Assume it was a general warning about animals in the area, 2) Assume it was a real-time warning about an animal being on or near the road at that time, 3) Stop suddenly in your lane to try and see the animal, 4) Slow down and move off to the side of the road to try and see the animal, and 5) Simply ignore the messaging. The results revealed that there were no significant differences in the perceived likelihood scores reported by participants to assume it was a general warning about animals in the area, Welch's $F(3, 241.41) = 0.62$, $p = .601$, assume it was a real-time warning about an animal being on/near the road at that time, $F(3, 437) = 0.74$, $p = .527$, stop suddenly in your lane to try to see the animal, Welch's $F(3, 240.14) = 1.71$, $p = .166$, slow down and move off the side of the

Condition	n	Third-person score M (SD)
1. Message Concept 1	110	-0.34 (0.86)
2. Message Concept 2	112	-0.33 (1.07)
3. Message Concept 3	107	-0.36 (1.02)
4. Message Concept 4	111	-0.42 (0.98)

Note: Third-person scores are derived from subtracting the scores on the perceived influence of a message on oneself item from perceived influence of the message on others (i.e., third persons) item. Each of these items was assessed on a 7-point scale with higher scores indicating greater influence. A negative mean third person differential score indicates perceived greater influence on self relative to others.

Table 4.7.: TPE of perceived influence of message concepts on self vs. other motorists of a similar age and gender.

road to try and see the animal, $F(3, 436) = 0.75$, $p = .525$, or simply ignore the messaging, Welch's $F(3, 240.52) = 1.03$, $p = .378$, across the four message concept conditions. The means and standard deviations of the perceived likelihood of performing each behaviour scores are reported in Table 4.8, and show that, on average, participants disagreed that they would stop suddenly in their lane or slow down and move off to the side of the road in order to see the animal (i.e., scored about 2 on the 7-point scale). However, the results also showed that while, on average, participants somewhat agreed that they would assume that the signage was a real-time warning about an animal being on/near the road, participants, on average, were also neutral or somewhat agreed (i.e., scored 4 or 5 on the 7-point scale) that they would assume the messaging was a general warning about animals being present in the area. On average, participants disagreed that they would simply ignore the messaging (i.e., scored about 2 on the 7-point scale). These results suggest that rejection of the messages was unlikely and, based on the mean scores, were more likely to assume it was a real-time warning rather than a general warning and were unlikely to perform undesirable behaviours such as stopping suddenly in attempts to see the cassowary (or animal) in response to the messaging.

Next, a series of paired sample t-tests were conducted across each of the four experimental conditions to determine whether there were any significant differences between the strength

	Message Concept 1		Message Concept 2		Message Concept 3		Message Concept 4	
	n	**M(SD)**	**n**	**M(SD)**	**n**	**M(SD)**	**n**	**M(SD)**
Assume it was a general warning about animals in the area	111	4.79 (1.88)	112	4.76 (1.96)	107	5.03 (1.87)	110	5.00 (1.59)
Assume it was a real-time warning about an animal being on or near the road at that time	111	5.50 (1.62)	112	5.70 (1.60)	107	5.39 (1.80)	111	5.42 (1.67)
Stop suddenly in your lane to try and see the animal	111	1.98 (1.52)	112	1.88 (1.48)	107	2.38 (1.92)	110	2.14 (1.69)
Slow down and move off to the side of the road to try and see the animal	111	2.70 (1.93)	112	2.48 (1.84)	106	2.87 (2.02)	110	2.73 (1.95)
Simply ignore the messaging	111	2.28 (1.70)	112	2.08 (1.52)	106	2.34 (1.79)	110	2.00 (1.53)

Note: items were measured on 7-point Likert scales with higher scores indicating greater agreement.

Table 4.8.: Perceived reactions to the message.

of participants' assumptions that the message shown was a general warning about animals in the area compared to their assumptions that the message shown was a real-time warning about an animal being on or near the road. The results are displayed in Table 4.9 and reveal a significant difference in assumption scores reported by participants who viewed message concept 1 and message concept 2. These findings indicate that participants who viewed message concept 1 and message concept 2 held stronger assumptions that the message shown was a real-time warning rather than a general warning.

Condition	M_{diff}	**df**	**t**	**p**
Message concept 1	-0.70	110	-2.75	.007
Message concept 2	-0.94	111	-3.71	$<$ .001
Message concept 3	-0.36	106	-1.32	.189
Message concept 4	-0.41	109	-1.88	.063

Table 4.9.: Difference between assumptions that the message shown was a general warning versus a real-time warning.

4.3.3.C. Indirect Measure of Effectiveness

Attitudes

First, a series of four one-way analysis of variance were performed to determine whether there were any differences in how favourably participants considered slowing down and scanning the road environment (each during the day and during the night) after seeing messaging in general (i.e., what came to participants' minds when prompted to imagine roadside messaging and not any of the four message concepts investigated in this study) indicating that there was an animal on or near the road to be between each of the four message conditions and the control condition. The results showed that there was no significant difference in mean attitude scores reported by participants between the five conditions towards slowing down during the day, $F(4, 545) = 1.42$, $p = .227$, slowing down during the night, Welch's $F(4, 271.21) = 1.29$, $p = .275$, scanning the environment during the day, $F(4, 545) = 0.91$, $p = .461$, and scanning the environment during the night, $F(4, 546) = 0.86$, $p = .490$. The overall means and standard deviations of participant's reported (pre-message and post-message) attitude scores are reported in Table 4.10. These findings highlight that on average, participants in all five conditions considered both slowing down and scanning to be relatively safe, good, and wise (i.e., provided scores of 5 or 6 on a 7-point Likert scale) driving behaviours to engage in after seeing general messaging alerting them to the presence of an animal in the road environment when driving during the day and during the night.

A second series of four one-way analysis of variance was conducted to investigate whether there were any differences in how favourably participants in the experimental condition considered slowing down and scanning the road environment (each during the day and during the night) after viewing their randomly allocated message concept, compared to participants in the control condition who did not view a message. The results showed that there was no significant difference in mean attitude scores reported by participants between the five conditions towards slowing down during the day, $F(4, 547) = 1.91$, $p = .108$, slowing down during the night, $F(4, 549) = 0.58$, $p = .679$, scanning the environment during the day, $F(4, 548) = 0.22$, $p = .929$, and scanning the environment during the night, $F(4, 550) = 0.20$, $p = .937$. These findings indicate that there was no significant difference between how safe, good, and wise participants in the experimental condition after viewing one of the four message concepts considered slowing down and scanning to be compared participants in the control condition who did not view a message. However, it should be noted that the post-message attitude scores reported my participants in each of the four message concept groups were consistently higher than the pre-message score reported by participants in control group (see Table 4.10).

Attitude Towards Slowing Down				
	Day		Night	
	Pre-Message Attitude Score M(SD)	Post-Message Attitude Score M(SD)	Pre-Message Attitude Score M(SD)	Post-Message Attitude Score M(SD)
Message concept 1	5.97 (1.14)	6.16 (1.12)	6.05 (1.22)	6.35 (1.14)
Message concept 2	6.08 (1.15)	6.30 (1.16)	6.20 (1.25)	6.31 (1.16)
Message concept 3	5.73 (1.37)	6.18 (1.22)	5.92 (1.46)	6.27 (1.34)
Message concept 4	6.03 (1.04)	6.25 (1.04)	6.28 (1.06)	6.33 (1.04)
No message (control)	5.92 (1.19)	-	6.14 (1.18)	-
Attitude Towards Scanning the Road Environment				
	Day		Night	
	Pre-Message Attitude Score M(SD)	Post-Message Attitude Score M(SD)	Pre-Message Attitude Score M(SD)	Post-Message Attitude Score M(SD)
Message concept 1	6.19 (1.24)	6.30 (1.10)	6.14 (1.20)	6.31 (1.16)
Message concept 2	6.33 (1.04)	6.41 (1.01)	6.26 (1.26)	6.34 (1.26)
Message concept 3	6.07 (1.47)	6.33 (1.28)	5.97 (1.56)	6.29 (1.37)
Message concept 4	6.32 (1.04)	6.32 (1.10)	6.24 (1.12)	6.24 (1.16)
No message (control)	6.29 (1.13)	-	6.21 (1.32)	-

Note: items were measured on 7-point Likert scales with higher scores indicating greater agreement and, thus, more favourable attitudes towards slowing down or scanning the road environment.

Table 4.10.: Overall means and standard deviations of attitudes towards slowing down and scanning the road environment before and after viewing message concept.

Next, a series of paired-sample t-tests were performed to determine whether there were any differences in how favourably participants in each of the four experimental message concept conditions considered slowing down (during the day and night) and scanning (during the day and night) to be before viewing the message concept and after viewing the message concept. As displayed in Table 4.11, the results show that for attitudes towards slowing down, there was a significant difference in the mean scores reported by participants before and after viewing message concept 1 during the day (p =.006) and night ($p < .001$), message concept 2 during the day ($p = .025$), message concept 3 during the day ($p < .001$) and night ($p < .001$), and message concept 4 during the day ($p = .027$), whereby post-message scores were higher than pre-message scores. Attitude scores were also higher post-message compared to pre-message for message concept 2 and message concept 4 when driving at night, however these differences were not statistically significant.

For attitudes towards scanning the road environment, and as presented in Table 4.11, the results show that there was a significant difference between participants' scores before and after viewing the message in the message concept 3 condition during the day ($p =.025$) and during the night ($p =.002$). No other significant differences were observed in the remaining message concept conditions, however post-message scores were consistently higher than pre-message scores across all groups, both during the day and night. Taken together, the results suggest that participants who viewed message concept 3 held more favourable attitudes towards both slowing down and scanning (regardless of the time of day) after viewing the message. In addition, the results indicate a trend whereby participants in all conditions reported significantly more favourably attitudes towards slowing down during the day after viewing their allocated message. It is also noted that all mean scores were 6 and above on the 7-point scale indicating that attitudes were, overall, relatively high towards engaging in these behaviours. It is encouraging that a brief one-off exposure to the messaging was able to increase positive attitudes in a number of instances, in a statistically significant manner even when mean scores were already relatively high prior to viewing any of the messages.

Intentions

First, a series of four one-way analysis of variance was conducted to determine whether there were any differences in participants' intention to slow down and to scan the road environment (each during the day and during the night) having seen messaging in general (i.e., what came to participants' minds when prompted to imagine roadside messaging and not any of the four message concepts investigated in this study) indicating that there was an animal nearby between each of the four message conditions and the control condition. The overall means and standard deviations of participant's reported intention scores (pre-message and post-message) are reported in Table 4.12. The results showed that there was no significant difference in mean scores reported by participants between the five conditions regarding their intention to slow down during the day, $F(4, 552) = 0.18$, $p = .947$, slow down during the night, $F(4, 552) = 0.57$, $p = .686$, scan the environment during the day, $F(4, 552) = 0.65$, $p = .626$, and scan the environment during the night, $F(4, 551) = 0.78$, $p = .671$. These findings highlight that on average, participants agreed (i.e., provided scores of 5 or 6 on a 7-point Likert scale) that they intend to slow down, and agreed that they intend to scan the

Attitude Towards Slowing Down						
	Day			Night		
Condition	M_{diff}	**df**	**t**	M_{diff}	**df**	**t**
Message Concept 1	-0.24	108	-2.78**	-0.29	109	-3.46***
Message Concept 2	-0.22	111	-2.27*	-0.11	111	-1.23
Message Concept 3	-0.45	103	-4.38***	-0.35	103	-3.77***
Message Concept 4	-0.23	109	-2.24*	-0.05	110	-0.47
Attitude Towards Scanning the Road Environment						
	Day			Night		
Condition	M_{diff}	**df**	**t**	M_{diff}	**df**	**t**
Message Concept 1	-0.12	108	-1.15	-0.16	108	-1.72
Message Concept 2	-0.07	109	-0.84	-0.13	110	-1.28
Message Concept 3	-0.25	104	-2.27*	-0.31	104	-3.14**
Message Concept 4	-0.02	108	-0.17	-0.10	110	-0.04

*p < .05, **p < .01, ***p < .001

Note: Mean difference scores based on cases being excluded pairwise. Negative mean difference scores indicate that the pre-message score was lower than the post-message score.

Table 4.11.: Difference in attitudes towards slowing down and scanning the road environment before and after viewing message concepts.

environment prior to seeing any messaging.

A second series of four one-way analysis of variance was conducted to investigate whether there were any differences in participants' intention to slow down and scan the road environment (each during the day and during the night) between the experimental condition after viewing their randomly allocated message concept and the control condition who did not view a message. The results showed that there was no significant difference in mean intentions scores reported by participants between the five conditions towards slowing down during the day, Welch's $F(4, 275.05) = 1.14$, $p = .340$, slowing down during the night, Welch's $F(4, 274.86) = 1.88$, $p = .115$, scanning the environment during the day, Welch's $F(4, 272.80) = 1.11$, $p = .351$, and scanning the environment during the night, Welch's $F(4, 273.56) = 1.35$, p = .250. These findings indicate that there was no significant difference in the degree to which participants in the experimental intended to slow down and scan for the environment (during the day and night) after viewing one of the four message concepts, compared to the control condition who did not view a message.

Intention to Slow Down				
Condition	**Day**		**Night**	
	Pre-Message Intention Score M(SD)	**Post-Message Intention Score M(SD)**	**Pre-Message Intention Score M(SD)**	**Post-Message Intention Score M(SD)**
Message concept 1	6.01 (1.20)	6.15 (1.03)	6.18 (1.06)	6.32 (0.92)
Message concept 2	5.94 (1.33)	6.14 (1.23)	6.19 (1.20)	6.05 (1.44)
Message concept 3	5.90 (1.48)	6.16 (1.20)	6.20 (1.25)	6.40 (0.99)
Message concept 4	5.89 (1.28)	6.20 (0.97)	6.31 (1.03)	6.30 (0.98)
No message (control)	5.88 (1.36)	-	6.07 (1.28)	-
Intention to Scan the Road Environment				
Condition	**Day**		**Night**	
	Pre-Message Intention Score M(SD)	**Post-Message Intention Score M(SD)**	**Pre-Message Intention Score M(SD)**	**Post-Message Intention Score M(SD)**
Message concept 1	6.43 (0.95)	6.36 (0.94)	6.33 (1.00)	6.34 (1.02)
Message concept 2	6.40 (1.14)	6.29 (1.24)	6.36 (1.21)	6.23 (1.38)
Message concept 3	6.29 (1.24)	6.37 (1.05)	6.21 (1.31)	6.50 (1.04)
Message concept 4	6.29 (1.16)	6.23 (1.06)	6.30 (1.20)	6.24 (1.24)
No message (control)	6.47 (0.77)	-	6.48 (0.93)	-

Note: items were measured on 7-point Likert scales with higher scores indicating greater agreement and, thus, stronger intentions of slowing down or scanning the road environment.

Table 4.12.: Overall means and standard deviations of intention to slow down and scan the road environment before and after viewing message concepts.

Next, a series of paired-sample t-tests were conducted to determine whether there were any differences in participants' reported intention to slow down (during the day and night) and scan the road environment (during the day and night) in each of the four experimental message concept conditions before and after viewing the message concept. The results, as displayed in Table 4.13, show a significant difference between intention to slow down scores for participants who viewed message concept 3 during the day ($p = .015$) and night ($p < .013$) and message concept 4 during the ($p = .011$), whereby post-message scores were higher than pre-message scores. Although not statistically significant, it should be noted that intention scores decreased or remained stable after viewing the message for message concept 2 (night only) and message concept 4 (night only).

For intentions to scan the road environment, and as displayed in Table 4.13, the results show that there was a significant difference between scores for participants who viewed message condition 3 when driving at night, who reported higher post-message scores compared to their pre-message scores ($p = .008$). No other significant differences were observed in the remaining message concept conditions. However, similar to the findings regarding intentions to slow down, participants intent to scan was also found to decrease (although not to a statistically significant extent) after viewing the message for message concept 1 (day), message concept 2 (day and night), and message concept 4 (day and night). Overall, the findings suggest message concept 3 had the strongest impact on participants intentions to slow down (during the day and night) and scan the environment (during the night). In addition, the findings also indicate a trend whereby intentions to scan the environment tended to decrease after viewing the message more often (i.e., for message concepts 1, 2, and 4 during the day, and message concepts 2 and 4 during the night) than intentions to slow down, which only decreased (message concept 2) or remained constant (message concept 4) when driving at night. However, it should be noted that mean scores remained high post-message across all groups for each driving behaviour (i.e., mean scores were 6 and above on the 7-point scale), indicating that participants still held relatively high intentions to engage in these positive behaviours regardless of the observed decreases in scores.

Willingness

First, a series of four one-way analysis of variance was performed to determine if there were any differences in participants' reported willingness to slow down and to scan the environment (during the day and during the night) having seen messaging in general (i.e., what came to participants' minds when prompted to imagine roadside messaging and not any of the four message concepts investigated in this study) indicating that there was an animal on or near the road between each of the four experimental message conditions

Intention to Slow Down						
	Day			Night		
	M_{diff}	df	t	M_{diff}	df	t
Message Concept 1	-0.14	110	-1.36	-0.14	110	-1.44
Message Concept 2	-0.20	111	-1.48	0.13	111	1.21
Message Concept 3	-0.26	106	-2.48*	-0.21	106	-2.24*
Message Concept 4	-0.32	110	-2.57*	0.00	110	0.05
Intention to Scan the Road Environment						
	Day			Night		
	M_{diff}	df	t	M_{diff}	df	t
Message Concept 1	0.06	110	0.92	-0.01	110	-0.11
Message Concept 2	0.11	111	0.82	0.13	111	1.44
Message Concept 3	-0.08	106	-0.71	-0.24	105	-2.71**
Intention to Scan the Road Environment						
	Day			Night		
Condition	M_{diff}	df	t	M_{diff}	df	t
Message Concept 4	0.06	110	0.58	0.05	110	0.71

*p < .05, **p < .01, ***p < .001

Table 4.13.: Difference in intention to slow down and scan the road environment before and after viewing message concepts.

and control condition. The results showed that there was no significant difference in mean scores between the four message concept conditions regarding participants' willingness to slow down during the day, $F(4, 549) = 0.88$, $p = .478$, scan the environment during the day, $F(4, 550) = 0.79$, $p = .529$, or scan the environment during the night, $F(4, 549) = 0.92$, $p = .454$. However, the results also revealed a significant main effect in the scores regarding participants' willingness to slow down during the night, Welch's $F(4, 270.10) = 3.34$, $p = .011$. Post-hoc comparisons showed that there was a significant difference between scores in the message concept 3 condition and the message concept 4 condition ($M_{diff} = -0.40$, $p = .024$), indicating that participants in message condition 3 reporter greater willingness to slow down during the night after seeing general messaging alerting them to the presence of nearby animals compared to participants in message condition 4. No significant differences were observed between any other condition pairs.

A second series of four one-way analysis of variance was conducted to investigate whether there were any differences in participants' willingness to slow down and scan the road environment (each during the day and during the night) between the experimental condition after viewing their randomly allocated message concept and the control condition who did not view a message. The results showed that there was no significant difference in mean willingness scores reported by participants between the five conditions towards slowing down during the day, $F(4, 551) = 1.36$, $p = .256$, slowing down during the night, $F(4, 550) = 1.25$, $p = .288$, scanning the environment during the day, $F(4, 551) = 0.40$, $p = .808$, and scanning the environment during the night, $F(4, 549) = 0.47$, $p = .755$. These findings indicate that there was no significant difference in the degree to which participants reported they would be willing to slow down and scan for the environment (during the day and night) after viewing one of the four message concepts, compared to the control condition who did not view a message. However, it should be noted that the post-message willingness to slow down scores reported my participants were consistently higher than the pre-message score reported by participants in control group, and most post-message willingness to scan scores were higher than those reported by participant in the control group. The overall means and standard deviations of participant's reported pre-message and post-message willingness scores are reported in Table 4.14.

Next, a series of paired-sample t-tests were performed to determine whether there were any differences in participants' reported willingness to slow down (during the day and night) and scan the road environment (during the day and night) in each of the four experimental message concept conditions before and after viewing the message concept. The results showed that there was a significant difference in the mean willingness to slow down during the night and scan the environment during the night reported by participants who viewed message concept 3 ($p =.003$), whereby post-message scores were higher than pre-message scores. However, like the results for intentions, participants who viewed message concept 2 and message concept 4 reported lower post-message scores for willingness to slow down during the day (message concept 2 only) and night (message concept 2 and 4). Although these differences did not reach statistical significance.

For willingness to scan the road environment, and as presented in Table 4.15, the results showed that participants who viewed message concept 3 reported significantly higher post-message scores compared to pre-message scores when driving at night ($p = .024$). However, the results showed that post-message willingness to scan scores were lower than pre-message

Willingness to Slow Down				
	Day		Night	
	Pre-Message Willingness Score M(SD)	Post-Message Willingness Score M(SD)	Pre-Message Willingness Score M(SD)	Post-Message Willingness Score M(SD)
Message concept 1	6.25 (1.08)	6.36 (0.95)	6.38 (0.95)	6.41 (0.85)
Message concept 2	6.34 (0.91)	6.24 (1.13)	6.40 (1.03)	6.29 (1.11)
Message concept 3	6.20 (1.26)	6.30 (1.13)	6.20 (1.19)	6.46 (1.05)
Message concept 4	6.28 (0.99)	6.37 (0.91)	6.59 (0.67)	6.52 (0.86)
No message (control)	6.09 (1.20)	-	6.27 (1.18)	-
Willingness to Scan the Road Environment				
	Day		Night	
	Pre-Message Willingness Score M(SD)	Post-Message Willingness Score M(SD)	Pre-Message Willingness Score M(SD)	Post-Message Willingness Score M(SD)
Message concept 1	6.60 (0.80)	6.52 (0.75)	6.49 (0.88)	6.47 (0.86)
Message concept 2	6.61 (0.90)	6.40 (1.14)	6.50 (1.05)	6.32 (1.22)
Message concept 3	6.67 (1.06)	6.53 (0.96)	6.58 (1.23)	6.47 (1.08)
Message concept 4	6.50 (0.86)	6.44 (0.97)	6.58 (0.99)	6.50 (0.99)
No message (control)	6.44 (0.83)	-	6.43 (1.15)	-

Note: items were measured on 7-point Likert scales with higher scores indicating greater agreement and, thus, greater willingness to slow down or scan the road environment.

Table 4.14.: Overall means and standard deviations of willingness to slow down and scan the road environment before and after viewing message concepts.

scores for participants who viewed message concept 1, message concept 2, and message concept 4 (day and night), and message concept 3 (day only). Of these results, the difference between scores was only significant for message concept 2 when driving during the day (p =.027). Overall, the findings suggest that participants who view message concept 3 reported significantly greater willingness to both slow down and scan the road environment but only at night. In addition, the findings also indicate a similar trend as observed for intentions, whereby participants reported lower willingness to scan scores after viewing the message across all groups when driving both during the day and night (except for message concept 3 at night as previously noted). Moreover, and like the results reported for intentions, only participants who viewed message concept 2 and message concept 4 reported lower willingness to slow down after seeing the message. Again, although some willingness scores were seen to decrease after viewing the message, the post-message scores remained high (i.e., mean scores were 6 and above on the 7-point scale). This finding suggests that participants were willing to both slow down and scan the road environment (during the day and night) regardless of the observed decreases in scores.

Willingness to Slow Down						
	Day			**Night**		
	M_{diff}	**df**	**t**	M_{diff}	**df**	**t**
Message Concept 1	-0.11	109	-1.17	-0.12	108	-0.26
Message Concept 2	0.21	110	1.01	0.11	111	1.01
Message Concept 3	-0.10	106	-1.24	-0.27	105	-3.09**
Message Concept 4	-0.09	110	-1.04	0.07	110	0.92
Willingness to Scan the Road Environment						
	Day			**Night**		
	M_{diff}	**df**	**t**	M_{diff}	**df**	**t**
Message Concept 1	0.08	109	1.26	0.12	109	0.33
Message Concept 2	0.21	111	2.24*	0.13	111	1.42
Message Concept 3	0.07	106	-1.02	-0.16	105	-2.30*
Message Concept 4	0.06	110	0.91	0.07	110	1.27

*p < .05, **p < .01, ***p < .001

Note: Mean difference scores based on cases being excluded pairwise. Negative mean difference scores indicate that the pre-message score was lower than the post-message score.

Table 4.15.: Difference in willingness to slow down and scan the road environment before and after viewing message concepts.

Likelihood of Stopping Suddenly

First, two one-way analysis of variance were performed to determine if there were any differences in participants' reported likelihood that they would stop suddenly in their lane in an attempt to see the animal after seeing messaging (in general) indicating that there was an animal nearby (when driving during the day and during the night) between each of the four experimental message conditions and the control condition. The results of the first one-way analysis of variance showed that there no significant difference in mean scores between the five conditions regarding participants' likelihood of stopping suddenly during the day, $F(4, 552) = 1.04$, $p = .366$. The results of the second one-way analysis of variance showed that there was a significant main effect in the scores regarding participants' likelihood of stopping suddenly during the night, Welch's $F(4, 275.06) = 2.61$, $p = .036$. Post-hoc comparisons revealed that there was no significant difference in mean scores between any of the condition pairs; however, mean difference scores did approach statistical significance for the message concept 2 and message concept 3 condition comparison ($M_{diff} = -0.83$, $p = .054$) and the message concept 2 and message concept 4 condition comparison ($M_{diff} = -0.78$, $p = .056$). These results suggest that participants who viewed message concept 2 may be less likely to stop suddenly compared to participants who viewed message concept 3 and message concept 4, albeit not significantly so. Overall, the findings suggest that, on average, participants were unlikely to stop suddenly to try to see the animal after seeing messaging alerting them to the presence of a nearby animal, both when driving during the day and during the night.

An additional two one-way analysis of variance were conducted to investigate whether there were any differences in the reported likelihood that they would stop suddenly in their lane to attempt to see the animal Between participants in the experimental condition after viewing their randomly allocated message concept and the control condition who did not view a message. The results of the first one-way analysis of variance showed that there as a significant main effect regarding participants' likelihood of stopping suddenly during the day, Welch's $F(4, 273.81) = 2.71$, $p = .031$. However, post-hoc comparisons revealed that there was no significant difference in mean scores between any of the condition pairs. The results of the second one-way analysis of variance showed that there was also a significant main effect in the scores regarding participants' likelihood of stopping suddenly during the night, Welch's $F(4, 274.57) = 4.63$, $p = .001$. Post-hoc comparisons revealed that there was a significant difference between message concept 2 condition and message concept 3 condition ($M_{diff} = -0.99$, $p = .005$), and message concept 2 condition and the control condition ($M_{diff} = -0.95$, $p = .003$). These findings indicate that participants who viewed message concept 2 may be less likely to stop suddenly to try and seen the animal when driving at night compared to participants who viewed message concept 3 or participants who were not exposed to a specific message concept. The overall means and standard deviations of participant's reported pre-message and post-message likelihood of stopping suddenly scores are reported in Table 4.16.

Likelihood of Stopping Suddenly				
	Day		Night	
	Pre-Message Stop Suddenly Score M(SD)	Post-Message Stop Suddenly Score M(SD)	Pre-Message Stop Suddenly Score M(SD)	Post-Message Stop Suddenly Score M(SD)
Message concept 1	2.81 (2.02)	2.47 (2.11)	2.96 (2.20)	2.56 (2.19)
Message concept 2	2.54 (1.85)	2.18 (1.56)	2.55 (2.02)	2.05 (1.75)
Message concept 3	3.07 (2.22)	2.89 (2.25)	3.38 (2.46)	3.05 (2.40)
Message concept 4	2.96 (2.06)	2.68 (2.11)	3.33 (2.27)	2.62 (2.06)
No message (control)	2.78 (2.05)	-	3.00 (2.15)	-

Note: items were measured on 7-point Likert scales with higher scores indicating greater likelihood to stop suddenly and, thus, more positive results from a safety perspective are for lower mean scores.

Table 4.16.: Overall means and standard deviations of likelihood of stopping suddenly to see the animal before and after viewing message concepts.

Next, a series of paired-sample t-tests were performed to determine whether there were any differences in participants' reported likelihood of stopping suddenly (during the day and night) in each of the four experimental message concept conditions before and after viewing the message concept. As presented in Table 4.17, the results showed that there was a significant difference in the mean likelihood of stopping suddenly (during the day) scores reported by participants who viewed message concept 1 ($p = .034$) and message concept 2 ($p = .009$). The results also showed that there was a significant difference in mean likelihood of stopping suddenly (during the night reported by participants who viewed message concept 1 ($p = .009$), message concept 2 ($p = .003$), and message concept 4 ($p < .001$). No significant differences were observed for message concept 3 (either during the day nor night). Overall, the findings suggested that participants who were presented with message concept 1 or message concept 2 reported that they would be less likely to stop suddenly to try and see the animal after viewing the message (both when driving during the day and during the night) than prior to viewing each of these respective messages, and participants who were presented with message concept 4 reported being less likely to stop suddenly after viewing the message when driving at night only relative to before seeing the message. Participants who viewed message concept 3 reported no change in the likelihood that they would stop suddenly after viewing the VMS message, regardless of the time of day. Thus, overall, mean scores were, on average, low, suggesting that participants were unlikely to engage in this behaviour; however, encouragingly, in the case of messages 1, 2 and 4, participants were significantly less likely to report intention to stop after seeing these messages than prior to.

Likelihood of Stopping Suddenly						
	Day			Night		
	M_{diff}	df	t	M_{diff}	df	t
Message Concept 1	0.34	110	2.15*	0.40	110	2.67**
Message Concept 2	0.37	111	2.89**	0.50	111	3.02**
Message Concept 3	0.18	106	0.98	0.34	106	1.92
Message Concept 4	0.28	110	1.63	0.71	110	4.07***

*p < .05, **p < .01, ***p < .001

Note: Mean difference scores based on cases being excluded pairwise. Negative mean difference scores indicate that the pre-message score was lower than the post-message score.

Table 4.17.: Difference in likelihood of stopping suddenly to see the animal before and after viewing message concepts.

4.3.3.D. Driving Strategies for the Message

Participants allocated to one of the message concept conditions were asked to rate the extent to which they agreed that the message had provided the following four driving strategies – 1) Slow down, look out, 2) Look out, slow down, 3) Reduce speed, be alert, and 4) Be alert, reduce speed, would be useful if they were to see a message about a cassowary having been detected ahead or near the road. Participants provided their responses on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree). The means and standard deviations of the perceived usefulness of each driving strategy are reported in Table 4.18, and indicate that, on average, participants agreed that all four strategies would be useful to have seen in a message about a cassowary being on or near the road. However, perceived usefulness scores were slightly higher for ‘slow down, look out’ and ‘reduce speed, be alert’, suggesting that participants preferred strategies which encouraged drivers to first reduce their driving speed before scanning the road environment. A one-way analysis of variance was then performed to determine whether there were any significant differences in participants' perceived usefulness of each driving strategy between each of the four message concept conditions. The results showed that there was no significant difference in perceived usefulness scores for 'slow down, look out' $F(3, 437) = 0.80$, $p = .497$, 'look out, slow down', $F(3, 436) = 1.54$, $p = .203$, 'reduce speed, be alert', $F(3, 437) = 1.30$, $p = .275$, and 'be alert, reduce speed', Welch's $F(3, 241.33) = 1.48$, $p = .220$ across the four message concept conditions.

Driving Strategy	Experimental Condition	Message Concept 1	Message Concept 2	Message Concept 3	Message Concept 4
	M (SD)	M (SD)	M (SD)	M (SD)	M (SD)
Slow down, look out	6.06 (1.31)	6.13 (1.18)	6.02 (1.38)	6.18 (1.20)	5.93 (1.45)
Look out, slow down	5.69 (1.45)	5.45 (1.55)	5.68 (1.47)	5.83 (1.34)	5.79 (1.43)
Reduce speed, be alert	6.09 (1.20)	6.04 (1.31)	5.98 (1.27)	6.07 (1.20)	6.28 (1.01)
Be alert, reduce speed	5.76 (1.45)	5.51 (1.61)	5.89 (1.34)	5.75 (1.46)	5.87 (1.37)

Note: items were measured on 7-point Likert scales with higher scores indicating greater agreement and, thus, more favourable views of a strategy.

Table 4.18.: Perceived usefulness of driving strategies.

Reasoning for Preferred Driving Strategies

Participants were also asked to briefly explain why they provided the scores that they did for the four driving strategies. A total of 433 participants responded to this question. Nearly half of participants in the experimental condition (n = 197, 44.7%) provided responses that indicated that they held no preference for a particular strategy, reported that they agreed (n = 60, 13.6%) or strongly agreed (n = 137, 31.1%) that all four driving strategies would be useful having seen messaging about the presence of an animal near or on the road. The most cited reasons participants reported for having no preference for specific strategies was that they would change their behaviour accordingly regardless of the wording out of 1) concern for the welfare of the animal, their vehicle and its occupants, and other road users, 2) a desire to be compliant with road safety messaging, and 3) because it is "common sense". Only a small number of participants reported disagreeing (n = 1) or strongly disagreeing (n = 2) that the four driving strategies were useful, citing that the strategies were "vague" and that there was a risk that "people could slow down to dangerous speeds" which could potentially create additional road hazards.

"I think any warning on a regional road to slow down and scan the environment is sensible and should be taken seriously." (Female, 45)

"If there is a warning, you should do all those things - be alert, look out, slow down, reduce speed." (Male, 66)

"I would be extremely worried about hitting a cassowary due to its size, so if warning had been giving about one, regardless of the wording of the sign, I would be slowing down anyway." (Female, 32)

"I am a cautious driver, I always drive carefully and will slow down if requested." (Female, 54 years)

Of the participants who expressed a preference regarding the four driving strategies, a total of 68 (15.7%) reported that they would consider the strategy more useful if the driving slower aspect was presented first. The most cited reasons for this preference were that slowing down is the most "important" and "immediate" of the two actions for driving safely in the specific situation, it is safe to scan the environment when driving slower, and that drivers should already be maintaining alertness while driving "regardless of warnings". A smaller number of participants (n = 11, 2.5%) reported a preference for presenting the environment scanning aspect first, citing that "people don't want to necessarily slow down" and as "animal may or may not be there, [it is] best to look and see first before reacting".

"I Put the most important action first. If I see a sign for only a few seconds, I shouldn't have to think about what you want me to do. The easiest action with the best outcome is to reduce speed. In case of any impact, it is more survivable for me, the animal, and the car. look out could have [drivers] looking for the animal and not the road." (Female, 40)

"I think the speed first is more important risk mitigation factor and makes sense to me as a driver." (Male, 29)

"Looking out without slowing down can be very dangerous, as would being alert but not slowing down would reduce the time to react if the animal was to jump on the road." (Male, 60)

"The action you would like everyone to take comes first: reduce speed, be alert are the two specific things you want drivers to do and in that order." (Female, 51)

When considering the four driving strategies as two sets (i.e., 'slow down, look out' and 'look out, slow down' as one set, and 'reduce speed, be alert' and 'be alert, reduce speed' as the second set), a similar number of participants reported a preference for each. Based on the explanations offered for the scores provided in the previous items, 32 participants (7.4%) reported a preference for the 'slow down, look out' set, and 35 participants (8.0%) reported a preference for the 'reduce speed, be alert' set. Participants who preferred the 'slow down, look out' set reported that these terms were "simpler", had a "stronger impact" and were "easier to understand", and considered the 'reduce speed, be alert' set to be too "generic". Participants who preferred the 'reduce speed, be alert' set reported that these terms were more "compelling", "persuasive" and would "make more of an impact on the driver", and expressed concerns that the 'slow down, look out' may be too "alarming" for drivers. However, participants (across both preferences) also often reported that their preferred set was "clearer" and better indicated the presence of "an immediate threat" compared to their least preferred set and suggest that preferences regarding specific wording of the message may be due to individual differences rather than reflecting what would be considered a more effective strategy for drivers more broadly.

Participant Suggestions to Improve Driving Strategies

In addition to providing an explanation for the scores they gave to each of the four driving strategies, participants were also invited to suggest ways the strategies could be improved. A total of 204 participants responded to this question. Five themes were identified from participants' suggestions – (1) alternative wording for the presented strategies, (2) including a reference (text or image) to the specific animal, (3) the need to ensure drivers are aware of the real-time nature of the message, and (4) suggestions relating to design and placement of the signage. These five themes are discussed below.

Alternative Wording of Strategies

A total of 44 participants offered new driving strategies for the message or suggested ways to improve the provided strategies. Common suggestions included amending the supplied message taglines to include using the 'slow down' strategy only (n = 16), the 'scan the environment' strategy only (n = 8), and including words that denote urgency such as warning, caution, or danger (n = 6). In addition to these specific suggestions, a further 6 participants emphasised that the messages need to be "spelt out clearly using simple and few words". The full list of the driving strategy suggestions offered by participants is presented in Table 4.19.

In addition to these alternative wordings to the presented strategies, a further 15 participants

Driving Strategy Suggestions	
• Prepare to stop	• Slow down/reduce speed, wildlife ahead
• Animals roaming, reduce speed	• SLOW DOWN[a]
• Be alert, stay responsible	• Be safe
• Big bird ahead, slow down	• Slow down, large wildlife ahead
• Slow down, look out, be safe	• BEWARE OF WILDLIFE ON ROAD
• Drive to the conditions	• Be alert
• ANIMALS MAY BE PRESENT AHEAD SO SLOW DOWN	• WATCH OUT, PREPARE TO REDUCE SPEED, CAUTION WILDLIFE
• Slow down, animals about	• Cassowary spotted. Slow down.
• Slow down, stay alert	• Slow down. Use caution. Wildlife hazard.
• Slow down, look out, save lives	• Animals in area, be alert
• Be wary of cassowary	• Be alert, animals!
• Be careful	• Animal seen in last 24 hours, be alert
• Danger. Possible animal on or near road. Reduce speed NOW	• Watch out — animals on the road ahead
• SLOW DOWN AND BE CAUTIOUS	• ANIMAL AHEAD, SLOW DOWN
• To prevent a potential damaging/serious collision with wildlife, please slow down and stay alert	• ANIMAL AHEAD, BE ALERT
• Only scan area if safe to do so	• Drive in the speed limit
	• Include 'detected ahead'
	• Include the word 'habitat'
	• Words like warning, caution[b], or danger

[a] $n = 3$. [b] $n = 2$.

Table 4.19.: Driving strategy suggestions offered by participants.

suggested the driving strategies could be improved by including more detailed instructions for drivers. Specifically, six participants suggested that it would be useful to include a specific speed limit in the message for drivers to adhere to, and nine participants suggested that it would be useful to include the number of kilometres that the detection zone (i.e., the area in which the driver can expect to potentially encounter the animal) extends for.

"Potentially changing the speed limits for the areas and have it written on the signs. Humans seem to cope better with clear instructions and when there's limits such as numbers to follow it may make people slow down more effectively." (Female, 31)

"Animal on the road within the next [x] km'. Be hand to know the know distance [the] animal was sighted on [the] road so as to resume normal speed." (Male, 58)

Reference to the Specific Animal

A total of 35 participants offered suggestions relating to whether they considered it important to reference the specific animal that has been detected within the message. Of this subsample, 28 participants reported that including name of the animal (n = 13) or an image of the animal (n = 15) in the message would be beneficial to help drivers understand what to expect. Conversely, seven participants suggested that the type of animal should not be identified, primarily due to concerns that drivers may become distracted while trying to spot an animal they are interested to see. In addition, a small number of participants also noted that the size of the animal is more important than the type of animal, and that the word 'cassowary' was difficult to read quickly.

"An image [of] the animal or clear messaging 'large animal on road ahead' or 'large animal near the road ahead', if you just say 'animal' that could mean a lizard which would not necessarily make me choose to slow down." (Female, 42)

"I personally like the identification of the exact animal in the area. I think it provides more authentication of the message and would influence me and hopefully other drivers to the urgency and validity of the signing." (Female, 73)

"I don't think identifying the type of animal is useful, and I'm concerned that some people might stop unnecessarily." (Male, 67)

Emphasising Real-Time Nature of Message

A total of 24 participants offered suggestions that revolved around emphasising the need for drivers to understand that the messages were real-time alerts about the presence of animal that poses a potential road hazard, rather than a general warning that animals inhabit the area. To help drivers understand the immediacy of the message, common suggestions offered by participants included using "direct" wording (e.g., "cassowary detected") to "convey a sense of emergency" (n = 3) and display additional real-time data on the signage such as the time frame the animal was detected within (n = 7), the chance (%) of encountering the animal (n = 1), rating the level of danger ahead (n = 1), the current date (n = 1), and the approximate distance the animal is from the road (n = 3). Additionally, a further eight participants specifically expressed concerns that drivers may ignore the messaging if they assume that the signage is a permanent fixture offering a general warning about animals in the animal or become complacent if they do not encounter any animals after seeing the message "like 'roadwork ahead' [signs] and there's no roadwork".

"Any messaging about animals on the road needs to be real time and not just a general warming message and in order to do this you also need to influence drivers and tell them that you now have real-time messaging." (Male, 44)

"Needs to be legit; if they are put in the sign the animals need to be around. If you put them in places where there [are] minimal animals eventually people will ignore the signs and speed through the area, and not care or believe the signs." (Female, 46)

Signage Design and Placement

A total of 47 participants offered suggestions that related to the visual design of the signage and factors related to the placement of the signage. The most common suggestions offered were to include flashing lights (n = 23) to attract attention, use bright colours (e.g., red to indicate that the message is a warning) (n = 6), and ensure drivers are able to read and enact the strategies offered in the message (i.e., slowing down and scanning the road environment) by placing the signs at an appropriate distance from the detection zone (n = 2) or placing multiple signs along the detection zone (n = 2).

"Flashing lights or signs are more likely to be noticed." (Female, 72)

"Colourful flashing lights will do the trick." (Female, 26)

"Give enough notice to avoid sudden stops or surprises" (Male, 39)

4.3.4 Summary on Study 2

Study 2 represented the final study in a mixed program of research that involved the devise and evaluation of messaging seeking to inform passing motorists that an animal had been detected on or near the road ahead and to encourage them to engage in two key desired behaviours – (1) slow down, and (2) scan the road environment. Study 2 sought to evaluate the relative effectiveness of four message concepts and when compared with a control group of participants who were not shown any messaging. The main findings emerging from Study 2 are as follows:

- Participants reported average scores of 5 and 6 (on a 7-point scale) for attitudes, intentions, and willingness to slow down and scan the road environment, and average scores of 2 and 3 (on a 7-point scale) regarding the likelihood of that they would stop suddenly in an effort to see the animal, both before and after viewing the message. These findings suggest that the current sample of participants inherently appreciate the importance of messaging designed to warn motorists of the presence of nearby animals.

- Overall, the sample was large and the distribution of participants within each of the five conditions was relatively even. However, it is acknowledged that the sample comprised a high proportion of older participants. Given that the results of Study 2 reflected similar findings to those found in Study 1 (where age was not seen to influence the results), the older age of the cohort in the present study was not considered to be the factor underpinning participants' responses.

- The findings from the direct measures of effectiveness and the indirect measures of effectiveness indicated that participants in the current sample would respond as intended to any of the four message concepts presented in Study 2. This is evidenced by the following:

  - Regarding the direct measures of effectiveness of the message concepts, the overall results revealed that there were no substantial differences between the concepts. The mean scores showed that participants perceived the four message concepts to be effective (i.e., convincing and persuasive). The mean scores of the message rejection items also showed that participants disagreed that they would stop suddenly in their lane to try and see the animal, slow down and move off to the side of the road to try and see the animal, or simply ignore the messaging if they saw the message while driving. These findings indicate that participants reported more acceptance rather than rejection of the four message concepts.

  - In terms of perceived influence of the message on self versus others, the results showed that were was no significant difference between the message concepts. The third-person differential scores showed that participants perceived that the message would have greater influence on themselves compared to other motorists (consistently found reverse TPEs).

  - Regarding the indirect measures of effectiveness, and as previously mentioned, participants in all message concept groups consistently reported relatively high scores for attitudes, intentions, and willingness to slow down and scan as desired before and after viewing the message. Despite reporting high pre-message scores, improvements in attitudes were still observed for all four message concepts and were significantly higher at post than pre for message concept 3 (both behaviours, day and night). Similarly, participants in all message concept groups reported consistently lower scores (as intended) regarding the likelihood that they would stop suddenly in their lane in an attempt to the see the animal after viewing their allocated message. These findings indicate that participants held more favourable attitudes towards these two positive driving behaviours and indicated less intention to stop suddenly following a single, brief exposure to the message.

- Although participants from some groups reported lower post-message scores on intentions and willingness to perform each driving behaviour at certain times of the day, it is important to recognise that the post-message scores across all groups remained high for both measure (i.e., 6 or above on a 7-point scale), and only one of these decreases was statistically significant. It is unclear what prompted these decreases in scores; however, the finding indicates that participants reporting that they were still willing to and intended to slow down and scan the environment after viewing their allocated message. However, although the overall results support the effectiveness of all four message concepts, the subtleties afforded by the SatMDT framework [1] show that each message differed in strength across the direct and indirect measures. The intricacies are discussed in the following points:

  - Regarding the direct measures of effectiveness, all four message concepts were seen to be equally effective and participants from all four groups perceived their allocated message would be more influential on themselves as opposed to other motorists (as desired). However, when comparing whether participants considered the message to be a real-time warning or a general warning about animals in the area, those who viewed message concept 1 and message concept 2 reported significantly higher real-time warning scores compared to general warning scores. It is noted that these two concepts also feature the same text (i.e., 'cassowary detected' and 'slow down, look out'). This finding indicates that participants who viewed message concepts 1 and 2 held stronger assumptions that the message was a real-time warning, which may be due to the language used in these messages. This finding is important given the intent of the system displaying these messages to be one indeed offering real-time warnings to motorists.

- In terms of attitudes, post-message scores were higher (as intended) for all message concepts for slowing down and scanning, both during the day and night. Message concept 3 was the only message that received significantly higher post-message scores for both behaviours when driving during the day and night. However, significant differences were also observed for message concept 1 (slowing down, day and night), and message concepts 2 and 4 (slowing down, day only). These findings suggest that message concepts 1, 2, and 4 may elicit different (though still positive) attitudinal responses depending on the driving behaviour and time of day, and message concept 3 may offer relatively consistent increases in attitude regardless of the behaviour or time of day.

- Regarding participants likelihood of stopping suddenly to see the animal, post-message scores were lower (as intended) for all four message groups. However, significant decreases in scores were observed for message concepts 1 and 2 (day and night), and message concept 4 (night only). This finding suggests that, like the results related to real-time versus general warning, participants who viewed message concept 1 and message concept 2 indicated less intent to stop suddenly which may be due to the language used in these messages. It also noticed that message concept 4, like 1 and 2, also specifies the type of animal that has been detected. This suggests that participants may be less inclined to stop suddenly because they are aware that the animal ahead is a cassowary and perhaps being more aware of what the animal is, are more prepared and less likely to engage in a risky behaviour such as stop suddenly in their lane.

- The findings related to intentions and willingness were mixed across both driving behaviours and time of day. Trends in the results reflected stronger intentions and willingness to slow down after viewing the message for all messages except message concepts 2 and 4, particularly at night. A contrasting trend was seen for scanning, whereby trends reflected stronger intentions and willingness to scan before viewing the message for all messages except message concepts 1 and 3, which showed some increased scores across the two measures. Participants who viewed message concept 3 were the only group that consistently reported higher post-message intention and willingness scores for both driving behaviours except for willingness to scan during the day.

- Notably, message concept 3 was the only concept that did not state that the animal detected was a cassowary (i.e., the message read 'Animal Ahead') and was also the only message that received significantly higher post-message scores for attitudes, intentions, and willingness to perform both driving behaviours at night. These findings suggest participants who viewed message 3, as the only message of the four messages tested, that did not identify the animal may be more inclined to engage in these safe driving behaviours because they are unsure what animal to expect, particularly when driving at night when visibility might be compromised.

- In terms of preferred driving strategies, there was no significant difference in the perceived usefulness of the four strategies investigated (i.e., 'Slow down, look out', 'Look out, slow down', Reduce speed, be alert', 'Be alert, reduce speed'). However, when asked to provide reasoning for their preferences, the most common response from participants was that slowing down was the more important of the two driving behaviours and, thus, should be presented fist. There were no substantial differences between participants' preference for the wording of this strategy, which suggests that 'slow down' or 'reduce speed' are both appropriate options.

- When asked to offer suggestions to improve the driving strategies, of those who did respond to this question, there were mixed responses regarding whether the type of animal should be identified or not, though a greater proportion of those who responded were in favour of specifying the type of animal (via text or image). This finding may reflect the discrepancies in performance observed between the four message concepts across the quantitative measures, and may further reiterate the possibility that the strength of certain messages (or aspects of) may differ depending on contextual elements (e.g., time of day, type of animal) and the priorities of the signage (i.e., whether the understanding that the message is a real-time warning is a higher priority than seeing increases in intentions to engage in the safe driving behaviour)

- When considering the practical implementation of the signage, participants offered several suggestions regarding design elements and placement of the signage. The most frequently offered suggestions were:

- The most common suggestion offered by participant regarding design elements was that the sign should feature flashing lights to attract attention. Several participants also emphasised the need for motorists to understand the real-time nature of the warning and expressed concerns that motorists may become complacent if the signs are consistently active and/or they do not see the animal that they have been informed has been detected. These findings speak to the importance that the sign remain blank and only activate (by flashing on) only when an animal has been detected. In the longer term, such findings also signal the potential value of a broader public education campaign to raise awareness of this messaging technology so that motorists are aware of it when they encounter it on-road.

- Although that the use of colour and typography was frequently commented upon in the focus groups in Study 1, very few participants mentioned these design elements in their feedback in Study 2. All four message concepts tested in the present study were monochromatic (amber) and featured the same style of lettering; and each received similarly strong results across measures. This finding suggests that the intricacies related to the design of the signage are unlikely to be important factors when it comes to influencing driving behaviour. Conversely, the findings could support the choice of lettering and font colouring were as relevant and effective as any other option that a participant could potentially consider.

- Several participants also reported that it was important for them to know how long, in terms of distance, that can expect to see the animal and when they can return to regular driving practices. This finding, alongside findings related to the need for motorists to understand that that the message is a real-time warning once again speaks to the importance of implementing a broader education campaign to accompany the instalment of the signage and that continues to evolve alongside the capabilities of the detection technology.

4.4. Conclusions

4.4.1 Key Findings

This program of research applied the SatMDT [1] to develop and evaluate messages that sought to (i) alert drivers to the real-time presence of an animal on or near the road, and (ii) encourage drivers to adopt safe driving behaviours (i.e., slow down and scan the road environment) to minimise the risk of a potential accident due to the presence of the animal. The messages were to be displayed as part of a larger project testing an innovative large animal activated roadside monitoring and alert (or LAARMA) system. The following section summaries the key findings that can be drawn from this research.

4.4.1.A. Message Development

Study 1 explored participants' responses and perceptions towards a series of preliminary dual-screened message concepts intended on display on a roadside VMS. There was no single message concept that was preferred as it was, instead participants drew out specific elements of each screen of each of the presented concepts that they found to be effective or ineffective. For Screen 1, participants reported that the combination of text and image, rather than a text-only or image-only' design, would be most effective. Participants reported a preference for terms including 'cassowary detected', 'cassowary ahead', and 'cassowary seen', citing that these terms were stronger indicators that the message was a real-time warning that an animal was in the vicinity. Some participants reported concerns about identifying the type of animal as it might encourage some motorists to become distracted to try and see the animal; however, most participants agreed that specifying the type of animal would help drivers scan more purposefully and anticipate how the animal might behave based on their prior knowledge. For Screen 2, participants reported a preference for the driving strategies 'Look out and slow down' and 'Reduce your speed. Be alert.', although the latter received mixed responses. Regardless of the specific wording of the strategies, participants reported that the instruction to slow down was the more important of the two strategies and, thus, ought to be presented first. Participants also reported that the strategies should be shortened, highlighting the need for the message to be simple and easy to read. For general comments about the messages, participants emphasised that it was essential that motorists understood it was a real-time warning that animals were in the immediate area, and that the presence of said animal is understood to be road hazard rather than a local attraction. To assist in disseminating this knowledge, participants suggested that a campaign should be run alongside the implementation of the signage to increase public awareness of the animal detection technology.

4.4.1.B. Message Concepts

Four message concepts were developed based on the findings from focus groups in Study 1 (see pages 15-16) and were further evaluated in Study 2. Overall, all four message concepts performed consistently well across all direct and indirect measures of effectiveness, which suggests that the implementation of any of these concepts would likely have the intended effects on driving behaviours. However, there were instances where some concepts outperformed others on specific measures and suggests that there is scope to selectively apply messages according to the parameters that are considered of highest priority. The following summaries the key findings from Study 2 and highlights the areas where specific message concepts were observed to have stronger effects.

Study 2 found no substantial differences between the four message concepts in terms of message effectiveness, with all having mean scores that suggest that participants found their allocated message relatively effective. Participants in all four message concept conditions also perceived their allocated message to be more influential on themselves than on other motorists in general and other motorists of a similar age and gender. Given that individuals may be more persuaded by messages that they perceive are more relevant to themselves than others, it is important that motorists perceive that message have a greater influence on themselves compared to other motorists.

The mean scores related to message rejection showed that participants generally disagreed that they would stop suddenly in their lane to try and see the animal, slow down and move off to the side of the road to try and see the animal, or simply ignore the messaging if they saw the message while driving. The mean scores also showed that participants had a stronger assumption that the message was a real-time warning rather than a general warning, with significantly higher scores reported by those who viewed message concept 1 and message concept 2. These two concepts featured the same text (i.e., Screed 1: 'Cassowary detected', Screen 2: 'Slow down, look out') and may suggest that the language used in these concepts better conveys the immediacy of the message.

The mean scores for attitudes, intentions, and willingness to slow down and scan when driving during the day and during the night were relatively high (i.e., 5 or 6 and above on a 7-point scale) both before and after viewing the message, indicating that sample were consistently well-receiving of the importance of messaging about the presence of animals in the road environment.

Participants in all four message concept conditions reported more favourable attitudes towards slowing down and scanning the road environment, during the day and night, after viewing the message. Participants reported significant increases in attitudes towards slowing down after viewing message concept 1 (day and night), and message concepts 2 and 4 (day only). Those who viewed message concept 3 reported significant increases in attitudes towards both behaviours during the day and night.

The results for intentions and willingness were mixed, with scores for some message concepts observed to increase for certain behaviours are certain times of the day and decrease for others. It is unclear why these discrepancies occurred, but it may due to ceilings effects given the already high pre-message scores (and noting that mean scores tended to be slightly lower for attitudes, hence why these effects may not have appeared in attitudes) Trends in the results showed that participants reported higher intent and willingness to slow down during the day after viewing the message but showed lower intent and willingness to scan regardless of the time of day. Notably, message concept 3 showed the most consistent increases in intent and willingness to perform both behaviours, and participants reported significantly higher intention and willingness to slow down and scan at night. As message concept 3 was the only message that did not identify the type of animal that had been detected (i.e., Screen 1: 'Animal ahead'), this finding may suggest that participants would be more inclined to slow down and scan when they are unsure what they are looking for during the night where visibility is already comprised.

Participants in all four message concept conditions reported that it was quite unlikely (i.e., reported scores of 3 or less on a 7-point scale) that they would stop suddenly to try and see the animal before viewing the message, and these scores decreased further after seeing the message. Significant decreases in scores were observed from Message concepts 1 and 2 (during the day and night) and message concept 4 (night only). These three message concepts all identify the type of animal and may suggest participants were less inclined to stop because they were aware of what they ought to be looking for (i.e., had some understanding of how to react to the situation) or potentially because the specific animal in question was a cassowary.

4.4.1.C. Preferred Driving Strategies

Study 2 evaluated participants' preferred driving strategies by asking them to rate the extent to which they agreed each strategy was useful. There were no significant differences found between the four driving strategies and participants reported all strategies to be relatively useful (i.e., provided scores of 5 or 6 or above on a 7-point scale). However, when asked to provide reasoning for their preferences, commonly reported that slowing down was the more important of the two driving behaviours and suggested that this strategy be presented first which reflects the findings of Study 1. Participants reported no substantial difference in preference for 'slow down' versus 'reduce speed', which suggests that either strategy would be appropriate for future messaging.

4.4.1.D. Additional Considerations

Three additional themes consistently emerged from the focus groups in Study 1 and the qualitative responses in Study 2. First, participants often expressed and opinion on whether the message should name the type of animal that has been detected. Across both studies, a greater proportion of participants reported that it would be useful to identify the animal in the message; however, this finding may also further underscore the possibility that messages (or elements of) may be more suited to specific contexts (e.g., time of day) or to fulfil higher priorities (e.g., emphasising the real-time nature of the warning). Second, participants reported that it was important that motorists understood that the message was a real-time warning and expressed concerns that motorists might become complacent if the sign were to remain activated and/or they did not come across any animals while driving. Third, and following on from the previous point, participants reported the implementation of the signage should be accompanied by a public campaign to raise awareness of the messaging and associated animal detection technology.

4.4.2 Strength and Limitations

A strength of this mixed-methods research was that it was guided by a theoretical framework (i.e., the SatMDT) in developing, concept-testing, and evaluating messages aimed to alert drivers to the presence of and animal on the road and to encourage safe driving behaviours to avoid collisions with the animal. Further, the research included several direct (i.e., TPE, message rejection) and indirect (i.e., attitudes, intentions, willingness, and likelihood of stopping) measures of message effectiveness to provide an in-depth evaluation of four of the message concepts examined in the evaluation study, Study 2. Also in Study 2, the inclusion of the control (no message) condition allowed for comparisons to made with the experimental (message) conditions on the indirect measures of effectiveness, thus providing insights into the effectiveness of messaging relative to a baseline of no messaging at all option.

Despite these strengths, there are some limitations of this research which also need to be acknowledged. First, participants comprised a convenience sample recruited via an Australian marketing recruitment company. Moreover, the sample of Study 2 comprised primarily of older, female motorists who held an open licence. Therefore, the Study 2 sample may not accurately represent the diversity of motorists in Australia who will encounter areas where this signage is displayed. Second, the research relied on self-report data which only assessed how participants perceived they would respond to each message. Additionally, the research only assessed the message concepts immediately as they were shown, and further longer-term assessment is required to determine the level of effectiveness these messages have in influencing actual driver behaviour. The latter forms part of subsequent research in the overall LAARMA project which will comprise a simulator study as well as an on-road field trial in North Queensland.

4.5. Practical Consideration for Implementation

Based on the findings from the current program of research, three key practical considerations are offered regarding the future implementation of messaging design to alert motorists that an animal has been detected in the area and, subsequently, engage in safe driving behaviours (i.e., slowing down and scanning). Specifically, these considerations relate to content of the message, the design of the signage and broader aspects associated with the implementation of the signage:

1. All four message concepts performed relatively well in Study 2; however, certain message concepts did demonstrate stronger performance on specific parameters. This finding suggests that, while all four message concepts are likely to have the anticipated impact on the two driving behaviours and thus could further developed into final, ready-to-be-implemented signage, it may be pertinent to identify what the key priorities for the messages and implement specific messages based on their performance in these metrics. For example, message concepts 1 and 2 (or elements of) would be more appropriate if it is determined that the most important factors are to ensure motorists understand that the message is a real-time warning, and that the message is unlikely to result in motorists stopping suddenly to see the animal.

2. Participants across both studies echoed the importance that motorists understand that the message is a real-time warning that an animal had been detected in the area, particularly in the interest of avoiding driver complacency. In Study 2, participants reported that including flashing lights would be useful to reflect the real-time nature of the messages. These findings speak to the importance that the signage does remain blank when no animal has been detected, and only activates (i.e., flashes on) when an animal has been detected (with the understanding that is how the signage was planned to work). Regarding other design elements, although participants in Study 1 reported preferences for different colours and certain typography styles, participants in Study 2 did not report strong preferences for these aspects. All four message concepts in Study 2 received strong results using the traditional monochromatic (amber) colour scheme

and using uppercase for the text on screen 1, and title case for screen 2, which suggests that, at least for the initial simulator and field testing, the current design elements will be appropriate, and any future changes to these elements will require further evaluation before implementation.

3. Participants in Study 2 reported that it was important to know the distance of the detection zone so that they knew when it was safe to return to their regular driving behaviours. This finding, alongside those related to the importance of understanding the real-time nature of the warning, speak to the need for broader public education about the animal detection technology, and for these education campaigns to continue to evolve alongside evolutions in the technology.

5

Simulation Study of Driver Behaviour (QUT)

5.1. Introduction

5.1.1 Background

This study was conducted by Dr Sebastien Demmel, Dr Xiaomeng Li, Dr Mohammed Elhenawy, and Prof Sebastien Glaser. This study represented the first of two studies devised as the means to evaluate individuals' behavioural responses to the messaging triggered as part of the LAARMA system. Specifically, this study investigated drivers' response to two messaging strategies using a driving simulator. The messaging strategies that were evaluated were defined previously in Chapter 4, and the two most effective were selected for assessment in this simulator study. The research consisted of testing several hypotheses regarding drivers' reaction regarding the effectiveness of the strategies and the impact of the messaging on driving behaviour (as measured within a driving simulator). The second of the behavioural evaluation studies, i.e., the field study, is presented in Chapter 7.

5.1.2 Method

The study comprised two balanced groups of participants resulting in a total of 54 drivers. Fifty-one participants completed the study (23 were males, 27 were females, and one reported as 'other'). The participants were aged between 17 and 71 years old, with an average age of 31.8 years old (SD = 14.0 years). The participants reported that they had held their driver licence for an average of 13.0 years, ranging from 1 year to 51 years, and they drove 8.8 hours in an average week. The driving simulation environment replicated the two initial sites where the LAARMA system was expected to be installed. These two sites were repeated three

(a) (b)

Figure 5.1.: Two scenarios with cassowary involvement: (a) cassowary walking along the road, and (b) cassowary crossing the road.

(a) (b) (c)

Figure 5.2.: Visuals for the VMS. The display for VMS_1 alternated the images (a) and (c), while the display for VMS_2 alternated the images (b) and (c).

times, with different scenarios: with a cassowary walking along the road, no cassowary, and a cassowary crossing the road. The two scenarios involving a cassowary are shown in Figure 5.1. Two different messages (from Study 2 - the messaging evaluation study) were assessed (see Figure 5.2). The driving simulator system recorded all information in terms of driver action and vehicle trajectory in relation to the scenario and messaging shown. Two zones were defined for the analysis, the approach zone at the time of message display and event zone after the message and the area of (potential) detection of a cassowary.

5.1.3 Key Findings

The comparative analysis of driver behaviour comprised assessing individuals' responses in scenarios involving an animal (i.e., a cassowary) crossing a road or walking alongside the road and for which messaging was triggered via the LAARMA system. These messages were compared with static sign-based messages. The results revealed distinct patterns. Both scenarios demonstrated that messaging triggered on the VMS effectively reduced the normalised average speed of drivers in the approach zone window (i.e., zone where messages are triggered 5 seconds to the actual positioning of the VMS). For the scenario involving a cassowary crossing the road, VMS_1 significantly reduced speed, while for the cassowary walking alongside the road, VMS_2 showed a statistically significant reduction in speed with VMS_1 trending towards statistical significance. During the event window zone (i.e., from the VMS into the detection zone where the cassowary appears), neither VMS_1 nor VMS_2 significantly reduced drivers' speeds in either scenario. However, VMS_1 was found to improve driving smoothness (celeration at the event) during the animal crossing scenario and significantly increased maximum deceleration; results which indicate overall improvements in driver responsiveness. These findings indicate that VMS, particularly the messaging as shown in VMS_1 (see Figure 5.2), have potential benefits for road safety by prompting cautious behaviour as drivers slow down when approaching potential hazards. The increased awareness (of a hazard) raised by display of a message on the VMS likely contributes to these safety benefits, even when animals remain roadside and do not cross the road. Overall, messaging displayed on roadside VMSs appear to be a valuable tool for managing high-risk areas, enhancing driver caution as evidenced by them slowing down their travelling speeds when approaching both cassowary-crossing and -walking scenarios. In the driving simulator, it is reasonable to suggest that the effect of such messaging is greatest in the approach zone where drivers respond and reduce speed on sighting of the messaging on the VMS. During the subsequent event zone, as a simulated drive, given there is no actual risk that a driver will collide with a cassowary, the speed reductions witnessed initially at the approach zone are relatively larger (and significant) compared with in the event zone window.

5.2. Study and Participants

The study was approved under a QUT low risk ethics application: "Understanding drivers' experiences with large animals crossing roads" (QUT Ethics Approval Number 7859).

A total of 54 participants were recruited for the study. Participants were recruited through social media posts, and emails which were shared with QUT classifieds (an online email list for QUT staff) and casual staff groups. All participants were required to have a valid Queensland (or interstate/international equivalent) open driver licence and drive a minimum of 3 hours per week. Two participants commenced but did not complete the study due to motion sickness experienced in the simulator, and one participant did not complete the experiment due to apparatus-related technical issues. Ultimately, 51 participants completed the experiment. Among the 51 participants, 23 (45.1%) were males, 27 (52.9%) were females and one reported as "other". The participants were aged between 17 and 71 years old, with an average age of 31.8 years old (SD = 14.0 years). The participants reported that they have held their driver licence for an average of 13.0 years, ranging from 1 year to 51 years, and they drove 8.8 hours in an average week.

The participants, during the experiment, were exposed to one specific messaging strategy, which included the visuals in Figure 5.2. The display for VMS_1 alternated the Figures 5.2a and 5.2c, while the display for VMS_2 alternated the Figures 5.2b and 5.2c.

5.3. Approach and Event Windows Analysis

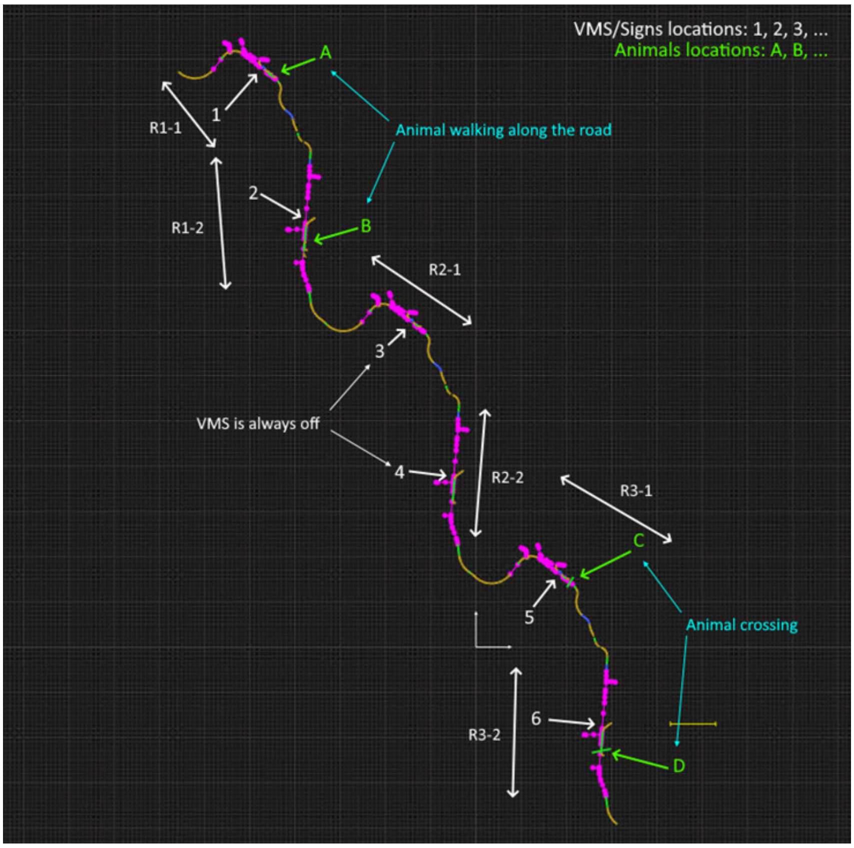


Figure 5.3.: Map of event zones highlighting driver-animal interaction points and signage locations.

The simulated road environment was based on two real-world locations in FNQ, one on the Kennedy Highway in Kuranda and the other on Tully Mission Beach Road in Mission Beach. Sections of the real roads were reproduced in the simulator and duplicated twice to form a longer road, where each site would appear three times. In Figure 5.3, the reproduced areas (labelled RX-Y, with X representing the number of the repeated section from 1 to 3, and Y representing the ID of the section: 1 for the Kuranda site and 2 for the Mission Beach site) are marked by pink dots along the road, whereas other sections were created ex-nihilo to connect those sections.

In the reproduced real sections in the simulator, the road layout was faithful to the real-world locations, with two lanes single carriageway and additional turning lanes at intersections if present (see Figure 5.4 for examples). The speed limit was also the same as on real roads: most of the time the speed limit was 80 km/h, but some sections were limited to 60 km/h or even 50 km/h. The connecting sections also consisted of a two lanes single carriageway with a speed limit of 80 km/h. The environment around the road was designed to be rural, like the real sites. In the reproduced sections, efforts were made to place objects

(a) (b)

(c) (d)

Figure 5.4.: Comparison of real (top) and simulated (bottom) environments. (a) and (c) show the Kuranda site, (b) and (d) represent the Mission Beach site.

in locations similar to their real-world counterparts, within the limits of the simulator's objects library. Road signs were also placed at their actual locations.

The analysis in this study was event-based, focusing on the specific zones where interactions between drivers and animals occurred. The map in Figure 5.3 identifies four main event zones: at locations R1-1 and R1-2, the animal (i.e., cassowary) is walking on one side of the road without crossing, while at locations R3-1 and R3-2, the animal (i.e., the cassowary) crosses the road. To effectively study driver behaviour, it was necessary to define a smaller analysis window. This window needed to be sufficiently large to capture driver's behaviour upon seeing the message on the VMS, yet not so large as to dilute the effect of the message in the event area (where the cassowary was detected). This approach window ensured that the analysis remained focused and accurately reflected driver's response to the messaging and presence of the cassowary.

In the analysis of the simulated driving behaviour, we defined two key windows: the event window and the approach window. The event window captured driver behaviour between the messaging on the VMS and the point where the Time-To-Collision (TTC) equals zero. The approach window started 5 seconds before reaching the message on the VMS and ended exactly at the VMS. In the following paragraphs, we provide detailed definitions of these two critical points: when TTC equals zero and when the driver reaches the VMS.

The two subfigures in Figure 5.5 illustrate the time series of distances on the road from

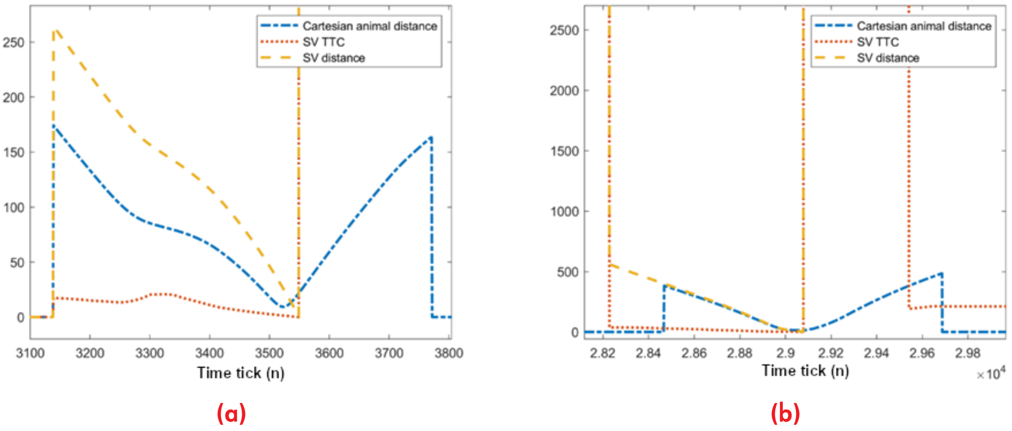


Figure 5.5.: Visualisation of the Cartesian animal distance, time to reach the "meeting point" for the subject vehicle (SV TTC), and SV distance during: (a) animal walking interactions (R1-1 and R1-2), and (b) animal crossing interactions (R3-1 and R3-2). Note that the y-axis represents time for the SV TTC curve, and distance for both the Cartesian animal distance and SV distance curves.

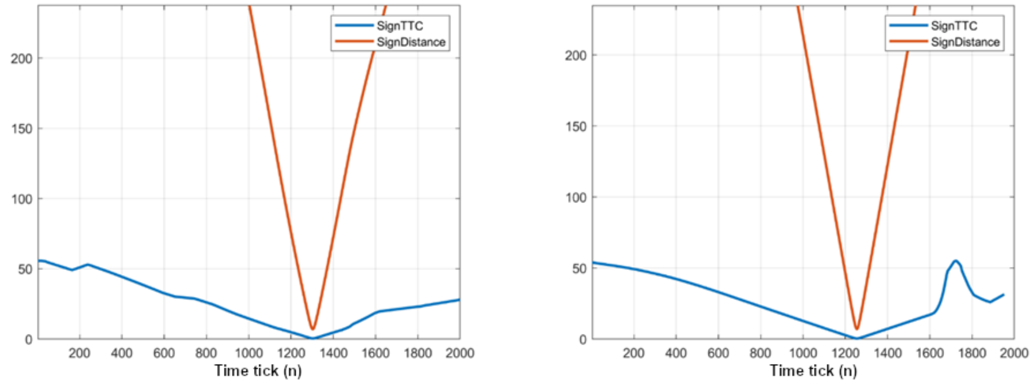
the vehicle to the meeting point with the animal, the TTC, and the Cartesian distance (i.e. straight-line distance) between the subject vehicle (SV) and the animal.

Figure 5.5a depicts the time series within the event zones where the animal does not cross the road, while Figure 5.5b shows the time series within the event zones where the animal crosses the road. In both subfigures, the blue dashed line represents the Cartesian animal distance, the red dotted line represents the SV TTC, and the yellow dashed line represents the SV distance.

It is clear from Figure 5.5 that the SV distance to the animal on the road and the TTC are crucial for selecting the event analysis window. This means that the analysis window should end at the point where both the TTC and the distance between the animal and the SV on the road are zero. The start point of the event analysis window should be the sign location which is identified using the Cartesian direct distance from the SV to the VMS/static sign and the time to reach the sign as illustrated in Figure 5.6.

5.3.1 Rationale for Event and Approach Windows Selection

Based on the setup of the LAARMA, the VMS is positioned relative to the sensors in such a way that it effectively extends the driver's vision, allowing them to become aware of the animal well in advance of actually seeing or interacting with it. This early awareness enables the driver to begin reducing speed before even seeing the animal. Given this, **the event**



(a) (b)

Figure 5.6.: Visualisation of the Cartesian direct distance from the SV to the VMS/static sign (Sign Distance) and the time to reach the sign (Sign TTC) during: (a) animal walking interactions (R1-1 and R1-2), and (b) animal crossing interactions (R3-1 and R3-2). Note that the y-axis represents time for the Sign TTC curve, and distance for the Sign Distance curve.

window is defined as starting from the VMS and ending when the TTC reaches zero, marking the point of direct interaction.

Additionally, we define **the approach window as the period leading up to the event, beginning 5 seconds before the VMS and ending at the VMS location itself.** This approach window captures the driver's initial response to the system, including any potential speed adjustments made upon seeing the VMS, before entering the critical event zone.

5.4. Background

5.4.1 Celeration

Celeration is a measure of driving smoothness. The following equation defines the celeration behaviour of the driver in a homogeneous driving environment.

$$c = \frac{1}{N}\left(\sum_{n=1}^{N} \left|a_n I_{\text{Speed}_n > 4.3\,\text{km/h}}\right|\right)$$

where c is the estimated celeration, N is the length of the analysis window, a_n is the measured acceleration at the timestamp n, and $I_{\text{Speed}_n > 4.3\,\text{km/h}}$ is an indicator function returns one if the vehicle is moving and zero otherwise.

5.4.2 Average Normalised Speed

Regarding the average normalised speed response, the average normalised speed is calculated using the formula:

$$\text{Average Normalised Speed} = \frac{\sum_{i \in AW} \frac{Speed_i}{SpeedLimit}}{|AW|}$$

where AW is the set of observed speeds in the Analysis Window, and $|AW|$ is the cardinality operator representing the number of observed speeds. This formula normalises the average speed by the speed limit, providing a comparative measure of how drivers' speeds relate to the posted speed limit within the analysis period.

5.4.3 Predictor Variables and Statistical Model Outputs

In the simulator data analysis, we used the following predictors to explain the variability in the studied response:

1. Participant age: This variable represents the age of the participant in years.
2. Participant gender: A categorical variable with three levels; male (participant_Gender_1), female (participant_Gender_2), and other (participant_Gender_3). Since the model uses k-1 (i.e., two) indicator variables to represent the three levels, male (participant_Gender_1) is coded as [0 0] and is included as part of the intercept, making it the reference category.
3. Participant driving experience: Represented by the variable participant_Licenceyears, it measures the participant's driving experience in years.
4. Participant driving hours per week: This variable (participant_HoursDrivePerWeek) represents the average number of hours the participant drives per week.
5. Treatment/intervention: A categorical variable with three levels: "Static" (representing a static sign), "Sign_VMS_1" (representing VMS_1), and "Sign_VMS_2" (representing VMS_2). As with the gender variable, we used two indicator variables to represent these levels in the model. The static sign is coded as [0 0] and is included in the intercept, serving as the reference category against which the other two levels (Sign_VMS_1 and Sign_VMS_2) are compared.

For the sake of completeness we provide the statistical model outputs description (column) below:

1. Name: Lists the predictor variables included in the model.
2. Estimate: The estimated effect of each predictor on the dependent variable.
3. SE (Standard Error): The uncertainty or variability around the estimate.
4. tStat (t-Statistic): The ratio of the estimate to its standard error, used to test significance.
5. DF (Degrees of Freedom): The number of degrees of freedom associated with the estimate.
6. pValue: The probability that the observed effect occurred by chance; indicates statistical significance.

5.4.4 Statistical Methods and Modelling

Advanced statistical modelling techniques were used to ensure the models captured the driving responses adequately. Generalised linear mixed effect (GLME) models are developed to enable analysis of dependent data by introducing random variables (i.e., random effects) at the lower levels of the model. For example, there are repeated measurements from the same participant and from the same location (i.e., R1-1, R1-2, R3-1 and R3-2). To capture the correlation between the repeated measurements at these levels, random effects were introduced at the participant and location levels.

5.5. Results Analysis

In this study, we analyse the data collected at locations where animals cross the road separately from the data collected at locations where animals only walk by the side of the road. We do this because we believe these two scenarios present different levels of risk, leading to distinct driver behaviours. The purpose of this statistical analysis is to test the following safety hypotheses related to the use of the LAARMA system in comparison to static signs:

1. Hypothesis 1: Using LAARMA reduces the normalised average speed of drivers.

2. Hypothesis 2: LAARMA enhances driving smoothness, as indicated by improved celeration during the event.

3. Hypothesis 3: LAARMA eliminates or reduces harsh deceleration of vehicles compared to static signs at the event window.

5.5.1 Animals Walk by the Side of the Road

5.5.1.A. Normalised Average Speed at the Approach

Name	Estimate	SE	tStat	DF	pValue
(Intercept)	0.933458	0.093152	10.02076	196	2.40E-19
participant_age	-0.00316	0.002154	-1.46742	196	0.143866
participant_Gender_2	-0.01906	0.013571	-1.40447	196	0.161761
participant_Gender_3	-0.03196	0.047889	-0.66733	196	0.505348
participant_Licenceyears	0.003371	0.002257	1.493814	196	0.136832
participant_HoursDrivePerWeek	0.000128	0.00131	0.097707	196	0.922265
Sign_VMS_1	-0.02859	0.015984	-1.78849	196	0.075241
Sign_VMS_2	-0.03369	0.015767	-2.13674	196	0.033859

Table 5.1.: Statistical analysis of normalised average speed at the approach window.

In this analysis, we examined the effect of the message on the VMS on the normalised average speed of drivers during the approach window, comparing these messages to static sign-based messages. The statistical results in Table 5.1 showed that both VMS_1 and VMS_2 had an impact on drivers' speed. Specifically, the estimate for VMS_1 was -0.02859 with a p-value of 0.075241, suggesting a trend towards reduced speed, though not reaching conventional levels of statistical significance. For VMS_2, the estimate was -0.03369 with a p-value of 0.033859, indicating a significant reduction in speed associated with the messaging on the VMS compared to the static sign-based messages.

These findings imply that messages on the VMS (as devised in the earlier studies of this project), and particularly VMS_2, effectively reduced drivers' speed in the approach window compared to the static sign-based messages. Thus, the findings suggest such messaging on the VMS contributed to improvements in road safety by encouraging drivers to slow down *as they approached the animal. For example, at a speed of 60 km/h, the average speed reduction for VMS_2 is approximately 2.02 km/h.*

5.5.1.B. Celeration at the Approach

Name	Estimate	SE	tStat	DF	pValue
(Intercept)	-0.13102	0.193962	-0.67551	196	0.500145
participant_age	0.017428	0.010151	1.716825	196	0.087591
participant_Gender_2	0.102233	0.063945	1.598771	196	0.111482
participant_Gender_3	-0.12253	0.225645	-0.54303	196	0.587726
participant_Licenceyears	-0.01639	0.010633	-1.5414	196	0.124833
participant_HoursDrivePerWeek	-0.00673	0.006171	-1.09098	196	0.276619
Sign_VMS_1	0.086838	0.075316	1.152981	196	0.250322
Sign_VMS_2	0.015922	0.074293	0.214321	196	0.83052

Table 5.2.: Statistical analysis of celeration at the approach window.

The analysis of celeration at the approach, where celeration is a measure of driving smoothness, focused on comparing the effects of messaging on the VMS relative to static sign-based messages. The statistical results in Table 5.2 indicated that neither VMS_1nor VMS_2 showed statistically significant differences in drivers' celeration compared to the static sign-based messages. Specifically, the estimate for VMS_1 was 0.086838 with a p-value of 0.250322, and for VMS_2, the estimate was 0.015922 with a p-value of 0.83052.

These findings suggest that the presence of messaging on the VMS did not significantly influence drivers' celeration behaviour in the approach window compared to the static sign-based messages.

5.5.1.C. Normalised Average Speed at the Event

The statistical analysis of normalised average speed at the event focused on comparing the effects of the messaging on the VMS to static sign-based messages. As shown in Table 5.3, neither VMS_1 nor VMS_2 had a statistically significant effect on drivers' speed during the event window. Specifically, the estimate for VMS_1 was 0.004813 with a p-value of 0.905227, and for VMS_2, the estimate was -0.01614 with a p-value of 0.685784.

These findings suggest that the presence of messaging on the VMS did not significantly influence drivers' speed during the event window compared to static sign-based messages.

Name	Estimate	SE	tStat	DF	pValue
(Intercept)	0.90783	0.103818	8.744447	94	8.57E-14
participant_age	-0.00181	0.005433	-0.33278	94	0.740041
participant_Gender_2	-0.02482	0.034227	-0.72515	94	0.470161
participant_Gender_3	-0.22419	0.120777	-1.85625	94	0.06655
participant_Licenceyears	0.00103	0.005691	0.18092	94	0.85682
participant_HoursDrivePerWeek	-0.00342	0.003303	-1.03592	94	0.302896
Sign_VMS_1	0.004813	0.040313	0.119382	94	0.905227
Sign_VMS_2	-0.01614	0.039765	-0.40584	94	0.685784

Table 5.3.: Statistical analysis of normalised average speed at the event window.

5.5.1.D. Celeration at the Event

Name	Estimate	SE	tStat	DF	pValue
(Intercept)	0.54001	0.141676	3.811582	93	0.000248
participant_age	-0.00871	0.007438	-1.17078	93	0.244679
participant_Gender_2	0.052128	0.046845	1.112776	93	0.268673
participant_Gender_3	-0.00573	0.164454	-0.03448	93	0.972283
participant_Licenceyears	0.007903	0.007778	1.016043	93	0.312245
participant_HoursDrivePerWeek	0.00769	0.00452	1.701109	93	0.092264
Sign_VMS_1	-0.03813	0.055042	-0.69278	93	0.490173
Sign_VMS_2	0.017519	0.054345	0.322376	93	0.747872

Table 5.4.: Statistical analysis of celeration at the event window.

The statistical analysis of celeration at the event examined the impact of the messaging on the VMS on drivers' celeration compared to static sign-based messages. The results in Table 5.4 showed that neither VMS_1 nor VMS_2 had a statistically significant effect on driver celeration. Specifically, the estimate for VMS_1 was -0.03813 with a p-value of 0.490173, and for VMS_2, the estimate was 0.017519 with a p-value of 0.747892.

These findings suggest that the presence of messaging on the VMS did not significantly alter drivers' celeration behaviour during the event compared to the static sign-based messages.

5.5.1.E. Max Deceleration at the Event

Name	Estimate	SE	tStat	DF	pValue
(Intercept)	-2.62151	0.921085	-2.84611	93	0.005445
participant_age	0.03923	0.048355	0.811289	93	0.419271
participant_Gender_2	-0.67282	0.304557	-2.20917	93	0.029619
participant_Gender_3	0.081093	1.06917	0.075847	93	0.939704
participant_Licenceyears	-0.03461	0.05057	-0.68438	93	0.495438
participant_HoursDrivePerWeek	0.001203	0.029389	0.040945	93	0.967427
Sign_VMS_1	0.593694	0.357846	1.659075	93	0.100469
Sign_VMS_2	0.43463	0.353313	1.230154	93	0.221742

Table 5.5.: Statistical analysis of maximum deceleration at the event window.

The statistical analysis of maximum deceleration at the event aimed to compare the effects of messaging on the VMS with static sign-based messages on driver behaviour. The results in Table 5.5 showed that neither VMS_1 nor VMS_2 had a statistically significant effect on drivers' maximum deceleration. The estimate for VMS_1 was 0.593694 with a p-value of 0.100469, and for VMS_2, the estimate was 0.43463 with a p-value of 0.221742. Moreover, **participant_Gender_2** (representing female participants) appears to have a statistically significant effect on maximum deceleration. The estimate for **participant_Gender_2** is -0.67282, with a p-value of 0.029619, which is below the typical significance threshold of 0.05. This indicates female participants tend to have stronger deceleration compared to male participants (the reference group).

Although VMS_1 approached significance, these findings suggest that when the animal is on the side of the road, the presence of the VMS does not substantially influence maximum deceleration compared to static signs.

5.5.1.F. Animal Walking Conclusion

The analysis highlights that messaging on the VMS effectively reduced the normalised average speed of drivers, particularly in the approach window, with VMS_2 showing a statistically significant reduction in drivers' speed and VMS_1 indicating a notable trend toward reduced drivers' speed. Such findings suggest that messaging on the VMS offers road safety benefits by prompting drivers to slow down as they approach potential hazards, such as animals. However, the findings also indicate that messaging on the VMS did not significantly impact other aspects of driver behaviour, such as celeration and maximum deceleration, during the event window. We hypothesise that the messages may be functioning to raise drivers' awareness of the animal's presence, but since the animals stayed on the roadside without crossing, drivers did not slow down significantly. Consequently, no significant differences in celeration or maximum deceleration were detected between the VMS and the static sign-based messages. It is also is reasonable to suggest that given assessment of driving behaviour within a simulator and there being no prospect of a participant actually colliding with a cassowary, the largest (and significant) reduction in drivers' speed would be found on approach when responding to the messaging being displayed rather than in the actual event zone.

5.5.2 Animals Cross the Road

5.5.2.A. Normalised Average Speed at the Approach

Name	Estimate	SE	tStat	DF	pValue
(Intercept)	0.859941	0.060821	14.1389	196	9.51E-32
participant_age	-0.00166	0.001876	-0.88542	196	0.377016
participant_Gender_2	-0.02484	0.01182	-2.10164	196	0.036863
participant_Gender_3	-0.03172	0.041709	-0.76054	196	0.447845
participant_Licenceyears	0.002382	0.001965	1.212004	196	0.22697
participant_HoursDrivePerWeek	-0.00147	0.001141	-1.28611	196	0.199921
Sign_VMS_1	-0.03422	0.013921	-2.45829	196	0.014828
Sign_VMS_2	-0.02647	0.013732	-1.92724	196	0.055396

Table 5.6.: Statistical analysis of normalised average speed at the approach window.

In this analysis, we examined the effect of VMS on the normalised average speed of drivers during the approach window, comparing these messages to static sign-based messages. As presented in Table 5.6, the statistical results showed that both VMS_1 and VMS_2 had an impact on drivers' speed. Specifically, the estimate for VMS_1 was -0.03422 with a p-value of 0.014828, indicated a significant reduction in drivers' speed compared to the static signs. For VMS_2, the estimate was -0.02647 with a p-value of 0.055396, suggesting a trend towards reduced drivers' speed, though not reaching conventional levels of statistical significance.

These findings imply that messaging on the VMS, particularly VMS_1, effectively reduced drivers' speed in the approach window compared to the static signs. For example, at a speed of 60 km/h, the average speed reduction for VMS_1 is approximately 2.05 km/h.

5.5.2.B. Celeration at the Approach

Name	Estimate	SE	tStat	DF	pValue
(Intercept)	-0.51684	0.306166	-1.68809	196	0.092983
participant_age	0.043367	0.016024	2.706416	196	0.007401
participant_Gender_2	0.20751	0.100937	2.055846	196	0.041123
participant_Gender_3	-0.29821	0.356179	-0.83725	196	0.403471
participant_Licenceyears	-0.04806	0.016785	-2.86316	196	0.004651
participant_HoursDrivePerWeek	0.001166	0.009741	0.119685	196	0.904855
Sign_VMS_1	-0.0486	0.118885	-0.40881	196	0.683124
Sign_VMS_2	0.040283	0.11727	0.343509	196	0.731584

Table 5.7.: Statistical analysis of celeration at the approach.

In this analysis, we focused on assessing the impact of messaging on the VMS on drivers' celeration during the approach window, comparing their response relative to static sign-based messages. The statistical results in Table 5.7 indicated that neither VMS_1 nor VMS_2 showed statistically significant differences in drivers' celeration compared to the messages on the static signs. Specifically, the estimate for VMS_1 was -0.0486 with a p-value of 0.683124, and for VMS_2, the estimate was 0.040283 with a p-value of 0.731584.

These findings suggest that the presence of messaging on the VMS did not significantly influence drivers' celeration behaviour in the approach window compared to the static signs, which serve as the sole reference point in the simulator study design.

5.5.2.C. Normalised Average Speed at the Event

Name	Estimate	SE	tStat	DF	pValue
(Intercept)	0.972047	0.10552	9.211945	196	5.00E-17
participant_age	-0.0095	0.004438	-2.14069	196	0.033535
participant_Gender_2	-0.07692	0.027959	-2.75132	196	0.006492
participant_Gender_3	-0.11744	0.09866	-1.1904	196	0.23533
participant_Licenceyears	0.011039	0.004649	2.374397	196	0.018543
participant_HoursDrivePerWeek	-0.00176	0.002698	-0.65209	196	0.515108
Sign_VMS_1	-0.03255	0.032931	-0.9885	196	0.324125
Sign_VMS_2	-0.04894	0.032483	-1.50661	196	0.133521

Table 5.8.: Statistical analysis of normalised average speed at the event window.

In this analysis, we examined the impact of VMS on the normalised average speed of drivers during the event window, comparing the VMS messages to static sign-based messages. The statistical results, presented in Table 5.8, showed that neither VMS_1 nor VMS_2 had a statistically significant effect on drivers' speed during the event window. Specifically, the estimate for VMS_1 was -0.03255 with a p-value of 0.324125, while the estimate for VMS_2 was -0.04894 with a p-value of 0.133521.

These results indicate that, unlike in the approach window, the presence of messaging on the VMS did not significantly influence driver behaviour in terms of speed reductions during the event window when compared to the static signs. As previously mentioned, we believe it is reasonable to suggest that given assessment of driving behaviour within a simulator and there being no prospect of a participant actually colliding with a cassowary in the event zone, the largest (and significant) reduction in drivers' speed would be found on approach when responding to the messaging being displayed rather than in the actual event zone.

5.5.2.D. Celeration at the Event

In this analysis, we examined the celeration behaviour of drivers at the event, where celeration is defined as a measure of driving smoothness. The statistical analysis, presented in Table 5.9, focused on the comparison between messaging on the VMS and static sign-based messages. The results showed that the presence of VMS_1 significantly impacted drivers' celeration, with

Name	Estimate	SE	tStat	DF	pValue
(Intercept)	0.397452	0.114529	3.470319	185	0.000647
participant_age	0.003192	0.00568	0.561861	185	0.574891
participant_Gender_2	0.054289	0.034769	1.561409	185	0.120136
participant_Gender_3	0.04443	0.119067	0.373148	185	0.709465
participant_Licenceyears	-0.00332	0.005902	-0.56226	185	0.574621
participant_HoursDrivePerWeek	0.005483	0.003389	1.617955	185	0.107376
Sign_VMS_1	-0.09901	0.040649	-2.43575	185	0.015809
Sign_VMS_2	-0.00764	0.040214	-0.189999	185	0.849522

Table 5.9.: Statistical analysis of celeration at the event.

an estimate of -0.09901 and a p-value of 0.015809, indicating smoother driving behaviour when VMS_1 was present compared to static signs. In contrast, VMS_2 did not show a statistically significant difference, with an estimate of -0.00764 and a p-value of 0.849522.

These findings suggest that VMS_1 was more effective in influencing driver behaviour towards smoother driving compared to the static signs, while VMS_2 did not significantly alter drivers' celeration.

5.5.2.E. Max Deceleration at the Event

The statistical analysis of the GLME model of the max deceleration at the event revealed significant findings related to the type of signs used. As presented in Table 5.10, the results showed that both the messages on the VMS, VMS_1 and VMS_2, had a significant, positive impact on the maximum deceleration of vehicles compared to the static sign-based messages, resulting in less harsh deceleration. In particular, VMS_1 had a stronger influence, with an estimate of 1.205 and a highly significant p-value of 0.000351, indicating a noticeably smoother deceleration. Similarly, VMS_2, with an estimate of 0.678 and a p-value of 0.0399, also significantly softer deceleration.

These findings suggest that implementing messaging on VMS can enhance driver responsiveness, resulting in less harsh deceleration rates (i.e. closer to zero since deceleration is negative) when compared to drivers' responses to traditional static sign-based messages.

Name	Estimate	SE	tStat	DF	pValue
(Intercept)	-4.13298	1.050923	-3.93271	185	0.000119
participant_age	0.04086	0.046254	0.883381	185	0.378177
participant_Gender_2	-0.13623	0.283104	-0.4812	185	0.630945
participant_Gender_3	0.996165	0.969473	1.027533	185	0.305511
participant_Licenceyears	-0.05439	0.04806	-1.1316	185	0.259266
participant_HoursDrivePerWeek	0.000122	0.027591	0.004411	185	0.996485
Sign_VMS_1	1.205308	0.33097	3.64175	185	0.000351
Sign_VMS_2	0.677627	0.32743	2.06953	185	0.039886

Table 5.10.: Statistical analysis of maximum deceleration with VMS and static signs at the event.

5.5.2.F. Animal Crossing Conclusion

The statistical analysis of driver behaviour in response to purpose-devised messaging on roadside VMS compared to static sign-based messages revealed several key insights. VMS_1 was particularly effective in reducing the normalised average speed of drivers in the approach window, indicating drivers were exhibiting increased caution as they slowed down and approached the animal's crossing point. However, neither VMS_1 nor VMS_2 significantly impacted drivers' speed during the event window. Interestingly, VMS_1 also promoted smoother driving behaviour during the event, as evidenced by significant improvements in celeration. Additionally, both VMS_1 and VMS_2 significantly increased maximum deceleration (i.e. speeds closer to zero), with VMS_1 showing a stronger effect relative to its other VMS counterpart. These findings suggest that implementing LAARMA, and particularly with VMS_1 displayed, offers road safety benefits in terms of drivers' increased caution and slowing down; thus, making such messages (on VMS) a valuable tool for helping to address AVCs.

5.5.3 Conclusions

The driving simulator study shows that the VMS messaging strategies effectively reduce driver speeds in the approach window, with VMS_1 reducing speed for animal crossings and VMS_2 for animal walking. While neither VMS_1 nor VMS_2 significantly impacted driver speed in the event window, VMS_1 improved driving smoothness and driver responsiveness during crossings. Overall, the VMS messaging enhances road safety by increasing driver caution in high-risk areas. A detailed comparison summary of VMS_1 and VMS_2 in animal crossing and walking scenarios is presented in Table 5.11.

Aspect	**Animal Crossing**	**Animal Walking**	**Comparison Summary**
Approach Window Speed	VMS_1 significantly reduced speed. At a speed of 60 km/h, the average speed reduction is approximately 2.05 km/h)	VMS_2 significantly reduced speed.at a speed of 60 km/h, the average speed reduction is approximately 2.02 km/h). VMS_1 showed a trend towards reduced speed.	Both scenarios show that VMS effectively reduces normalised average speed in the approach window.
Event Window Speed	Neither VMS_1 nor VMS_2 significantly impacted speed.	Neither VMS_1 nor VMS_2 significantly impacted speed.	VMS did not significantly impact driver speed during the event window in either scenario.
Celeration (Driving Smoothness)	VMS_1 improved driving smoothness (celeration at event) significantly.	VMS did not significantly impact celeration.	VMS_1 enhances driving smoothness during animal crossings; no significant impact observed during animal walking.
Event Window Maximum Deceleration	Both VMS_1 and VMS_2 significantly increased maximum deceleration by 1.21 m/sec^2 and 0.68 m/sec^2, respectively, with VMS_1 showing a stronger effect.	VMS did not significantly impact maximum deceleration.	Both VMS_1 and VMS_2 significantly increased maximum deceleration (make it closer to zero) in animal crossing scenario, suggesting better driver responsiveness.
Overall Insight	VMS, particularly VMS_1, enhance driver caution and responsiveness in high-risk animal crossing zones.	VMS enhance road safety by prompting drivers to slow down in the approach window, but no significant impact on other behaviours.	VMS are valuable for managing high-risk areas, improving driver caution and responsiveness. Messages likely raise awareness, contributing to safety benefits even when animals do not cross the road.

Table 5.11.: The comparison summary of the two messaging strategies in animal crossing and walking scenarios.

6

Field Trial (USYD)

6.1. Introduction

This chapter provides details about the field trial of the developed LAARMA system in FNQ. This study was approved by USYD Animal Ethics Committee (project number: 2023/2398).

The chapter begins with an introduction of the two data collection locations and a summary of the findings from the collected data in Section 6.2. This is followed by detailed information about the on-road trial in Section 6.3. Importantly, Section 6.4 explains the data extraction processes and data usage for model training, serving as a bridge between field data collection and self-training machine learning. Section 6.5 summarises the challenges faced and the technological lessons learnt during the data collection and the on-road trial. Lastly, the conclusions are drawn with recommendations provided in Section 6.6.

6.2. Data Collection

The developed animal detection system was set up at two sites for data collection in Kuranda, QLD, before the on-road trial commenced. The collected data include RGB images, thermal images, and LiDAR point clouds. Field data collection is essential for training a machine learning model that works well for animal detection in a particular environment. For this Kuranda field trial, a total of 97 days' worth of data has been collected from two locations for model training. After multiple iterations of updates, the performance of the trained model has improved significantly before it was deployed for the on-road trial.

The timeline of important activities during the data collection stage is listed in Table 6.1. Note that the VMS did not show any message during the data collection stage.

Date Range	Activity	Location
24 January 2024	Field Installation	A
24 January 2024 - 6 March 2024	Data Collection	A
6 March 2024	System Relocation	B
6 March 2024 - 30 April 2024	Data Collection, Model Training	B

Table 6.1.: Timeline of activities during the field data collection.

6.2.1 System Installation

(a) (b)

(c) (d)

Figure 6.1.: Installation of the animal detection system onto the VMS trailer and its deployment in the field are shown. (a) shows the VMS trailer in the field with the detection system installed. In (b), the VMS trailer is being set up in the field. (c) takes a closer look at the sensor head of the detection system installed onto the pole of the VMS trailer. Its components, from top to bottom, include: a black cap housing WiFi, GPS, and 4G antennas for communication; a white electrical junction box; an aluminium enclosure for the thermal camera; two RGB cameras (the left being the medium-angle camera and the right, the telephoto camera); and the solid-state LiDAR. (d) shows the edge computing and networking devices, as well as cabling in the control box. From left to right: the NVIDIA Orin computing unit; the QNAP network switch; and the Teltonika router.

The developed animal detection system was installed onto a VMS trailer with technical assistance from RoadTek. The sensor head was mounted on the mast of the trailer, at the back of the display board, as depicted in Figure 6.1c, while the network equipment and the edge computing components were installed in the white control box of the trailer, as Figure 6.1d shows. The system draws 12V DC power from the trailer's solar power system. After installation, the trailer was towed to the field for data collection and the subsequent on-road trial, as Figure 6.1a and Figure 6.1a illustrate. Note that, at the time of installation, the signal connection between the animal detection system and the VMS was not complete. However, this was resolved before the on-road trial began, as explained in Chapter 6.3.

6.2.2 Collection Locations

Figure 6.2.: The Google Earth image showing the bird's eye view of the field trial site in Kuranda, QLD. It highlights two locations, A and B, for the field data collection. The yellow polygon marks the frequent crossing area for cassowaries according to the field-collected data.

The system was first set up at Location A in late January 2024, as illustrated in Figure 6.1b and also in Figure 6.2, for the initial stage of field data collection. This is also the pilot stage where the actual cassowary crossing area is identified to provide insights for location optimisation.

Although there was no visual detection model trained for cassowary detection available at the beginning of the data collection stage, an instance of the YOLOv8 model pre-trained on the popular COCO dataset was running continuously for each of the four camera image channels to validate the computational capability of the edge computer in handling the four image processing pipelines in parallel. An example of the camera images with real-time detection results is illustrated in Figure 6.3.

There are technical and environmental challenges such as the solar power issue, weather influence, and the sensor occlusion problem, which are detailed in Section 6.5. The major limitation for sensing at Location A is the combination of visual occlusion caused by the red traffic signage and the hilly terrain of the road, and the heavy bias of crossing cases at a far distance. As Figure 6.4 shows, at a distance of 180 metres and over, the crossing cassowary

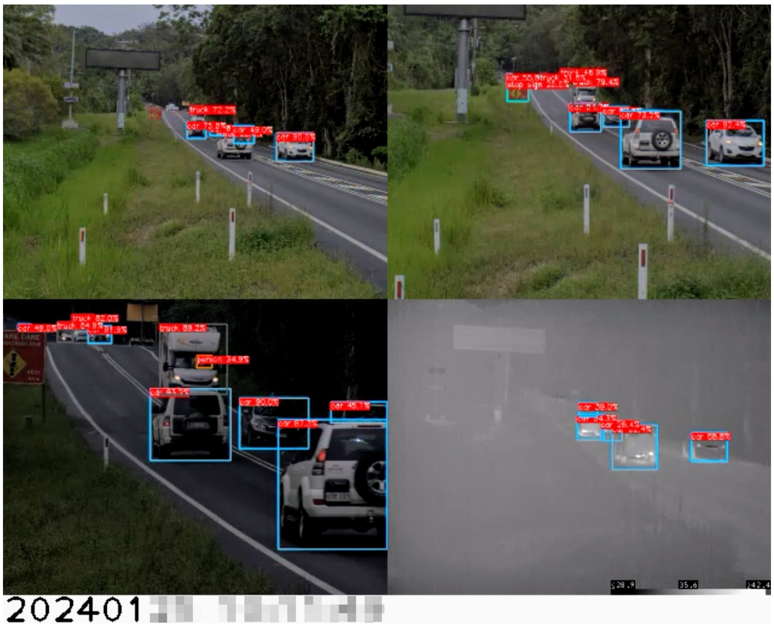


Figure 6.3.: A screenshot of the H.265 video recording shows example RGB and thermal camera images from Location A. Top left: RGB image from the medium-angle camera; Top right: digitally zoomed RGB image from the medium-angle camera; Bottom left: RGB image from the telephoto camera; Bottom right: image from the thermal camera. The timestamp of these images is shown at the bottom. Each image also has the overlay of bounding boxes of detected objects generated by its corresponding YOLOv8 detection model.

appears at a reasonable size only in the telephoto camera but is too small to be detectable by the medium-angle and thermal cameras. This causes a lack of range diversity in the crossing cases for testing the effectiveness of the cameras, which otherwise can cover short-, mid-, and long-ranges.

The data collected at Location A has helped formulate a guideline for finding a more optimal location for the next stage of data collection and the on-road trial. It should balance different considerations, including the optimal distance to the actual crossing area, minimal optical occlusion, maximum sunlight exposure, and terrain and safety constraints for deploying the LAARMA system. After analysing the recorded crossing cases, it was found that the vast majority of crossing cases occur in the area highlighted by the yellow polygon in Figure 6.2. With the above criteria taken into consideration, a more optimal location was proposed as the new location for data collection, which is Location B.

The VMS trailer, together with the detection system, was relocated to Location B in early March 2024. In the meantime, extra solar panels were connected to the VMS trailer's power system to alleviate the power issue.

As Figures 6.5 and 6.6 show, Location B has improved visibility of cassowaries crossing

Figure 6.4.: An example of a cassowary crossing case at a distance of 180 metres from Location A. (c) shows the cassowary on the road in the telephoto camera image. (a), (b), and (d) show the same cassowary in medium-angle, digital-zoomed, and thermal images, respectively. As the figures illustrate, the cassowary appears too small to be detectable in (a), (b), and (d).

at different ranges. Data collected at this location are richer in terms of range diversity and sensor modality, thus contributing more to the training and evaluation of the cassowary detection models. Also, with the increase in solar power capacity, the system managed to perform 24-hour continuous recording for most days before the trial commenced. This gave us an opportunity to monitor the cassowary crossing scenarios at night, if there were any.

Those technical and environmental challenges at Location A still existed at Location B. Some of them have improved, such as the solar power issue and the sensor occlusion problem. The sensor angle shift issue, however, remained severe at Location B. Please refer to Section 6.5.4 for details.

During the data collection, several findings related to the cassowary crossing were observed. Please refer to Section 7.2.1 for detailed statistics and data analysis results.

(a)

(b)

(c)

(d)

Figure 6.5.: An example of cassowary crossing case with a distance of 45 metres from the Location B. (a), (b), and (d) show the same cassowary in medium-angle, digital-zoomed, and thermal images, respectively. Earlier, the cassowary was in the view of the telephoto image. As the figures illustrate, the cassowary appears a good size to be detectable by YOLOv8 in all images.

6.3. On-Road Trial

The on-road trial started on 30 April 2024 at Location B. The trial required the readiness of the following four important components:

- A reasonably well-trained animal detection model. After many iterations of training using the collected field data, the trained detection model has shown excellent performance in the model evaluation. Two examples are provided in Figure 6.7. Despite still producing false positive detections, the model has the potential to be further improved by fine-tuning parameters and retraining with the false positive data.

- The signal interface between the animal detection system and the VMS for turning on

(a) (b) (c) (d)

Figure 6.6.: Another example of cassowary crossing case with a distance of 135 metres from the Location B. (a), (c), and (d) show the same cassowary in medium-angle, telephoto, and thermal images, respectively. (b) shows the view from the digital-zoomed image. As the figures illustrate, the cassowary appears a good size to be detectable by YOLOv8 in the telephoto image.

and off the message display. After a few site visits, RoadTek technicians managed to connect the digital output of the animal detection system with the VMS's designated digital input pin for controlling its message display.

- The developed message content. The QUT team provided message concepts for use in the on-road trial after the message development, concept testing, evaluation survey study, and the driving simulator study. The message content was loaded to the VMS, and the message screen duration was configured before the on-road trial started, as Figure 6.8 shows.

- The capability of monitoring driver behaviour as a response to the message. The driver behaviour data are mainly collected from traffic detection sensors, such as the pneumatic road tubes RoadTek installed at four locations before and after the VMS location prior to the on-road trial. Additionally, the data from the cassowary detection sensors can provide extra sensor modality for analysing driver behaviour.

(a) (b)

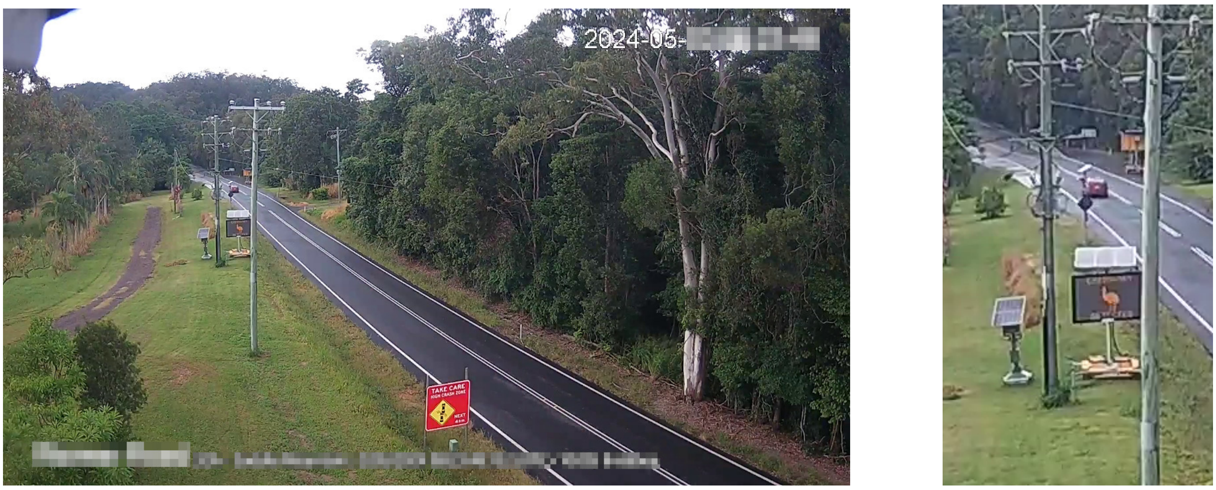
Figure 6.7.: Two examples of using a trained model for cassowary detection in image frames from (a) the telephoto camera and (b) the medium-angle camera.

(a) (b)

Figure 6.8.: The developed two-part message displayed on the VMS for notifying motorists the real-time cassowary detection event. Once triggered, the two parts, shown in (a) and (b), are looping for a variable period of time depending on how long the detection event persists before the display turns off.

The programmed logic for the VMS operated as follows:

- When the detector registers a cassowary, the sign is activated immediately, initiating a countdown of t seconds
- If the detector continues to detect the cassowary, the countdown resets to t seconds
- The sign deactivates t seconds after the last detection



(a) (b)

Figure 6.9.: A screenshot of the traffic camera recording confirms the VMS turned on as soon as a cassowary was detected in the scene. (a) shows the original screenshot, and (b) has the important area zoomed in for better visualisation.

In the field, cassowary detection can be intermittent due to factors such as distance, temporary occlusion by vehicles, or the cassowary moving out of the camera's FoV. The value of t is a design parameter. A longer t smooths out intermittent detections but may keep the VMS active longer than necessary. A shorter t provides a more real-time warning but results in more frequent sign activations and deactivations. For the on-road trial, t was set to 60 seconds.

The recording from a TMR traffic camera monitoring the on-road trial area was used to check the VMS status in correspondence with the triggering signal from the cassowary detection system. After checking the first two weeks of the on-road trial, it was found that in many cases the VMS was working as expected. One such case is shown in Figure 6.9. However, in the remaining cases, the VMS was not turned on despite the reception of the triggering signal from the detection system. It was later found that in those missed message display cases the VMS trailer did not have sufficient power to turn on the sign due to low battery voltage in the early mornings or on bad weather days. As discussed in detail in Section 6.5.1, the issue was mitigated after a RoadTek site visit on 14 May 2024, where the battery was charged up, and the LiDAR was disconnected from the detection system to cut the power consumption.

Those missed message display cases, if not properly identified, can affect the accuracy of the driver behaviour analysis. To address this, TMR conducted manual inspection in the recording from the traffic camera to verify the VMS status for each case.

6.4. Data Extraction and Usage

There are two data logging schemes implemented in the animal detection system—continuous data logging and event-triggered data logging—for different purposes.

The continuous logging operates as long as the system is running, providing low frame rate sensory data for 1) model training, validation, and testing using the proposed self-training pipeline, and 2) providing ground truth for system evaluation after human inspection. Along with the low frame rate sensory data, there are lightweight H.265 encoded videos of camera images for the convenience of previewing scenes of interest in the field without needing to extract the complete set of logged files from the system, thus saving on 4G data usage and transmission time. As a comparison, the H.265 video has a size of 1 MB per minute, which is only 2% of the size (55 MB per minute) of the low frame rate data.

The event-triggered logging provides full frame rate sensory data just before and after the cassowary detection events. With a size of around 500 MB per minute, the full frame rate sensory data are primarily for post-analysis of driver behaviour and event playback. They are not a required part of the self-training pipeline.

All the data are initially stored within the edge computer after being logged. Extracting the entire set of logged data off the edge computer incurs prohibitively high cost via the 4G network, and is not necessary either. Instead, only a small subset of collected data, for instance, less than 1.5% for this particular field data collection and trial, are of interest for training and evaluation purposes. They are selectively transferred to Amazon Web Services (AWS) through the 4G connection.

6.4.1 Selective Data Extraction and Iterative Model Update

With a detection model running in the system, the process of selective data extraction and iterative model update is summarised as follows:

- The timestamp of every animal detection event is recorded. The corresponding raw data files (low and full frame rate data) are first tagged, and uploaded to the AWS cloud later.
- The raw data files are downloaded, and the low frame rate data are fed into the self-training pipeline for auto-labelling. The labelled data are then used for model retraining, validation, and testing.

- The retrained model is deployed to the detection system, and the above steps repeat.

As one can see, an initial detection model is required to kick off the above iterative process. There are different ways an initial detection model can be produced:

- The initial model is trained using the pseudo-labelled field data.
- The initial model is trained using only synthetic data. With the field data available after the first iteration, the model is retrained using the combination of synthetic data and field data.

Both methods have been experimented with at different points during the data collection stage. The synthetic data method is more preferable as it can start without the availability of any field data and requires less manual intervention.

The field data collected during this process contains both true and false positive detection cases. Both types are useful for model training in the self-training pipeline. Nevertheless, false negative cases are not captured in this process, as a model is never capable of detecting cases that it will miss. Arguably, true and false positive cases are considered sufficient for model training, given that the data amount and diversity are not compromised by the absence of false negatives. Also, it is recommended to set a low detection threshold for the detection model during the data collection phase, which brings two benefits: 1) reducing the occurrence of false negative cases, and 2) exposing more false positive cases, which then contribute to the model training.

Figure 6.10.: The images illustrate the effectiveness of our pipeline on thermal imagery. Initially pre-trained on RGB images, the model has successfully adapted to process thermal images.

The iterative update of the trained models resulted in improved detection performance over time during the field trial. Additionally, we tested the model's capability to adapt to different domains by assessing its performance on thermal images, validating the robustness of our self-training pipeline across varying data types. Two examples are presented in Figure 6.10. Detailed evaluation results are presented in Section 7.2.2.

6.4.2 Selective Data Extraction for Manual Inspection

The above process covers both the true positive and false positive cases. However, it won't be able to include false negative cases regardless of how well the detection model works. All types of cases—true and false positive, and false negative cases—are required for system performance evaluation. To identify false negative cases, manual inspection of the raw sensory data is required. The process of selective data extraction for manual inspection is summarised as follows.

- All of the H.265 videos are automatically uploaded to the AWS cloud. They are then downloaded for manual inspection, creating a list of animal sightings as ground truth, along with other scenes of interest.
- Only sensory data of the listed scenes are then uploaded to the AWS cloud. They are then downloaded and processed to be used for performance evaluation. Optionally, the data can be added to the training dataset to help model training.

Manual data inspection, admittedly, is a time-consuming and labour-intensive process, but it is a common way to generate ground truth, and is only required for the purpose of performance evaluation. Since the H.265 videos are recorded at a rate of 1 frame per second, skimming through a one-hour long video takes as little as 2 minutes. There is a software tool developed to facilitate the inspection, with features such as play, pause, next frame, previous frame, fast forward, fast rewind, zoom in, and zoom out. It also supports a shortcut key to log the timestamps of interesting events.

6.5. Challenges

6.5.1 Solar Power Issue

Soon after the field data collection started, it was found that the solar power system that came with the VMS trailer was not capable of continuously powering the VMS itself and the attached animal detection system. As soon as the issue emerged, three software measures were applied to reduce the power consumption in an attempt to mitigate the issue:

- Fine-tune the CPU and GPU clocks on the edge computer, which saves about 7 W during the daytime.
- Run the detection system with all sensors streaming except for the LiDAR sensor during the daytime. This saves an unknown amount of power on the LiDAR side, which cannot be measured remotely.
- Put the detection system into idle mode during the night, i.e., not running the sensor drivers and detection algorithms. This saves an extra 15 W on the edge computer side during the night. It should also save some power on the LiDAR side, which cannot be measured remotely.

Additionally, the VMS trailer's battery voltage started to be monitored continuously by the edge computer to help track the power situation over the remaining course of data collection and throughout the on-road trial. These power-saving measures helped but still couldn't prevent the system from running into a situation where power cutouts happened almost daily during the early hours of the day, with power being restored when the battery voltage improved around the middle of the morning. This heavily affected data collection during the power cutout periods, especially the morning sessions.

In the meantime, TMR was sourcing extra solar power for the VMS trailer. On 6 March 2024, when the VMS trailer was relocated from Location A to B, a solar light tower was connected to the VMS trailer to provide extra solar power. Since then, the power situation has significantly improved. The detection system managed to operate 24/7 with all sensors active for most of the days before the trial started. Yet, despite only a few cases of power cutout happening due to bad weather, the battery voltage stayed on the low side for the majority of the time. When the battery voltage was found very low, some power-saving measures were reinstated to preserve energy.

The power issue garnered attention again at the beginning of the on-road trial, mainly for two reasons. First, the overall power consumption increased in the on-road trial compared with that during data collection, because the VMS was not yet electrically connected during the data collection phase. Secondly, it was found that there is a higher voltage requirement for turning on the VMS than for running the detection system. This causes an issue where the VMS may not have enough power to turn on when needed due to insufficient battery voltage. This affected the trial not just in the early morning but also on rainy days or even cloudy days. Those existing power-saving measures were exercised but were found insufficient to improve the battery voltage fast enough. There was a power cutoff event on the night of 9 May 2024, and the power was restored the next morning.

To mitigate this power issue, TMR arranged a site visit on 14 May 2024 to conduct three tasks:

- Checking the solar charging systems to make sure they work as expected
- Improving the battery voltage by charging it up using a generator
- Disconnecting the power supply of the LiDAR, which saves at least 20 W. Removing the LiDAR from the sensor suite does not affect the cassowary detection because it was not the primary sensor for this task. This, however, does pose challenges to the collection of LiDAR data for the subsequent driver behaviour analysis.

Additionally, a CCTV camera on the VMS trailer was found operating and consuming power. It was disconnected to save some power. After the site visit, the battery voltage was significantly improved, and it was confirmed later by tracking the battery voltage that the overall power consumption had dropped.

6.5.2 Sensor Occlusion

The detection system faces sensor occlusion issues caused by environmental and traffic factors when set up at either Location A or Location B. The issue is found particularly severe at Location A, where the causes of occlusion include the red traffic warning signage, the hilly terrain, and vehicles on the road. Examples of sensor occlusion are presented in Figure 6.11. The occlusion brings a detrimental effect on the quality of data collected at the location for model training and evaluation. Additionally, it poses extra challenges for the trained model to operate effectively at this location, particularly given the distance of 180 metres and over from the frequent crossing area.

The occlusion situation has significantly improved since relocating the system to Location B. As Figure 6.12 shows, the environmental factors, for instance, a traffic pole or the bush, still exist but are not considered the primary cause, as was the case at Location A. At the new location, traffic becomes the major factor for sensor occlusion, which causes the system to detect the cassowary late and delay triggering the VMS in some crossing cases.

(d) (e) (f)

Figure 6.11.: Sensor occlusion examples at Location A. (a) - (f) illustrate cases with different severity levels of sensor occlusion caused by environmental and traffic factors, such as the red warning signage, the hilly terrain, and vehicles. When the cassowary is crossing from left to right, the occlusion caused by the warning signage eliminates the advantage of detecting the animal early on, before it crosses the road. As (d) and (e) show, the partial occlusion caused by the hilly terrain for distant cassowaries presents challenges for the cassowary detector. Lastly, vehicles on the road also cause temporary occlusion for the cassowaries, as (c) and (f) illustrate. In (f), a cassowary was heavily occluded by both the signage and the red car.

The sensor occlusion caused by the traffic can be alleviated by installing the sensor head at an elevated point on the roadside. For this particular field trial, however, the height of system installation is constrained by the VMS trailer. Another solution is to install multiple sensor heads in the field to jointly monitor the crossing area from different perspectives. In this case, the sensor heads complement one another, reducing the chance of sensor occlusion.

6.5.3 Weather Influence

During the data collection and on-road trial, weather is an important factor influencing the performance of the detector. In bad weather, as shown in Figure 6.13, the images captured are blurry and distorted due to raindrops on the camera lenses, posing challenges for the cassowary detection. There are two potential solutions worth investigating to improve the system's robustness against rainy weather and mitigate this issue:

- Adding lens hoods to the cameras to keep the lens free from raindrops

(a) (b)

Figure 6.12.: Sensor occlusion examples at Location B. In (a), a cassowary was temporarily occluded when it walked behind a traffic pole and bush. In (b), a cassowary was occluded by the heavy traffic for more than 10 seconds when crossing the road.

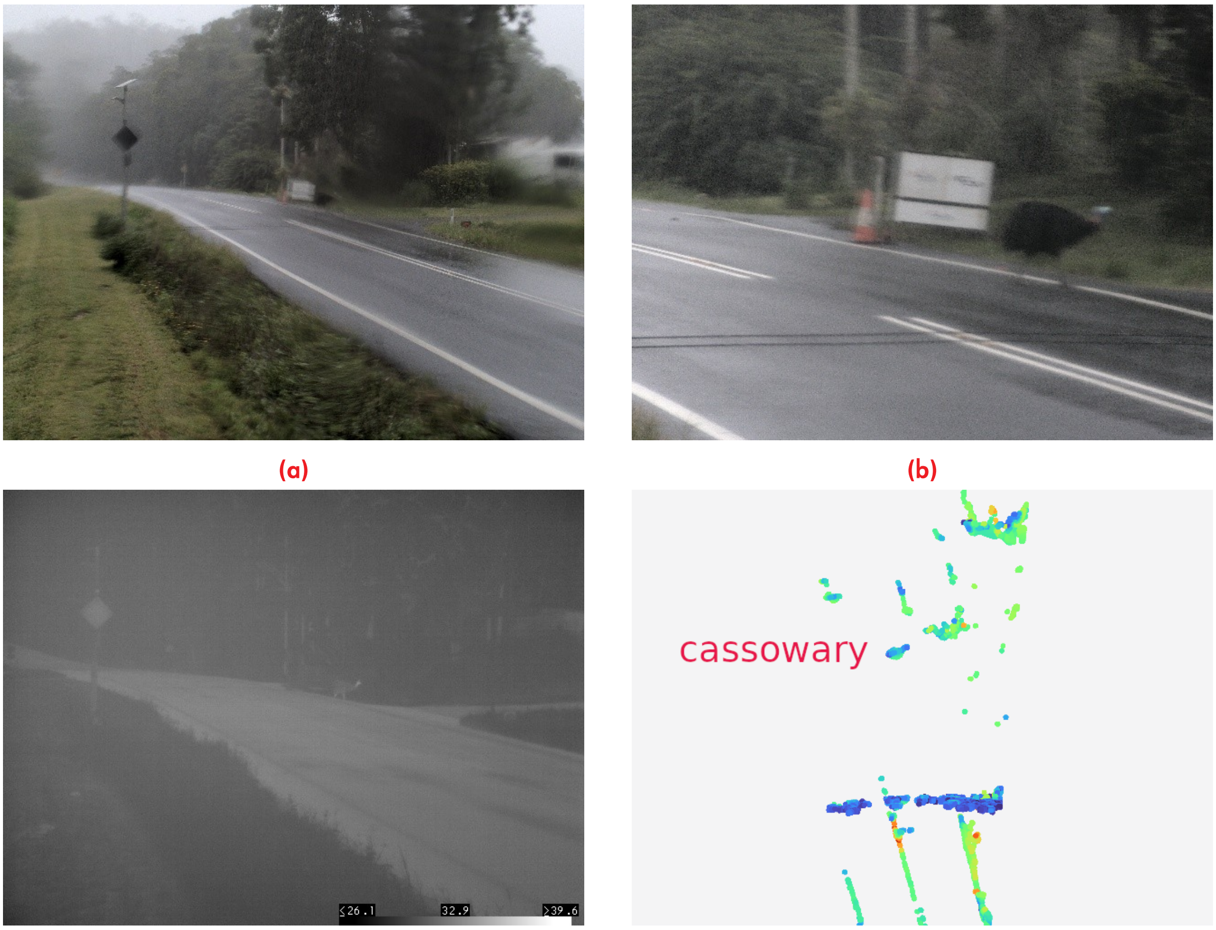
- Fusing RGB imaging with other sensor modalities, such as thermal and LiDAR, as Figures 6.13c and 6.13d demonstrate.

Additionally, sunny weather also poses challenges for detection due to shadows and high lighting contrast on the road surface or in the bush, which can be misclassified as cassowaries, causing false positive detections. Two examples are presented in Figure 6.14. To rectify this issue, the false positive data were collected and incorporated into the model training to reduce this occurrence of such errors.

6.5.4 Sensor Angle Shift

As mentioned in Section 6.2.1, the sensor head was installed on the mast of the VMS trailer. Over time, the sensor head was found to slowly shift to the right (i.e., towards the road) for unclear reasons. Hypotheses include the inherent mechanical properties of the mast, the sinking of some of the VMS trailer's legs into the soil, and the influence of the wind. Figure 6.15 illustrates the angle shift of the telephoto camera over one week. Despite several corrective efforts by TMR and RoadTek during site visits, the issue has persisted.

This shifting issue has resulted in late detection of cassowaries at distances over 100 m. When the sensor is pointing at the desired angle, as shown in Figure 6.15a, the system is capable of detecting the cassowaries on the left roadside, allowing it to provide motorists with several seconds of warning time before the cassowaries start crossing the road. After the sensor angle shifts, however, the system cannot detect the crossing cassowaries until



(a) (b) (c) (d)

Figure 6.13.: Raindrops on camera lenses during rainy weather cause blurry and distorted images, presenting challenges for cassowary detection. (a) and (b) present images from the RGB cameras. (c) shows the thermal image. The LiDAR point cloud from a bird's-eye view is shown in (d), where the LiDAR points from the cassowary are clearly visible.

seconds after they have started crossing from left to right, as Figure 6.15b illustrates. This leads to late detection and delayed triggering of the VMS, compromising the road safety outcome of the detection system. The angle shift has also caused a few missed detection cases where cassowaries were on the left roadside, attempting to cross the road. They were not detected because they were out of the telephoto camera's field-of-view after the angle shift.

In addition to manually correcting the sensor angle periodically, a software solution has been implemented to compensate for the angle shift of the telephoto camera by introducing a new digitally-zoomed image channel from the wide-angle camera, which aims at the desired direction. This is considered a temporary solution; having the telephoto camera pointing at the desired angle is still the preferred approach.

(a) (b)

Figure 6.14.: The shadows and high lighting contrast in a sunny day can cause false positive detections.

(a) (b)

Figure 6.15.: The sensor angle shift over the period of one week.

6.6. Conclusions

The field trial in FNQ has demonstrated the effectiveness and robustness of the developed large animal-activated roadside monitoring and alert system in a real-world traffic environment. The field data collection, on-road trial, and the self-training machine learning pipeline have provided valuable insights into the system performance and areas for further improvement. Key conclusions from the trial are summarised as follows.

First, the data collection at two locations allowed for the collection of a diverse dataset. Despite challenges such as sensor occlusion and power issues, the collected data played an important role in the self-training machine learning pipeline. The on-road trial validated the system's capability to detect the cassowaries and trigger alert messages on the VMS for motorists.

Besides, the self-training machine learning pipeline, which combines cloud and edge computing technologies, proved to be a robust method for continuous model improvement. The field trial demonstrated that using synthetic data for initial training and auto-labelling with a VLM is effective in overcoming the data scarcity problem and improving the model performance. Quantitative evaluation results are presented and discussed in Chapter 7.

7

Data Analysis

7.1. Introduction

This chapter provides insights into and outcomes of two essential components of the field trial; namely, the developed animal detection system, discussed in Section 7.2, and the evaluation of the LAARMA system's impact on actual on-road driver behaviour. The latter is covered in Section 7.3, and is based on the field trial conducted as the final study within the LAARMA project at a site based in FNQ.

7.2. Animal Detection System Analysis (USYD)

7.2.1 Field Data Analysis

The developed animal detection system was set up at Location A and subsequently relocated to Location B in Kuranda, QLD. Please refer to Section 6.2.2 for details about these locations. Compared to Location A, Location B was chosen as a more optimal location for data collection and the on-road trial. The field data collected from 8 March to 30 June 2024 at Location B are more complete and of higher quality, and thus are used for analysis in this section.

In this document, a cassowary sighting case is defined as the observation of one or more cassowaries on the road or either roadside, reported either manually or automatically by the detection model, in the deployed system's camera images in the field. Note that in some sighting cases, the cassowary attempted to cross the road or remained on the roadside without actually crossing the road. From the road safety perspective, these cases are equally important to those where the cassowary did cross the road, as the possibility of crossing at any time exists.

According to the recorded data, there were 287 cassowary sightings over a total 115 days from 8 March to 30 June 2024, resulting in an average of 2.5 cases per day. The overall cassowary sightings over these dates are illustrated in Figure 7.1. Note that there was an interruption in system operation from 17 April to 19 April 2024, causing there to be no data available for these three days. This was due to an electrician unintentionally leaving the system power off after a site visit. It is also noteworthy that despite the system running, there were no sightings for a period of up to two weeks in June, specifically, from 12 June to 23 June 2024, as revealed in Figure 7.1. In addition, out of the total 287 sighting cases, 238 involve a single cassowary, while 49 have two cassowaries sighted in the scene.

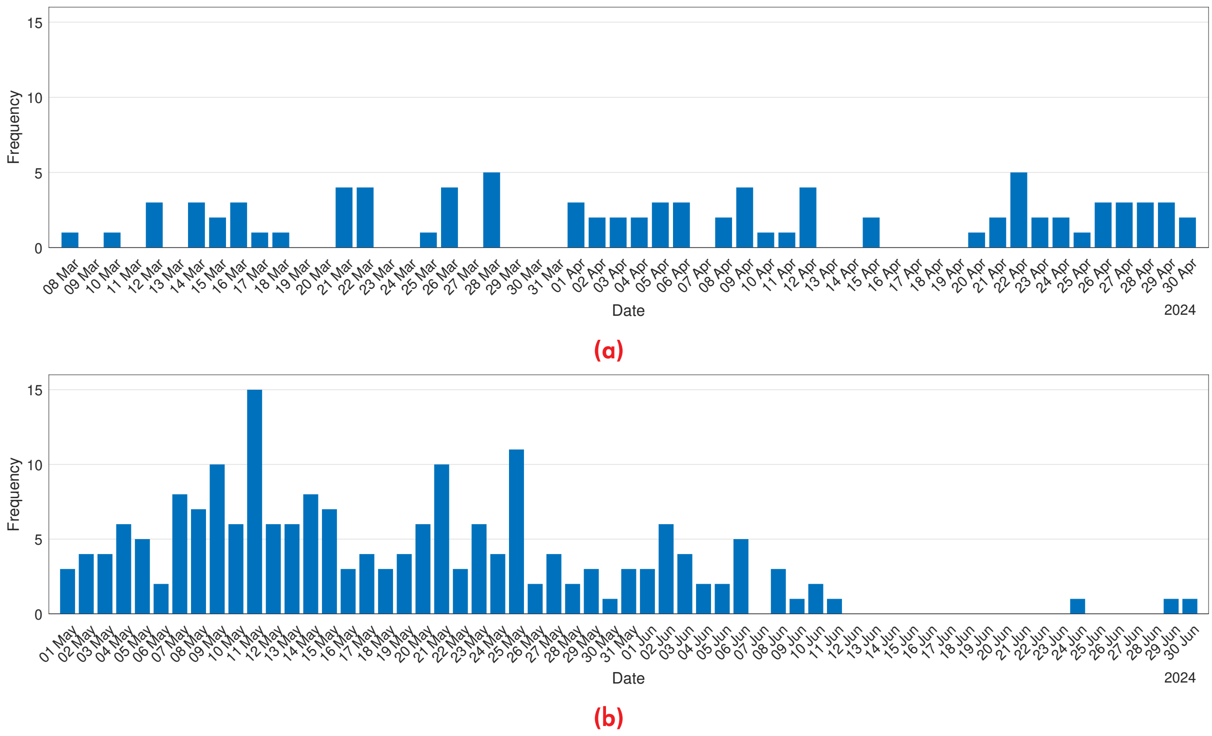


Figure 7.1.: Cassowary sightings distribution over dates. The highest number, 15, was recorded on 11 May 2024. Note that there is no data available from 17 April to 19 April 2024, during which the system was not running.

The sightings were obtained by manual inspection of recorded videos before the first detection model was deployed on 22 March 2024. Afterwards, the sightings were first reported by the detection models, before being manually verified in the recorded videos. Although the vast majority of sightings were reported by the detection models, manual inspection was still used as an important measure to identify a few true cases missed out by the model, i.e., the false negative (FN) cases. The produced cassowary sighting dataset plays an important role as the ground truth in subsequent detection model and system performance evaluations. The dataset also can be used by wildlife conservation community to study cassowary behaviours. It should be emphasised that manual data inspection in this project is solely for performance evaluation purposes. No manual data labelling is required for the developed self-training machine learning pipeline.

From Figure 7.1, it can be seen that the sightings varied each month from March to June. To gain more insights into monthly cassowary activities, Figure 7.2 summarises the sightings for each month over these four months. It is observed that the sightings increased significantly from March to May, peaking at 166 cases in May, before a steep drop in June. The on-road trial period covers May and June, which correspond to the busiest and the quietest months, respectively, among all four months.

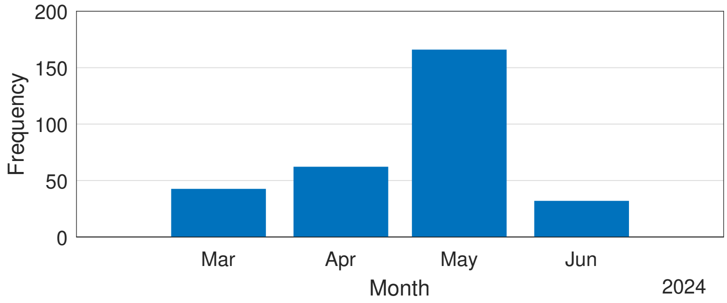


Figure 7.2.: Cassowary sightings from March to June 2024. Note that the figure shows projected results for March and April, considering that there are 24 days of data collected in March, and there are 3 days in April without data available.

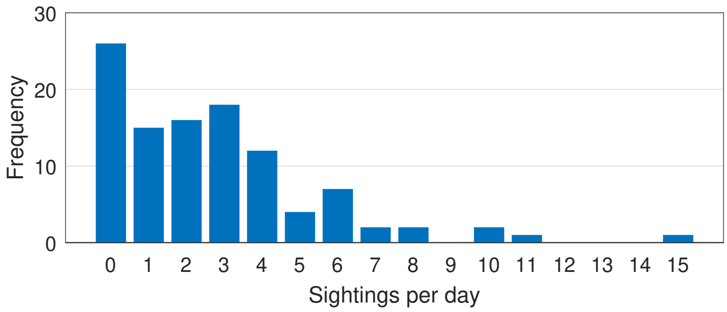


Figure 7.3.: The histogram of cassowary sightings per day.

Figure 7.3 presents a histogram showing the distribution of cassowary sightings per day. This histogram suggests that while there are many days with no sightings at all, a small number of sightings per day is quite common, and very high numbers of sightings per day are rare. Specifically, the number of sightings per day ranges from 0 to 15. Most of the data fall within the range of 0 to 6 per day. The most frequent number of sightings per day is 0, with a count of 26 days. There are only 4 days with sightings greater than 10 per day.

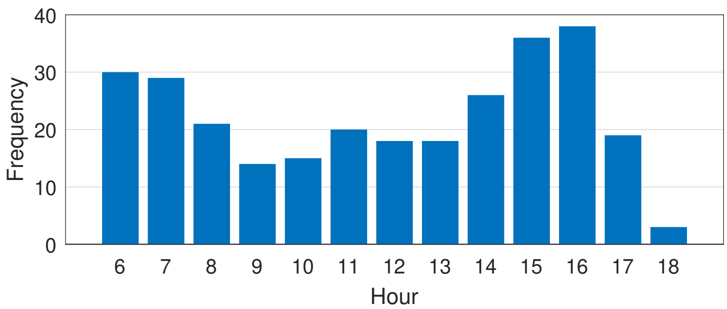


Figure 7.4.: The histogram of cassowary sightings over hours of a day. Note that the number for 6am is under-reported due to data unavailable for this slot for 14 days in March.

With the timestamps recorded for each sighting case, it is also insightful to analyse which hours of a day the cassowaries appeared most frequently from the data. As Figure 7.4

demonstrates, the 4pm and 5pm time slots have the highest numbers of cassowary sightings. They are followed by the 6am and 7am slots. Note that for the first two weeks after the relocation in March, the system started running from 7am. This causes the number at 6am to be under-reported due to the absence of data recorded during the 6am slot for these two weeks.

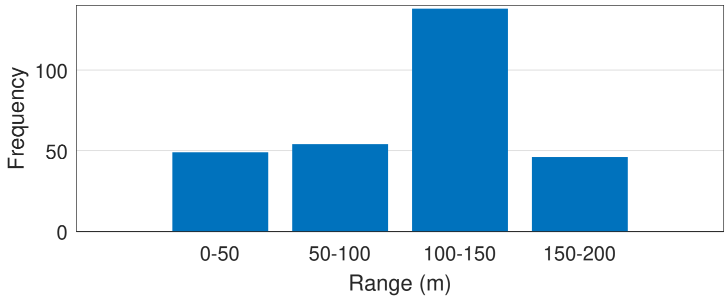


Figure 7.5.: The histogram of ranges for cassowary sightings.

Lastly, the range of the cassowary in the scene was estimated for each sighting case. The estimated range was obtained from LiDAR data when available, or through RGB images using salient environment features as references. Based on the range information, Figure 7.5 presents a histogram showing the distribution of sighting ranges from 0 to 200m. The figure clearly shows that the highest number of sightings, totalling 138 cases, occurred within the 100 to 150m range. In comparison, each of the remaining range groups has approximately 50 cases.

7.2.2 Detection Performance Evaluation

7.2.2.A. Model Evaluation

The field-collected data are split into training data and evaluation data. The training data were used for training the cassowary detection models. There are in total 10 models trained during the data collection and on-road trial periods, using data available up to different dates. Most of the model training work occurred during the data collection period, i.e., March and April, in preparation for the subsequent on-road trial. For a fair comparison, their performance is assessed using the same evaluation dataset in this section. The evaluation dataset consists of two parts:

- The true positive (TP) part contains 4577 images (3127 RGB + 1450 thermal) containing cassowaries from all cameras over 38 cassowary sighting cases. Specifically, there are 16 cases from March, 17 from April, 3 from June, and 2 from July. All images are labelled with bounding boxes around cassowaries. Each sighting case is labelled with the estimated range for evaluating the model performance in detecting cassowaries at different distances. There are 15 cases within the range of 0-100m, and 23 cases within the 100-200m range.

- The false positive (FP) part contains 11975 images (9166 RGB + 2809 thermal) without cassowaries from all cameras over 34 FP cases from March to July. There is no range information for this part because the images do not contain cassowaries.

This evaluation dataset does not include cases from May because all data in May have been used for training the model M240618. Two metrics are employed to evaluate the model performance, True Positive Rate (TPR), and False Positive Rate (FPR), which are calculated based on the number of occurrences of true negatives (TN), FP, FN, and TP. Specifically,

$$TPR = \frac{TP}{TP + FN}$$
$$FPR = \frac{FP}{FP + TN}$$

According to the above equations, the TPR represents the proportion of images where a model correctly detects a cassowary out of all the images where cassowaries are actually present. The FPR, on the other hand, is the proportion of images where a model incorrectly identifies a cassowary, divided by all images where cassowaries are not present. To put it simply, TPR measures how well the model correctly detects cassowaries, while FPR measures how often the model makes mistakes by falsely identifying something else as a cassowary. A perfect model would achieve a TPR of 100% and an FPR of zero.

The TPR evaluation results for the trained detection models are presented in Table 7.1. To evaluate the performance of models intended for field deployment, we focus on how each model performs in individual sighting cases. Therefore, the TPR is first calculated for each of the 38 sighting cases in the evaluation dataset. These case-specific TPR values are then averaged for all cases within each range group to obtain the mean TPR, thus mitigating the bias from cases containing more images than others. The FPR results are calculated based on all RGB images contained in the FP part of the evaluation dataset.

Generally, given a model, both TPR and FPR vary depending on the confidence threshold used during the model inference. A lower confidence threshold results in a higher TPR, but the FPR increases in the meantime. A higher FPR causes lower precision of the model in detecting targets. Thus, instead of using a fixed confidence threshold across all models, an

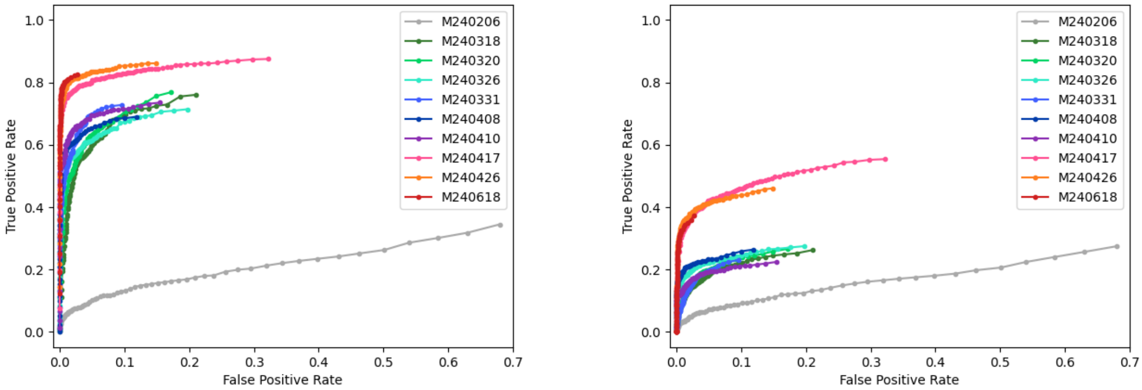
Model Name	Mean TPR (0-100m)	Mean TPR (100-200m)	FPR
M240206	4.2%	2.6%	0.37%
M240318	19.4%	10.6%	0.39%
M240320	32.3%	6.9%	0.37%
M240326	45.3%	14.7%	0.38%
M240331	45.8%	6.4%	0.39%
M240408	54.5%	17.1%	0.37%
M240410	53.6%	11.8%	0.38%
M240417	71.3%	25.7%	0.37%
M240426	73.7%	29.9%	0.35%
M240618	78.5%	30.0%	0.37%

Table 7.1.: The evaluation results of 10 trained detection models. The models are listed following a chronological order of their dates of training. For each model, the TPR results are first calculated for RGB frames in every sighting case in the evaluation dataset, and then averaged over all cases in each range group. The FPR results are calculated based on all RGB frames combined in the FP part of the dataset.

FPR cut-off threshold of 0.4% is employed to ensure that all the models are evaluated fairly. This approach is essentially to ask the question, "What is the best TPR a model can achieve without exceeding an given FPR limit?"

The mean TPR results in Table 7.1 show a clear trend that models trained at a later date have higher mean TPR values, primarily because of more field data used for training. Also, as expected, the mean TPR for the 0-100m range is higher than that for the 100-200m range across all models due to the closer distance. The worst performing model is the earliest one, M240206, which was trained using synthetic data only. The best-performing models are M240426 and M240618. The model M240426, trained with data collected in March and April, was used throughout the on-road trial period. Compared with earlier models, the model M240618 was trained with the largest dataset, spanning from March to early June. It achieves the highest mean TPR in both the 0-100m and 100-200m ranges. However, this model was not deployed in the field as it was close to the end of on-road trial. Nevertheless, its results are significant in validating the developed self-training machine learning pipeline.

In addition, a collection of Receiver Operating Characteristic (ROC) curves are presented in Figure 7.6 to summarise the performance for different models and ranges. A curve that



(a) 0-100m

(b) 100-200m

Figure 7.6.: Receiver Operating Characteristic (ROC) curves for different models and ranges on RGB images. A curve closer to the top left corner indicates better performance, characterised by a higher TPR and lower FPR.

bows towards the top left corner indicates better performance, as it shows a high TPR and low FPR. It is clearly seen that the overall performance of the models M240618, M240426, and M240417 are close, and are significantly better than that of others.

It is important to note that both TPR and FPR results in Table 7.1 and Figure 7.6 are obtained based on this specific evaluation dataset. The model's FPR in this context does not directly translate to the actual system's FPR when operating in the field. There are other factors influencing the system-level performance. For instance, a Bayesian filter is employed after the image detection to filter out spikes in FP detections. This is the main reason we present the system-level performance results in Section 7.2.3 in addition to the model performance results.

7.2.2.B. Sensor Modality Evaluation

RGB Cameras

More in-depth and comprehensive evaluation results of the trained models are presented in Table 7.2, for different cameras and ranges. From Table 7.2, it is clearly seen that overall the best performing models are M240618 and M240426, aligned with the conclusion from the model evaluation section.

The performance of different RGB cameras varies significantly across different ranges. First, it is evident that each camera performs better in the 0-100m range than in the 100-200m

Model Name	Medium-Angle Cam		Digital-Zoomed Cam		Telephoto Cam	
	0-100m	100-200m	0-100m	100-200m	0-100m	100-200m
M240206	9.4%	0%	0.5%	2.2%	0%	8.2%
M240318	19.9%	0%	25.9%	5.8%	10.6%	20.3%
M240320	23.2%	0%	45.2%	6.9%	31.7%	19.9%
M240326	40.8%	0%	48.3%	18.2%	49.1%	35.7%
M240331	30.9%	0%	57.5%	5.9%	56.1%	19.5%
M240408	48.3%	0.1%	63.0%	22.1%	54.6%	39.6%
M240410	44.9%	0.1%	62.6%	11.3%	57.2%	35.3%
M240417	62.3%	0.9%	77.5%	36.1%	78.6%	52.1%
M240426	67.8%	2.0%	77.3%	43.5%	79.0%	56.1%
M240618	69.4%	2.2%	84.5%	44.6%	86.5%	53.9%

Table 7.2.: The mean TPR results for different RGB cameras, models, and ranges.

range, which is expected due to a higher pixel density of cassowaries at closer distances. The medium-angle camera, in particular, only performs well for the 0-100m range.

When comparing the cameras across both the 0-100m and 100-200m ranges, the telephoto camera performs the best, followed by the digital-zoomed camera and the medium-angle camera. The superior performance of the telephoto camera is attributed to its narrower FoV compared to the other two, which concentrates more pixels on the target.

In the 0-100m range, the performance of the telephoto camera is only slightly better than that of the digital-zoomed camera. However, at the 100-200m range, the telephoto camera outperforms the digital-zoomed camera by a larger margin. It also has the potential of using lenses with even higher optical zoom, making it more suitable for scenarios requiring longer range detection. However, its narrower FoV results in a shorter detection window for cassowaries within its view. Covering a wider crossing area in the field would require the use of multiple telephoto cameras, leading to a higher hardware cost.

The digital-zoomed camera, which operates as a virtual camera by cropping images from the medium-angle camera, offers flexibility in changing direction digitally and can have multiple instances covering a wider area without additional hardware costs, despite its inferior performance to that of the telephoto camera. However, its digital zooming capability is con-

Camera Type	Pros	Cons	Recommended Use Case
Medium-Angle Cam	Wider FoV for a longer detection window	Degraded performance for longer ranges	Shorter-range animal detection
Digital-Zoomed Cam	Flexible angle and FoV without extra cost on top of the medium-angle cam	Zooming capability constrained by camera's native resolution	Mid-range animal detection
Telephoto Cam	Good detection performance over longer ranges	Narrower FoV causing a shorter detection window, and a higher cost to cover a wide monitoring area	Longer-range animal detection

Table 7.3.: Comparison of different RGB camera types.

Model Name	Mean TPR (0-100m)	Mean TPR (100-200m)	FPR
TM240520	15.8%	0%	0.46%
TM240523	34.9%	0%	0.46%
TM240626	44.5%	0%	0.49%

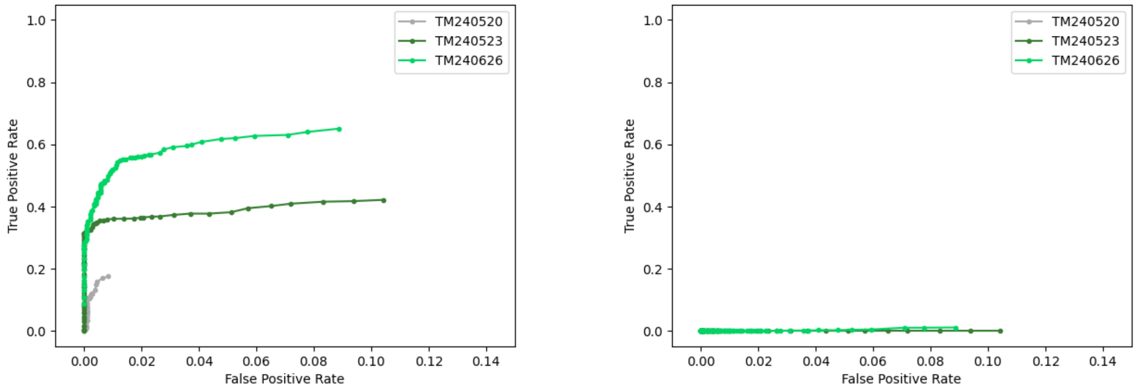
Table 7.4.: The evaluation results of 3 trained detection models for thermal imaging. The models are listed following a chronological order of their dates of training. For each model, the TPR results are first calculated for thermal frames in every sighting case in the evaluation dataset, and then averaged over all cases in each range group. The FPR results are calculated based on all thermal frames combined in the FP part of the dataset.

strained by the native resolution of the medium-angle camera, limiting its maximum detection range.

Lastly, the strengths and limitations of different RGB cameras as per the above discussion are summarised in Table 7.3. It provides a general guideline for choosing the suitable sensor configuration when deploying the system at a new animal crossing site.

Thermal Camera and LiDAR

There are three thermal models trained for detecting cassowaries on thermal images. Their performance evaluation results are presented in Table 7.4 and also compared in Figure 7.7. In Table 7.4, an FPR cut-off threshold of 0.5% is employed to ensure a fair comparison. As



(a) 0-100m

(b) 100-200m

Figure 7.7.: ROC curves for the thermal camera over different models and ranges.

the results show, the model TM240626 is the top-performing model among all three models. However, all the models can only detect cassowaries within the 0-100m range. This is due to the low resolution of the particular thermal camera model used in the project. While the thermal camera excels in showing warm-blooded animal activities than RGB cameras, in particular under low light and nighttime conditions, it lacks the pixel density required for animal classification tasks beyond 100m, and it has a higher cost compared with RGB cameras. In the future work, other sensing strategies, such as dynamic object tracking, could be considered to improve thermal camera's performance at longer ranges.

The sensor suite of the detection system also includes a solid-state LiDAR. With a horizontal FoV as narrow as 15°, this LiDAR can produce denser point clouds on animals compared with mechanically scanning LiDARs that distribute their points over 360°. However, there are two technical challenges in using this LiDAR for animal detection during the field trial. The first one is that attributed to its narrow FoV, the LiDAR suffered from the same sensor angle shift issue observed with the telephoto camera, as detailed in Section 6.5.4. The issue prevented the LiDAR from pointing at the optimal angle for detecting cassowaries. The second one is related to the solar power, as discussed in Section 6.5.1 in the Field Trial report. The LiDAR was disconnected from the system on 14 May 2024 to conserve power for the rest of the system. Due to these challenges, the potential use of LiDAR data for cassowary detection has not been well investigated in this project. Despite these difficulties, there are LiDAR data recorded during part of the field trial period, which can be used for analysing interactions between vehicles and cassowaries.

7.2.3 System Evaluation

The model evaluation results discussed in Section 7.2.2 do not fully reflect the overall detection system performance. The system's detection events are initiated by the event-triggering pipeline running on the edge computer, which aggregates the Bayesian-filtered results from multiple instances of YOLOv8 object detector across different cameras. Therefore, the performance of the detection system based on the model M240426 is evaluated based on detection events recorded during the on-road trial, spanning from 30 April to 30 June 2024.

Over the 62 days of trial period, a total of 259 events were reported by the detection system. Each event has been checked against the ground truth data, as described in Section 7.2.1, to classify them as TP, FN, and FP detection events. The distribution of different types of detection events over the trial dates is presented in Figure 7.8. The total and average numbers for each event type are summarised in Table 7.5, which highlights that the system missed as few as 6 cassowary cases during the trial period. These FN events were identified through manual inspection of the recorded data. It is found that 4 of them were caused by the sensor angle shift issue of the telephoto camera.

Precision and recall are employed as the performance metrics for the detection system evaluation, calculated as

$$Precision = \frac{TP}{TP + FP}$$
$$Recall = \frac{TP}{TP + FN}$$

Based on the summarised events, the precision and recall for the system during the on-road trial are 0.77 and 0.97, respectively. This means 77% of the events the system triggered involved cassowaries, and the system accurately triggered for 97% of the events where cassowaries were present. The exceptionally high recall demonstrates the system's high sensitivity in detecting cassowaries crossing the road or on the roadsides, a critical aspect for road safety-related use cases.

As Table 7.5 also presents, the system reported on average less than one FP event per day. This level of average FP result is reasonable, considering that the deployed detection model examines 1.4 million RGB images from 6am to 7pm each day.

A histogram of the FP events per day is presented in Figure 7.9. It is demonstrated that the vast majority of days have three or fewer FP events per day. There are only two days

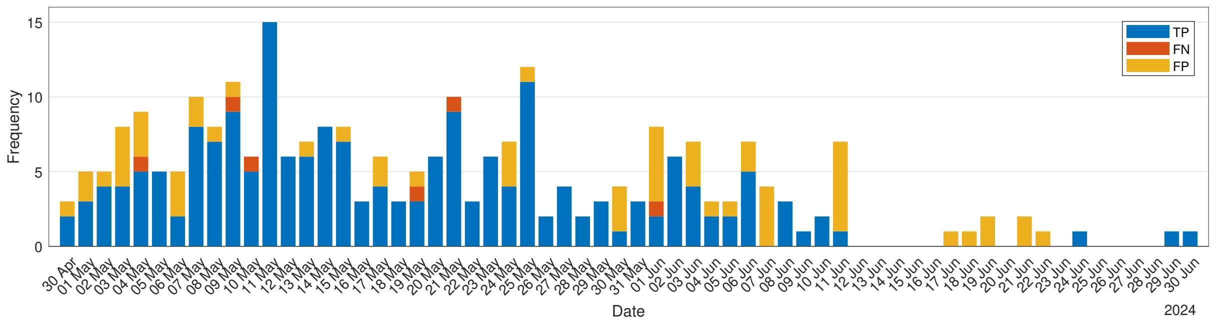


Figure 7.8.: The distribution of cassowary detection events over dates.

	TP	FN	FP
Total	194	6	59
Average (per day)	3.13	0.10	0.95

Table 7.5.: A summary of detection events during the 62-day on-road trial.

with four FP events, and one day each with five and six FP events. The causes of the FP events primarily fall into a few categories, including vehicles, persons, vegetation, animals, and shadow. Many FP events were caused by the same objects over a short period of time. A summary of how many cases for each type of causes are illustrated in Figure 7.10.

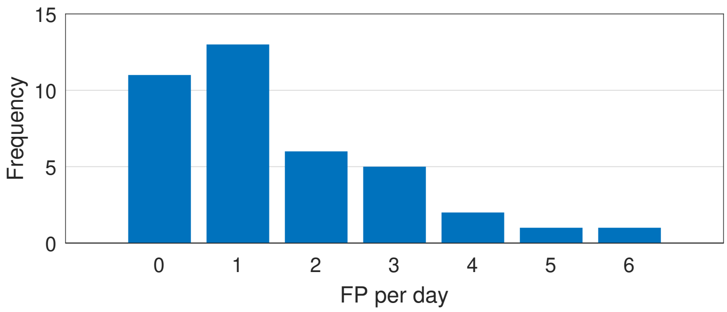


Figure 7.9.: The histogram of FP events per day during the on-road trial.

The occurrence of FP events can be reduced by incorporating similar FP cases into the model training. For instance, the model M240618 was trained using a dataset containing more recent data compared to the model used during the on-road trial period and has shown improved overall performance, as discussed in Section 7.2.2.

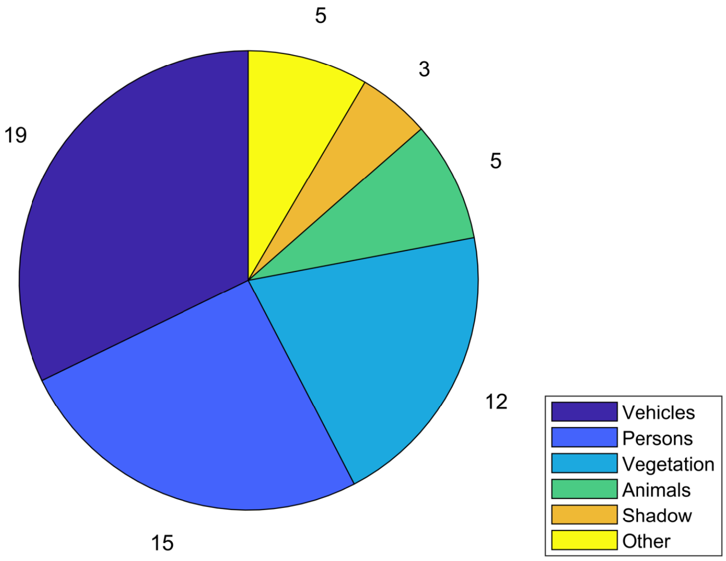


Figure 7.10.: The pie chart of different categories of FP causes. Vehicles, persons, and vegetation are the three most common causes.

7.2.4 Conclusions

The developed animal detection system demonstrated effective performance in detecting cassowaries at Location B in Kuranda, Queensland. The field data collected from 8 March to 30 June 2024 provided valuable insights into cassowary activities from month to month. The on-road trial, spanning 62 days from 30 April to 30 June 2024, validated the system's high sensitivity and reasonable precision in detecting cassowaries, with an impressive recall of 0.97. Despite some false positive events, the system's overall performance was robust, providing a reliable tool for monitoring animals and enhancing road safety in areas with AVCs hazards.

7.3. Driver Behaviour Analysis (QUT)

As noted in Chapter 5, while the simulator study represented the first of two studies to evaluate behavioural responses to messaging triggered on the VMS via the LAARMA system, the on-road field trial comprised the second of these two studies. This section first outlines the site-related information and nature of the data collection (via pneumatic road tubes) of motorists' behaviour in the field trial area.

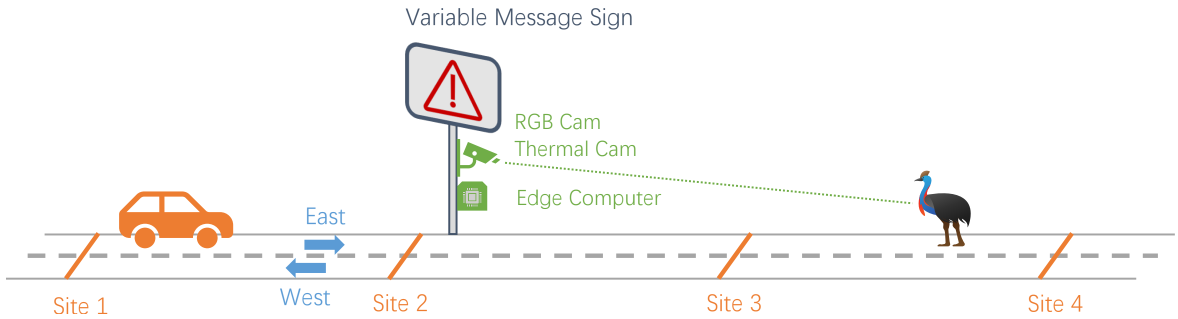


Figure 7.11.: Layout of the vehicle speed monitoring sites with VMS and animal detection technologies. The diagram shows the eastward direction of travel, with vehicle speed sensors located at four sequential sites leading up to an animal crossing zone. The figure is for illustrative purposes only.

7.3.1 Site Information

Figures 7.11 and 7.12 show the four vehicle speed monitoring sites in the trial area. Note that Figure 7.11 is only for illustrative purposes. The GPS coordinates of the four sites were recorded during the pneumatic tubes installation. Table 7.6 summarises the site locations and the distances between these sites calculated using Google Earth Pro.

Figure 7.12.: Aerial view of the study segment along Kennedy Hwy, showing the four measurement sites (Site 1 to Site 4) with distances between each site labelled to facilitate speed and acceleration analysis in this study.

Site	GPS Coordinates	Distance (in metres) to next site
Site 1	16°48′57.9″S 145°38′32.5″E	57
Site 2	16°48′58.8″S 145°38′34.2″E	107
Site 3	16°49′01.2″S 145°38′36.8″E	162
Site 4	16°49′04.1″S 145°38′41.4″E	N/A

Table 7.6.: Geographic coordinates and distances in metres between measurement sites along Kennedy Hwy for traffic data analysis.

7.3.2 Traffic Data Cleaning

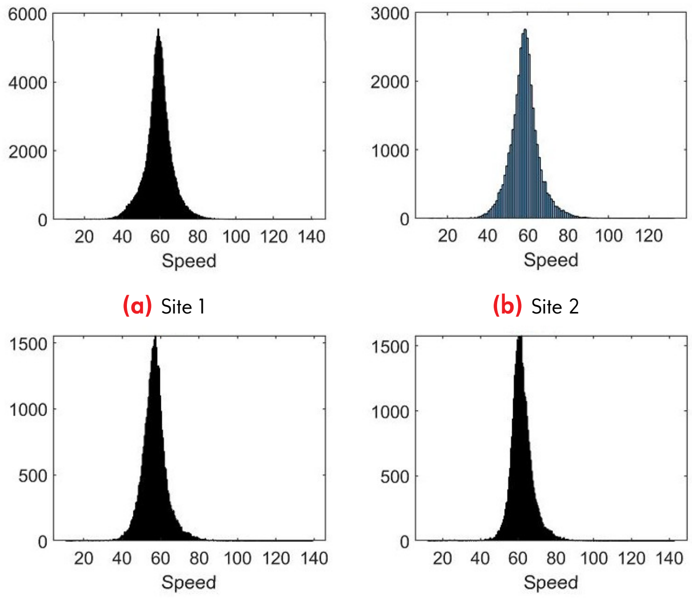
Figure 7.13 displays a portion of traffic data recorded at Site 3, captured in a tabular format with various traffic parameters. Columns include identifiers like DS, TrigNum, and Ht, along with temporal data such as Date and Time. Other crucial traffic metrics displayed are Dr (Direction), Speed (km/h), Wb (tonne), Hdwy (sec), and Gap (sec). Notably, Figure 7.13 reveals instances of duplicate entries and potential errors, indicated by the recurrence of identical Speed and Wb values across different rows, alongside conflicting direction indicators ('W0' vs 'E1') for the same vehicle. These duplicate entries consistently show zero values for Gap and Headway, suggesting data inaccuracies or system misreadings. To improve data quality and accuracy, all rows with zero values in both Gap and Headway columns were removed, streamlining the dataset for more reliable analysis and interpretation.

WSite1 | WSite2 | WSite3 | WSite4

75459x16 table

	1 DS	2 TrigNum	3 Ht	4 Date	5 Time	6 Dr	7 Speed	8 Wb	9 Hdwy	10 Gap
118	1	"000d3d89"	12	02/04/2024	04:48:43	W0	67.7100	15.4200	112.9000	112.7000
119	1	"000d3d95"	4	02/04/2024	04:48:45	W0	66.5700	2.6400	2.4000	1.5000
120	1	"000d3d99"	4	02/04/2024	04:48:47	W0	64.6500	3.1300	1.5000	1.3000
121	1	"000d3d9d"	4	02/04/2024	04:48:51	E1	79.7900	3.0100	111.2000	111.1000
122	1	"000d3da1"	4	02/04/2024	04:50:38	E1	61.9500	2.6800	107.5000	107.4000
123	1	"000d3da5"	17	02/04/2024	04:50:47	E1	62.8600	2.6900	8.5000	8.3000
124	1	"000d3da5"	17	02/04/2024	04:50:47	W0	62.8600	2.6900	0	0
125	1	"000d3da5"	17	02/04/2024	04:50:47	E1	62.8600	2.6900	0	0
126	1	"000d3da5"	17	02/04/2024	04:50:47	W0	62.8600	2.6900	0	0
127	1	"000d3db6"	13	02/04/2024	04:51:47	W0	65.2800	4.5200	180.2000	180
128	1	"000d3db6"	13	02/04/2024	04:51:47	E1	65.7700	4.5200	0	0
129	1	"000d3db6"	13	02/04/2024	04:51:47	W0	65.2800	4.5200	0	0
130	1	"000d3dc3"	4	02/04/2024	04:52:21	W0	58.0900	2.7200	33.6000	32.9000

Figure 7.13.: Table displaying traffic data collected at Site 3, highlighting vehicle direction, speed, and spacing discrepancies. Rows with zero values for both Gap and Headway, indicative of data errors, were identified for removal to ensure data integrity. Note: WSite4, WSite3, WSite2 and WSite1 in the table are renamed to Site 1, Site 2, Site 3, and Site 4, respectively, in the data analysis.



(a) Site 1 (b) Site 2 (c) Site 3 (d) Site 4

Figure 7.14.: Histograms depicting the distribution of vehicle speeds at four sites. Each panel represents the frequency of observed speeds at a particular site, with Sites 1 through 4 showing distinct patterns in speed variability and central tendencies.

7.3.3 Traffic Statistics

The analysis presented in this section uses data collected across four sites from 2 April 2024 to 10 April 2024, inclusive. This data pertains exclusively to eastbound traffic, which is the direction targeted by the LAARMA intervention. It is important to note that the traffic data were collected prior to the on-road trial of the LAARMA system, which started on 30 April 2024. During this data collection period, the VMS was inactive (i.e., not displaying any messages). Therefore, the analysis results are intended to provide insights into regular traffic conditions in the field trial area, without the influence of the LAARMA system.

7.3.3.A. Speed Distributions

Figure 7.14 illustrates the distribution of vehicle speeds across the four sites. Sites 1 and 2 show greater variability in speeds, as indicated by their higher standard deviations, compared to Sites 3 and 4. Specifically, Site 2 has the highest standard deviation of 7.35 km/h, while Site 1 also demonstrates significant speed variation. In contrast, Sites 3 and 4 exhibit more consistent speeds, with lower standard deviations, suggesting less fluctuation in vehicle speeds at these locations.

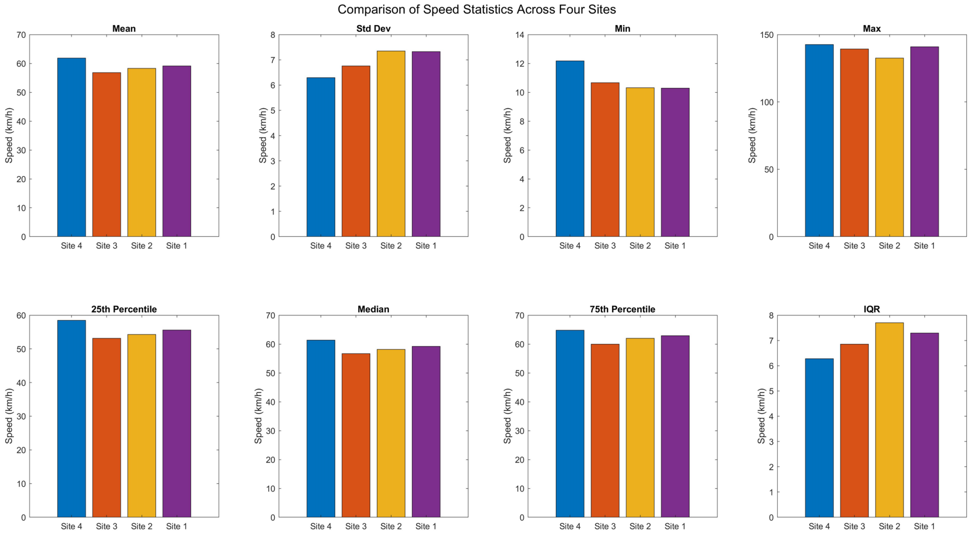


Figure 7.15.: Comparative analysis of speed metrics across four sites (from the event's end to the approach's start). This collection of bar charts illustrates the mean, standard deviation, minimum, maximum, 25th percentile, median, 75th percentile, and interquartile range (IQR) of vehicle speeds recorded at each site. The colours consistently represent each site across all statistics, facilitating a clear visual comparison of speed dynamics and variability.

7.3.3.B. Summary Statistics

Speed Summary Statistics

As Figure 7.15 illustrates, the mean speed across the four sites shows modest variation, with Site 4 exhibiting the highest mean speed at approximately 61.85 km/h and Site 3 displaying the lowest at 56.79 km/h. This suggests that traffic flow at Site 4 is typically faster, possibly due to road characteristics. The standard deviation values, which measure speed variability, range from 6.30 km/h at Site 4 to 7.35 km/h at Site 2, indicating more consistent speeds at Site 4 and slightly more varied speeds at Site 2. The maximum speeds recorded across the four sites suggest instances of extreme speeding, particularly at Site 4.

The interquartile range (IQR) is used to measure statistical dispersion, highlighting the spread or variability within the collected data. Specifically, the IQR represents the range between the third quartile (Q3) and the first quartile (Q1), capturing the middle 50% of the speed values. Here, IQR is fairly consistent across the sites, from 6.28 km/h at Site 4 to 7.70 km/h at Site 2, pointing to a similar distribution of speed between the lower and upper quartiles across the different locations.

Headway Summary Statistics

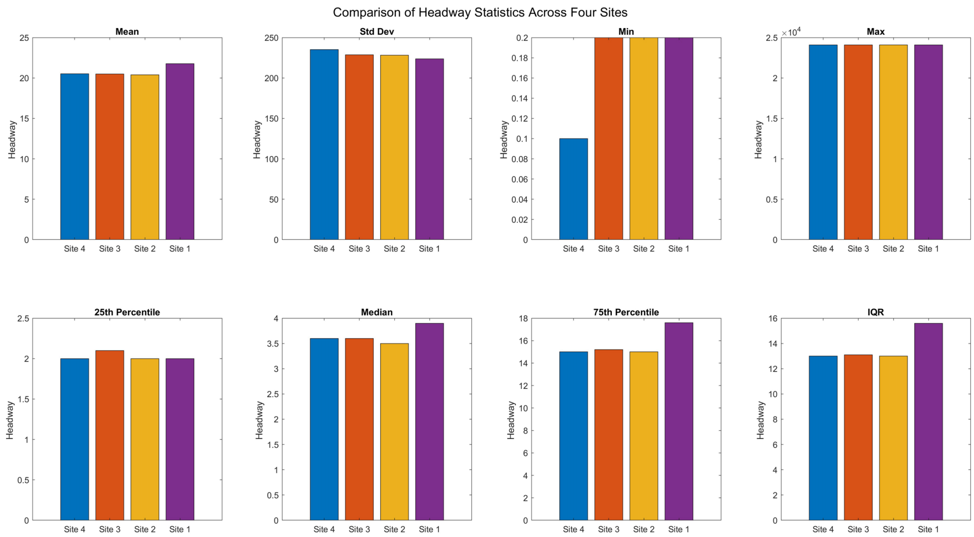


Figure 7.16.: Comparative analysis of headway metrics across four sites (from the event's end to the approach's start). This collection of bar charts illustrates the mean, standard deviation, minimum, maximum, 25th percentile, median, 75th percentile, and IQR of vehicle speeds recorded at each site. The colours consistently represent each site across all statistics, facilitating a clear visual comparison of speed dynamics and variability at each site.

As shown in Figure 7.16, the mean headway across the sites is relatively stable, with the values ranging from 20.38 seconds at Site 2 to 21.78 seconds at Site 1, indicating uniform traffic density conditions across these locations. Despite this consistency in the mean distance, the standard deviation of headway shows high variability, ranging from 223.54 seconds at Site 1 to 235.26 seconds at Site 4, which suggests fluctuating vehicle distances that might reflect varying traffic conditions or times of data collection.

Maximum headway values are exceedingly high across all sites, with values exceeding 24082 seconds, indicating the presence of unusually large gaps between vehicles at times, likely during low-traffic periods. The IQR for headway shows minimal variation from 13 seconds at Site 4 to 15.6 seconds at Site 1, which further signifies a consistent distribution of mid-range vehicle spacing across different traffic environments. Note that a smaller IQR indicates less variability or more consistency in the headway values, meaning vehicles maintain more uniform spacing, while a larger IQR suggests greater variation in the headways.

The minimum values of headway, particularly those less than 1 second, could be erroneous given that some instances could be where a vehicle was towing a trailer, for example.

Site	Site 1		Site 2		Site 3		Site 4	
Hour	Mean Speed	Mean Headway	Mean Speed	Mean Headway	Mean Speed	Mean Headway	Mean Speed	Mean Headway
0	57.58	2689.65	60.71	2689.57	59.69	2689.35	70.47	2279.41
1	58.83	2420.03	61.88	2296.14	59.91	2296.14	66.06	4487.2
2	57.87	1992.21	59.28	1992.12	58.04	2010.22	66.65	1937.15
3	54.98	1340.69	58.35	1381.15	57.6	1424.07	66.09	1077.35
4	64.77	69.47	65.39	69.19	63.29	68.89	67.91	65.81
5	65.96	35.50	65.95	35.35	63.61	35.62	67.12	30.93
6	61.71	15.27	60.94	15.29	58.42	15.29	62.36	13.82
7	60.46	11.89	59.93	11.92	57.57	11.93	61.81	11.78
8	58.70	11.73	58.64	11.73	56.63	11.81	61.55	11.07
9	58.10	11.15	58.08	11.19	56.21	11.22	60.87	10.11
10	57.80	12.09	57.69	12.12	55.74	12.26	60.79	11.1
11	57.45	11.98	57.73	11.99	55.82	12.14	61.02	11.31
12	57.42	12.26	57.49	12.31	55.93	12.39	61.01	11.62
13	57.22	12.35	57.22	12.36	55.63	12.43	60.59	12.17
14	57.34	11.57	57.30	11.59	55.62	11.67	60.75	11.34
15	57.93	10.68	57.75	10.72	55.73	10.76	61.14	10.65
16	59.36	11.95	58.88	11.94	56.49	11.98	62.05	11.34
17	60.43	16.74	59.87	16.74	57.48	16.8	62.17	15.73
18	62.36	28.23	61.90	28.18	59.51	28.3	63.82	26.82
19	64.71	47.43	64.89	47.31	62.71	47.32	66.63	44.14
20	63.78	72.50	64.51	71.92	62.63	71.9	68.03	74.85
21	61.83	309.06	62.98	310.34	61.29	309.79	68.84	258.91
22	63.21	470.70	64.08	470.66	62.26	470.87	67.68	493.47
23	62.17	794.13	62.92	787.55	60.89	794.65	67.61	714.21

Table 7.7.: Mean speed and headway by hour of the day from the four sites.

7.3.3.C. Time of the Day Analysis

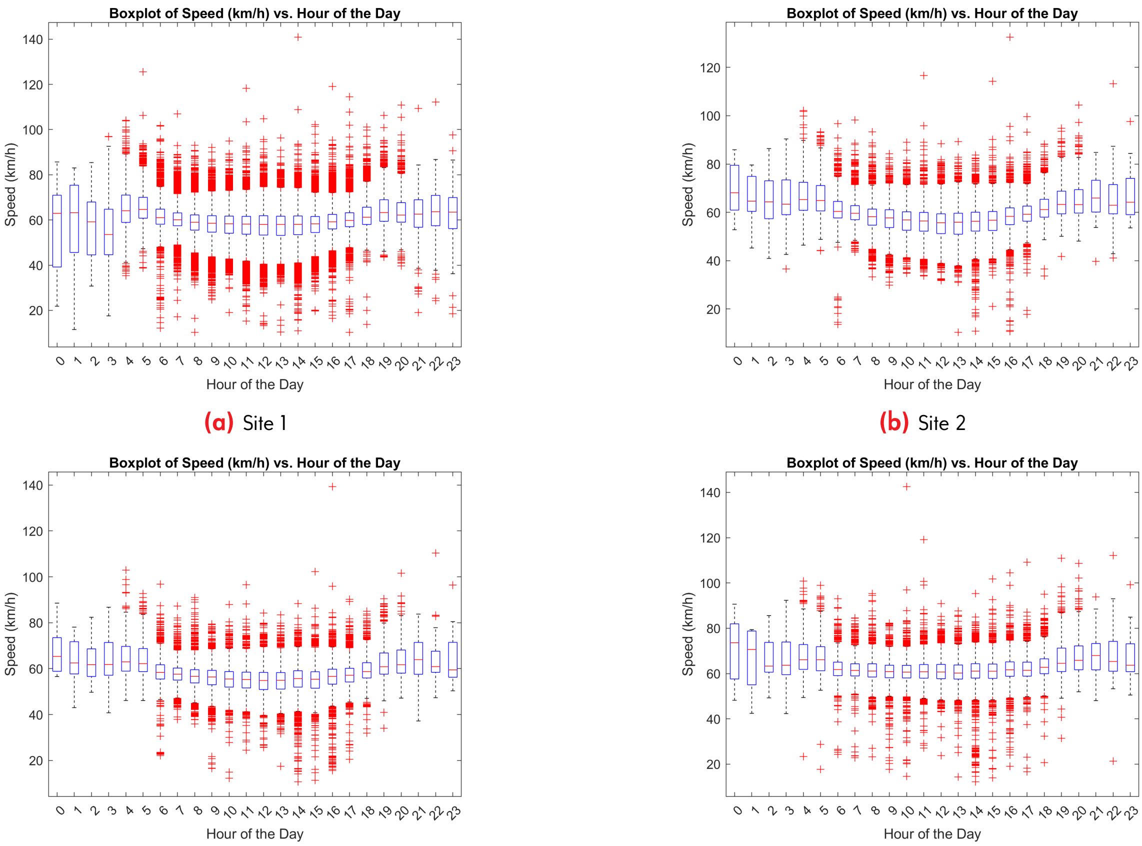
Based on the Table 7.7, for the mean speed and headway at different hours of the day across four sites, we can derive some insights into traffic patterns specific to each location.

Analysis of Mean Speed Variation Across Hours and Sites

Figure 7.17 presents the variation of the mean speed across hours and sites. Specifically,

Site 1: Shows a dip in speeds during the early morning (3 AM) and afternoon, with a gradual rise in speed later in the evening, reflecting typical traffic slowdowns during rush hours and increased speeds during off-peak times.

Site 2: Demonstrates a similar pattern to Site 1, with the same drop in speeds during midday and an increase in the evening, consistent with lighter traffic in the later hours.



(a) Site 1 **(b)** Site 2

(c) Site 3 **(d)** Site 4

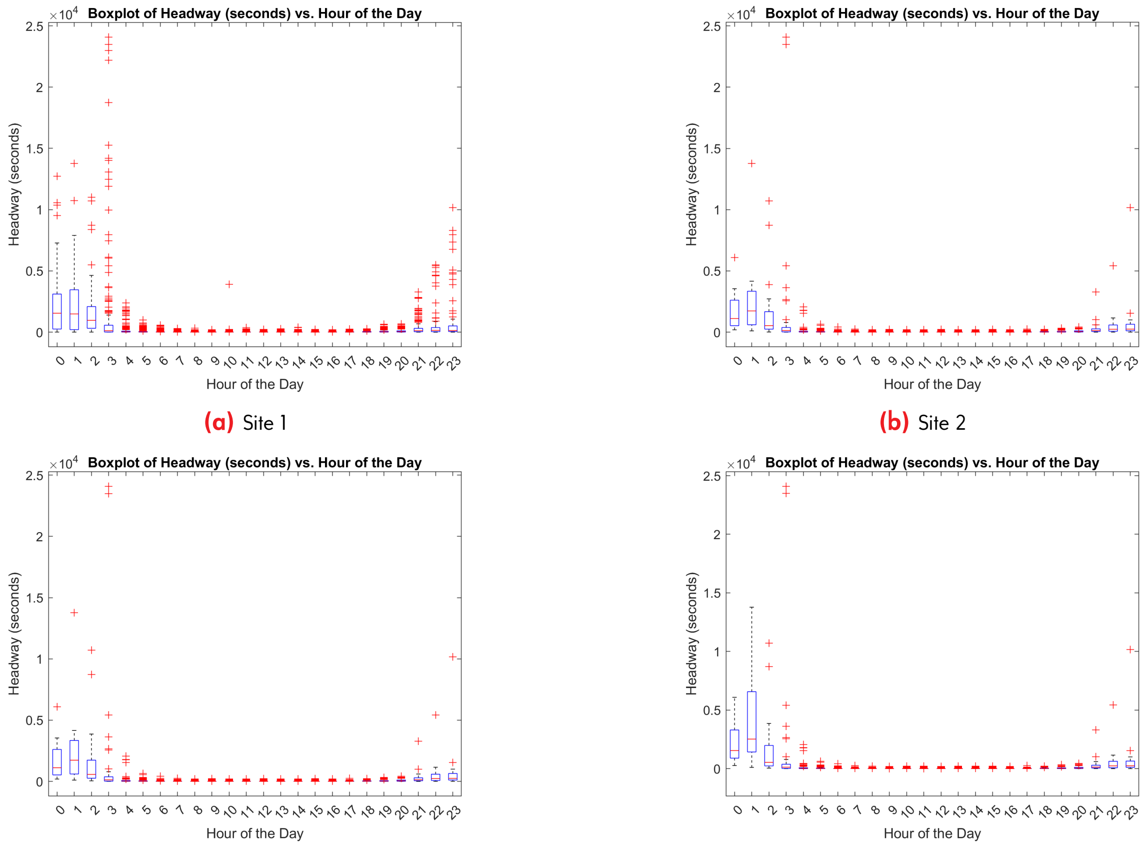
Figure 7.17.: Boxplots of the speed vs hours of the day at the four sites.

Site 3: Displays moderate speed variations, with lower speeds during the morning and evening rush hours. The midday period shows a slight increase in speed, although less pronounced than in the other sites.

Site 4: Stands out from the other sites due to its consistently higher speeds, particularly during the late evening. Speed fluctuations are evident throughout the day, with the lowest speeds observed in the early morning, followed by a peak late in the evening, likely due to reduced traffic density. We should emphasise that Site 4 differs from the other sites due to the presence of an overtaking lane at its location. Fluctuations in speed are apparent throughout the day, with the lowest speeds likely during peak hours, hinting at increased traffic. Conversely, late-night hours record the highest speeds, suggesting reduced traffic density.

Analysis of Mean Headway Variation Across Hours and Sites

Figure 7.18 shows the variation of headway (seconds) vs. hour of the day at the four study sites. For all sites, the headway is shortest during peak hours, reflecting higher traffic



(a) Site 1 (b) Site 2 (c) Site 3 (d) Site 4

Figure 7.18.: Boxplots of the headway vs hours of the day at the four sites.

density and possibly slower-moving vehicles. The y-axis uses a scale of 10^4, illustrating the significantly larger headway values observed during the early morning and late-night hours. This scale highlights the notable variation in headways at off-peak times, as compared to the more consistent, lower headway values during daytime hours when traffic is more regular.

7.3.4 Impact of LAARMA on Driver Behaviour and Vehicle Speeds

This study evaluates the effectiveness of the LAARMA system and the messaging it triggers in improving motorists' behaviour and, ultimately, enhancing road safety through efforts to reduce AVCs. The on-road trial setup is presented in Figure 7.19, where the approach zone and event zone for the driver behaviour analysis are labelled. Specifically, we explore whether purpose-devised messaging displayed on the roadside VMS, which are triggered by the LAARMA system on detection of a cassowary on or near the road, affect drivers' speeds at designated locations in the field trial area. We hypothesised that vehicle speeds would decrease at these sites when messages were displayed (and thus triggered by the

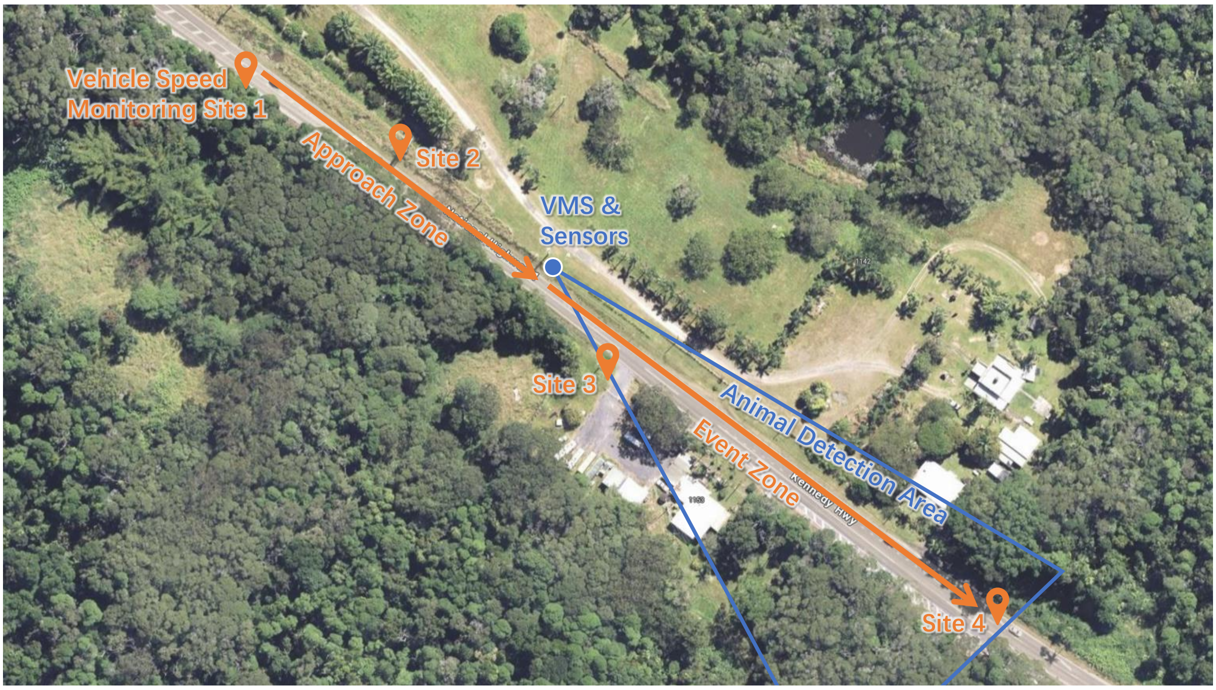


Figure 7.19.: Map of the four vehicle monitoring sites corresponding to the approach zone (i.e., Sites 1 and 2) and the event zone (i.e., Sites 3 and 4).

LAARMA system) signalling a cassowary had been detected on or near the road. The analysis presented in this section uses traffic data recorded across the four vehicle speed monitoring sites from 10 April 2024 to 30 June 2024, inclusive.

7.3.4.A. Methodology

To test our study's hypothesis, we employed a comprehensive methodology, as presented in Figure 7.20 using objectively-measured traffic data from pneumatic tubes situated on-road at four specific sites in the field trial area. The following steps outline our approach:

1. Traffic Data filtering based on the triggers timing: At each of the four sites, we gathered all available traffic records within a specified time range (from timestamp_from to timestamp_to).

2. Traffic Data Filtering Based on Direction: As only drivers moving from west to east could see the message displayed on the VMS, our analysis focused on sites positioned before and after the VMS. Sites 1 and 2, located before the VMS in the approach zone, and Sites 3 and 4, situated after the VMS in the event zone, were crucial for capturing interactions between drivers and animals. We concentrated on eastward traffic (labelled 'E') and excluded westward traffic (labelled 'W').

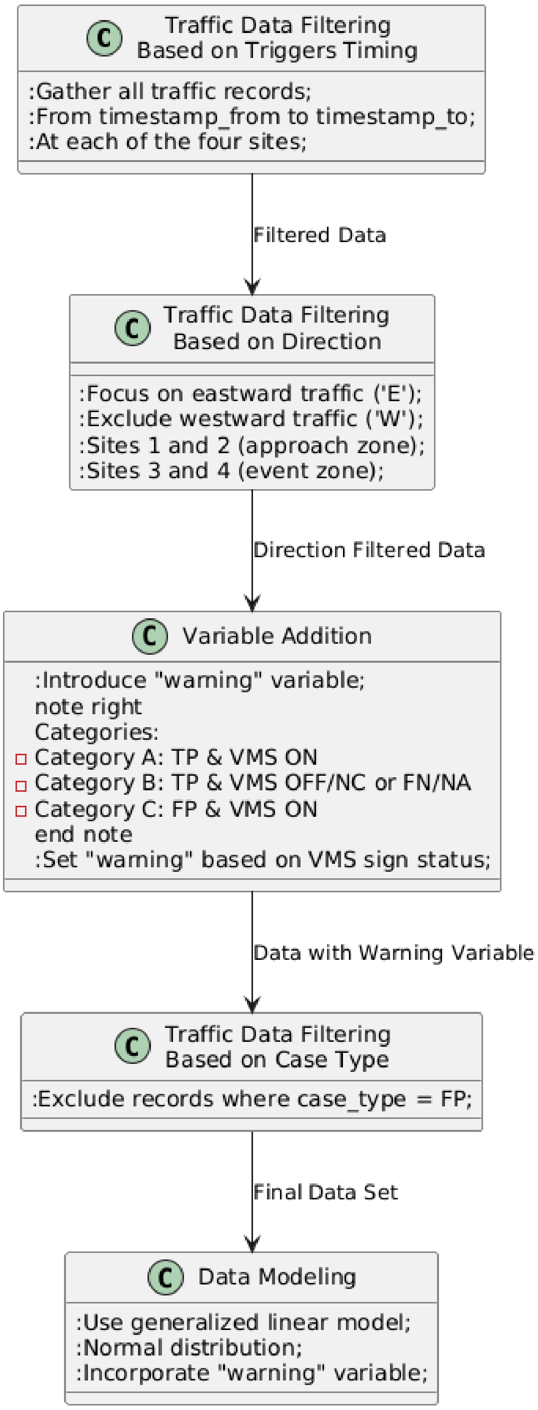


Figure 7.20.: The methodology flow to evaluate the effectiveness of the LAARMA system and the messaging it triggers in improving motorists' behaviour.

3. Variable Addition: A new variable, "warning," was introduced for each traffic record to indicate whether a message was displayed on the VMS. This variable allowed a more nuanced analysis based on the type of case and the status of the VMS:

    - Category A: True positives (TPs) with an active VMS. Drivers' reactions would have been based on both the message on the VMS and their direct observation of a cassowary (case_type = TP and sign_status = ON).

- Category B: TPs with an inactive VMS due to disconnection or low power, and false negatives (FNs). Drivers' reactions would have been based on their reactions solely to direct observation of a cassowary (case_type = TP and sign_status = OFF or NC, or case_type = FN or NA).

- Category C: False positives (FPs) with an active VMS. In this condition, drivers' reactions would involve them having seen a message on the VMS, but no cassowary would have been encountered (case_type = FP and sign_status = ON).

In our analysis, the 'warning' indicator variable was set to one for TP cases where the VMS was active. For all other scenarios, including FNs and TPs with the sign off, the 'warning' variable was set to zero as shown in Eq(1). This stratification helped us assess the impact of the messaging on the VMS on driving behaviour.

$$warning = \begin{cases} 1 & \text{for TP cases and the VMS was active} \\ 0 & \text{for FNs and TPs with the sign off} \end{cases} \qquad Eq(1)$$

4. Traffic Data Filtering Based on Case Type: Traffic records corresponding to a trigger with case_type = FP are excluded to control for variance due to the absence of actual animal presence.

5. Data Modelling: We analyse the speed data using a generalised linear model with a normal distribution, incorporating the newly added variable for warnings.

This methodology tested our hypothesis and also provided insights into how effectively the LAARMA system is as potentially modifying driver behaviour in the presence of potential road hazards posed by animals.

7.3.4.B. Analysis Results

In the subsequent subsections, we present results of the analysis of vehicle speeds at four measurement sites. This analysis explored how variations in speed could be explained through the use of two key variables: the 'warning' variable, which was set to one when the VMS was active and zero otherwise, and the 'headway' variable.

Approach Zone Sites

Site 1

Table 7.8 provides statistical evaluation of the influence of headway and warning signals on vehicle speeds. Here, the intercept stands at approximately 56.19 km/h, which represents the average vehicle speed in the absence of any external influencing factors such as headway adjustments or warning signals. The impact of the 'Warning' variable is notably significant, demonstrating a reduction in vehicle speed by approximately 4.26 km/h when a warning is active (p-value <.00001). This substantial decrease provides support for the effectiveness of messaging on the VMS (as triggered by the LAARMA system) in prompting drivers to reduce their speed.

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
(Intercept)	56.19078	0.420474	133.6368	2324	0	55.36624	57.01532
Hdwy	0.048525	0.008961	5.41517	2324	6.75E-08	0.030953	0.066097
Warning	-4.26409	0.482921	-8.82979	2324	2.02E-18	-5.21109	-3.31709

Table 7.8.: Model estimates at Site 1.

Conversely, the 'Hdwy' (headway) variable is associated with a slight but statistically significant increase in speed by about 0.049 km/h for each unit increase in headway (p-value <.00001). This indicates that drivers tended to accelerate slightly when the distance between vehicles increased, although the effect is relatively minor compared to the relatively stronger reduction in speed associated with display of the messaging on the VMS. These findings provide support for the positive impact of messaging on the VMS (triggered by the LAARMA system) in influencing driver behaviour under various traffic conditions.

Site 2

The statistical analysis provided in Table 7.9 evaluates the effects of headway and visual warnings on vehicle speeds. The intercept value at approximately 52.00 km/h indicates the base speed in scenarios without the influence of messaging on the VMS or adjustments in headway. Notably, the presence of a message on the VMS was shown to lead to a significant reduction in drivers' speed, with a decrease of about 3.44 km/h when the messaging is displayed (p-value <.00001). This finding thus provides support for the positive impacts of messaging on the VMS (as triggered by the LAARMA system) on reducing drivers' speed. On the other hand, the 'Hdwy' variable, which represents the distance between vehicles, shows a small but statistically significant increase in speed by 0.06 km/h for each unit increase in headway (p-value <.00001). This suggests that drivers tended to slightly increase their speed when given more space ahead, although the impact is considerably less significant compared to the relatively stronger reduction in speed associated with display of messaging on the VMS.

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
(Intercept)	51.99648	0.487961	106.5587	2371	0	51.03961	52.95336
Hdwy	0.064206	0.010786	5.952591	2371	3.03E-09	0.043055	0.085357
Warning	-3.4364	0.568945	-6.03995	2371	1.78E-09	-4.55208	-2.32072

Table 7.9.: Model estimates at Site 2.

Event Zone Sites

Site 3

Table 7.10 presents a detailed statistical analysis of the factors affecting vehicle speeds, specifically examining the effects of headway and messaging on the VMS. The intercept of 46.85 km/h indicates the baseline speed when neither headway adjustments nor messaging are considered. The 'Warning' variable demonstrates a significant reduction in vehicle speed, decreasing by approximately 6.18 km/h when warnings are active (p-value <.00001), highlighting positive effects of the messaging on the VMS in reducing drivers' speeds and thus promoting increased caution as approaching a potential hazard. In contrast, the 'Hdwy' (headway) variable is associated with a small but statistically significant increase in speed, approximately 0.06 km/h per unit increase in headway (p-value <.00001). This suggests that greater headway between vehicles might encourage slightly faster driving, though the effect is relatively minor compared to the relatively more pronounced positive effects relating to reductions in vehicle speeds associated with display of messaging on the VMS.

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
(Intercept)	46.85146	0.54412	86.10503	2258	0	45.78444	47.91849
Hdwy	0.059842	0.011826	5.06007	2258	4.53E-07	0.03665	0.083033
Warning	-6.1764	0.640332	-9.64562	2258	1.33E-21	-7.4321	-4.9207

Table 7.10.: Model estimates at Site 3.

Site 4

The analysis of vehicle speed in relation to the activation of messaging on the VMS and headway distance at Site 4 is shown in Table 7.11. The coefficient for the intercept indicates that the baseline speed, without the influence of messaging or varying headway, is approximately 54.70 km/h. Notably, the 'Warning' variable shows a significant decrease in vehicle speed by about 4.75 km/h when messaging is displayed on the VMS (p-value $<$ 0.00001), thus, providing support for the positive impacts of messaging on the VMS in reducing drivers' speeds. Conversely, the 'Hdwy' (headway) variable, representing the distance between vehicles, has an estimated coefficient that suggests a negligible effect on speed (a decrease of 0.00168 km/h per unit increase in headway), with a non-significant p-value (0.802), indicating that headway, within the range observed, does not substantially influence vehicle speed under the conditions studied.

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
(Intercept)	54.69558	0.346466	157.8671	2119	0	54.01613	55.37503
Hdwy	-0.00168	0.006727	-0.25026	2119	0.802414	-0.01488	0.011508
Warning	-4.74912	0.412546	-11.5117	2119	8.68E-30	-5.55815	-3.94008

Table 7.11.: Model estimates at Site 4.

Refining Traffic Data Analysis at Event Sites: Adjusting Trigger Timings to Mitigate Noise in Treatment Group Observations

The analysis for Site 3 and Site 4 contains potential noise due to the methodology employed in filtering traffic data based on trigger timing. At the event sites, Site 3 and 4 often include vehicle traffic that is coincidental with the onset of triggers. This inclusion can result in 'noise' within the treatment group data, where it is assumed that drivers observe the messaging on the VMS. However, in reality, the VMS may activate their messaging only after the vehicles have passed, meaning that drivers do not actually see the messaging. To mitigate this issue and enhance the accuracy of our analysis, we adjusted the timing of our data filtering at these sites. Specifically, we shifted the start and end times of the triggers by 32 seconds for Site 4 and 16 seconds for Site 3. These adjustments correspond to the estimated travel times from Site 2 to Sites 4 and 3, respectively. This strategy aimed to increase the likelihood that the vehicles included in the filtered data at Sites 3 and 4 have actually seen the messaging on the VMS, thereby reducing the noise in the analysis and improving the reliability of our findings.

The adjustment of trigger timings at Sites 3 and 4 yielded distinct changes in the analysis results, highlighting the impact of more accurate data filtering techniques. After adjusting the triggering times to account for the actual visibility of the messaging on the VMS to drivers, the results demonstrated a more pronounced effect of the messaging on reducing vehicle speeds at both sites compared to the unadjusted data.

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
(Intercept)	46.46724	0.552268	84.13894	2255	0	45.38424	47.55025
Hdwy	0.063821	0.012282	5.196248	2255	2.22E-07	0.039735	0.087906
Warning	-6.29849	0.645047	-9.7644	2255	4.35E-22	-7.56344	-5.03355

Table 7.12.: Model estimates at Site 3 after adjusting the triggering times at the location of the Site 3.

At Site 3, the adjusted analysis results in Table 7.12 indicate a stronger effect of the messaging on the VMS on reducing driver' speeds, with the coefficient for the warning increasing from -6.176 to -6.298. This result is supported by a very low p-value, reinforcing the statistical significance of the VMS messaging's positive impact on reducing drivers' speed. Additionally, the estimate for headway became more positive, and its significance improved, suggesting that the greater spacing between vehicles might encourage slightly faster driving, yet this effect appears to have been mitigated by the drivers' response to the messaging on the VMS in terms of reductions in speeds.

Name	Estimate	SE	tStat	DF	pValue	Lower	Upper
(Intercept)	54.02682	0.373115	144.7996	2264	0	53.29514	54.75851
Hdwy	0.002918	0.007187	0.405962	2264	0.684809	-0.01118	0.017011
Warning	-5.055	0.430614	-11.7391	2264	6.21E-31	-5.89945	-4.21056

Table 7.13.: Model estimates at Site 4 after adjusting the triggering times at the location of the Site 4.

Similarly, at Site 4, the results of the adjusted analysis in Table 7.13 shows that the impact of the messaging on the VMS on drivers' speed reduction increased even further, with the warning coefficient increasing from -4.749 to -5.055. This increase supports there having been an even more substantial behavioural response when accounting for accurate trigger exposure. The p-value remains significant, further supporting the positive impact of the messaging on reducing drivers' speed, despite a slight increase in the standard error of the warning estimate. Notably, the headway parameter changed from slightly negative to slightly positive, though it remains statistically insignificant, suggesting that headway has a minimal impact on drivers' speed at this site.

7.3.5 Crash Reduction Estimation

The calculation of crash reduction rates plays a pivotal role in the safety assessment for the future deployment of LAARMA. This estimation process is essential for understanding the potential returns on investment from implementing these technologies at scale. This section focus on determining the crash reduction rate for LAARMA, utilising the Nilsson power model.

This model, established by Nilsson in 1981, is grounded in the principle that the safety level of a transport system is intimately linked to its speed levels. According to the model, even minor adjustments in driving speeds can lead to significant and quantifiable reductions in crash risks. This model is particularly versatile, capable of estimating the impact on various injury severities, such as slight and fatal injuries, across different road types like urban arterials and freeways.

The Nilsson power model formula is rearranged to calculate the reduction in injuries from the LAARMA technology is as follows:

$$Crash\ Reduction\ Factor = 1 - \left(\frac{Mean\ speed_{VMS-ON}}{Mean\ speed_{VMS-OFF}}\right)^{C}$$

and

$$Mean\ speed_{VMS-ON} = \beta_{0(i)} + \beta_{Hdwy(i)} \times headways + \beta_{Warning(i)}$$

$$Mean\ speed_{VMS-OFF} = \beta_0 + \beta_{Hdwy} \times headways$$

where

$\beta_{0(i)}$ is the intercept estimated at the study site $i \in \{1, 2, 3, 4\}$,

$\beta_{Hdwy(i)}$ is the headway coefficient estimated at the study site $i \in \{1, 2, 3, 4\}$,

$headways$ is the observed headway in seconds,

$\beta_{Warning(i)}$ is the estimated coefficient of the warning indicator variable at the study site $i \in \{1, 2, 3, 4\}$,

C is is an exponent dependent on the injury severity and location type from [201] described in Table 7.14.

Road type considered	Fatal crashes exponent	Serious injury crashes exponent	Slight injury crashes exponent	All injury crashes exponent
Rural roads/freeways	4.1	2.6	1.1	1.6
Urban/residential roads	2.6	1.5	1.0	1.2
All roads	3.5	2.0	1.0	1.5

Table 7.14.: Exponents applied in Nilsson power model for crash reduction determination.

7.3.5.A. Crash Reduction Results

Figure 7.21 presents the calculated crash reduction factors (CRF) for fatal, serious, slight injuries, and all injuries combined across four urban/residential road sites using the Nilsson power model. The respective exponents used are 2.6 for fatal crashes, 1.5 for serious injury crashes, 1.0 for slight injuries, and 1.2 for all injury types, reflecting the expected reduction in crash severity as speeds decrease.

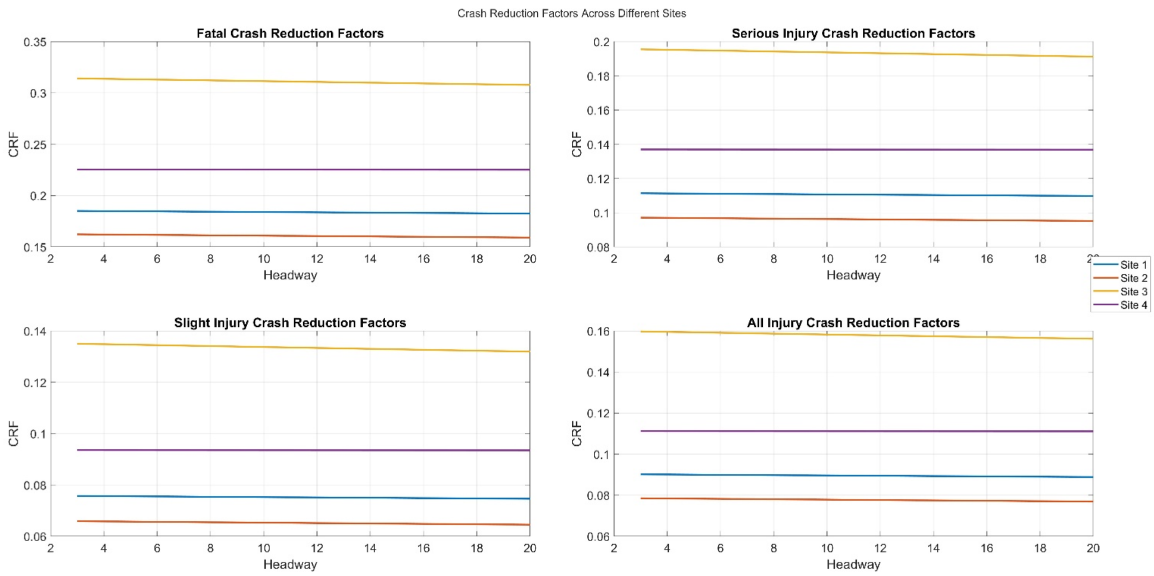


Figure 7.21.: Crash reduction factors (CRF) by injury severity across the sites: This figure illustrates the effectiveness of LAARMA reducing crash severities across four sites. Sites 3 and 4, located in the event zone, demonstrate higher reductions in crash severities, particularly for fatal and serious injuries, compared to Sites 1 and 2 in the approach zone. The graph highlights the impact of targeted safety measures in enhancing road safety and reducing potential injuries and fatalities in high-risk zones.

7.3.5.B. Analysis by Site and Injury Severity

Fatal CRF: Site 3 shows the highest reduction in fatal crashes, indicating a significant impact of LAARMA on fatal crash rates, followed closely by Site 4. In contrast, Sites 1 and 2 (approach zone) demonstrate lower reductions.

Serious Injury CRF: Similar to fatal crashes, Site 3 leads in reducing serious injuries, followed by Site 4. The difference between the event zone (Sites 3 and 4) and the approach zone (Sites 1 and 2) is noticeable but less pronounced than with fatal crashes.

All Injury CRF: Reflecting a mix of severity types, all injury reductions are highest in Site 3 and lowest in Site 1, with Sites 2 and 4 showing intermediate values.

Slight Injury CRF: Similar to that of all injury crash reductions.

The above analysis shows that event zone (Site 3 and Site 4) consistently shows higher reductions across all injury types, particularly for more severe injuries. This suggests that LAARMA in these zones are highly effective at reducing speeds sufficiently to impact the more severe outcomes significantly. The approach zone, while still benefiting from LAARMA, shows less reductions.

These findings underscore the critical role of LAARMA in specific road zones where animal crossing to maximise safety benefits, particularly where severe injuries or fatalities are a concern.

7.3.6 Conclusions

The comprehensive analysis across four distinct sites provided valuable insights into the effects of messaging on the VMS and headway on vehicle speeds. Overall, the results support there being positive effects of the LAARMA system and the messaging it triggers on reducing driver's speeds. At the event zone sites (Sites 3 and 4), significant reductions in vehicle speeds were observed when messaging was displayed on the VMS, with decreases of approximately 6.18 km/h and 4.75 km/h, respectively.

With the adjusted data, the observed reductions in vehicle speeds were more pronounced when messaging was displayed on the VMS, showing decreases of approximately 6.30 km/h at Site 3 and 5.06 km/h at Site 4. These adjustments from the previously noted reductions of about 6.18 km/h and 4.75 km/h at these sites, respectively, provide support for the positive effects of the LAARMA system and the messaging it triggers on reducing drivers' speeds in high-risk zones where AVCs are probable.

At the approach zone sites (Sites 1 and 2), while the VMS still played a significant role in reducing speeds, the decrease was slightly less pronounced, with reductions of 4.26 km/h and 3.44 km/h, respectively.

Interestingly, across all sites, headway showed a consistent, albeit minor, influence on increasing vehicle speeds. These slight increases, ranging from approximately 0.048 to 0.064 km/h per unit of headway, suggest that when headway reaches a value equivalent to the absence of a leading vehicle, drivers have greater freedom to choose their speed, though this behaviour may be considered largely mitigated by the positive effect on reducing drivers' speeds that results from messaging displayed on the VMS.

Using the Nilsson power model, the crash reduction estimation confirms that the LAARMA system is more effective in the event zone (Sites 3 and 4), where significant reductions in fatal and serious injuries are observed, compared to the lower reductions seen in the approach zone (Sites 1 and 2).

8

Conclusions and Recommendations

In conclusion, the development and implementation of the LAARMA system represent an important Australian initiative in mitigating AVCs, thereby enhancing road safety and promoting wildlife conservation. By integrating advanced sensing technologies with cutting-edge machine learning models together with purpose-devised messaging displayed on a roadside VMS, this system has demonstrated its capability to detect cassowaries with high accuracy and robustness in challenging environments in FNQ and issue real-time messaging to alert motorists to an upcoming hazard. The innovative approach of using a self-training machine learning pipeline, combined with synthetic data for initial training and auto-labelling through a VLM, has shown to be effective in overcoming challenges related to data scarcity. This approach has facilitated continuous model improvement, ensuring that the system remains responsive and effective across various deployment sites.

Prior to the field trial, purpose-devised messages for display on the roadside VMS were developed, concept-tested, and evaluated via two studies. The first study comprised a qualitative study featuring a series of 8 focus groups with N = 36 drivers to concept-test 20 concepts. The second study, a larger online survey, assessed the effectiveness of 4 of the messages with a sample of 557 licensed drivers. Overall, the messages assessed in the survey performed well on the various outcome measures of effectiveness that were implemented in accordance with the SatMDT [1]. Among just some of the key findings highlighted across these studies was the importance of identifying the type of animal on the signage and prioritising the "slow down" strategy before the "scan" strategy. Participants also emphasised the need for motorists to understand the real-time nature of the messaging and supported the implementation of broader public education campaigns about the LAARMA system to aid understanding about the system and how it operates.

Two of the four messages were subsequently tested further with drivers' behavioural responses to them evaluated within a driving simulator study. The study comprised two balanced groups of participants for a total of 51 drivers. The findings indicated that the messages had positive impacts on reducing drivers' speeds particularly in the approach zone window on sighting of the message on the VMS. It was thought that the effect was more pronounced in this approach zone rather than in the event zone in the simulator study given that participants were aware that there was no possibility that they would actually collide with a cassowary in the event zone.

The field trial conducted in FNQ provided valuable insights into the real-world performance of the LAARMA system. The trial not only validated the system's ability to detect large animals like cassowaries, achieving an impressive recall of 0.97, but also identified areas for further refinement, such as improving power and sensor head designs, and enhancing the system's robustness against adverse weather conditions. The analysis of field data also discussed the strengths and weaknesses of different sensor modalities in detecting cassowaries at different distances, offering practical guidance for selecting the optimal sensor configuration when deploying the system at new animal crossing locations.

In addition to the animal detection results, the field traffic data analysis revealed significant reductions in vehicle speeds in the event zone, with decreases of 6.30 km/h and 5.06 km/h at Sites 3 and 4, respectively, when messaging was displayed on the VMS (as triggered by the LAARMA system). The crash reduction analysis further supported this, showing that LAARMA's impact is more pronounced in the event zone, where significant reductions in fatal and serious injuries were observed using the Nilsson power model. Although the speed and crash reduction was slightly less significant in the approach zone (Sites 1 and 2), the findings underscore the importance of targeted safety interventions in reducing vehicle speeds and mitigating AVCs.

Overall, the successful integration of the detection system with purpose-devised messaging on the roadside VMS highlights the practical applicability of the developed system in real-world traffic scenarios, offering a proactive approach to alerting motorists and helping to prevent AVCs.

Looking ahead, future enhancements to the LAARMA system should focus on incorporating more recent data to further refine the system's accuracy and reduce false positives. Additionally, expanding the system's deployment to other regions will provide further opportunities to assess its scalability and broader impact on road safety and wildlife conservation.

Lastly, the knowledge gained from the project and the lessons learned from addressing the environmental and technological challenges during the field trial are of importance for future real-world implementations. Based on these insights, there are several areas where future research and development could enhance the system's effectiveness and reliability:

- Given the solar power issues, exploring higher-capacity solar panels and battery system could ensure uninterrupted system operation. Also, further optimisation of power-saving measures and energy-efficient hardware and software components should be considered.

- To mitigate sensor occlusion and improve detection accuracy, systematic location optimisation should be performed. Besides, installing the sensor head at a more elevated point, and the deployment of multiple sensor heads to monitor the animal crossing area from different locations and perspectives should be explored.

- To enhance the system's robustness against adverse weather conditions, adding lens hoods or implementing fusion techniques for multiple sensor modalities could be beneficial. Also, developing better solutions for the mechanical mounting of the detection system should be explored to prevent the sensor angle shift issue.

- More research is needed to expand the system to detect a wider range of animal species and test it in different geographical locations to enhance its scalability and generalisation capabilities. This could involve training the model on diverse datasets and conducting field trials in various environments.

- From the message design perspective, more efforts would be required to confirm and test targeted messages insofar as other types of animals are being detected. While the strategies recommended may not change, there could be different perceptions and expectations regarding the warning information presented about different animals.

- As the system can be easily deployed at different sites, the long-term effect of the system must be evaluated, in order to understand what strategies can be employed regarding the deployment of the VMSs at multiple sites.

By addressing these recommendations, the LAARMA system may be further refined and scaled, contributing to improved road safety and wildlife conservation efforts in Queensland and Australia wide.

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Appendices (QUT)

A. VMS Message Concepts (Study 1)

Figure 8.1.: Text only message concepts.

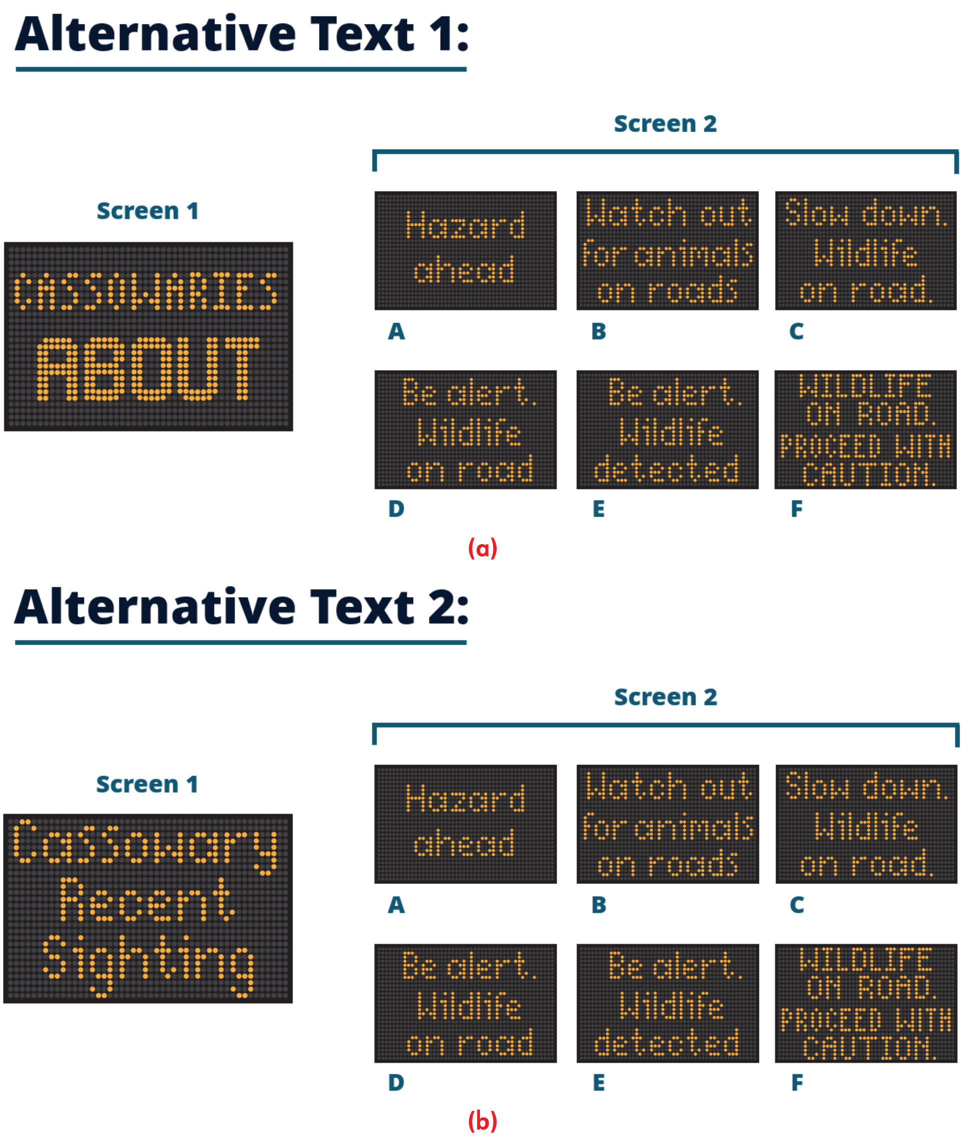

Figure 8.2.: Alternative text options.

Figure 8.3.: Text and image message concepts.

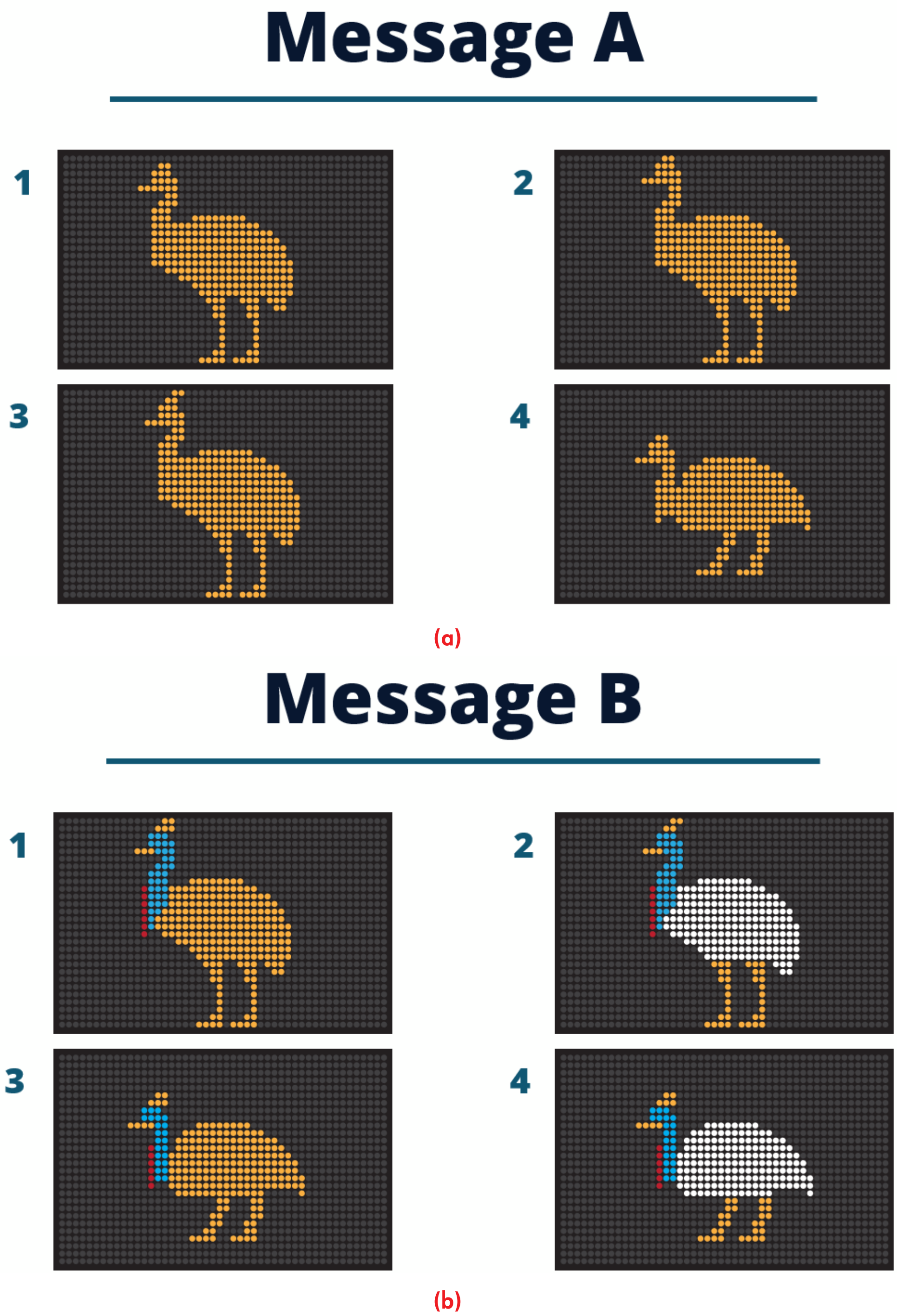

Figure 8.4.: Image only message concepts.

B. Demographic Survey (Study 1)

1.	Are you aged 18 years or older, reside in Australia, hold a valid motor vehicle or motorcycle licence, and drive/ride for at least one hour per week?	☐ Yes ☐ No If no, we thank you for your interest in this study. Unfortunately, we are looking for people aged 18 years or older, who reside in Australia, hold a valid motor vehicle or motorcycle license, and drive for at least one hour per week.
2.	What is your current age in years?	________ years
3.	What is your gender?	☐ Male ☐ Female ☐ Other ☐ Prefer not to say
4.	What type of licence do you hold? If you hold a motorcycle licence only, please select the closest equivalent.	☐ Learner ☐ Provisional 1 ☐ Provisional 2 ☐ Open ☐ International
5.	How long have you held your motor vehicle/motorcycle licence (including your learners) (in years)?	________ years
6.	How many hours in an average week do you drive and/or ride?	________ hours per week
7.	Which Australian State or Territory do you currently reside in?	☐ Queensland ☐ New South Wales ☐ Australian Capital Territory ☐ Victoria ☐ Tasmania ☐ Northern Territory ☐ South Australia ☐ Western Australia
8.	What is your postcode?	________

C. Focus Group Schedule (Study 1)

Overview:

Thank you for agreeing to participate in this focus group. Today we will be sharing some message concepts for a variable messaging sign (VMS) to alert drivers of the presence of large animals on the road. The VMS will be connected to a device that detects that an animal is near the road. When the device detects an animal, a message will be displayed on the VMS to warn approaching drivers. The purpose of this focus group is to discuss what you think about these message concepts for that warning.

The messages which you will be shown are in the early stage of development. There are no right, or wrong answers, we are interested in learning about your current perceptions and thoughts about these messages.

Questions (asked after presentation of each message):

Q1. What was your first reaction to this message?

Q2. Was the message easily understood?

- Was there more than one possible meaning to the message?
- Did you need to read it more than once to be certain of its meaning?
- Did you know what was being depicted in the image?
- Is it important for the image to clearly show what specific animal is nearby? Why/why not?
- Could it be delivered in a more effective way (text/image/combination)?

Q3. Did the message make you aware of a potential safety hazard?

- Why/why not?
- Was the type of hazard made clear?

Q4. If you were driving on an open road and saw this message, how do you think you would respond?

- Would you change how you were driving in any way?

- PROMPT: key behaviours of reducing speeding and monitoring road environment (if not raised organically)

- PROMPT: interest/intention/willingness to pull up/stop on the road to see the animal (if not raised organically)

Q5. Do you think the message is effective?

- Why/why not?

Q6. What if anything would you change about the message? Keep the same?

- Why should this be changed? How?

Q7. Any final comments about this message?

Q8. What are your thoughts about this alternative wording/design? Which do you prefer? (asked for paired concepts only)

Final questions (after all messages have been shown):

Q9. The VMS is designed to only display a message when the system detects that there is an animal nearby. The rest of the time, the screen will be blank. That being said, if you saw one of these messages, would you understand that it meant that there was an animal nearby right now? Or would you assume it was a general warning that there are animals in the area?

Q10. Were there any particular messages that stood out for you? Why?

Thank you for taking part in today's focus group.

D. Online Survey (Study 2)

D.1 Part A: Demographics

1.	Are you aged 18 years or older, reside in Australia, hold a valid motor vehicle or motorcycle licence, and drive/ride for at least one hour per week?	☐ Yes ☐ No If no, we thank you for your interest in this study. Unfortunately, we are looking for people aged 18 years or older, who reside in Australia, hold a valid motor vehicle or motorcycle license, and drive for at least one hour per week.
2.	What is your current age in years?	________ years
3.	What is your gender?	☐ Male ☐ Female ☐ Other ☐ Prefer not to say
4.	What type of licence do you hold? If you hold a motorcycle licence only, please select the closest equivalent.	☐ Learner ☐ Provisional 1 ☐ Provisional 2 ☐ Open ☐ International
5.	How long have you held your motor vehicle/motorcycle licence (including your learners) (in years)?	________ years
6.	How many hours in an average week do you drive and/or ride?	________ hours per week
7.	Which Australian State or Territory do you currently reside in?	☐ Queensland ☐ New South Wales ☐ Australian Capital Territory ☐ Victoria ☐ Tasmania ☐ Northern Territory ☐ South Australia ☐ Western Australia
8.	What is your postcode?	________

D.2 Part B: Pre-Acceptance Measures

The following section relates to your general attitudes and intentions to perform specific actions while driving after being alerted that there is an animal on or near the road.

PART B1: DAYTIME

When answering the questions in this section, please imagine that it is daytime, the weather is fine, and you are travelling on a single lane, regional road, like the image below.

1. To what extent would **slowing down** after seeing messaging about an animal being on or near the road be (please select a response on each line):

Unsafe	1	2	3	4	5	6	7	Safe
Bad	1	2	3	4	5	6	7	Good
Unwise	1	2	3	4	5	6	7	Wise

2. To what extent would **scanning the road environment** after seeing messaging about an animal being on or near the road be (please select a response on each line):

Unsafe	1	2	3	4	5	6	7	Safe
Bad	1	2	3	4	5	6	7	Good
Unwise	1	2	3	4	5	6	7	Wise

3. If you were to see messaging about an animal being on or near the road, to what extent would you agree or disagree with the following:

	Strongly disagree			Neither agree nor disagree			Strongly agree
I intend to **slow down**	1	2	3	4	5	6	7
It is likely that I would **slow down**	1	2	3	4	5	6	7
I intend to **scan the road environment**	1	2	3	4	5	6	7
It is likely that I would **scan the road environment**	1	2	3	4	5	6	7

4. How willing would you be to **slow down** after seeing messaging about there being an animal on or near the road?

Not at all willing 1 2 3 4 5 6 7 Very willing

5. How willing would you be to scan the road environment after seeing messaging about there being an animal on or near the road?

Not at all willing 1 2 3 4 5 6 7 Very willing

6. If you were **driving along a regional road in an area you were unfamiliar with** and saw messaging about there being an animal on or near the road, how likely do you think you would be to just **stop suddenly in an attempt to** see the animal?

Extremely unlikely			Neither likely nor unlikely			Extremely likely

PART B2: NIGHTTIME

We would now like to know your general attitudes and intentions to perform the same driving actions, when driving at **nighttime** instead of daytime.

When answering these questions, please imagine that it is **nighttime, the weather is fine, and you are travelling on a single lane, regional road**.

1. To what extent would **slowing down** after seeing messaging about an animal being on or near the road be (please select a response on each line):

Unsafe	1	2	3	4	5	6	7	Safe
Bad	1	2	3	4	5	6	7	Good
Unwise	1	2	3	4	5	6	7	Wise

2. To what extent would **scanning the road environment** after seeing messaging about an animal being on or near the road be (please select a response on each line):

Unsafe	1	2	3	4	5	6	7	Safe
Bad	1	2	3	4	5	6	7	Good
Unwise	1	2	3	4	5	6	7	Wise

3. If you were to see messaging about an animal being on or near the road, to what extent would you agree or disagree with the following:

	Strongly disagree			Neither agree nor disagree			Strongly agree
I intend to **slow down**	1	2	3	4	5	6	7
It is likely that I would **slow down**	1	2	3	4	5	6	7
I intend to **scan the road environment**	1	2	3	4	5	6	7
It is likely that I would **scan the road environment**	1	2	3	4	5	6	7

4. How willing would you be to **slow down** after seeing messaging about there being an animal on or near the road?

Not at all willing	1	2	3	4	5	6	7	Very willing

5. How willing would you be to **scan the road environment** after seeing messaging about there being an animal on or near the road?

Not at all willing	1	2	3	4	5	6	7	Very willing

6. If you were **driving along** and saw messaging about there being an animal on or near the road, how likely do you think you would be to just **stop suddenly in an attempt to** see the animal?

Extremely unlikely			Neither likely nor unlikely			Extremely likely

D.3 Part C: Responses to the Message

1. In a few words can you please describe what the messaging was about?

____

____

2. How convincing do you think the messaging was?

Not at all convincing			Neither convincing nor not convincing			Very convincing

3. How persuasive do you think the messaging was?

Not at all persuasive			Neither persuasive nor not persuasive			Very persuasive

4. Please indicate on the scale below to what extent the following people would be influenced by this messaging?

	Not at all influenced						Very influenced
How much would **you yourself** be influenced?	1	2	3	4	5	6	7
How much do you think **other motorists in general** would be	1	2	3	4	5	6	7
How much would **other motorists of similar age and gender** to you	1	2	3	4	5	6	7

5. If you were driving along and saw this messaging, to what extent would you agree with the following statements?

	Strongly disagree			Neither agree nor disagree			Strongly agree
Assume it was a general warning about animals in the area	1	2	3	4	5	6	7
Assume it was a real-time warning about an animal being on or near	1	2	3	4	5	6	7
Stop suddenly in your lane to try and see the animal	1	2	3	4	5	6	7
Slow down and move off to the side of the road to try and see the animal	1	2	3	4	5	6	7
Simply ignore the messaging	1	2	3	4	5	6	7

D.4 Part D: Post-Acceptance Measures

Part D1: DAYTIME

We would now like to understand your general attitudes and intentions to perform specific driving actions after seeing the previous message.

When answering these questions, please imagine that **it is daytime, the weather is fine, and you are travelling on a single lane, regional road**, like the image below.

1. To what extent would slowing down after seeing messaging about an animal being on or near the road be (please select a response on each line):

Unsafe	1	2	3	4	5	6	7	Safe
Bad	1	2	3	4	5	6	7	Good
Unwise	1	2	3	4	5	6	7	Wise

2. To what extent would scanning the road environment after seeing messaging about an animal being on or near the road be (please select a response on each line):

Unsafe	1	2	3	4	5	6	7	Safe
Bad	1	2	3	4	5	6	7	Good
Unwise	1	2	3	4	5	6	7	Wise

3. If you were to see messaging about an animal being on or near the road, to what extent would you agree or disagree with the following:

	Strongly disagree			Neither agree nor disagree			Strongly agree
I intend to **slow down**	1	2	3	4	5	6	7
It is likely that I would **slow down**	1	2	3	4	5	6	7
I intend to **scan the road environment**	1	2	3	4	5	6	7
It is likely that I would **scan the road environment**	1	2	3	4	5	6	7

4. How willing would you be to slow down after seeing messaging about there being an animal on or near the road?

Not at all willing 1 2 3 4 5 6 7 Very willing

5. How willing would you be to scan the road environment after seeing messaging about there being an animal on or near the road?

Not at all willing 1 2 3 4 5 6 7 Very willing

6. If you were driving along a regional road in an area you were unfamiliar with and saw messaging about there being an animal on or near the road, how likely do you think you would be to just stop suddenly in an attempt to see the animal?

Extremely unlikely			Neither likely nor unlikely			Extremely likely

PART D2: NIGHTTIME

Once again, we would now like to know your general attitudes and intentions to perform the same driving actions when driving at **nighttime**, instead of daytime.

When answering these questions, please imagine that **it is nighttime, the weather is fine, and you are travelling on a single lane, regional road**.

1. To what extent would slowing down after seeing messaging about an animal being on or near the road be (please select a response on each line):

Unsafe	1	2	3	4	5	6	7	Safe
Bad	1	2	3	4	5	6	7	Good
Unwise	1	2	3	4	5	6	7	Wise

2. To what extent would scanning the road environment after seeing messaging about an animal being on or near the road be (please select a response on each line):

Unsafe	1	2	3	4	5	6	7	Safe
Bad	1	2	3	4	5	6	7	Good
Unwise	1	2	3	4	5	6	7	Wise

3. If you were to see messaging about an animal being on or near the road, to what extent would you agree or disagree with the following:

	Strongly disagree			Neither agree nor disagree			Strongly agree
I intend to **slow down**	1	2	3	4	5	6	7
It is likely that I would **slow down**	1	2	3	4	5	6	7
I intend to **scan the road environment**	1	2	3	4	5	6	7
It is likely that I would **scan the road environment**	1	2	3	4	5	6	7

4. How willing would you be to slow down after seeing messaging about there being an animal on or near the road?

Not at all willing	1	2	3	4	5	6	7	Very willing

5. How willing would you be to scan the road environment after seeing messaging about there being an animal on or near the road?

Not at all willing	1	2	3	4	5	6	7	Very willing

6. If you were driving along a regional road in an area you were unfamiliar with and saw messaging about there being an animal on or near the road, how likely do you think you would be to just stop suddenly in an attempt to see the animal?

Extremely unlikely			Neither likely nor unlikely			Extremely likely

D.5 Part E: Message Strategies

1. To what extent do you agree that the following driving strategies would be useful if you saw a message about a cassowary having been detected ahead or near the road?

	Strongly disagree			Neither agree nor disagree			Strongly agree
Slow down, look out	1	2	3	4	5	6	7
Look out, slow down	1	2	3	4	5	6	7
Reduce speed, be alert	1	2	3	4	5	6	7
Be alert, reduce speed	1	2	3	4	5	6	7

2. Please briefly explain why you provided these scores.

3. Do you have any other suggestions to improve these messages?