Concepts and Questions

Emerging opportunities for wildlife with sustainable autonomous transportation

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In a nutshell:

- Wildlife-vehicle collisions (WVCs) are an ongoing and widespread source of biodiversity loss. Although autonomous vehicles (AV) have the potential to mitigate this impact, current knowledge gaps may cause AVs to respond incorrectly during wildlife-vehicle interactions.
- Understanding how vehicles interact with wildlife has implications for human safety and animal conservation. Our framework explores this dynamic by incorporating WVC reduction as a critical step towards achieving sustainable AV technology and minimizing biodiversity loss.
- Researchers can utilize this framework to identify key research goals regarding wildlife-vehicle interactions and patterns, and to encourage AV companies and developers to integrate conservation goals within their research.

Abstract

Autonomous vehicles (AV) are expected to play a key role in the future of transportation, and to introduce a disruptive yet potentially beneficial change for wildlife-vehicle interactions. However, this assumption has not been critically examined, and reducing the number of wildlife-vehicle collisions may be beyond current technological capabilities. Here, we introduce a new conceptual framework covering the intersection between AV technology and wildlife conservation to reduce wildlife-vehicle collisions. We propose an integrated framework for developing robust warning systems and animal detection methods for AV systems, and incorporating wildlife-vehicle interactions into decision-making algorithms. With large-scale AV deployment a looming reality, it is vital to incorporate conservation and sustainability into the societal, ethical, and legal implications of AV technology. We intend our framework to help ecologists and conservationists foster the necessary interdisciplinary collaborations with AV developers and policymakers to reduce wildlife vehicle collisions and concomitant biodiversity loss.

Keywords**:** sustainability, self-driving cars, automated vehicles, traffic accidents, animal-vehicle collisions, conservation

The future of sustainable transportation

A shift towards autonomous transportation has begun. There are over one billion cars registered worldwide, and this number is expected to double by 2030 (Mora *et al.* 2020). By 2050, a quarter or more of the vehicles traveling in the US and Europe could feature autonomous driving technology (**Panel 1**) (Miskolczi *et al.* 2021). Countries in North America, South America, Europe, Asia, and Australia have shared national visions integrating research, development, and pilot deployment of autonomous vehicles. The sustainable transportation concept harnesses autonomous driving technology as a tool to promote traffic flow efficiency and safety, facilitate mobility and accessibility, and reduce global emissions of greenhouse gases (Cugurullo *et al.* 2020; Mora *et al.* 2020; Acheampong *et al.* 2021), ultimately reimagining urban environments into smart and green cities. Tangential effects, related to energy consumption, light pollution, land use, or public health (Duarte and Ratti 2018; González-González *et al.* 2020; Singleton *et al.* 2020), are frequently highlighted and examined. Several visions for the future —such as those put forward by the United Nations sustainable development goals (SDGs), and The New Urban Agenda (https://habitat3.org/the-new-urban-agenda/)— are directly linked to sustainable transportation and road safety, and the protection of biodiversity or natural habitats. The integration of biodiversity and ecosystem conservation into SDGs focuses primarily on sustainable infrastructure and urban development, but fails to consider the interface between wildlife and sustainable (or autonomous) transportation. Moreover, existing research is mainly limited to urban landscapes or impacts on human safety (Duarte and Ratti 2018; González-González *et al.* 2020; Seuwou *et al.* 2020; Singleton *et al.* 2020; Cugurullo *et al.* 2020; Acheampong *et al.* 2021). Deployment of AVs at any scale will have far-reaching societal, ethical, legal, and environmental implications. However, the intense focus on urban settings has, so far, left the ability of AVs to safely interact with wildlife as a key challenge at the frontier of AV research.

As core components of the future of transportation, AVs will have major implications for sustainability and biodiversity. Here, we present a conceptual framework that expands the concept of sustainable transportation to address the interface between wildlife and AVs, evaluating this technology beyond human safety concerns and urban environments. Our framework gives an overview of the emerging trends and dynamics within this field, combining open questions with relevant research approaches, and provides an entry point for ecologists and conservationists to integrate wildlife concerns into AV research, development, and deployment.

Autonomous vehicles: the problem or the solution?

Given the transformative yet disruptive nature of autonomous technology, its potential benefits are only achievable if risks are properly identified. This task requires a proactive and adaptive approach here and now, at the early stages of AV development (Niehaus and Wilson 2018; Mora *et al.* 2020). Akin to current transportation modes, we can expect AVs (at all automation levels) to interact with urban wildlife and, as their deployment expands beyond cities and into suburban or rural ecosystems (von Mörner 2019), or through naturalized or protected areas (Phillips *et al.* 2020; Eskandarian *et al.* 2021), with less urban-adapted species.

Wildlife-vehicle collisions (WVCs) are the second-largest source of anthropogenic mortality for many animal species (Hill *et al.* 2019), and the most conspicuous environmental effect of linear infrastructures (**Panel 2**). Our framework helps to define current and future priorities for research following the overview presented in **Figure 1**. Correctly anticipating wildlife-vehicle interactions (and collision events), is crucial for the implementation of preventive countermeasures or mitigations at three levels linked with the *environment*: (1) *infrastructure*: construction, expansion, and maintenance of road and support infrastructures, particularly when roads border or intersect biodiversity hotspots, naturalized or rural areas (such as parks, agricultural or plantation fields), or are near water sources; (2) *society*: government regulations and utilization policies to manage deployment within these sites, and account for potential travel pattern shifts and consumption; and (3) *transport systems*: mobility services and transportation modes that balance human and wildlife concerns for an efficient and safe traffic flow. These factors may have additive, synergistic, or antagonistic effects. For example, incorporating WVC mitigation measures, such as wildlife-crossing structures, may limit the impacts of existing highways with higher speed limits. While we recognize the inherent complexity of these relationships, disentangling them is contingent on the concurrent stage of AV development (*e.g.*, how fast can an autonomous vehicle react) and the conditions of their deployment (*e.g.*, what mitigation measures are in place). A necessary first step is to clarify these relationships by fostering collaborations with industry and policymakers.

Public acceptance of AVs relies primarily on traffic accident prevention (Pettigrew *et al.* 2019; Cugurullo *et al.* 2020), and WVCs not only pose a substantial threat to wildlife but may also jeopardize the safety of drivers and passengers. In the US, over 59,000 passengers per year are injured in WVCs, resulting in over 440 human fatalities (Conover 2019) and with associated costs between 6 to 12 billion dollars (Huijser *et al.* 2017). Approximately 40% of species involved in WVCs represent a real threat to human lives (mainly large mammals), and 94% may result in significant material damage, with an average cost of 885 US dollars per collision (for species > 1 kg) (Ascensão *et al.* 2021). Our proposed framework guarantees human safety while integrating the reduction of wildlife-vehicle collisions as a coexisting goal, increasing the reliability and sustainability of this technology.

Current prevention of WVCs primarily targets the *infrastructure* (*e.g.*, wildlife-crossing structures, fencing) and *societal* dimensions (*e.g.,* temporary road closures, speed limits) —although the effectiveness of these measures can vary considerably and is often taxon-specific (Rytwinski *et al.* 2016). Applying our framework to reduce WVC risk requires targeted research to better integrate wildlife-vehicle interactions at the AV design and operation levels. Autonomous technology needs to successfully (i) pinpoint the presence of the animal in or near the lane, (ii) monitor and predict their motion, (iii) assess collision risk, and (iv) trigger warning systems (for levels 0–4), or (v) determine the appropriate autonomous response with decision-making algorithms (levels 4–5). As scientists, we can further inform this process by accounting for (i) species traits and species-level behavioral responses to (ii) roads and to (iii) vehicles, (iv) when and where animals cross (dependent on environmental or weather conditions), and (v) the likelihood of causing material damages and threatening human safety. Overall, a deeper understanding of animal behavior and movement, as well as WVC patterns (e.g., which species are involved, known mortality hotspots) can provide crucial baseline information for developing safe and reliable autonomous driving systems.

Integrating conservation into autonomous vehicle research

Obstacle detection and motion tracking

Animal detection in image and video processing has experienced considerable progress in recent years (Weinstein 2018; Smith and Pinter-Wollman 2021), but mainly as a post-processing step after ecological data collection (*e.g.*, camera traps, citizen science record verification). The majority of these methods require at least some manual processing and minimal background clutter, or rely on the animal "posing" towards the camera. Therefore, the transferability of these methods to AV systems is low. First, AVs require high accuracy and precision combined with low response times (no manual processing). Second, animals may not be facing the camera during crossing attempts. Finally, as both the animal and the vehicle are moving, the road is quite unlike the environments where animal detection typically takes place (*e.g.*, stationary camera trap).

Object detection algorithms for AVs focus primarily on road signs, pedestrians, cyclists, or other vehicles (e.g., Fang and López 2019; Jahromi *et al.* 2019; Rosique *et al.* 2019; Hnewa and Radha 2020; Ahmed *et al.* 2022), with comparatively fewer methods designed for animal detection (Sharma and Shah 2017; Munian *et al.* 2020; Saxena *et al.* 2020; Gupta *et al.* 2021). The high levels of morphological variation across animal species, along with a wide range of sensory perception processes, behavioral responses, and means of locomotion, introduce several obstacles to automated animal detection methods. Munian *et al.* (2020) employed thermal imaging and a convolutional neural network (CNN) with the Histogram of Oriented Gradient (HOG) transform, to reach an average accuracy of 89%. This particular method experiences limitations with cold-blooded species, as it is based on thermal images, or for higher vehicle speeds, as the processing time is between 1 to 3 seconds. For context, a previous HOG-based system could only alert the driver in time when the vehicle speed was below 35 km/h, as the response time was 2.04–3.24 seconds (with an accuracy of 82.5%) (Sharma and Shah 2017). Saxena *et al.* (2020), based on a Single Shot Detector and Faster Region-based CNN (Faster R-CNN) algorithm, improve object detection speed but do not incorporate motion tracking. Gupta *et al*. (2021) incorporate motion tracking and prediction, leveraging the Mask R-CNN model for multiple species and using lane detection to develop a predictive feedback mechanism, but require clear lane demarcation and only achieved an accuracy of 81%. All of these methods require either visible-light or thermal cameras, and the majority are trained on a single species (Mammeri *et al.* 2016; Sharma and Shah 2017; Saleh *et al.* 2018). Therefore, future AV research should take advantage of the available multisensory systems to overcome sensor-specific weaknesses (Jahromi *et al.* 2019), and create faster and more robust animal detection algorithms.

Incorporating real-time species identification may allow for a more appropriate vehicle response to a collision event, but there are two major constraints. First, although CNNs achieve state-of-the-art performance, these techniques require large amounts of labeled data during training. Synthetic or simulated data may help fill these gaps (Saleh *et al.* 2018), particularly for cryptic, rare, or data-deficient species, but should be deployed with caution if these are the only available training datasets. Second, species identification algorithms may delay AV responsiveness; for example, applying content-based image retrieval algorithms is slower the bigger the database used. This bottleneck may be partially offset by using the vehicle's current location (filtering out species by their distribution range) and time of year (*e.g.*, migratory species) to limit database size.

Collision risk and decision-making algorithms

Autonomous vehicles may reduce WVCs but this is dependent on our ability to program them correctly. Although we can expect some compatibility in collision risk assessments for vehicle-pedestrian and wildlife-vehicle interactions, the former may rely on pedestrian communication or contextual cues —such as signal or pose estimation (Fang and López 2019) and human motion prediction (Rudenko *et al.* 2020)— which differ from that of wild animals (Sharma and Shah 2017). Wildlife-vehicle collision risk also depends on the species, the individual's sex and age, the time of day and year, or the surrounding environment. Comprehensive databases of behavioral responses to prior WVC events can help assess collision risk, but will not be possible to acquire for the majority of species. Recreating animal motion in a simulated environment may also address this knowledge gap if behavioral and morphological studies are available (Cutrone *et al.* 2018; Font and Brown 2020), though researchers can also extrapolate these parameters from similar species.

Deploying AVs within urban centers requires complex decision-making frameworks for road intersections, lane-changing, or driving style preferences during mixed-flow traffic (Li *et al.* 2021). We can expect that complex collision scenarios involving wildlife will require equally extensive research. Introducing any collision avoidance response into the decision-making system can put the AV at risk, as braking or evasive maneuvers can set off an unforeseen chain of events. However, as the loss of vehicle control is inherently more dangerous than a controlled stop, most collision scenarios may be solved by programming the vehicle to brake in a straight line (Davnall 2020). Incorporating such a response into the AV's decision and control block may result in a significant improvement for its passengers and for wildlife. Another way to improve human safety is to inform drivers if they are traveling through high-risk WVC sites. Developers could incorporate similar warning systems into existing smartphone apps (Wildwarner; https://wuidi.com/), programming AVs to alert human drivers (for autonomous levels 1–4) or to reduce vehicle speed (4–5) based on historical WVC datasets.

Infrastructure and technical limitations

The safe and efficient operation of AVs requires extensive work on current and future infrastructure (Liu *et al.* 2019; González-González *et al.* 2020), but roads will remain a ubiquitous part of our landscapes and their impacts are not limited to direct animal mortality due to vehicle collisions. Tropical and subtropical regions are already encumbered with several major development corridors, such as the "Belt and Road Initiative" throughout Eurasia and Africa (Hughes *et al.* 2020). These corridors may increase mobility and accessibility, but will likely cause extensive biodiversity loss as they cut through previously inaccessible regions and thus will increase habitat fragmentation, poaching pressure, and illegal wildlife trade. Dedicated lanes are a potential scenario for AV operation (Rad *et al.* 2020), reducing congestion and increasing traffic efficiency. However, if these lanes are created using hard barriers, mitigation measures (such as under- or overpasses) will have to be applied to compensate for potential connectivity losses.

The development of decision-making algorithms may require AV systems to be trained within simulated environments (Rosique *et al.* 2019). Although researchers can then safely evaluate a myriad of atypical situations, these simulations have inherent biases and are not always transferable to the real word. The lack of data on wildlife-vehicle interactions for rare and cryptic species (or in controlled, repeatable conditions) is a substantial constraint for their development and transferability. In practice, autonomous vehicles could function as opt-in data collection systems, recording WVC events to improve AV responses over time; and as this feature could compromise privacy, data anonymization should be insured during this process.

The development of more appropriate animal detection methods is also necessary. Relying only on algorithms tailored for human detection may lead to inaccurate interpretations of animal behavior or their impending motion, and current animal-specific methods still face many obstacles: relatively high response times only applicable at low vehicle speeds (Sharma and Shah 2017; 2020), the need for clear lane demarcation (Gupta *et al.* 2021), no motion tracking (Saxena *et al.* 2020), or limited training datasets (Sharma and Shah 2017; Saleh *et al.* 2018).

The technological limitations of AV sensors also need to be recognized. Visible-light cameras function poorly at high speeds, in adverse weather and low-light conditions, or with "busy" backgrounds (Rosique *et al.* 2019). The latter is likely to occur in natural landscapes with cluttered roadside vegetation (Font and Brown 2020; Phillips *et al.* 2020). Object detection with LiDAR is challenging for non-grounded objects. As the ground is used as a reference point to determine an object's distance, LiDAR has trouble dealing with unique means of locomotion (such as a hopping kangaroo) (Pettigrew *et al.* 2019). AV systems may also fail to detect small volant species (*e.g.*, birds, bats, gliding animals), which can suffer significant losses from vehicle collisions: for birds, c. 200 million individuals and 194 million individuals are killed annually on US (Loss *et al.* 2014), and European (Grilo *et al.* 2020) roadways, respectively. Similarly, small non-volant animals are likely to remain undetected, unless the sensors are mounted sufficiently low, the road and weather conditions are ideal, and the AV system is suitably trained to detect tiny objects (Li *et al.* 2020).

Concluding remarks

Hailed as essential components of a sustainable future for transportation within smart cities, AVs have the potential to improve accessibility and mobility while reducing traffic congestion, accidents, energy costs, and pollution. However, as transportation remains one of the main pressures on biodiversity (Maxwell *et al.* 2016) and hundreds of millions of animals die from vehicle collisions every year, we must consider the impact of AVs beyond urban landscapes and examine how they will interact with wildlife.

Although WVCs will not fully cease, making roads safer for people and wildlife should be a top research priority, and current challenges underscore the need to invest in further WVC research as well as complementary solutions within transportation policy, regulation, and roadway design. If AVs can redefine urban environments into sustainable or smart cities, they also offer an opportunity to integrate the safety of wildlife populations occurring near roads with that of drivers, passengers, and pedestrians. Roads are expanding exponentially, further fragmenting our remaining natural environments and exacerbating the impact of WVCs. Given the promise of AV technology, we provide clear suggestions to guide future research in **Panel 3**. Sustainable transportation centers on the realization of ambitious targets: traffic safety and efficiency, socioeconomic inclusion, and the reduction of human impacts. Our expectations for autonomous transportation must be matched by effective technological advances, and require targeted ecological research to fill knowledge gaps. Unlike existing approaches, our framework highlights specific steps that we must address to integrate conservation goals and achieve sustainable autonomous transportation (**Panel 3**). Our framework calls for a deeper understanding of animal movement and behavior towards roads and vehicles, as well as WVC patterns, to address human safety and the reduction of WVCs as co-existing targets for autonomous technology.

Declaration of interests

The authors declare no conflicts of interest.

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Panels

Panel 1. Autonomous vehicles: terminology and operation

The Society of Automotive Engineers (http://www.sae.org) sets the international standard for AVs, and defines six levels of automation (**Figure 2**). Vehicles equipped with advanced driver-assistance systems (levels 0–2) are currently in use, while levels 3–5 are still being developed or tested. Although levels 4 and 5 do not require a human driver to take control, as the automated system manages all aspects of driving, level 4 is limited to specific conditions (*e.g.*, favorable weather conditions, clear lane markings) or environments (*e.g.*, freeways, dedicated lanes) (Rad *et al.* 2020).

To achieve high levels of automation, AVs incorporate multisensory systems for navigation, obstacle detection, and recognition, while merging technologies to offset the weakness of each system (Jahromi *et al.* 2019; Rosique *et al.* 2019; Eskandarian *et al.* 2021). This sensor fusion allows AVs to function even in poor visibility environments or bad weather conditions. Common perception sensors include visible-light cameras, infrared imaging, Light Detection and Ranging (LiDAR), and radar, but level 5 AVs will likely not depend solely on their own inputs and instead will integrate vehicle-to-vehicle, vehicle-to-infrastructure, and vehicle-to-pedestrian communication systems. Although sensors are the fundamental building blocks, the AV operation also requires (i) processing data into meaningful information (object detection, identification, mapping, and tracking), (ii) mission, motion, and behavioral planning using decision-making algorithms and, for higher automation levels, (iii) motion and vehicle control (*e.g.*, steering, braking, signaling) through actuators.

Just as with conventional vehicles, autonomous driving technology must safely operate within narrow margins of processing time, failure rate, and maintainability. Ideally, AVs are programmed to make more immediate and accurate risk mitigation decisions than human drivers due to multisensory inputs. Moreover, artificial intelligence technology is not confounded by human weaknesses of fatigue, distraction, or intoxication that may hinder decision-making processes (Cunneen *et al.* 2019). An AV that achieves functional safety must be able to detect, identify, and react to a diverse set of challenges and threats while traveling through complex, uncertain, and cluttered environments —including those related to *wildlife-vehicle interactions*. As with vehicle-vehicle or vehicle-pedestrian interactions, deciding on the appropriate response requires an intersection of moral philosophy, law, and public policy to appropriately deal with moral dilemmas (*e.g.*, “the trolley problem”) (Davnall 2020; Li *et al.* 2021).

Panel 2. Wildlife-vehicle collisions as a threat to biodiversity

Transportation poses a significant threat to biodiversity through collisions with vehicles (Hill *et al.* 2019). In the US, it is estimated that hundreds of millions of vertebrates are killed annually from vehicle collisions (Loss *et al.* 2014). Similar patterns are predicted for European roads, with over 194 million birds and 29 million mammals killed annually (Grilo *et al.* 2020). These patterns are not exclusive to the Global North. In Brazil, for example, over 8 million birds and 2 million mammals may be killed per year due to collisions with vehicles (González-Suárez *et al.* 2018). Furthermore, at least 3.0–4.7 million kilometers of new roads will be built by 2050, and predominately in South and East Asia, Africa, and South America (Meijer *et al.* 2018).

Understanding why WVCs occur requires knowledge of animal behavioral responses to roads and to vehicles (**Figure 3**). *Road avoidance* can be caused by traffic noise, road surface, or the presence of vehicles (Hill *et al.* 2021), and is linked to the more indirect impacts (*e.g.*, as barriers or filters to movement). Conversely, *road attraction* increases wildlife-vehicle interactions by prompting a crossing attempt or increasing road use due to *thermoregulation*, *habitat or food resource availability*, *and dispersal or breeding behavior*. For example, reptiles use road surfaces for basking (Baxter-Gilbert *et al.* 2015) and bats forage for insects near streetlights (Azam *et al.* 2018), while other species may scavenge roadkill carcasses. Animals may also exhibit higher road crossing rates during mating or nesting seasons (Zhou *et al.* 2020). For an animal, avoiding a collision requires successful vehicle detection, threat assessment, and evasive behavior. For many species an approaching vehicle triggers a "flight" response (moving away from danger), while for others it results in a "freeze" response (remaining motionless) (Lima *et al.* 2015). The outcome of this interaction also depends on the driver's response (remain on course, slow down, swerve or brake) and various external factors, such as road and landscape features, nearby vehicles or pedestrians, and weather conditions. Failure at any of these stages may lead to severe injury or death, for the animal or the passengers of the vehicle.

Panel 3. Sustainable autonomous transportation

Autonomous vehicles offer new opportunities by increasing efficiency and safety over conventional vehicles: 90% of traffic accidents are partially due to human error or negligence (Guanetti *et al.* 2018), and human drivers may intentionally hit animals —particularly smaller non-charismatic species (Beckmann and Shine 2012; Mesquita *et al.* 2015). Future research efforts should follow five priority areas (**Figure 4**), leveraging our understanding of WVC patterns to inform the operation of automated systems. Database integration (animal motion, behavior, susceptibility to collisions, threatened status) should occur in a phased approach: first, incorporate only commonly-occurring species likely to cause damage to the vehicle or its passengers; later, as sensors and algorithms improve, species-level classification. Lower-level automation systems (0–4) can alert drivers of a "high-risk" species or potential crossing site, while higher automation levels (4-5) can incorporate specific responses to each behavioral type.

The reduction of WVC events requires modifications at three levels: *infrastructure*, *society*, and *transport systems* (**Figure 5**). First, crucial upgrades to existing *infrastructures* will extend to the implementation of specific mitigation measures, and can likewise facilitate AV deployment (*e.g.*, clear lane markings) (Liu *et al.* 2019; Nandutu *et al.* 2022). Although some measures require a large initial investment, WVC prevention offsets their cost within 16–40 years, or earlier for animal mortality hotspots (Ascensão *et al.* 2021). Second, new *regulations and utilization policies* can balance successful WVC reduction and AV deployment. Speeding and limited forward vision are the main factors affecting the outcome of wildlife-vehicle interactions (DeVault *et al.* 2015; Gharraie and Sacchi 2020), and speed limits are frequently suggested as a mitigation measure for WVC hotspots. Although their efficacy is somewhat limited (Rytwinski *et al.* 2016; Riginos *et al.* 2019), this may be due to the unpredictable behavior of human drivers and difficulties in enforcing speed limits. If properly programmed, AVs will follow speed zoning and limits better than human drivers. Low-speed limits allow for longer response times, particularly with fast-moving animals. Limited forward vision can be addressed by reducing roadside vegetation in high-risk WVC sites, which will limit the use of roadside verges as movement corridors (Phillips *et al.* 2020) and increase visibility and response time for AV systems. Lastly, AVs could serve as opt-in data collection systems to record WVC events for accident forensics, and to upload animal detections to existing biodiversity databases (*e.g.*, http://www.gbif.org) after proper anonymization procedures.

Figures

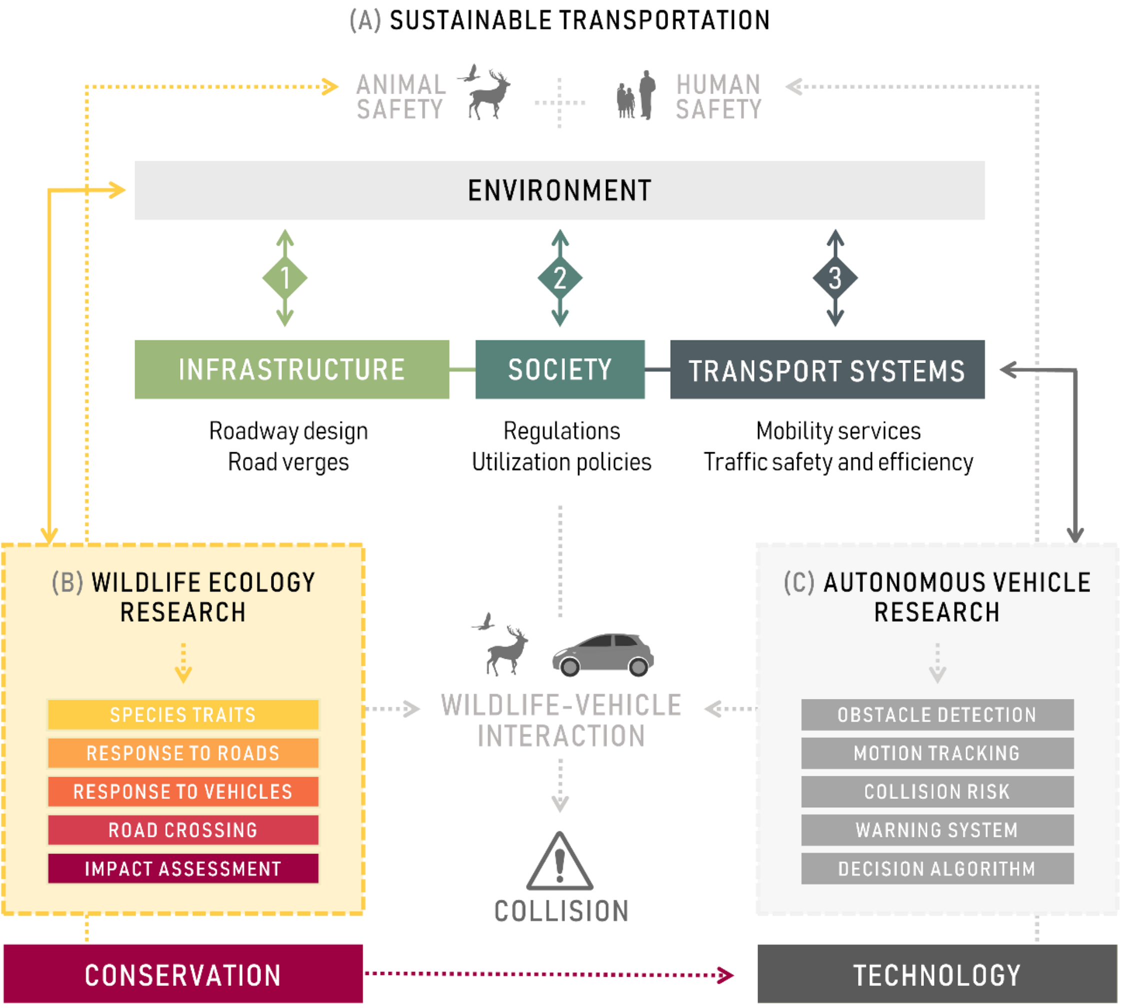

Figure 1. Conceptual framework of the key elements of (A) *sustainable transportation*, interlinked with (B) *wildlife conservation* (and corresponding ecological research areas) and with (C) *technological development* (and corresponding AV research areas). To achieve sustainable transportation, it is critical to explore how transport infrastructure, regulations and utilization policies, and the management of transportation systems can be optimized to reduce wildlife-vehicle interactions.

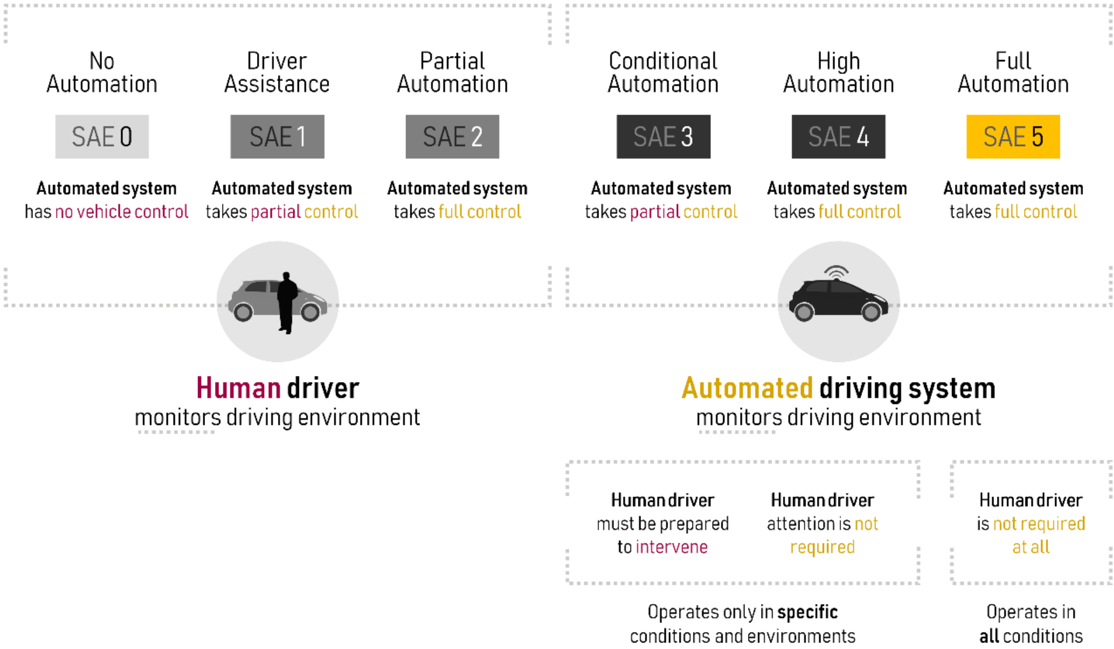

Figure 2. The six levels of AV automation defined by the Society of Automotive Engineers (SAE), ranging from 0 (fully manual) to 5 (fully autonomous).

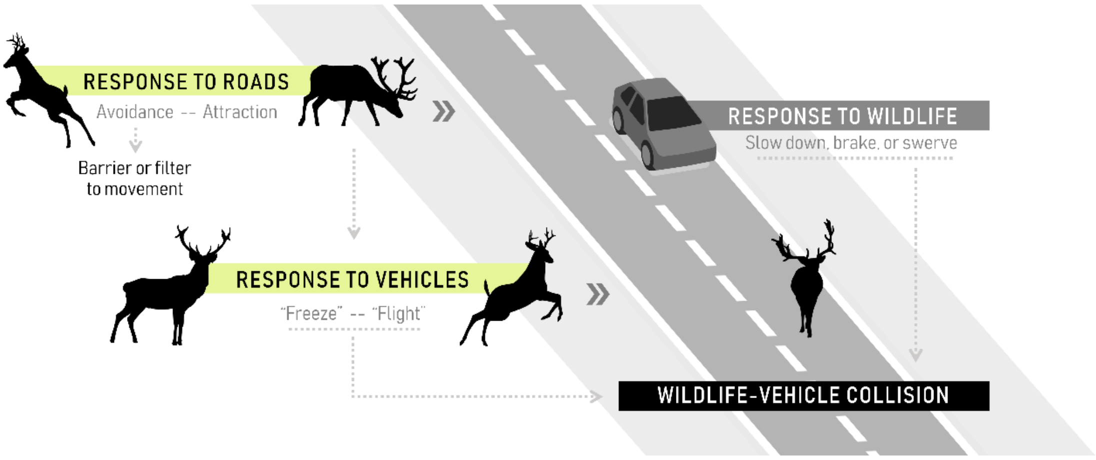

Figure 3. Animal behavioral responses to roads and to oncoming vehicles, and the driver's response to wildlife presence, leading to a wildlife-vehicle collision.

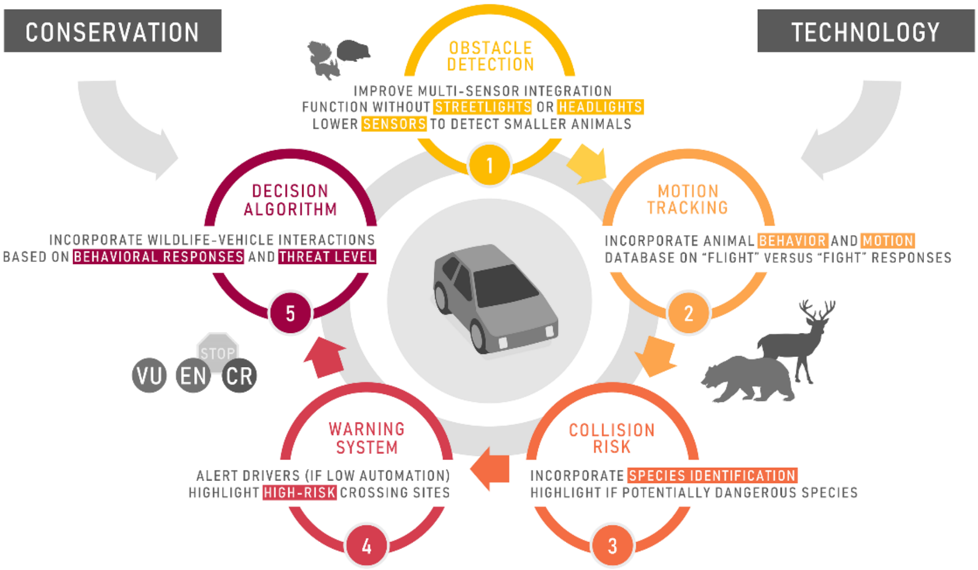

Figure 4. Research priorities within AV development that may reduce wildlife-vehicle collisions. For example, lower reliance on streetlights can reduce light pollution, improve the effectiveness of wildlife-crossing structures (Bhardwaj *et al.* 2020), or reduce foraging near roads (Azam *et al.* 2018).

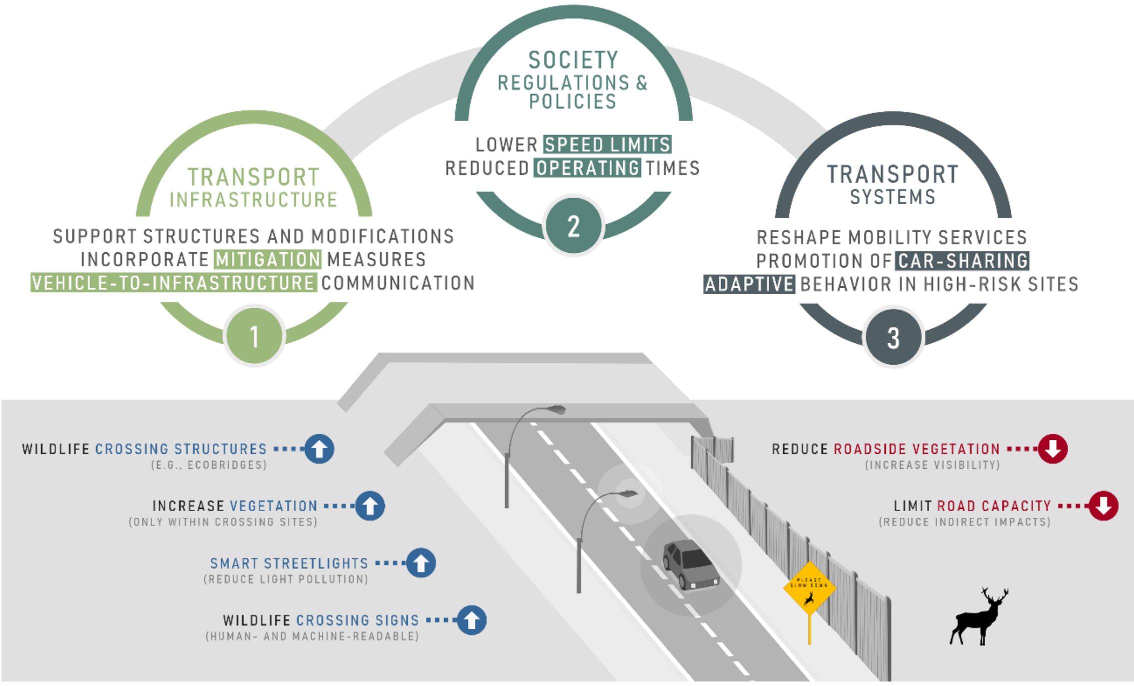

Figure 5. Mitigation measures for AV deployment and infrastructure that may reduce wildlife-vehicle interactions. These measures include infrastructure changes (*e.g.*, dedicated lanes, wildlife-crossing structures), regulations and utilization policies (*e.g.*, lowering speed limits), and redesigning our transport systems (*e.g.*, promoting car-sharing).