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FOUNDATION FOR TRAFFIC SAFETY

Examining the Safety Benefits of Partial Vehicle Automation Technologies in an Uncertain Future

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Title

Examining the Safety Benefits of Partial Vehicle Automation Technologies in an Uncertain Future

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Foreword

Emerging vehicle technologies have the potential to make driving not only more comfortable but also safer. Many motor vehicle crashes result from mistakes made by drivers. Advanced driver assistance systems (ADAS), common in today's new vehicles, have the ability to warn the driver or even intervene automatically in many situations to help the driver avoid a crash. These technologies have a clear role to play in our efforts to minimize vehicle crashes and save lives on our roads. However, it is important to have realistic expectations regarding the magnitudes of the safety benefits offered by technology, as well as how soon those benefits will be seen.

This report presents a methodology to estimate safety benefits of ADAS and describes potential reductions in motor vehicle crashes, injuries, and deaths that ADAS and partial vehicle automation technologies may prevent in the future. This study also examined many factors that will influence how large those benefits will be and how quickly they will materialize, as well as the continued need to invest in a comprehensive array of traffic safety measures. This report should be of interest to researchers, transportation officials, practitioners such as automobile manufacturers, as well as other traffic safety stakeholders.

C. Y. David Yang, Ph.D.

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About the Sponsor

AAA Foundation for Traffic Safety
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Table of Contents

List of Figures

List of Tables

List of Abbreviations and Acronyms

ACC:	Adaptive Cruise Control
ADAS:	Advanced Driver Assistance System
AEB:	Automatic Emergency Braking
AES:	Automatic Emergency Steering
AV:	Automated Vehicle
BSD:	Blind Spot Detection
CLD:	Causal Loop Diagram
CR:	Consumer Reports
CRSS:	Crash Report Sampling System
DDA:	Dynamic Driving Assistance
FARS:	Fatality Analysis Reporting System
FCW:	Forward Collision Warning
FHWA:	Federal Highway Administration
GHSA:	Governors Highway Safety Association
HLDI:	Highway Loss Data Institute
IIHS:	Insurance Institute for Highway Safety
LDW:	Lane Departure Warning
LKA:	Lane Keeping Assistance
NHTSA:	National Highway Traffic Safety Administration
NTSB:	National Transportation Safety Board
PD:	Pedestrian Detection
SAE:	Society of Automotive Engineers
SD:	System Dynamics
TRB:	Transportation Research Board
UI:	Uncertainty Interval
UNC:	University of North Carolina at Chapel Hill

Executive Summary

Background and Objective

Vehicle technology advancements are a crucial piece of the Safe System Approach, with the potential to contribute to significant transportation safety gains over the next several decades. Advanced driver assistance systems (ADAS) technologies represent a range of advanced vehicle functions that increase driver comfort by automating parts of the driving task under certain conditions, as well as increase safety by warning drivers of dangerous situations and braking or steering automatically to prevent or mitigate collisions. ADAS technologies have become increasingly popular in vehicles over the last several years, yet there is substantial uncertainty in the likely magnitudes of their safety benefits, as well as the rate at which safety benefits will be realized.

The objective of this work was to estimate how many motor vehicle crashes, injuries, and deaths ADAS technologies are likely to prevent over the next 30 years, taking into account the many complex and interconnected factors affecting the availability, effectiveness, uptake, and use of current as well as future ADAS technologies.

Methods

This study involved four key steps: (a) defining the combinations of ADAS technologies likely to be available on vehicles during the study period; (b) estimating the probabilities that vehicles equipped with specific ADAS technologies would avoid various types of crashes; (c) modelling broader system dynamics affecting ADAS technology adoption, diffusion, and safety performance over time; and (d) using the results of the preceding steps to estimate the numbers of crashes, injuries, and deaths that will be avoided due to ADAS technologies each year through 2050.

First, the research team defined specific combinations of technologies, informed by existing literature and market projections, broadly representative of the combinations of ADAS technologies expected to be available on vehicles over the time horizon of the study: (a) collision warning systems only; (b) collision warning systems plus adaptive cruise control; (c) collision intervention systems (plus warning systems and adaptive cruise control); and (d) dynamic driving assistance (plus collision intervention, warning systems, and adaptive cruise control); as well as vehicles with no ADAS technologies. The study did not examine higher levels of automation, which are not currently available to consumers in the U.S. market, as there were no data to inform assumptions about their uptake or performance.

The team then created a detailed matrix to categorize types of crashes that these technologies did versus did not have the potential to prevent. For crashes deemed potentially preventable, the probability of successful crash avoidance was estimated for vehicles equipped with the above-described combinations of technologies, taking into account the type of crash, the impact of contextual factors present in crashes that might influence system performance (e.g., weather, lighting conditions), as well as the probability that the relevant technology would be in use at the time.

Next, the team developed a causal loop diagram to depict key variables and causal relationships hypothesized to influence technology availability, uptake, use, and performance over time in relation to many interrelated factors hypothesized to influence them. This theoretical model was converted into a simulation model using a system dynamics modeling approach.

This model was then used to simulate potential future crashes annually through 2050 based on data from individual crashes that occurred in years 2017–2019 and an assumed 1% annual growth rate of total vehicle travel. For each simulated future crash, the probability that ADAS technologies on one or more of the vehicles involved would avoid the crash was estimated based on the probability that that each vehicle in the crash would be equipped with the relevant technology, the probability that the technology would be in use at the time, and the probability that it would successfully avoid the crash, given the capability and maturity of the technology as well as the circumstances of the crash. Results were aggregated over all simulated crashes in each year to estimate the numbers of crashes, injuries, and deaths that ADAS technologies would be expected to prevent, annually, as well as cumulatively over the 30-year period 2021–2050. Three sets of results are provided throughout the report: results based on assumptions that the research team regarded as most probable, as well as results based on alternative scenarios in which uptake and use of ADAS technologies were higher or lower than assumed in the main analysis.

Results and Discussion

Using the above-described simulation methodology, the current study estimates that ADAS technologies will prevent approximately 25% of all crashes, 24% of nonfatal injuries, and 33% of fatalities that would otherwise occur in 2050 if ADAS availability, uptake, effectiveness, and use were to remain at their 2017–2019 levels. Cumulatively, these technologies are anticipated to prevent approximately 37 million crashes, 14 million injuries, and 249,000 fatalities in the 30 years from 2021 through 2050, which represent approximately 16% of crashes and injuries, and 22% of fatalities predicted to occur on U.S. roads over the same 30-year period without these technologies.

Variation in ADAS technology uptake and use, however, could contribute to different safety outcomes. For example, in a scenario in which ADAS technology uptake and use are higher than expected, up to 38% of fatalities and 27%–28% of total crashes and nonfatal injuries in 2050 might be prevented by ADAS. In a scenario where uptake and use were lower than expected, ADAS could prevent as few as 22% of fatalities and 16%–17% of total crashes and injuries in 2050. Even in the more pessimistic scenario, however, ADAS technologies are predicted to prevent a total of nearly 8.7 million injuries and save more than 150,000 lives cumulatively by 2050. Thus, it is clear that driver support features already available today, when deployed at scale, have the potential to contribute to major improvements in road safety.

Although the results of the current study suggest that increases in the availability, uptake, use, and effectiveness of ADAS technologies over the next 30 years will contribute to substantial reductions in motor vehicle crashes, injuries, and deaths, there are still many scenarios and contexts in which ADAS technologies may not be able to intervene effectively or at all. Even in the optimistic scenario—in which ADAS is predicted to prevent more than 16.8 million injuries and save nearly 300,000 lives cumulatively in years 2021–2050, more than 73 million people would still be injured and nearly 850,000 would still die in crashes over the same 30-year period. Thus, while ADAS technologies have the potential to prevent large numbers of injuries and save many lives, there remains a clear need to continue to invest in other proven traffic safety measures in addition to vehicle technology.

The model and its results should be interpreted as a tool and test bed to consider the complex dynamics that may influence safety outcomes, and several limitations should be noted. The study does not account for the potential safety impacts of more advanced crash avoidance technologies or higher levels of vehicle automation that are not yet available on the U.S. market but that may emerge in the future. The study also does not account for other vehicle technologies besides ADAS (e.g., technology to limit speed, prevent impaired driving, or protect occupants in the event of a crash), other traffic safety policies (e.g., changes to road design or laws), other factors beyond transportation safety policy that may influence the uptake of vehicles equipped with ADAS (e.g., vehicle electrification policy, cybersecurity concerns), or factors that may influence traffic safety more broadly (e.g., changes in land use or commuting patterns, the COVID-19 pandemic). The numbers of deaths and injuries potentially prevented by ADAS were estimated by totaling the numbers of injuries and deaths in crashes that ADAS was predicted to prevent; actual numbers of deaths and injuries prevented could be somewhat greater if ADAS helps to reduce the impact speed of some crashes that still occur. Additionally, further research is needed to estimate safety benefits of ADAS disaggregated by demographic group and geography to examine potential inequities in access to new technologies and their anticipated safety benefits.

In conclusion, this research makes an important contribution to the field by estimating how many crashes, injuries, and deaths ADAS technologies are expected to prevent in the coming years, taking into account many interconnected factors and sources of uncertainty that are expected to influence the safety benefits of ADAS and the rate at which those benefits accrue. Overall, results corroborate previous research findings that while driver assistance and vehicle automation technologies will provide substantial safety benefits in the coming years, they are unlikely to eliminate all or most traffic fatalities and injuries within the next few decades. Thus, consistent with the Safe System Approach, which calls for a layered, redundant approach to safety, there remains a clear need to continue to invest in a wide array of proven traffic safety measures, including but not limited to vehicle technology.

Introduction

As the United States adopts a Safe System Approach to transportation safety, stakeholders are working to accelerate improvements across key transportation system domains (e.g., roadway design, speed management, vehicle safety innovation). Vehicle technology advancements are a crucial piece of the Safe System Approach, with the potential to contribute to significant transportation safety gains over the next few decades. In fact, the U.S. Department of Transportation, the U.S. Safe System consortium, the National Safety Council, and numerous other organizations and agencies have called for expanded and accelerated availability of advanced driver assistance systems (ADAS) in all new vehicles as an essential component to advancing Safe System implementation (JHCIRP, 2021; NSC, 2022; U.S. DOT, 2022).

ADAS technologies represent a range of advanced vehicle functions that can serve to notably improve driving safety through driver alerts and warnings, as well as crash avoidance and mitigation maneuvers. They can also serve to increase driver comfort by assisting with common driving and parking tasks. ADAS technologies have become increasingly popular in vehicles over the last several years. Current estimates indicate that nearly all new vehicles available in the United States have at least one ADAS technology, with the most common technologies including warning systems (e.g., blind spot detection (BSD)) (AAA, 2019; SBD Automotive, 2018). More recently, active ADAS crash avoidance systems have become increasingly popular and prevalent as well (e.g., automatic emergency braking (AEB)) (AAA, 2019; SBD Automotive, 2018). The National Highway Traffic Safety Administration (NHTSA) provides annual updates on progress made by 20 automakers regarding the increased adoption of low-speed AEB, for example (NHTSA, 2020).

A growing body of literature indicates that ADAS technologies have substantial safety benefits. For example, research from the Insurance Institute for Highway Safety (IIHS) and Highway Loss Data Institute (HLDI), utilizing police-reported crash data and insurance claims, estimated that forward collision warning (FCW) may reduce front-to-rear crashes by 27% and front-to-rear crashes with injuries by as much as 20%; benefits more than doubled when AEB was used in conjunction with FCW (Cicchino, 2017; HLDI, 2020; IIHS, 2020). Finally, other prevalent ADAS warning technologies, such as lane departure warning (LDW) systems and BSD have also demonstrated notable benefits, with research indicating 20%–25% reductions in relevant injury crashes (Cicchino, 2018a, 2018b; HLDI, 2020; IIHS, 2020).

While early research indicates promising safety benefits from ADAS technologies, there is substantial uncertainly in how quickly, and the extent to which, widespread safety benefits might be realized across the United States. ADAS diffusion into the U.S. vehicle fleet is affected by several factors, including price, technological maturity, and how quickly technologies become standard in vehicles. Several agencies, including the National Transportation Safety Board (NTSB), have called for increased adoption of ADAS technologies as standard packages on vehicles; however, there are several industry and policy dynamics that affect these processes (NTSB, 2022; VSI Labs, 2020). Even with increased ADAS diffusion, there are several causal factors that affect crash occurrence, and therefore, several factors that determine the extent of ADAS safety benefits. For example, crashes are often the result of factors operating across several domains, including factors in the built environment (e.g., roadway design, land use), at the vehicle level (e.g., technology, functionality), related to a person's decision making (e.g., vehicle maneuvers, decision to turn on/off ADAS technology), and associated with environmental conditions (e.g., icy conditions, poor lighting). ADAS technologies will help reduce crashes and improve safety only to the extent that they help to address or overcome one or more critical links in a crash's causal chain, and perform in the conditions in which crashes are likely to occur. Even under optimal deployment of redundant ADAS technologies, the design domains in which sensors will reduce crashes are limited. While many new vehicles sold today offer AEB with pedestrian detection, most pedestrian fatalities occur on relatively high-speed roads and in darkness, conditions in which sensors used in current generation systems do not perform well (AAA, 2021; Cicchino, 2022; Combs et al., 2019; NCSA, 2022). Additionally, there are several prevalent crash scenarios in which current ADAS technologies do not perform well. For example, straight-crossing-path ("T-bone") crashes and crashes involving a vehicle turning across the path of another vehicle represent nearly 40% of fatalities in two-vehicle crashes. While drivers might expect technologies such as automatic emergency braking (AEB) systems to aid in these scenarios, recent research indicates that many systems often fail to avoid or even mitigate such crashes (AAA, 2022). Given the overall complexity in diffusion rates, crash causal chains, and technological capability and maturity, there is considerable uncertainty regarding the potential safety gains that might be realized by ADAS technologies over the next several years in the United States.

The overall objective of the current study is to estimate the number of motor vehicle crashes, injuries, and deaths that existing ADAS technologies are likely to prevent over the next 30 years, accounting for the complex and interconnected factors affecting the availability, uptake, use, and performance of the technologies. Results are provided across a range of scenarios to demonstrate potential impacts of assumptions on safety outcomes.

Methods

The purpose of this study was to estimate the numbers of deaths, nonfatal injuries, and crashes on U.S. roads that would potentially be prevented by ADAS and partial vehicle automation technology each year through 2050 given realistic assumptions regarding changes over time in ADAS technology adoption, use, and effectiveness, as well as in the total amount of U.S. vehicle travel. The study approach involved four major sub-steps, listed below and outlined in Figure 1.

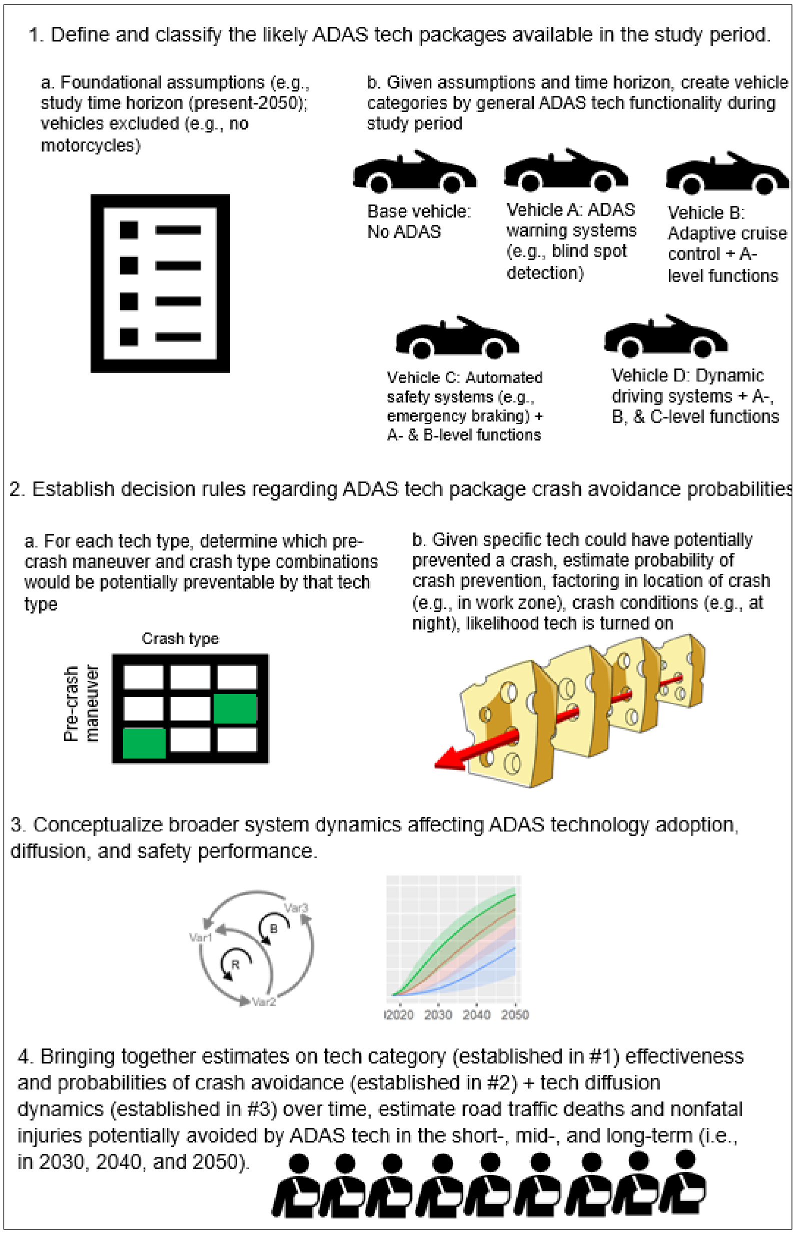


Figure 1. Key project tasks and steps.

1. Defining combinations of ADAS technologies ("packages") available on vehicles during the study period.
2. Estimating crash avoidance probabilities for ADAS, by technology package and crash type
3. Modelling dynamics affecting the diffusion, use, and effectiveness of ADAS.
4. Estimating future numbers of crashes, injuries, and deaths potentially avoided by ADAS.

The following sections describe the methodology and information sources used in each of these specific steps.

Step 1: Defining combinations of ADAS technologies ("packages") on vehicles

This task involved defining and classifying the various combinations of ADAS technologies likely to be available on vehicles in the United States during the study period. Within this task, the team made several decisions and assumptions about the technologies and the types of vehicles on which they would be installed. Core assumptions and decisions are outlined below.

Scoping Decisions

The research team made several overarching design, data, and analytic decisions from the outset to shape this work. A time horizon of 30 years was selected, such that the model estimates safety outcomes each year through 2050, based on crash data from 2017–2019. The study considered ADAS and partial vehicle automation technologies up to and including SAE Level 2, i.e., driver support features that provide simultaneous steering and braking/acceleration support to the driver. Technologies considered in the current study are shown in Table 1.

Table 1. ADAS technologies considered in this study. Definitions from AAA (2019).

ADAS technology	Definition
Blind spot warning	Detects vehicles to rear in adjacent lanes while driving and alerts driver to their presence.
Pedestrian detection	Detects pedestrians in front of vehicles and alerts drivers to their presence.
Lane departure warning	Monitors vehicle's position within driving lane and alerts driver as the vehicle approaches or crosses lane markers.
Forward collision warning	Detects impending collision while traveling forward and alerts driver.
Adaptive cruise control	Controls acceleration and/or braking to maintain a prescribed distance between it and a vehicle in front. May be able to come to a stop and continue.
Automatic emergency steering	Detects potential collision and automatically controls steering to avoid or lessen the severity of impact.
Forward automatic emergency braking	Detects potential collisions while traveling forward and automatically applies brakes to avoid or lessen the severity of impact.
Lane keeping assistance	Controls steering to maintain vehicle within driving lane. May prevent vehicle from departing lane or continually center vehicle.
Dynamic driving assistance	Controls vehicle acceleration, braking, and steering. SAE standard definition of Level 2 driving automation systems outlines this functionality.

The current study estimated the future safety benefits of installing these technologies on automobiles, pickup trucks, minivans, vans, or sport utility vehicles (hereafter collectively "passenger vehicles") and large trucks. Automation on other types of vehicles (e.g., motorcycles, off-road vehicles, micro-mobility devices) was not considered. Higher levels of automation were not considered due to lack of data on their safety performance. Technologies designed to assist with vehicle parking were not considered due to lack of data regarding the incidence of crashes involving parking as most such crashes likely occur on private property (e.g., in parking lots) and thus are not included in most state and national motor vehicle crash databases. Safety technologies unrelated to vehicle automation (e.g., night vision systems, alcohol ignition interlocks, technology to improve vehicle crashworthiness) were not considered as they were outside the scope of the study. Additional details on specific model inclusion and exclusion criteria are further discussed subsequently in Methods subsection 3 and summarized in Table 2.

Defining combinations of ADAS technologies on vehicles

The research team developed a set of technology "packages" representing different combinations of ADAS and partial driving automation technologies expected to be available on vehicles in the United States during the study period. The packages were developed to detail technologies in vehicles at a more granular level than SAE level (SAE, 2021), while also recognizing that disentangling each individual ADAS technology was beyond the scope of the study. Therefore, the vehicle categories represented a compromise between delineating potential safety impacts of specific technologies and managing model complexity, recognizing that many of these technologies co-occur in the same vehicles. The vehicle technology packages examined in the current study were defined as follows:

- **Base Package**: No ADAS or automation
- **Package A**: Warning systems (blind spot warning, lane departure warning, forward collision warning, and pedestrian detection systems)
- **Package B**: Adds adaptive cruise control to Package A
- **Package C**: Adds automatic emergency braking, emergency steering assistance, and lane keeping assistance to Package B
- **Package D**: Adds dynamic driving assistance (i.e., simultaneous operation of adaptive cruise control and lane centering assistance) to Package C

Note that as defined here, each higher technology package includes all of the systems present in all lower packages.

Step 2: Estimating crash avoidance probabilities for ADAS

In this task, the research team first established decision rules regarding what general types of crashes could versus could not potentially be prevented by each ADAS technology. For crashes deemed potentially preventable, the research team then estimated the probability that the applicable technology would prevent the crash. These decision rules (preventable vs. not preventable, and probability of prevention among the preventable) were then mapped onto specific crash types, pre-crash maneuvers, and environmental factors recorded in national crash databases used to quantify the baseline incidence and estimate the likely future incidence of such crashes.

Data on motor vehicle traffic fatalities examined in the current study were from NHTSA's Fatality Analysis Reporting System (FARS) database, which is a census of all crashes that occur on public roads in the United States, involve a motor vehicle in transport, and result in a death within 30 days of the crash (NHTSA, 2022a). Data on nonfatal injuries and total crashes were from the NHTSA's Crash Report Sampling System (CRSS) database, which comprises a geographically stratified sample of police-reported crashes, which are weighted to produce statistical estimates regarding all police-reported crashes nationwide (NHTSA, 2022b). Together, these data systems provided a holistic understanding of the characteristics, associated factors, and outcomes of crashes across the United States.

Using these data sources, the research team extracted key crash-level (e.g., crash conditions such as road surface conditions, lighting, weather), vehicle-level (e.g., number of vehicles involved, types of vehicles involved, pre-crash maneuver of vehicles, crash geometry from the perspective of each vehicle), and person-level (e.g., severity of injuries) characteristics from respective 2017–2019 FARS and CRSS data files.

Decision rules regarding whether each general type of crash identified in the crash databases could potentially be prevented by ADAS, and if so, the probability of successful prevention given the specifics of the crash, were informed by literature reviews and expert opinion. Further details on specific decision rules are included below.

Identifying potentially preventable crashes

To identify crashes that each ADAS technology had some possibility of preventing, the team examined variables in the FARS and CRSS data systems that described pre-crash maneuvers (variable name: p_crash2) and crash type/geometry (variable name: acc_type). The team then assessed whether each specific ADAS technology included in the study had any potential to prevent each general type of crash as defined by combination of pre-crash maneuver and crash type/geometry. Note that the purpose of this step was simply to distinguish between crashes that the ADAS considered in the current study had any possibility versus no possibility of preventing; the probability of prevention among those deemed possibly preventable is assessed in a subsequent step.

Decisions regarding whether a given technology had any potential to prevent a particular type of crash were made independently by two members of the research team based on literature reviews and expert opinion. Disagreements were resolved through discussions with the larger research team. The following broad categories of crashes were deemed not preventable by ADAS and thus were not examined in further detail: (a) crashes resulting from vehicle malfunctions (e.g., tire blow out, stalled engine), (b) crashes involving pre-crash loss of control/traction, (c) wrong-way crashes, (d) straight-crossing-path ("T-bone") collisions, (e) turn-across-path collisions (AAA, 2022), (f) crashes occurring on non-trafficways or ramps, (g) crashes involving vehicles entering or leaving driveways, and (h) crashes involving objects (e.g., debris) on the roadway.

The following summarizes the research team's determinations regarding the potential of each technology included in the study to prevent various general types of crashes. Appendix Table A1 shows the specific combinations of crash type and pre-crash maneuvers that the team determined ADAS had some possibility of preventing (and thus carried forward to the next step of the analysis) versus those deemed not preventable.

Forward collision warning and *automatic emergency braking* systems were assumed to help prevent crashes in which another vehicle or entity ahead was stopped or rapidly decelerating just prior to the crash and in situations where the ultimate crash type was a forward impact, including but not limited to rear-end collisions (IIHS, 2022; Tan et.al;

2020). While the probability of successful prevention by FCW versus AEB differed (as discussed in next section), they were assumed to have some potential to prevent the same general types of crashes.

Pedestrian detection systems were determined to be relevant in crashes that involved a pedestrian approaching or in the roadway, but not in all crash-type scenarios. For example, if a vehicle was turning, it was assumed the detection system would not have sufficient time to detect the pedestrian and avoid the collision, as such systems have been shown to perform poorly such scenarios (Cicchino, 2022; AAA, 2019).

Lane departure warning and *lane keeping assistance* systems were assumed to have the potential to prevent crashes in which a vehicle traveled over its lane boundaries or departed the road prior to the occurrence of the crash. These include simple road-departure crashes (often resulting in vehicle rollovers or collisions with fixed objects) as well as other types of crashes immediately preceded by unintentional lane departure (e.g., a forward collision with another vehicle in an adjacent lane). These technologies, however, were assumed not to prevent crashes occurring due to vehicle turning movements, nor crashes resulting from evasive actions taken by the driver in attempt to avoid a collision with a vehicle or pedestrian on the roadway.

Blind spot detection systems are designed to detect other vehicles immediately beside the vehicle and should assist in avoiding collisions related to side or lateral maneuvers (most commonly sideswipe collisions). Blind spot detection was assumed unable to contribute meaningfully to the prevention of other crash types such as forward impacts or unintentional lane departures.

Automatic emergency steering was assumed to have some potential to prevent many road departure, forward impact, and rear-end collisions by helping the driver to steer or redirect the vehicle to avoid an imminent collision. However, similar to other technologies, it was assumed that the technology would not intervene during turning maneuvers. It was also assumed to have limited ability to intervene in sideswipe collisions.

Adaptive cruise control is designed to help keep a vehicle at a safe following distance from the vehicle in front of it, this technology was assumed to help to prevent front-to-rear crashes in certain scenarios.

Dynamic driving assistance is designed to keep a vehicle centered in its lane and maintain speed and following distance. It was assumed that the technology would be able to prevent many of the crashes involving road departures, forward impact, rear-end collisions with another vehicle, and sideswipe collisions. However, it was assumed that the technology would not be able to prevent crashes that involved turning movements based on research indicating limited efficacy for ADAS technologies in turning maneuvers (Yue et al., 2020).

Estimating probability of avoidance for individual crashes

For crashes determined to be potentially preventable in previous step based on their crash type and pre-crash maneuvers, the research team then estimated the probability that a given technology would avoid the crash. (Note that for simplicity, the approach only considers crash avoidance. It does not consider whether ADAS technology packages may reduce injury severity in the event a crash is not prevented, for example by reducing impact speed.) The probability that a crash (i) would be avoided (P_i) was computed as the product of the following:

i. The baseline effectiveness of the technology for a given crash type, expressed as a probability of crash avoidance (A_i)
ii. A multiplier representing any reduction in effectiveness due to the particular hazards present in the crash (e.g., weather, lighting, etc.) (H_i)
iii. The probability that the technology would be activated and in use at any given moment, given that the vehicle was equipped with the technology (U_i)

The baseline effectiveness estimates, multipliers for reduction in effectiveness due to hazards present, and assumed probabilities of system activation/use are provided in Table A2 in Appendix A. Using the values from Table A2, the probability that a given technology package (j) in isolation would prevent a given crash i, given that the vehicle was equipped with the technology and that the technology was in use at the time, is thus:

$$P_{i,j}|\left(E_j \cap U_j\right) = \delta_{i,j} A_{i,j} H_j \qquad (1)$$

where $\delta_{i,j}=1$ if crash i is a type of crash deemed potentially preventable by any of the ADAS included in technology package j (crash type marked "Y" in Table A1 in Appendix A) and 0 otherwise, and E_j is the probability that the relevant vehicle is equipped with technology package j. The probability that technology package j would avoid the crash given only that the vehicle is equipped with package j is thus:

$$P_{i,j}|E_j = \left(P_{i,j}|E_j \cap U_j\right)U_j = \delta_{i,j} A_{i,j} H_j U_j \qquad (2)$$

When more than one hazard potentially reducing system effectiveness was present (e.g., if a crash occurred during a rainstorm and in darkness), the largest reduction in effectiveness associated with any of the individual conditions was used. (The research team also considered treating each condition as acting independently and multiplying the corresponding hazard reductions, but determined this would be inappropriate, as oftentimes multiple conditions impair the performance of the technology through similar or overlapping mechanisms. For example, darkness and precipitation both restrict cameras' vision.)

Given the prevalence of lane departure crashes (approximately one third of nonfatal and one half of fatal crashes) and literature showing high percentage of drivers that deactivate lane departure and lane keeping assistance technologies (Reagan & McCartt, 2016), the research team disaggregated crashes according to whether they were lane-departure or non-lane-departure crashes and by whether the lane keeping systems (lane departure warning or lane keeping assistance) included within any given technology package were assumed to be in use. The probability shown above in Equation 2 was thus decomposed into a weighted average of the probability of prevention given the lane keeping features of the system were active (denoted below in Equation 3 by subscript j+) and the probability of prevention given the lane-keeping features were inactive (denoted by subscript j–), calculated using the applicable values in Table A2 (i.e., for lane-departure or non-lane-departure crashes, with lane keeping features active or inactive) for system effectiveness, probability of use, and reduction in effectiveness due to hazards present, and weighted by the probabilities of system use with the lane keeping features active versus inactive as shown below in Equation 3.

$$P_{i,j}|E_j = \frac{1}{U_{j+}+U_{j-}}\Big(\big(P_{i,j+}|E_{j+} \cap U_{j+}\big)U_{j+} + \big(P_{i,-}|E_{j-} \cap U_{j-}\big)U_{j-}\Big) \quad (3)$$

Note that because each higher ADAS package as defined in the current study includes all lower packages, the probability that each technology would be in use at any given time was determined using a "step-down" approach. For example, Package D comprises all technologies considered in the current study up to and including dynamic driving assistance. If a vehicle was equipped with ADAS Package D, there is some probability (per Table A2) that dynamic driving assistance would be in use. However, when not in use, any of the technologies included in Package C could be in use, and their associated effectiveness and usage parameters would then apply. Thus, the probability that a *vehicle* equipped with Package A would avoid a crash is simply given by Equation 2, the probability that a vehicle equipped with Package B would avoid it is given by the sum of the probabilities that Package B would avoid the crash plus the probability that Package B systems were not in use and that Package A would avoid the crash, as shown below in Equation 4.

$$P_i|E_B = \big(P_{i,B}|E_B\big) + \big(P_{i,A}|E_A\big)\overline{U_B} = \big(P_{i,B}|E_B\big) + (P_i|E_A)(1-\ U_B) \quad (4)$$

Similarly, Equations 5 and 6 show corresponding probabilities of crash avoidance for vehicles equipped with packages C and D, respectively.

$$P_i|E_C = \big(P_{i,C}|E_C\big) + (P_i|E_B)(1-\ U_C) \quad (5)$$

$$P_i|E_D = \big(P_{i,D}|E_D\big) + (P_i|E_C)(1-\ U_D) \quad (6)$$

For each parameter referenced in the equations above, Table A2 provides an initial value (i.e., the value for the base year, 2017) and a final value, representing the team's assumptions of how effective the technology is likely to be by 2050, given improvement and maturation in the technology. Improvements/maturation over time between the starting year and ending year were modelled using an S-shaped curve, with values in intermediate years determined by simulation as described in the next section. Documentation in Appendix A summarizes the team's rationale for each value. Given the scope of the types of technologies considered, various manufacturer-specific implementations of them, as well as the range of crash scenarios and unique circumstances present, exact technology effectiveness values for specific crash types were often unavailable in existing literature, thus the values used reflect the research team's best judgment informed by existing literature where applicable as well as by expert opinion. Various sensitivity analyses described in the Uncertainty and Sensitivity Analyses section below were conducted to take into account the uncertainty around these parameter estimates.

Step 3: Modelling dynamics affecting diffusion of ADAS

The purpose of this step was to conceptualize the broader system dynamics affecting the adoption, diffusion, and safety performance of ADAS technology. To do this, the team used a system dynamics (SD) modeling approach to examine and account for the underlying complexity affecting ADAS diffusion trends. SD is an approach used to analyze complex and dynamic systems. SD is particularly useful when there is a web of factors interacting and changing over time such that cause-and-effect relationships are particularly difficult to intuit or trace through several steps. SD helps to model complexity exhibited by non-linear trends (which are common in transportation safety outcomes); feedback behavior (i.e., closed chains of endogenous factors; see more on this below); delays between causes and effects (i.e., how quickly an action causes a reaction); and adaptiveness (Sterman, 2000). SD simulation models have been used to study ADAS and AV system deployment, electric vehicle infrastructure diffusion and readiness, and other specific road safety outcomes and vehicle technology uptake trends over time (Harrison et al., 2021; Keith et al., 2019; Nieuwenhuijsen et al., 2018; Puylaert et al., 2018; Rakoff et al., 2020; Stanford, 2015; Struben & Sterman, 2008).

At the core of an SD approach is a mapping method called causal loop diagramming (Sterman, 2000). Causal loop diagramming depicts key variables believed to be most important for understanding specific outcomes over time, and the hypothesized causal relationships between them. Causal loop diagrams (CLDs) are generally created using the best available literature and data, as well expert input to supplement literature where gaps are encountered. These CLDs ultimately depict the theoretical underpinning and core causal structure that then shapes the development of simulation models. They also serve as living maps that can be updated over time as new research improves the collective understanding of the system and as stakeholders discuss and debate modifications to assumptions, additions to the model, or scenarios to examine.

In the current study, the research team created a CLD to guide this work and inform simulation model development (Figure 2). This CLD depicts the research team's best understanding of the most important and/or basic dynamics to consider when modeling ADAS diffusion within the overall project scoping decisions described previously. The development of this CLD was informed by literature reviews, discussions among the project staff, discussions with external experts, and reviews of previous ADAS- and AV-related SD models. In particular, the previous work of Nieuwenhuijsen et al. (2018), with advancements by Harrison et al. (2021), provided the foundation for the CLD used in the current study. Those studies used SD simulation models to examine ADAS and AV diffusion into the vehicle fleet in the Netherlands under a variety of scenarios. Several feedback loops in the top third of Figure 2, related to technology maturity, industry experience, purchase price, sales, and attractiveness, were derived from those models. While the quantitative estimates attached to these dynamics differ between the United States versus European settings, it is expected that some of the underlying *structure* related to vehicle technology diffusion is similar.

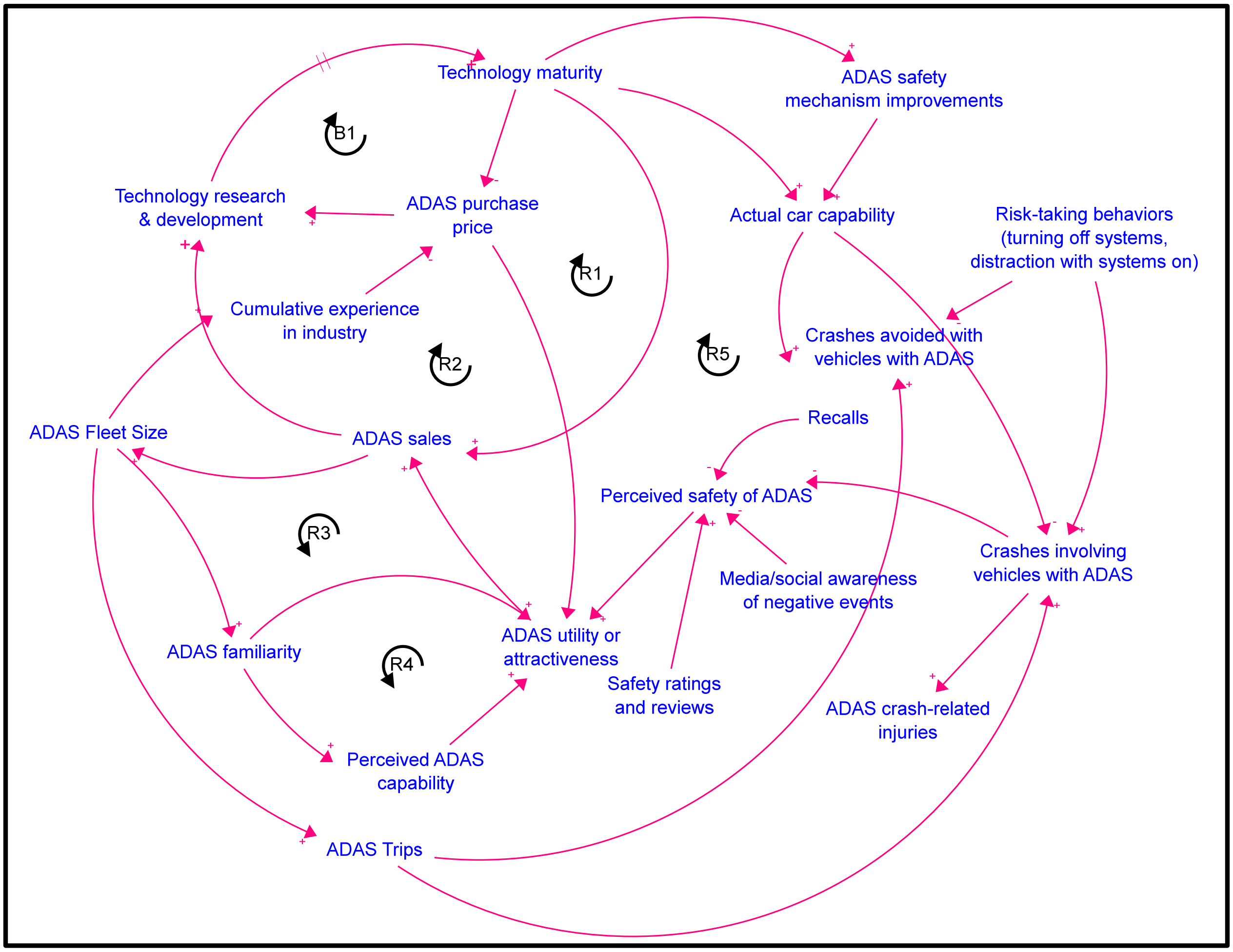


Figure 2. Causal loop diagram of important interconnected mechanisms likely to impact ADAS diffusion and related safety trends.

The CLD shown in Figure 2 includes key variables, causal relationships, and feedback processes hypothesized to be most important to understanding ADAS diffusion and related safety outcomes in the context of the current study. Factors in the diagram are connected via causal arrows with polarity. Casual arrows with a positive polarity (+) indicate that a change in the variable from which the arrow originates causes a change in the same direction in the destination variable (i.e., if the first variable increases, then the second also increases), assuming all else is equal. Causal arrows with a negative polarity (−) indicate that the two connected variables change in opposite directions. When causal connections form a closed chain of effects, over time, they create a balancing or reinforcing loop, depending on the combined polarities of the arrows in that loop. In transportation models, there are several key dynamics operating over time, including some that are balancing and others that are reinforcing. Simulation models help researchers to understand and test potential dynamics to learn what might be contributing to safety-related trends over time.

Balancing loops are critical dynamics in the system that tend to resist change and seek equilibrium. One example of a balancing loop is related to ADAS technology development and maturity (e.g., Loop "B1" in Figure 2). This balancing loop theorizes that as there is more research and development in a specific ADAS technology, the technology matures, and production efficiency increases. This has the effect of reducing the purchase price for that technology over time, which eventually reduces the funds and investments for further development of that specific technology. As technology peaks, iteration becomes less profitable, and investment in further development of that specific technology decreases in favor of investment in research and development of other new technologies (c.f., Sterman, 2000). This hypothesized feedback loop is a balancing feedback loop because increases in the initial variable (here, technology maturity) eventually cycle through a chain of connected factors over time to decrease (or slow) the rate of change in that initial variable, all else held equal.

Reinforcing loops are critical to understanding the behavior of a complex system. In contrast to balancing loops, reinforcing loops generate exponential growth (or decline/decay) in the system. This system includes several potential reinforcing loops (see loops labeled with an "R" in Figure 2). For example, a "word of mouth" reinforcing loop is found in many complex health and safety systems (see Loop "R3" in Figure 2). In the context of the current study, this loop posits that as sales of vehicles with certain ADAS features increase, the general public's familiarity with this type of technology increases (e.g., people become increasingly likely to know others who have the technology or have experienced it). This increases the attractiveness of and willingness to adopt the technology, causing sales of vehicles with those specific technology features to continue to increase, all else held equal. This type of loop causes quick growth in uptake (when observed in isolation).

To further facilitate simulation model development and explicitly document decisions pertaining to the model boundary and scope related to ADAS diffusion and safety, Table 2 lists factors included in the current study as well as factors acknowledged as potentially important but declared outside the scope of the current study. Within the list of included variables, the research team further divided these variables into variables assumed to be influenced or determined by other variables included in the model (i.e., endogenous variables) and variables that are inputs to the model but are modeled as unaffected by changes within the model (i.e., exogenous variables). Future research needs and model extensions beyond the scope of the current study are discussed in the Discussion section.

Table 2. Inclusion and exclusion decisions to further define model boundary and scope.

Included Endogenous Factors	Included Exogenous Factors	Not Included in Current Study
Sales, price, uptake, fleet size, trips of vehicles equipped with ADAS (and non-ADAS-equipped vehicles)	Information (media, safety ratings, recalls, etc.) affecting perceptions related to ADAS safety	SAE Level 3–5 systems (due to lack of real-world safety performance data and time horizon of study)
Technology maturity, research and development, industry experience related to ADAS development	Risk-taking behaviors (and/or cognitive overload) related to ADAS technology (e.g., sleeping at the wheel) and use of systems (e.g., turning off systems)	Crashes solely involving buses, motorcycles, or other/unknown vehicles (due to lack of data on ADAS effectiveness in these vehicle types)
Perceived and actual capability and safety of ADAS technology		Crashes occurring off public roads (e.g., parking lots and other private property) due to lack of data on incidence
Crashes involving vehicles equipped with ADAS (and without ADAS) and crashes avoided by these vehicles		Potential supply chain disruptions and availability of materials/labor for ADAS technology and vehicle production
Number and types of injuries occurring in crashes involving ADAS-equipped vehicles (and non-equipped vehicles)		Exogenous factors affecting consumer vehicle purchasing decisions (e.g., economic shocks, developments related to electric vehicle technology and policy, etc.)
		Vehicle cybersecurity risks

As shown in Table 2, the model included core dynamics related to vehicle technology development, sales, fleet size, and consumer decisions to purchase vehicles with different ADAS technologies and features. These purchase decisions were modeled as driven by a variety of factors, including price, familiarity with the technology, perceived safety, and perceived capability of the vehicle. Price was modeled as affected by technology maturity and cumulative industry experience for manufacturing a given technology. Familiarity was modeled as driven by sales and the likelihood of knowing others who used the technology, hearing about it, or seeing it often in the media. Crashes occurring or avoided were modeled as influenced by the number of trips occurring, as well as the vehicle's crash avoidance capability as influenced by the technology with which it was equipped, its baseline effectiveness, technological maturity, as well as the actions of the vehicle operator (e.g., response/non-response to alerts from warning systems, turning off/deactivating safety technology). Together, these dynamics interacted to generate model simulated crash trends over time.

Using the CLD and explicit model boundary decisions, the research team converted the theoretical model into an SD simulation model using Any Logic software (AnyLogic, 2022; Sterman, 2000). As mentioned, CLDs can serve as a theoretical underpinning and high-level view of an SD model, which can then be quantitatively defined and simulated, linking the defined elements in the system. The research team used literature reviews to parameterize and inform the model assumptions. For example, starting values for the approximate number of vehicles with each technology package at model initiation (i.e., in 2017) were estimated by triangulating data from Consumer Reports (CR, 2021), Highway Data Loss Institute (HDLI, 2019, 2020), and automotive research companies (Hedges & Co, 2022). Similarly, estimates of the current average vehicle lifespan and vehicle miles traveled growth rates in the United States were obtained from S&P mobility data and Federal Highway Administration (FHWA) forecasts, respectively (S&P Global Mobility, 2022; FHWA, 2022a). Additionally, several estimates and assumptions regarding the speed of technological maturity (i.e., measure of technology reliability and performance modeled on a scale of 0%–100% with 100% representing perfect performance and reliability) and knowledge growth (i.e., measure of research and development output that is then used to drive technological maturity) were assumed to be roughly similar to prior modeling efforts in this space (Harrison et al., 2021; Nieuwenhuijsen et al., 2018). Sensitivity analyses (described subsequently) examined alternative scenarios where the uptake and use were both higher and lower than the value predicted by the SD simulation model.

Step 4: Estimating future numbers of crashes, injuries, and deaths potentially avoided by ADAS

In this step, the research team brought together the results of the previously described steps 1–3 to estimate the total number of crashes, injuries, and deaths potentially avoided by ADAS technologies each year through 2050. To do this, the research team built a model structure to simulate the number and characteristics of crashes, injuries, and deaths occurring in future years, and then estimated the probability that each simulated crash would be prevented by ADAS.

Predicting future crashes, injuries, and deaths before accounting for avoidance by ADAS

Future crashes were simulated using data from fatal crashes in NHTSA's FARS data system and nonfatal crashes from NHTSA's CRSS. Because CRSS is a sample of all police-reported crashes each year in the United States, statistical weights in CRSS were used to determine the number of crashes in the full population represented by each crash in the database. Fatal crashes in FARS were assigned a statistical weight of 1 because FARS includes a record of every fatal crash; fatal crashes in CRSS were excluded to avoid double-counting. All crashes that involved at least one passenger vehicle or large truck that was on a trafficway at the time of the critical event that led to the occurrence of the crash were included, with the exception that crashes involving more than 4 vehicles (<1% of all crashes) were excluded due to the difficulty in determining the roles of the many vehicles involved and thus the ability of technology on any particular vehicle to prevent the crash.

For simplicity, the model assumed that before accounting for crashes potentially prevented by ADAS, the future rate of crashes per mile driven would be similar to the rate in the base year. Thus, the number of crashes in each future year would be expected to be similar to the number in the base year plus any change proportional to the change in total amount of driving. The model assumed a 1% annual increase in total vehicle miles driven, similar to the FHWA's forecast that vehicle miles of travel will increase by an annual average of 0.9% in years 2018–2048 (FHWA, 2020). Thus, the expected number of crashes in each future year was modeled as the average number in the base year plus the 1% annual increase due to increased driving mileage.

To account for random variability in the crashes that occur as well as to represent the full range of potential crash characteristics as well as possible, the current study used an aggregate of FARS and CRSS data from 2017–2019 as the base year. The numbers of crashes, nonfatal injuries, and deaths in the base year are shown in Table 3. The number of crashes expected to occur in each future year was thus the average number in 2017–2019 plus a 1% annual increase.

Table 3. Number of crashes, nonfatal injuries, and deaths in base year used for simulations.

	Crashes	Nonfatal Injuries	Deaths
2017	6,205,000	2,641,000	33,727
2018	6,492,000	2,609,000	33,131
2019	6,533,000	2,629,000	32,603
Total	19,230,000	7,879,000	99,461
Base Year	6,410,000	2,626,000	33,154

Base year for study = annual average numbers of crashes, injuries, and deaths in years 2017–2019. Data are from NHTSA's FARS and CRSS databases and include all crashes involving ≥1 passenger vehicle or large truck on a trafficway prior to critical event and ≤4 vehicles total. Statistics shown are weighted estimates from records of 146,559 nonfatal crashes and 91,236 fatal crashes.

The characteristics of crashes in each future year were predicted by sampling with replacement the corresponding number of crashes (i.e., the average in the base year plus 1% annual increase) from among the entire pool of crash records from 2017–2019. Sampling was performed separately for each month to account for seasonal variation in the number, severity, characteristics, and environmental conditions of crashes (e.g., crashes in each future January were simulated by sampling from among all crashes that occurred in January 2017, January 2018, and January 2019.)

Predicting the probability that ADAS would avoid each simulated future crash

The probability that each future crash, simulated as described above, would be avoided by ADAS was estimated as a function of the probability that the vehicles involved in the crash would be equipped with any given ADAS package, the probability that the ADAS package would be able to avoid the crash given details about the crash, and the probability that the relevant ADAS feature would be in use at the time (i.e., not turned off or deactivated).

For each vehicle involved in a simulated crash, its probability of being equipped with a given ADAS package was estimated based on the year of the crash and the proportion of all vehicles predicted to be equipped with each ADAS package in that year (predicted as described in the Step 3). For each simulated crash, the model first assessed whether there was any possibility that the ADAS technologies on any of the involved vehicles could have avoided the crash, and if so, its probability of successful avoidance, as described previously in Step 2. The probability that a given vehicle would avoid a given future crash was thus computed as sum of the probabilities that a vehicle equipped with each respective technology package would avoid the crash (from equations 2, 4, 5, and 6) weighted by the probability that the vehicle was equipped with each respective technology package, as shown in Equation 7, below.

$$P_i = \sum_{j=A,B,C,D} \left(P_i | E_j\right) E_j \qquad (7)$$

If a crash involved only one vehicle, the probability of avoiding the crash was based on that vehicle's predicted probability of avoiding it. In crashes involving two vehicles, the crash was assumed to be prevented altogether if either of the vehicles was predicted to avoid it. In crashes involving three or four vehicles, the model assumed that each vehicle predicted to avoid the crash has a 50% probability of preventing the entire crash from occurring. (Note that fewer than 10% of all crashes involve more than two vehicles, and sensitivity analyses indicated that changes to assumptions regarding the prevention of crashes involving more than two vehicles had negligible impact on the overall results.)

Finally, the prevention of each crash was assumed to prevent all of the deaths and nonfatal injuries that occurred in the original crash sampled from the FARS and CRSS base year data. For simplicity, the study did not attempt to estimate any potential additional reduction in injuries due to reductions in the severity of crashes still predicted to occur (e.g., due to reduced impact speed).

In summary, the model estimated the probability that each simulated future crash, and thus any deaths or injuries occurring in the crash, would be prevented by ADAS features on the vehicles involved in the crash. The probabilities of prevention for each individual crash were then aggregated over all crashes to estimate the total numbers of crashes, injuries, and deaths prevented by ADAS in each future year, as well as the number that would still occur. For example, if the model ultimately determined that a crash had a 30% probability of being avoided by ADAS, this indicates for every 100 such crashes that would otherwise occur without considering ADAS, 30 would be avoided by ADAS and 70 would still occur.

Model verification and analyses

The last step in the model building process consisted of performing verification and validation checks consistent with model building best practice. The research team assessed unit and dimension consistency, completed code verification, and conducted extreme value testing.

The model was then used to conduct substantive analyses that were the focus of the current study. Specifically, the research team used the model to forecast the number of crashes, injuries, and deaths that ADAS will help to prevent, and the number that will still occur, annually and cumulatively through 2050. Results compare the numbers crashes, injuries, and deaths expected to be avoided in future years given anticipated ADAS technology advancement, diffusion, and use, relative to the numbers that would be expected if levels of ADAS effectiveness, diffusion into the vehicle fleet, and use remain at their base year levels.

Results are presented in terms of three scenarios: a "best estimate," a "low uptake & use" scenario, and "high uptake & use" scenario. The "best estimate" represents the safety outcomes obtained through simulation with model parameters set to values that the research team regards as the most probable based on available data, literature, and expert opinion. The “high uptake & use” and “low uptake & use” scenarios represent more optimistic and more pessimistic scenarios, respectively, simulated by modifying the following key parameters (shown in the CLD, Figure 2) affecting technology uptake and utilization:

- *Attractiveness weight* represents how important non-price attributes of the vehicle are, including comfort, familiarity, and safety. Increasing this parameter increases all of these attributes, including safety, which in turn increases ADAS sales.
- *Industry learning effectiveness* represents how effectively or quickly industry spending on each technology package gets transferred into technology maturity and can bring down ADAS costs to the consumer. Increasing this would also then directly increase ADAS sales.
- *Learning speed* represents how quickly perceived safety catches up to actual safety. A value of 1 represents a scenario where public perceptions of the safety of the technology perfectly track its actual safety, 0 represents a scenario where public perceptions of safety do not change even as actual safety does. Increasing learning speed increases safety benefits.
- *Initial perceived safety relative to actual safety* represents how accurate the initial driver perception of technology safety is. A value of 1 represents a scenario in which initial public perceptions of the safety of the technology agree perfectly with its actual safety; a value of 0 represents a scenario in which the public perceives the technology as being much less safe than it actually is. [Note: While the current model does not allow perceived safety to exceed actual safety, sensitivity analyses revealed little influence of this parameter on overall model inferences.]
- *Technology usage modifier* represents the likelihood of having ADAS technology turned on and in use (i.e., as opposed to having been deactivated by the driver, or the driver ignoring warnings), which affects ADAS safety benefits or lack thereof. Values shown in Table A2 in Appendix A are multiplied by this value.

The values of these parameters that were used to define the “best estimate,” “high uptake & use,” and “low uptake & use” scenarios and produce the results presented in this report are provided in Appendix B.

Uncertainty and sensitivity analyses

In addition to these analyses, the research team performed uncertainty and sensitivity analyses. Uncertainty analysis was used to estimate the outcomes of interest in the face of stochasticity and parameter uncertainty in the model, while sensitivity analysis was used to identify the uncertain parameters with the largest influence on model estimates.

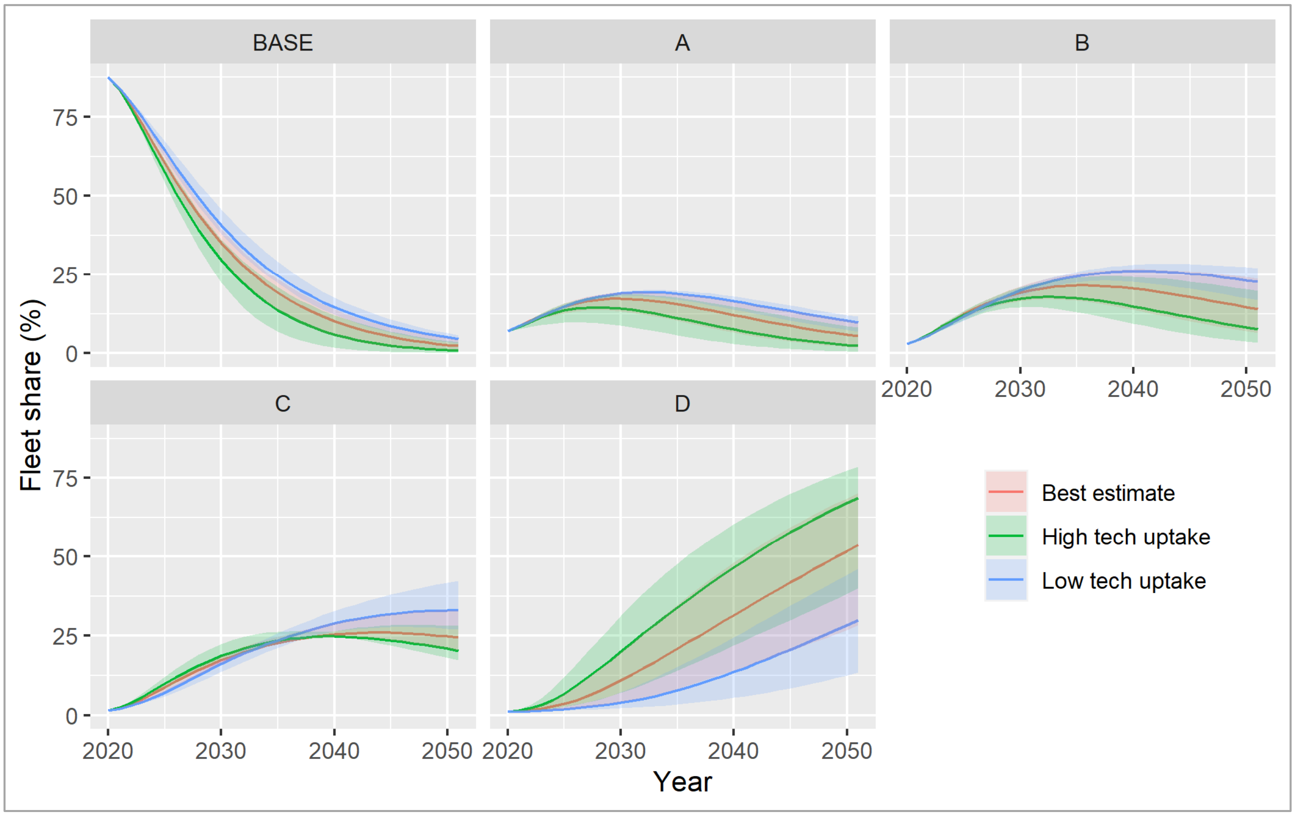
In uncertainty analysis, the research team was concerned with two types of uncertainty in the model: (a) stochasticity and (b) parameter uncertainty. Stochasticity refers to the underlying randomness in the simulation model estimates of the probability of avoidance of crashes. Parameter uncertainty refers to the inherent uncertainty in the values of the model parameters used to define the model and simulate outcomes. To carry out uncertainty analysis, each scenario was simulated 500 times, sampling values for the model parameters from a normal distribution centered on the best estimate and with a standard deviation of 25% of the starting value. This normal distribution was truncated to the range of plausible values for a given parameter (e.g., a probability could only vary between 0 and 1). All model runs for a given scenario were aggregated together, and for each year, the 50th percentile value was taken as the main estimate and the 2.5th and 97.5th percentiles were taken as the endpoints of the 95% UI, which represents the extent of variation in the relevant outcome measure (e.g., number of crashes prevented by ADAS in a year) due to stochasticity and parameter uncertainty.

Finally, the team conducted a sensitivity analysis in which uncertain model parameters were varied, one at a time, in increments of 10%, 20%, 30%, 40%, and 50%, with each model run simulated 100 times to account for stochastic variation. When any one parameter was changed, all other parameters were kept at their original "best estimate" values. Values were truncated at plausible parameter boundaries (e.g., a probability could only vary between 0 and 1). These parameters were then rank ordered based on the magnitude of their impact on fatal and nonfatal injuries avoided in 2050.

Results

To estimate the likely future safety benefits of ADAS, the SD model developed by the research team was first used to estimate the percentage of all vehicles on U.S. roads that would be equipped with various configurations of ADAS technologies over the 30-year time horizon examined. Figure 3 presents the share of the U.S. vehicle fleet expected to be equipped with each distinct combination or package of ADAS technologies considered under each of the technology diffusion scenarios modelled (best estimate, low tech uptake & use, high tech uptake & use).

Figure 3. Expected proportion of total U.S. vehicle fleet represented by each of five different technology packages under three different technology diffusion scenarios, 2020–2050.

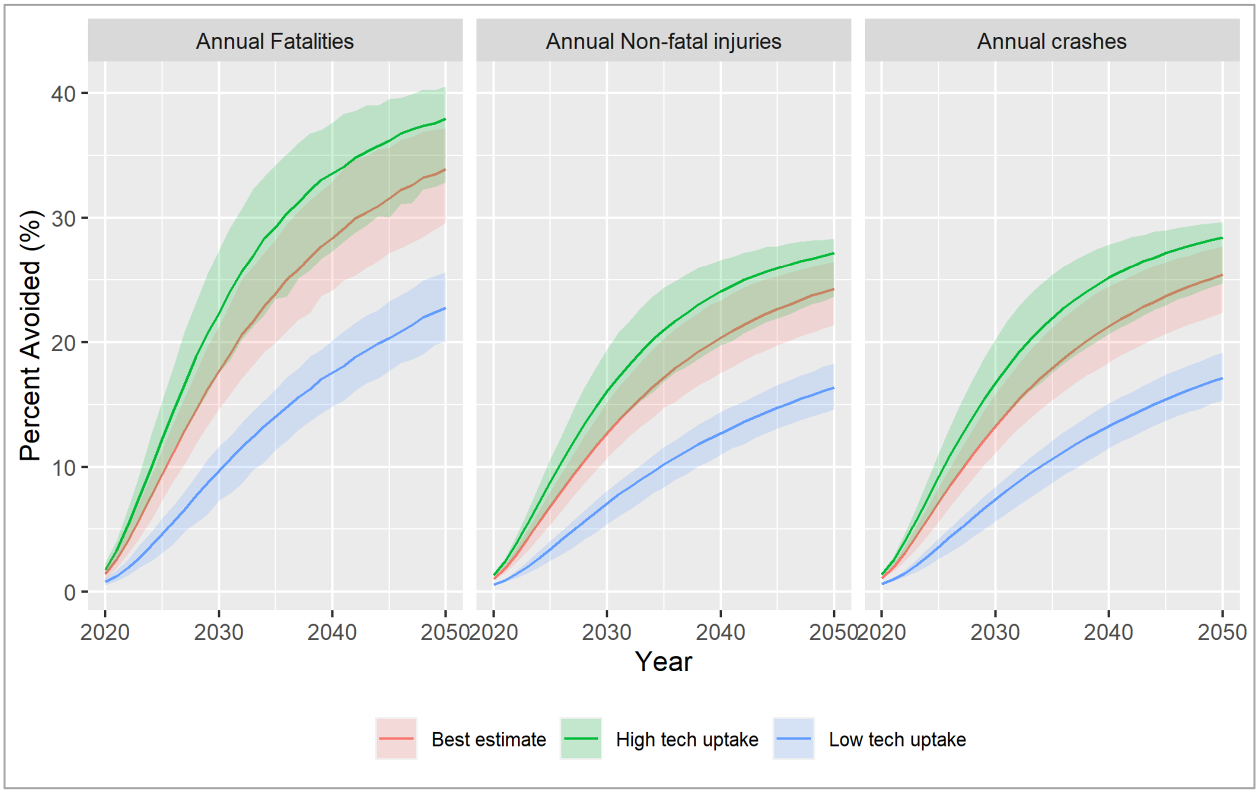


Note: Shaded ribbons show 95% UIs for estimates based on 1,000 model simulation runs.
Base: No ADAS.
A: Warning systems (blind spot, lane departure, forward collision, pedestrian detection).
B: A + adaptive cruise control systems.
C: B + automated safety systems (automatic emergency braking, emergency steering assistance, lane keeping assistance).
D: C + dynamic driving assistance.

In the best estimate scenario, vehicles equipped with a full suite of ADAS technology including dynamic driving assistance or SAE Level 2 partial automation (Package D) are expected to account for approximately 54% of the entire U.S. vehicle fleet (95% UI: 28%, 70%) by 2050. In the high uptake & use scenario, approximately 69% (95% UI: 40%, 79%) of vehicles would be equipped with Package D by 2050. In the low uptake & use scenario, 30% (95% UI: 13%, 46%) would be expected to be equipped with this level of automation. Note that in even the low uptake & use scenario, more than 95% of all vehicles on U.S. roads are expected to be equipped with at least some ADAS (i.e., Package A or higher) by 2050.

Figure 4 presents the expected numbers of crashes, injuries, and deaths prevented by ADAS technologies each year through 2050 under the technology diffusion scenarios presented in Figure 3. As in Figure 3, three sets of estimates are shown: a best estimate based on assumptions deemed most probable, low uptake & use, and high uptake & use scenarios. Figure 5 shows summary estimates for the same scenarios for three individuals representing the short-term (2030), mid-term (2040) and long-term (2050) safety impact of ADAS.

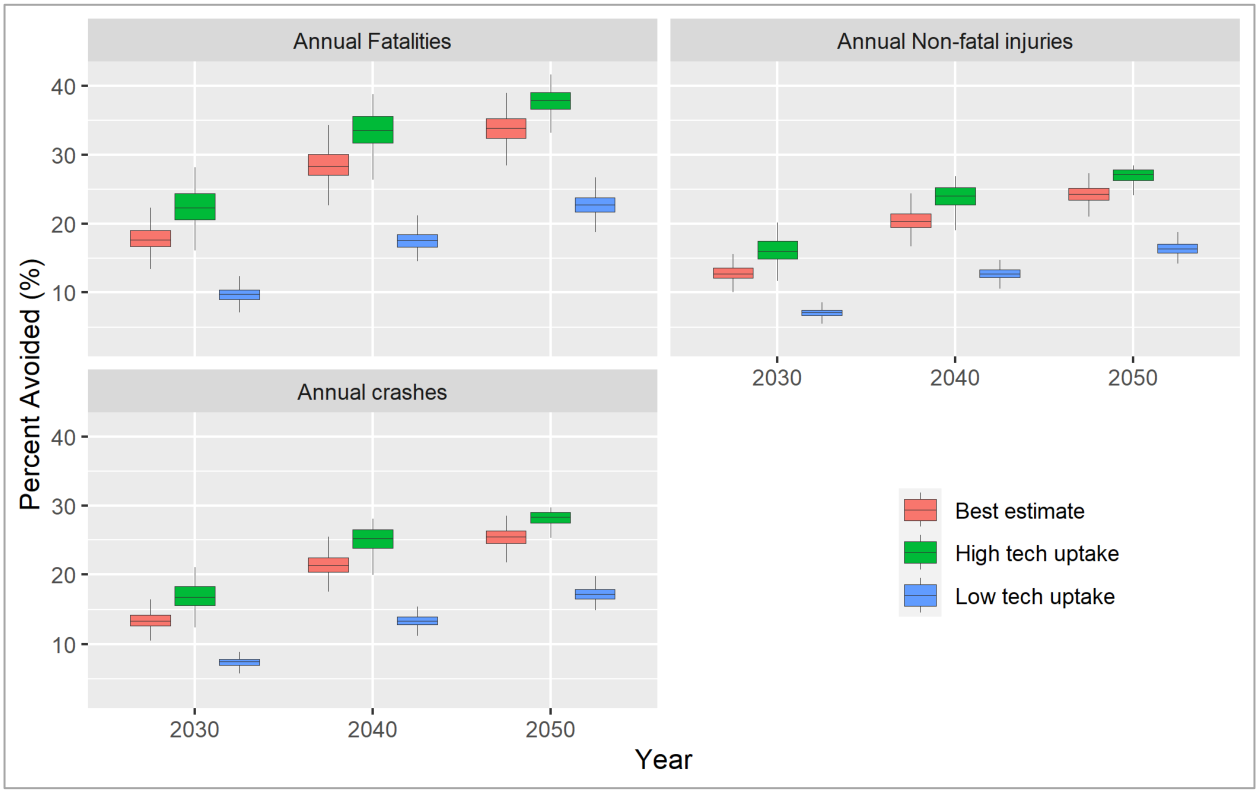
Figure 4. Expected percent of fatalities, nonfatal injuries, and crashes prevented annually by ADAS technologies under each of three technology uptake and use scenarios, United States, 2020–2050.



Note: ADAS technologies considered were warning systems, adaptive cruise control, collision intervention systems, and dynamic driving assistance. Annual estimates of crash prevention are based estimated fleet share for various technologies shown in Figure 3.
Base for percentages: Number of crashes, injuries, deaths expected to occur in each future year given levels of ADAS market penetration, effectiveness, and use in 2017–2019. (Crashes not involving a car or truck, involving 4 or more vehicles, or occurring off public roads were excluded.)

In the best estimate scenario, results indicate that 16% (95% UI: 13%, 20%) of fatalities, representing nearly 6,000 fatalities, could be potentially avoided by ADAS in 2030, with estimates increasing to 34% (95% UI: 29%, 37%) in 2050. Proportions of nonfatal injuries and total crashes prevented by ADAS technologies were somewhat lower than fatalities, reflecting the varying severity of the types of crashes on which ADAS technology has the potential to intervene. Finally, variation in ADAS uptake and technology use could contribute to important outcome differences in the future. For example, differences in low versus high uptake & use scenarios could lead to an approximately 11 to 15 percentage point difference in the proportions of crashes, injuries, and deaths prevented in 2050.

Figure 5. Expected percent of fatalities, nonfatal injuries, and crashes prevented annually by ADAS technologies under each of three technology uptake and use scenarios in the United States in 2030, 2040, and 2050.



Note: ADAS technologies considered were warning systems, adaptive cruise control, collision intervention systems, and dynamic driving assistance. Annual estimates of crash prevention are based estimated fleet share for various technologies shown in Figure 3.
Base for percentages: Number of crashes, injuries, deaths expected to occur in each future year given levels of ADAS market penetration, effectiveness, and use in 2017–2019. (Crashes not involving a car or truck, involving 4 or more vehicles, or occurring off public roads were excluded.)

Tables 4 through 6 provide the corresponding estimates and uncertainty intervals for Figure 5, in terms of annual and cumulative counts of fatalities, injuries, and crashes expected to be avoided by ADAS technologies and those still expected to occur in 2030, 2040, and 2050 in each of the three technology uptake and use scenarios. Findings indicate that despite substantial numbers of crashes, injuries, and deaths prevented by ADAS, large numbers of crashes, injuries, and deaths will nonetheless remain, even as far into the future as 2050.

In the best estimate scenario, ADAS is estimated to prevent approximately 16,500 traffic fatalities in 2050 (Table 4). However, the model indicates that an estimated additional 27,400 fatalities would still be expected to occur. Similarly, under the best estimate scenario, the model predicts that ADAS will help vehicles to avoid 832,000 injuries (Table 5) and 2,179,000 crashes (Table 6) in 2050, yet 2,629,000 injuries and 6,493,000 crashes are still expected to occur despite those crash reductions due to ADAS.

Cumulative numbers of crashes, injuries, and deaths anticipated to occur in the 30-year period from 2021 through 2050 after accounting for the benefits of ADAS are also notable. Under the best estimate scenario in which various ADAS technologies enter the vehicle fleet at the rates shown previously in Figure 3, ADAS technologies collectively are expected to prevent approximately 37 million crashes, 14 million nonfatal injuries, and 249,000 deaths cumulatively between 2021 and 2050, representing approximately 16% of crashes and injuries, and 22% of fatalities that would be expected to occur without ADAS. However, despite these savings, an estimated 189 million crashes are still expected to occur, resulting in an estimated 76 million nonfatal injuries and 896,000 deaths. The cumulative estimates also highlight the substantial importance of the rates of uptake and use of ADAS technology in determining how rapidly their safety benefits will accrue. The numbers of crashes, injuries, and deaths expected to be prevented by ADAS cumulatively through 2050 are nearly twice as large in the high uptake & use scenario compared with the low uptake & use scenario.

Table 4. Percent and count of fatalities avoided by ADAS technologies and anticipated to occur under each of three technology uptake and use scenarios over time through 2050.

	Annual Fatalities			Cumulative Fatalities *	
(values in thousands)	**% Avoided (95% UI)**	**Number avoided (95% UI)**	**Number anticipated (95% UI)**	**Number avoided (95% UI)**	**Number anticipated (95% UI)**
2030					
Best estimate	16.3% (13.3%, 19.6%)	5.8 (4.8, 7.2)	30.1 (28.4, 31.9)	30.3 (24.4, 35.4)	314.3 (308.2, 320.6)
High uptake and use	20.7% (15.9%, 25.4%)	7.5 (5.7, 9.3)	28.6 (26.6, 30.7)	38.9 (30.6, 47.0)	306.0 (297.0, 315.1)
Low uptake and use	8.7% (6.2%, 10.6%)	3.1 (2.2, 3.8)	32.8 (31.5, 34.3)	15.5 (11.2, 18.0)	329.6 (324.9, 334.8)
2040					
Best estimate	27.7% (23.7%, 32.2%)	11.0 (9.4, 12.9)	28.7 (26.6, 30.6)	118.4 (100.5, 139.3)	606.5 (585.9, 624.8)
High uptake and use	33.1% (26.7%, 37.0%)	13.1 (10.6, 14.7)	26.6 (24.7, 29.3)	147.1 (117.1, 172.6)	578.9 (552.2, 606.3)
Low uptake and use	17.1% (14.3%, 19.4%)	6.8 (5.6, 7.8)	33.0 (31.6, 34.6)	67.5 (53.8, 76.6)	658.2 (648.0, 671.8)
2050					
Best estimate	33.5% (29.0%, 37.0%)	14.7 (12.7, 16.4)	29.2 (27.3, 31.5)	249.4 (214.8, 285.2)	896.0 (858.4, 932.1)
High uptake and use	37.6% (32.5%, 40.2%)	16.5 (14.6, 17.8)	27.4 (25.9, 29.9)	298.3 (244.7, 334.4)	847.8 (811.6, 899.3)
Low uptake and use	22.4% (19.8%, 25.3%)	9.8 (8.7, 11.2)	34.1 (32.2, 35.9)	152.1 (129.6, 171.8)	994.1 (973.6, 1,016.3)

Note: ADAS technologies considered were warning systems, adaptive cruise control, collision intervention systems, and dynamic driving assistance. Annual estimates of crash prevention are based estimated fleet share for various technologies shown in Figure 3.
Base for percentages: Number of fatalities expected to occur in each year shown given levels of ADAS market penetration, effectiveness, and use in 2017–2019. (Crashes not involving a car or light truck, involving 4 or more vehicles, or occurring off public roads were excluded.)
*Cumulative fatalities represent the number avoided and number anticipated to occur cumulatively in 2021 through the year shown.

Table 5. Percent and count of nonfatal injuries avoided by ADAS technologies and anticipated to occur under each of three technology uptake and use scenarios over time through 2050.

	Annual Nonfatal Injuries			Cumulative Nonfatal Injuries *	
(values in thousands)	**% Avoided (95% UI)**	**Number avoided (95% UI)**	**Number anticipated (95% UI)**	**Number avoided (95% UI)**	**Number anticipated (95% UI)**
2030					
Best estimate	11.7% (9.7%, 13.8%)	331 (277, 393)	2,505 (2,441, 2,559)	1,722 (1,393, 1,999)	25,415 (25,133, 25,740)
High uptake and use	14.8% (11.7%, 18.0%)	420 (331, 510)	2,412 (2,325, 2,502)	2,199 (1,747, 2,616)	24,933 (24,503, 25,387)
Low uptake and use	6.4% (4.7%, 7.3%)	181 (134, 208)	2,656 (2,625, 2,700)	892 (662, 1,031)	26,247 (26,102, 26,469)
2040					
Best estimate	19.8% (17.0%, 23.0%)	621 (533, 721)	2,513 (2,409, 2,598)	6,703 (5,715, 7,820)	50,416 (49,264, 51,388)
High uptake and use	23.6% (19.2%, 26.3%)	739 (602, 825)	2,393 (2,307, 2,529)	8,296 (6,720, 9,690)	48,807 (47,434, 50,352)
Low uptake and use	12.3% (10.5%, 13.9%)	385 (330, 437)	2,749 (2,698, 2,804)	3,862 (3,081, 4,347)	53,246 (52,761, 53,993)
2050					
Best estimate	24.0% (21.1%, 26.3%)	832 (731, 909)	2,629 (2,546, 2,731)	14,138 (12,242, 16,090)	76,093 (74,089, 77,997)
High uptake and use	27.0% (23.3%, 28.3%)	933 (807, 978)	2,528 (2,480, 2,648)	16,814 (13,941, 18,816)	73,399 (71,401, 76,258)
Low uptake and use	16.1% (14.4%, 18.0%)	557 (497, 625)	2,904 (2,838, 2,964)	8,673 (7,350, 9,778)	81,550 (80,465, 82,792)

Note: ADAS technologies considered were warning systems, adaptive cruise control, collision intervention systems, and dynamic driving assistance. Annual estimates of crash prevention are based estimated fleet share for various technologies shown in Figure 3.
Base for percentages: Number of injuries expected to occur in each year shown given levels of ADAS market penetration, effectiveness, and use in 2017–2019. (Crashes not involving a car or light truck, involving 4 or more vehicles, or occurring off public roads were excluded.)
*Cumulative injuries represent the number avoided and number anticipated to occur cumulatively in 2021 through the year shown.

Table 6. Percent and count of crashes avoided by ADAS technologies and anticipated to occur under each of three technology uptake and use scenarios over time through 2050.

	Annual Crashes			Cumulative Crashes *	
(values in thousands)	**% Avoided (95% UI)**	**Number avoided (95% UI)**	**Number anticipated (95% UI)**	**Number avoided (95% UI)**	**Number anticipated (95% UI)**
2030					
Best estimate	12.2% (10.2%, 14.5%)	868 (724, 1,033)	6,240 (6,071, 6,380)	4,507 (3,646, 5,236)	63,481 (62,746, 64,314)
High uptake and use	15.5% (12.3%, 18.8%)	1,102 (874, 1,334)	6,005 (5,773, 6,229)	5,761 (4,581, 6,852)	62,226 (61,129, 63,399)
Low uptake and use	6.7% (5.0%, 7.7%)	476 (355, 544)	6,631 (6,562, 6,750)	2,331 (1,736, 2,701)	65,656 (65,274, 66,247)
2040					
Best estimate	20.7% (17.8%, 24.0%)	1,625 (1,400, 1,886)	6,226 (5,956, 6,446)	17,552 (14,938, 20,531)	125,530 (122,555, 128,153)
High uptake and use	24.6% (20.1%, 27.5%)	1,933 (1,578, 2,162)	5,918 (5,688, 6,273)	21,715 (17,585, 25,360)	121,373 (117,726, 125,472)
Low uptake and use	12.8% (11.0%, 14.6%)	1,007 (862, 1,145)	6,844 (6,705, 6,981)	10,120 (8,072, 11,390)	132,972 (131,675, 134,894)
2050					
Best estimate	25.1% (22.1%, 27.5%)	2,179 (1,913, 2,384)	6,493 (6,284, 6,758)	37,022 (32,046, 42,155)	189,028 (183,895, 193,948)
High uptake and use	28.2% (24.4%, 29.6%)	2,448 (2,120, 2,564)	6,224 (6,109, 6,551)	44,067 (36,443, 49,277)	181,950 (176,723, 189,417)
Low uptake and use	16.8% (15.1%, 18.9%)	1,461 (1,308, 1,636)	7,212 (7,036, 7,364)	22,729 (19,260, 25,608)	203,323 (200,424, 206,546)

Note: ADAS technologies considered were warning systems, adaptive cruise control, collision intervention systems, and dynamic driving assistance. Annual estimates of crash prevention are based estimated fleet share for various technologies shown in Figure 3.
Base for percentages: Number of crashes expected to occur in each year shown given levels of ADAS market penetration, effectiveness, and use in 2017–2019. (Crashes not involving a car or light truck, involving 4 or more vehicles, or occurring off public roads were excluded.)
*Cumulative crashes represent the number avoided and number anticipated to occur cumulatively in 2021 through the year shown.

Finally, Figures 6 and 7 present results from the one-at-a-time sensitivity analysis in which model parameters were varied by specified amounts (from a 50% reduction to a 50% increase at 10% increments) relative to their "best estimate" values used in the main analysis. In addition to illustrating the impact on the overall results of alternative assumptions about the values of these parameters, this analysis also illustrates which parameters are the most influential overall. Figures 6 and 7 show the impact that specified parameter changes have on the main study results (i.e., number of injuries and deaths predicted to be prevented by ADAS in 2050) in percentage terms. The 10 parameters to which overall results were found to be most sensitive are shown.

Results from sensitivity analyses indicate that the overall "attractiveness weight" of ADAS technology has a notable impact on results and inferences. As described in the Methods section, "attractiveness" represents the extent to which consumers are willing to pay more for vehicles equipped with ADAS because of convenience, safety, and/or other factors. Attractiveness directly impacts ADAS uptake. Due to its influence and importance, this was a key parameter varied through the high and low uptake and use scenarios presented in the main study results. As shown in Figure 6, when attractiveness is altered to be 20% higher, the predicted number of fatalities avoided in 2050 increases by about 5% relative to the best estimate scenario. When attractiveness is altered to be 20% lower, the predicted number of fatalities prevented in 2050 decreases by about 5%. Parameter increases or decreases exhibited generally symmetric results. Additionally, results of sensitivity analyses for this parameter were generally similar for fatalities (Figure 6) and nonfatal injuries (Figure 7).

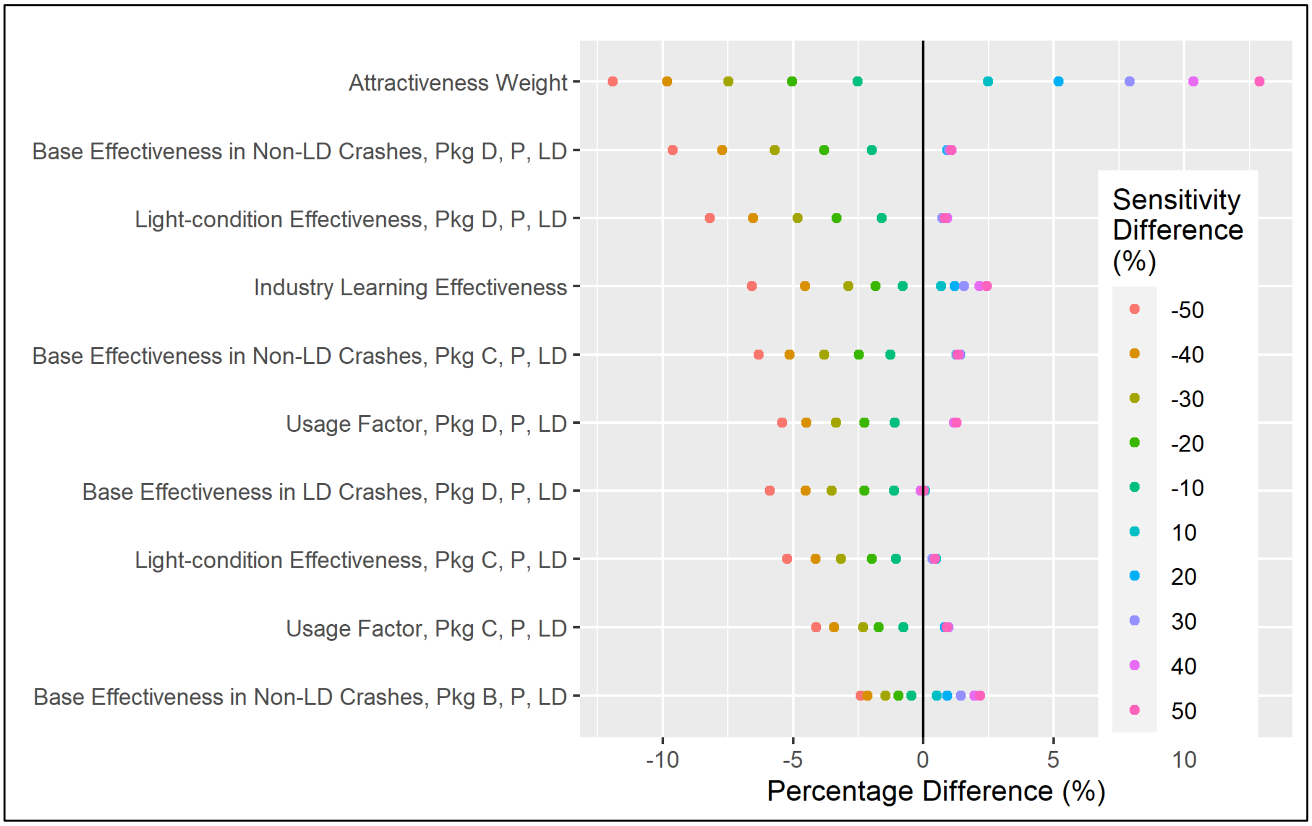
Other variables with a meaningful influence on fatalities and nonfatal injuries avoided included the base effectiveness of the various technology packages in preventing both lane-departure and non-lane-departure crashes, as well as effectiveness of the systems in preventing lane-departure crashes specifically in poor lighting conditions. Many traffic fatalities involve lane departure and occur in darkness. These results indicate that the ability of lane departure warning and lane keeping assistance systems to prevent lane departures in general, and particularly in darkness, are expected to have a substantial impact on the magnitude of the safety benefits of ADAS technologies.

Also among the most influential parameters was the proportion of driving for which the lane departure warning/lane keeping assistance/lane centering systems included in the various technology packages were turned on, used, and in the case of warning systems, also the proportion of time that the driver responded appropriately to warnings (collectively termed "usage factor" in Figures 6 and 7). As noted previously, recent research has shown that consumers deactivate lane departure warning and lane keeping assistance systems more often than other systems. These results show that levels of consumer usage of lane departure warning and lane keeping assistance technology are expected to have an important influence on the actual safety benefits realized by the diffusion of ADAS technologies into the vehicle fleet.

Finally, also included among parameters to which results were most sensitive was "industry learning effectiveness." This is a measure of the rate at which improvements in technology, design, manufacturing, etc., lead to reductions in the cost to consumers of equipping vehicles with ADAS technologies.

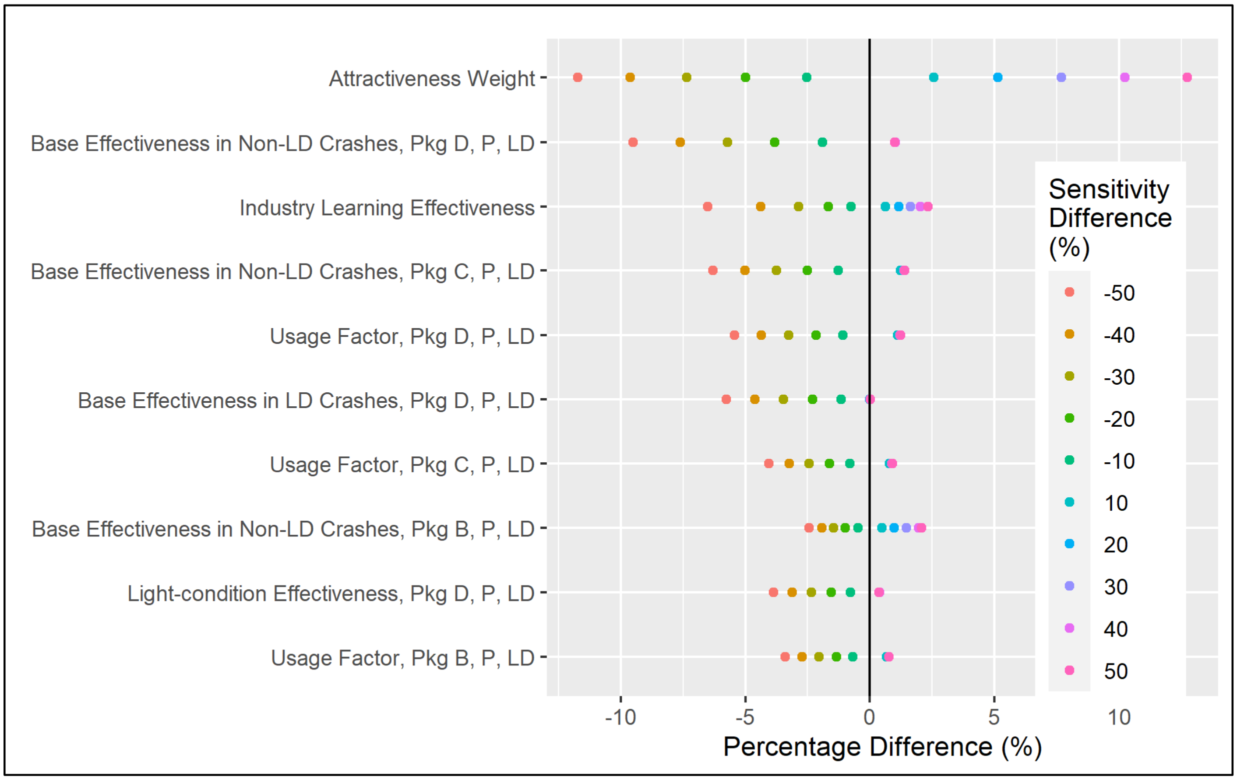
Sensitivity results for many of these variables reveal nonsymmetric influence. Other than for technology attractiveness, even large increases in parameter values generally result in increases of less than 2.5% in the predicted numbers of fatalities and injuries prevented by ADAS in 2050. This is because many of the parameter values in 2050 are already approaching their theoretical maximum values, limiting the potential for gains to be achieved by increases/improvements in many of these parameters. By contrast, decreasing the values of the same parameters was predicted to lead to relatively larger reductions in the numbers of fatalities and injuries prevented by ADAS.

Figure 6. One-at-a-time sensitivity analyses results demonstrating the 10 most impactful uncertain parameters on estimated annual fatalities avoided in 2050.*



* Parameter definitions:
<u>Attractiveness weight:</u> represents the extent to which people are willing to pay more for vehicles equipped with ADAS features because of convenience, safety, and other factors.
<u>Base effectiveness:</u> estimated effectiveness of technology package at preventing a crash in "simple" crash situations (i.e., crashes without other hazards involved, like dim light, rain, being in a work zone).
<u>LD:</u> lane departure, indicating parameter values that pertain to crashes that involve lane departure technology.
<u>Industry learning effectiveness</u>: a measure of how quickly the industry can bring down ADAS costs to the consumer.
<u>P:</u> peak value of the usage factor in 2050 relative to initial value in 2017.
<u>Pkg B:</u> adaptive cruise control systems + warning systems in package A.
<u>Pkg C:</u> automated safety systems (automatic emergency braking, emergency steering assistance, lane keeping assistance) + packages A and B.
<u>Pkg D</u>: dynamic driving assistance systems + packages A, B, and C; Light condition effectiveness: a measure of how much poor light conditions affect the effectiveness of different ADAS technology packages.
<u>Usage Factor:</u> a measure of the proportion of time that a technology is turned on and in use.

Figure 7. One-at-a-time sensitivity analyses results demonstrating the 10 most impactful uncertain parameters on estimated annual nonfatal injuries avoided in 2050.*



* Parameter definitions:
Attractiveness weight: represents the extent to which people are willing to pay more for vehicles equipped with ADAS features because of convenience, safety, and other factors.
Base effectiveness: estimated effectiveness of technology package at preventing a crash in "simple" crash situations (i.e., crashes without other hazards involved, like dim light, rain, being in a work zone).
LD: lane departure, indicating parameter values that pertain to crashes that involve lane departure technology.
Industry learning effectiveness: a measure of how quickly the industry can bring down ADAS costs to the consumer.
P: peak value of the usage factor in 2050 relative to initial value in 2017.
Pkg B: adaptive cruise control systems + warning systems in package A.
Pkg C: automated safety systems (automatic emergency braking, emergency steering assistance, lane keeping assistance) + packages A and B.
Pkg D: dynamic driving assistance systems + packages A, B, and C; Light condition effectiveness: a measure of how much poor light conditions affect the effectiveness of different ADAS technology packages.
Usage Factor: a measure of the proportion of time that a technology is turned on and in use.

Discussion

Vehicle technology advancements have significant potential to contribute to improvements in motor vehicle traffic safety in the coming years. In particular, ADAS technologies can help to prevent crashes by warning the driver of hazards, momentarily taking control of the vehicle's steering and/or brakes. ADAS technologies have become increasingly popular in vehicles over the last several years. Several studies have estimated the relative crash involvement of vehicles with versus without particular ADAS technologies. However, predicting the overall number of crashes, injuries, and deaths that will be prevented by ADAS in the future requires consideration of a wide array of interconnected factors that all act to influence bottom-line safety benefits, including not only the effectiveness of the technology itself but also factors influencing consumer uptake and use of such technologies. This project sought to estimate how many motor vehicle crashes, injuries, and deaths ADAS technologies are likely to prevent over the next 30 years.

Overall, this project makes a unique contribution to the field by offering a novel, systems-grounded approach to modeling the uncertain, complex, and dynamic factors that may affect the estimates of ADAS technology adoption and their resulting crash avoidance benefits over time. Using a system dynamics approach, the current study estimates that improvements in ADAS technology and increases in uptake and use are likely to prevent approximately 5,800 traffic fatalities (or approximately 16% of fatalities) and 331,000 injuries (12% of injuries) that would otherwise be expected to occur in year 2030 if ADAS effectiveness, uptake, and use were to remain at the levels they were in 2017–2019 (the base year for the models used in this project). Moreover, the current study estimates that increased effectiveness, uptake, and use of ADAS technologies will result in the prevention of approximately 249,400 traffic fatalities and 14 million nonfatal injuries cumulatively in 2021 through 2050.

While these represent critical potential contributions to road safety, there are still many scenarios and contexts in which ADAS technologies may not be able to effectively intervene, as reflected in estimates of crashes, nonfatal injuries, and deaths expected to remain on U.S. roads even in 2050, when the current study predicts that basic ADAS technologies will be ubiquitous and a substantial majority will be equipped with collision intervention systems including automatic emergency braking and lane keeping assistance. The model estimates that in the highest ADAS uptake and use scenario considered, ADAS would be expected to prevent approximately 38% of all traffic fatalities that would have occurred in 2050 given current levels of ADAS effectiveness, uptake, and use, meaning that 62% of those fatalities (or approximately 27,000 fatalities) would still be expected to occur despite the anticipated ubiquity of ADAS by 2050. These findings are consistent with previous research cautioning that automated vehicle safety systems are unlikely to eliminate all or most traffic fatalities and injuries in the near future (e.g., Mueller, 2020; Shetty et al., 2021). Thus, consistent with the Safe System Approach, which calls for a layered, redundant approach to safety, there remains a clear need to continue to invest in a wide array of proven traffic safety measures, including but not limited to vehicle technology.

With respect to underlying ADAS technology diffusion over time, the model forecasts were similar to previous forecasts by others for basic warning systems, but somewhat lower for collision intervention features and partial driving automation. HDLI (2022) estimates that in 2045, the proportion of registered vehicles in the United States that are equipped with both lane departure warning and blind spot monitoring systems and automatic emergency braking will reach 95%. Similarly, the current study predicts 95% of registered vehicles will be equipped with lane departure warning and blind spot monitoring systems in 2045. However, the current study predicts only 65% of the vehicle fleet will be equipped with automatic emergency braking (Packages C and D) in 2045, rising to just under 85% in the most optimistic scenario. In 2050, HDLI predicts the proportion of vehicles equipped with

SAE Level 2 partial driving automation will be 90%, reaching 95% “sometime after 2050.” By contrast, even under the highest technology diffusion scenario considered, the current study predicts that 69% of U.S. vehicles will be equipped with such systems (Package D) in 2050. Estimates and forecasts of SAE Level 2 vehicle diffusion and higher levels of automation have shown wide variation in the literature and have been typified by considerable uncertainty (Collie et al., 2017; Lewis & Grossman, 2019; Litman, 2022). Regarding fleet share of vehicles without any ADAS technology (i.e., not even basic warning systems), uncertainty peaked around year 2035, with 5%–25% projected fleet share, but dropped significantly by 2050, by which time over 95% of all vehicles on U.S. roads were predicted to be equipped with at least basic ADAS in even the lowest technology diffusion scenario considered.

In terms of overall crash prevention, the model results showed reasonable agreement with previous studies that have attempted to quantify the numbers of crashes, injuries, and deaths potentially preventable by ADAS given large-scale deployment (e.g., Benson et al., 2018; IIHS, 2022; Mueller et al., 2020; Sherony & Gabler, 2020). The current study estimates that ADAS will help to avoid roughly 15%–30% of crashes and nonfatal injuries and 20%–40% of traffic fatalities in 2050—corresponding to nearly 15,000 total annual fatalities and more than 800,000 nonfatal injuries avoided in 2050. Notably, the scenarios indicated rapid safety gains in the first two decades modeled, with the rate of increase in the annual number of crashes avoided slowing in later years. The predictions of “best estimate” and “high uptake & use” scenarios became relatively close by 2050, while the low uptake & use scenario remained considerably lower; this may be explained by the assumption that by this time, nearly all vehicles in the fleet would have ADAS technology, reducing opportunities for additional safety benefits attributable solely to increases in technology uptake.

In another study that sought to estimate future crash prevention by ADAS in relation to its diffusion into the vehicle fleet, Sherony & Gabler (2020) estimated that a theoretical suite of ADAS features would reduce severe injuries to vehicle occupants by 33% in 2040. While the current study estimates smaller proportions of avoided injuries, Sherony & Gabler examined injuries coded as 2 or greater on the Abbreviated Injury Scale (AIS), which represent approximately the 15% most severe injuries that occur in crashes (NHTSA, 2023). Thus, their estimates may be more comparable to the current study’s estimates of fatalities than injuries. The current study estimates that ADAS will avoid 28% of fatalities in 2040 in the best estimate scenario and 33% in the high uptake & use scenario. Sherony & Gabler’s estimates are also greater than those of the current study because they include Intersection-ADAS (I-ADAS), not considered in the current study, which they estimate would help to prevent a substantial proportion of straight-crossing-path (“T-bone”) and left-turn-across-path crashes. The current study did not consider I-ADAS as it is not yet available on vehicles available for purchase in the United States at the time the study was being performed, and existing ADAS technologies have been shown to have little if any ability to intervene in these types of crashes (AAA, 2022).

Notably, this study predicts ADAS will avoid greater proportions of fatalities compared to injuries and crashes. The research team posits that this difference is due to underlying assumptions regarding the ability of the types of ADAS technologies considered to prevent specific types of crashes and the relative severity of those types of crashes as reflected in the data input into the model (i.e., police-reported crashes that occurred in the United States in 2017–2019). For example, the model assumes that lane departure crashes are highly avoidable when appropriate usage of the technology is high. The proportion of crashes that involve lane departure is higher among fatal crashes (approximately half) than among nonfatal crashes (approximately one-third), thus high effectiveness and use of technology that prevents lane departures would be expected to yield a greater percentage reduction in fatalities than in total crashes. Alternatively, if future effectiveness and/or use of lane keeping technologies differ from current study assumptions and/or if forward collision prevention technologies are relatively more effective, the relative proportions of fatal versus nonfatal crashes avoided by ADAS would differ.

From the sensitivity analysis of ADAS diffusion scenarios, a key finding was the importance of the attractiveness of ADAS technology to the public, and to a lesser extent also industry learning on the numbers of future deaths and injuries avoided by ADAS and the rates at which benefits accrue. These measures notably impact ADAS uptake through the willingness of consumers to pay for ADAS-equipped vehicles because of the safety and convenience they afford, as well as the speed in which industry brings down ADAS costs to the consumer. In other words, speed of uptake through these and potentially other mechanisms has an important impact on the numbers of deaths and injuries potentially prevented over time. To maximize safety benefits and the rate at which they accrue, there is a need for industry and other stakeholders to increase the attractiveness of ADAS-equipped vehicles to consumers and to ensure that their cost does not reduce their attractiveness or render them unaffordable.

Sensitivity analyses also revealed that the proportion of time that drivers choose to use the technology may also have a major impact on the magnitudes of future safety benefits, especially for lane departure warning and lane keeping assistance systems. Previous research has found consumers often choose to turn these systems off (e.g., Reagan & McCartt, 2016). More work is needed to improve drivers' experiences with lane departure warning and lane keeping assistance systems, so that users do not opt to deactivate them and thus negate their potential safety benefits.

Results of the sensitivity analysis also highlight the potential role for future technological improvements such as improved performance in low-light conditions. This is especially important for prevention of severe injuries and deaths. Half of all traffic fatalities in 2017–2019 occurred in darkness, as did more than three quarters of all pedestrian fatalities. Research has shown that many systems available on vehicles today perform less well in darkness than they do in daylight (Cicchino, 2022). While many of the systems examined also tend to be less effective in other specific scenarios such as when driving in adverse weather or roadway surface conditions, sensitivity analysis suggests that improving ADAS performance in these conditions is much less important than improving performance in darkness, as the proportions of crashes that occur in such conditions are smaller.

Limitations and Future Research

Limitations

The current study has several limitations that should be noted. In general, the current study sought to make predictions about future crashes avoided by ADAS. The general approach to doing this was to model the number and type of crashes that would occur in future years given current availability, effectiveness, and use of ADAS technologies; the probability that a given vehicle involved in a future crash would be equipped with particular technology; the probability that the technology would be in use (i.e., not deactivated) at the time; and the probability that the technology would be able to avoid the crash given its presence and use (a function of its base effectiveness as well as the impact of any special circumstances, e.g., darkness) that could reduce its effectiveness. Each stage of this process incorporates many assumptions with the potential to influence study outcomes.

When estimating the number and characteristics of future crashes, the study sampled police-reported crashes that occurred in 2017–2019 and assumed that future years would be similar, before accounting for crashes prevented by ADAS, other than that the absolute number of crashes would increase due to uniform increases in the total amount of driving. The study did not attempt to account for other external factors unrelated to ADAS that might affect the number or characteristics of crashes in the United States. For example, nonuniform changes in driving patterns (e.g., differing trends in urban versus rural areas or between different demographic groups) could influence the total number of crashes, their characteristics, the probability that they could be prevented by ADAS, or the probability that the vehicles involved would be equipped with ADAS, in ways that the current study did not account for. The COVID-19 pandemic presents a salient contemporary example. Data from the NHTSA indicate that rate of traffic fatalities per mile driven increased to their highest levels in more than a decade (and much higher than in the base year used in the current study) in 2020 and remained elevated in 2021, leading to a large increase in the total number of traffic fatalities (Stewart, 2023). Although the study methodology should still validly estimate the percentage of crashes, injuries, and deaths avoided by ADAS in the event of changes to the overall crash rate or fatality rate, it appears that the characteristics of fatal crashes also shifted. For example, Tefft & Wang (2022) found large increases in the proportion of single-vehicle fatal crashes in 2020. Changes in the characteristics of future crashes could potentially change the percentage of future crashes preventable by ADAS.

Another limitation of the approach is that the study focused on estimating the probability that ADAS would prevent the occurrence of a given crash. In reality, ADAS might fail to prevent some crashes yet still reduce the severity of any resulting injuries (e.g., by reducing impact speed). The current study might thus underestimate to some degree the numbers of fatalities and injuries prevented by ADAS.

The study is also limited by the quality of the data used as inputs. Several studies have indicated that police-reported crash and injury data often underestimate total vehicle related injuries, particularly those involving pedestrians, bicyclists, single-vehicle crash events, and injuries caused in situations that don't trigger the threshold for reporting or in which injured parties perhaps seek to avoid contact with law enforcement for various reasons. NHTSA (2023) estimates that as many as 32% of nonfatal injury crashes and 60% of crashes not resulting in injuries go unreported. Harmon et al. (2021) estimated that for every police-reported crash involving a pedestrian, there were an additional 8 to 10 pedestrians treated in emergency departments for injuries sustained in crashes not reported to the police. Given the focus of this work on understanding broad trends in fatal and nonfatal injury, these data should appropriately capture the focal outcomes; however, it is important to interpret the model results as relating to crash prevention among the police-reported incidents, which are not necessarily transferrable to all traffic-related crashes and injuries.

The study did not attempt to account for all possible changes or events that might influence the availability and uptake of ADAS-equipped vehicles. In the years since the onset of the COVID-19 pandemic there have been previously unanticipated supply chain disruptions as well as large increases in the price of new and used vehicles. Shifts related to consumer interest in battery-electric vehicles and/or associated policy could influence the rate of fleet turnover and thus the rate at which older vehicles without ADAS are replaced by new vehicles with ADAS. Also not considered were cybersecurity issues, which could potentially influence consumer demand for or use of technologies that automate parts of driving. Such factors were deemed beyond the scope of the current study but should be investigated in future research.

While the research team sought the best available data regarding the effectiveness of existing ADAS technologies, existing research and literature do not quantify the effectiveness of all types of ADAS, the effectiveness of all implementations of any particular type of ADAS, or the impact of adverse conditions (e.g., darkness, rain) on the effectiveness of most systems. Thus, in many cases, the research team had to rely on expert judgment to supplement existing literature and data. In addition, the effectiveness of future iterations of ADAS are by definition unknown. The research team assumed that there would be improvements in the base effectiveness of systems, as well as improvements in their effectiveness under adverse conditions such as darkness. The research team used its best judgment in estimating the eventual effectiveness of the systems considered as well as the rate at which the technology would mature, however, the actual evolution of the effectiveness of these technologies may be faster or slower than anticipated. Note that probabilistic uncertainty analyses revealed that even large increases in ADAS effectiveness had little impact on the main study results; however, the numbers of crashes, injuries, and deaths prevented may be lower than reported here if actual ADAS effectiveness is substantially lower than assumed.

Relatedly, the research team made some simplifying assumptions to limit the scope of the current study. For example, research has shown that ADAS that are reliant on cameras perform poorly in bright direct sunlight (Yoneda et al., 2021); however, the current study does not account for the proportion of systems that are camera-based or the distribution of the angle of the sun relative to vehicle trajectories in the crashes examined. Many of today's ADAS have been shown to be reasonably effective in preventing crashes at low speeds but far less effective at higher speeds; however, the current study was unable to consider speed due to limitations of the input data, which do not report pre-crash speeds in most crashes. While the ability of ADAS to intervene in higher-speed crashes may improve in the future, the current study's inability to account for speed likely resulted in some degree of overestimation of the numbers of crashes avoided, especially early in the study period before substantial maturation of the relevant technologies.

While the study did attempt to account for maturation of the technology over time, this was operationalized in terms of increasing effectiveness in preventing types of crashes deemed preventable in the first place. For example, the study does not account for future ADAS, such as the I-ADAS described by Sherony & Gabler (2020), that could prevent turn-across-path or "T-bone" crashes. Relatedly, the study also did not attempt to predict the safety impacts of higher levels of automation, e.g., SAE Levels 3 and higher, as no such vehicles are yet available for consumers to purchase in the United States as of when this research was performed, and thus there were no data on which to base any assumptions about their uptake, use, or safety performance.

Finally, the study also did not account for crashes caused directly or indirectly by ADAS. It is theoretically possible that ADAS could cause crashes directly through malfunctions or errors, as well as indirectly by performing unexpected movements that surprise other drivers. The current study assumes such crashes would be extremely rare. ADAS could also contribute indirectly to crashes if drivers do not understand it, rely on it excessively, or misuse or abuse it on purpose (e.g., using partial driving automation systems to facilitate disengagement from driving or engagement in distracting secondary tasks). While there is some suggestive evidence that drivers may do this (e.g., Mueller et al., 2022), there are not yet sufficient data to quantify the numbers of new crashes to which ADAS might contribute.

Future directions and research needs

The ADAS technologies included in the current study may be viewed as "building blocks" of higher levels of automation. While this study intentionally excluded SAE Level 3–5 vehicles due to the lack of data to inform baseline assumptions about their crash involvement or crash prevention performance, future research will need to focus on estimating the long-term fleet penetration of more highly automated systems and defining realistic expectations of their safety performance. To date, estimates regarding readiness for deployment of higher-level automated vehicles (i.e., SAE Level 3 or above) are extremely variable (SAE, 2021). Some manufacturers previously predicted that highly automated vehicles would be available to consumers by 2020 (Lewis & Grossman, 2019) and "fully automated" vehicles by 2022 (Collie et al., 2017). More conservative estimates range from 2045 for half of all new vehicles to be "autonomous" (Litman, 2022) to 2050 before vehicles equipped with Level 3 and higher automation will achieve even 66% of market share (Nieuwenhuijsen et al., 2018). In the current study, it was only in the high uptake & use scenario that Level 2 automation was predicted to reach 66% fleet share in 2050. Speculation about the safety effects of fully automated vehicles in relation to crashes involving other vehicles, trucks, pedestrians, bicyclists, and motorcyclists is even more variable. Transportation researchers need valid and reliable estimates of not only adoption rates, but also crash avoidance performance under a wide range of scenarios, especially those likely to produce fatal and serious injuries.

Relatedly, there is a need for future research to examine mode-specific safety effects of ADAS technologies. The current study was unable to provide estimates of the safety benefits of ADAS disaggregated by road-user type. Although crashes involving pedestrians, bicyclists, passenger vehicles, and large trucks were all included in the study, the data required to specify precise probabilities of crash avoidance for specific crash types for specific modes of travel were generally not available, thus the crash avoidance probabilities used in the current study represented averages over all included modes and road-user types. However, in practice, the probability that a given ADAS technology would prevent a car from striking another car versus a large truck versus a pedestrian might differ, and the simulation model would need to incorporate such mode-specific crash avoidance probabilities to produce reliable mode-specific estimates of safety benefits. Additionally, this study excluded crashes that involved neither a passenger car nor a heavy truck. Future research and data to support assumptions, model decisions, and parameters would be valuable in refining model performance by mode and/or creating separate SD models that can be calibrated to specific road-user types, ADAS performance, and crash scenarios.

In addition, as the web of factors affecting the rollout of vehicles equipped with ADAS and higher levels of automation can be refined with the support of additional research, there is also a need to further refine the estimated safety outcomes. For example, the current study was unable to account for the relationship between pre-crash vehicle speed and the probability of crash avoidance. Past studies have found that many ADAS, such as pedestrian detection systems, do not perform well at high speeds (AAA, 2019; Cicchino, 2022). However, the crash databases used as inputs in the current study contain no information on pre-crash speed for many crashes, and the reliability of the speed data, when present, is largely unknown. Thus, it is possible that ADAS would fail to prevent some of the crashes that the current study predicted it would prevent, due to the speeds involved. Reliable pre-crash speed data would enable more precise estimates of safety benefits. Moreover, it would also enable estimation of the safety impact of improving ADAS performance at higher speeds, or alternatively, of other strategies to reduce speeding. Relatedly, the current study did not consider technology that would restrict vehicles from exceeding speed limits. Such technologies are already being introduced on vehicles available for sale in Europe (European Transport Safety Council, 2023). Given the importance of kinetic energy management as foundational to a Safe System Approach to injury prevention, future research and model expansion to account for dynamics and influences related to speed would be useful.

Additionally, several studies in the planning/travel behavior literature speculate on how higher-level automation will affect the relationships among travel behavior and land development, with many predicting substantial increases in trip generation, vehicle miles traveled, and automobile dependency (Gruel et al., 2016; Larson et al., 2020; Wellik et al., 2020; Zakharenko, 2016). The extent to which these conclusions apply at lower levels of automation has not been examined. However, it is logical to assume that technology that eases the mental burden or opportunity cost of driving—such as technology that explicitly permits the driver to disengage from driving and attend to work or other interests while traveling—may lead to increases in individuals' willingness to travel more further and more frequently, thus increasing exposure to conditions associated with crashes. More research is needed to understand how increasing levels of vehicle automation may influence such factors, and how that will in turn impact traffic safety.

Finally, motor vehicle traffic injuries and fatalities in the United States disproportionally affect disadvantaged populations including those with lower levels of education (Harper, 2015) and Black and Indigenous communities (GHSA, 2021; Raifman et al., 2022). There is a need to further explore the ways in which anticipated benefits of ADAS technology are likely to be distributed across the population. The current study predicted the future fleet share of ADAS-equipped vehicles at a national level; however, in practice, adoption rates are likely to vary greatly in relation to demographic characteristics such as education, income, age, and geography (Girasek and Taylor, 2010; Metzger et al., 2020). Although beyond the scope of the current study, research is needed to examine ways in which ADAS and vehicle automation are likely to mitigate or exacerbate inequities in safety and mobility.

Conclusions

Predicting how many crashes, injuries, and deaths are likely to be prevented in the future by advanced vehicle technology requires consideration of a wide array of interconnected factors that all act to influence bottom-line safety benefits. This study produced a simulation model and test bed to consider the complex dynamics of ADAS diffusion into the vehicle fleet and the safety outcomes expected to result. Results suggest that ADAS technologies will prevent large numbers of crashes and save many lives in the future. While the study considered a wide range of potential technology uptake and use scenarios, in the scenario the authors regard as most probable, ADAS is anticipated to avoid over 249,000 traffic fatalities, 14 million nonfatal injuries, and 37 million police-reported crashes cumulatively between 2021 and 2050. However, even accounting for the avoidance of these crashes, the study predicts that nearly 900,000 traffic fatalities, 76 million nonfatal injuries, and 189 million crashes will still occur over the same period. This research model makes an important contribution to the field in that it takes into account various exogenous and endogenous factors to forecast the safety outcomes associated with the proliferation of ADAS and partial vehicle automation across the vehicle fleet. While the current study has limitations related to its underlying data sources, assumptions, and modeling decisions constraining the scope of the study, it offers a robust way to conceptually examine ADAS system dynamics, transparently test assumptions, and produce crash avoidance estimates over a long time horizon. Future research could expand upon this methodology and account for additional factors, higher levels of automation, and advancements in knowledge regarding the effectiveness and performance of such technologies, as well as further disaggregate estimated safety benefits in relation to demographic and other road user characteristics. From the current study, it is clear that ADAS technologies are expected to make a significant contribution to preventing injuries and saving lives on U.S. roads; however, it is not realistic to expect for them to prevent all or most crashes within the next 30 years. Thus, there remains a need to continue to invest in a wide array of proven traffic safety measures including but not limited to vehicle technology.

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Appendices

Appendix A. Assumptions and Decision Rules Regarding Crashes ADAS May Help to Prevent

As described in the Methods section, determination of the probability that a particular ADAS technology would avoid or prevent a given crash was assessed in two major steps. In the first step, the research team assessed whether each technology considered in the study had any possibility (versus none) to prevent a given crash based solely on the general type of crash as defined by the combination of the crash type/geometry (FARS and CRSS variable: acc_type) and the pre-crash maneuvers of each vehicle (FARS and CRSS variable: p_crash2).

Decisions regarding whether a given technology had any potential to prevent a particular type of crash were made independently by two members of the research team based on literature reviews and expert opinion. Disagreements were resolved through discussions with the larger research team and are summarized below in Table A1. Crashes deemed potentially preventable are identified by a “Y” in the corresponding cell; empty cells denote no possibility of prevention.

The following broad categories of crashes were deemed not preventable by ADAS and thus not examined in further detail nor shown in the tables: crashes resulting from vehicle malfunctions (e.g., tire blow out, stalled engine), crashes involving pre-crash loss of control/traction, wrong-way crashes, straight-crossing-path (“T-bone”) collisions, turn-across-path collisions (AAA, 2022), crashes occurring on non-trafficways or ramps, crashes involving vehicles entering or leaving driveways, and crashes involving objects (e.g., debris) on the roadway.

Tables A1 shows the specific combinations of crash type and pre-crash maneuvers that the team determined ADAS had some possibility of preventing (and thus carried forward to the next step of the analysis) versus those deemed not preventable.

Note that the purpose of this step was simply to distinguish between crashes that the ADAS considered in the current study had any possibility versus no possibility of preventing, not to determine decisively that a particular crash would be prevented. The probability of prevention for crashes deemed possibly preventable in this step is assessed subsequently in the next step of the analysis.

*Table A1 a-g. Decision rules regarding potentially avoidable crashes according to pre-crash maneuver, crash type, and specific ADAS technology type **

Pre-crash maneuver (FARS/CRSS "p_crash2" codes)	Crash Type (FARS, CRSS "acc_type" codes)																	
	A. Roadside Departure (1, 6)									**B.** Motorist Forward Impact (11-14)								
	PD	BSD	LDW	FCW	ACC	AES	AEB	LKA	DDA	PD	BSD	LDW	FCW	ACC	AES	AEB	LKA	DDA
Over the Lane Line or Edge of Road (10-13)			**Y**					**Y**	**Y**			**Y**	**Y**		**Y**	**Y**	**Y**	**Y**
Road End Depature Crash (14)			**Y**		**Y**	**Y**		**Y**	**Y**			**Y**	**Y**	**Y**	**Y**	**Y**		**Y**
Turning Left or Right (15, 16)					**Y**			**Y**	**Y**				**Y**	**Y**	**Y**	**Y**		**Y**
Going Straight (17)						**Y**		**Y**	**Y**				**Y**	**Y**	**Y**	**Y**		**Y**
Vehicle in Lane Stopped, Decelerating (50-53)				**Y**	**Y**	**Y**	**Y**		**Y**				**Y**	**Y**	**Y**	**Y**		**Y**
Pedestrian in Road or Approaching Road (80, 81, 82)	**Y**			**Y**	**Y**	**Y**	**Y**		**Y**	**Y; 13 only**			**Y**		**Y**	**Y**		**Y**

Pre-crash maneuver (FARS/CRSS "p_crash2" codes)	Crash Type (FARS, CRSS "acc_type" codes)																	
	C. Rear-End Another Vehicle (20, 24, 28)									**D.** Forward Impact (38, 40)								
	PD	BSD	LDW	FCW	ACC	AES	AEB	LKA	DDA	PD	BSD	LDW	FCW	ACC	AES	AEB	LKA	DDA
Over the Lane Line or Edge of Road (10-13)			**Y**	**Y**		**Y**	**Y**	**Y**	**Y**			**Y**			**Y**	**Y**	**Y**	**Y**
Road End Depature Crash (14)			**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**			**Y**		**Y**	**Y**	**Y**	**Y**	**Y**
Turning Left or Right (15, 16)				**Y**	**Y**	**Y**	**Y**		**Y**						**Y**	**Y**		
Going Straight (17)				**Y**	**Y**	**Y**	**Y**		**Y**						**Y**	**Y**		
Vehicle in Lane Stopped, Decelerating (50-53)				**Y**	**Y**	**Y**	**Y**		**Y**				**Y**	**Y**	**Y**	**Y**		**Y**
Pedestrian in Road or Approaching Road (80, 81, 82)				**Y**			**Y**		**Y**						**Y**	**Y**		

Table A1. Continued.

Pre-crash maneuver (FARS/CRSS "p_crash2" codes)	Crash Type (FARS, CRSS "acc_type" codes)																	
	E. Sideswipe/Angle Collisions (46&47)									**F.** Same Trafficway, Opp. Direction (50, 58, 60, 64)								
	PD	BSD	LDW	FCW	ACC	AES	AEB	LKA	DDA	PD	BSD	LDW	FCW	ACC	AES	AEB	LKA	DDA
Over the Lane Line or Edge of Road (10-13)		Y	Y					Y	Y			Y; 50,64 only			Y		Y; 50,64 only	Y; 50,64 only
Road End Depature Crash (14)		Y						Y	Y						Y		Y	Y
Turning Left or Right (15, 16)		Y							Y									Y
Going Straight (17)		Y							Y				Y	Y				Y
Vehicle in Lane Stopped, Decelerating (50-53)		Y		Y			Y		Y				Y	Y		Y		Y
Pedestrian in Road or Approaching Road (80, 81, 82)	Y	Y					Y		Y							Y		

Pre-crash maneuver (FARS/CRSS "p_crash2" codes)	Crash Type (FARS, CRSS "acc_type" codes) **G.** Vehicle Turning Right or Left Across Other Vehicle (70 & 72)								
	PD	BSD	LDW	FCW	ACC	AES	AEB	LKA	DDA
Over the Lane Line or Edge of Road (10-13)			Y			Y			
Road End Depature Crash (14)									
Turning Left or Right (15, 16)		Y							
Going Straight (17)		Y							
Vehicle in Lane Stopped, Decelerating (50-53)		Y		Y			Y		
Pedestrian in Road or Approaching Road (80, 81, 82)				Y			Y		

*Note: a few cells indicate where only specific crash type codes were relevant (e.g., “13 only” in Table 2B), instead of all crash type codes represented by the given box (e.g., in that example, codes 11-14).
Abbreviations: DDA: dynamic driving assistance; LKA: lane keeping assistance; AEB: automatic emergency braking; AES: automatic emergency steering; ACC: adaptive cruise control; FCW: forward collision warning; LDW: lane departure warning; BSD: blind spot detection; and PD: pedestrian detection.
Color coding shows technologies grouped into packages in subsequent analyses. Light blue codes represent those technologies included in Package A (i.e., FCW and everything to the left of it). The next level of darkness represents those in Package B (i.e., ACC along with everything to the left of it). Package C included LKA and everything to the left. Finally, Package D included all ADAS technologies listed here and represents an SAE Level 2 system.

Estimating the Probability of Avoidance/Prevention for Crashes Deemed Potentially Preventable

As described previously, if it was determined that there was any possibility that an ADAS technology considered in the current study could have helped to prevent a given crash, the model then estimated the probability that the ADAS would successfully avoid or prevent the crash. To do this, the model took into account the assumed baseline effectiveness of the relevant ADAS for the relevant crash type, any hazards present in the crash that would reduce system effectiveness (e.g., rain, darkness, a work zone), and the probability that the relevant ADAS would be activated or in use at the time, as opposed to turned off.

Given the prevalence of lane departure crashes (approximately one third of nonfatal and one half of fatal crashes) and the high probability of turning off lane departure and lane keeping technologies as compared to other ADAS technologies (Reagan & McCartt, 2016), estimates of effectiveness were disaggregated to address lane-departure crashes and non-lane-departure crashes separately, and probabilities of system use were disaggregated to address lane-keeping features (lane departure warning and lane keeping assistance) separately from other features typically present on the same vehicle (e.g., forward collision warning, automatic emergency braking, etc.). The table below displays the assumed model effectiveness estimates, disaggregated according to whether it was a lane departure crash or not and if the vehicle was equipped with LDW or LKA technology or not.

The top two rows provide baseline technology effectiveness estimates (i.e., proportion of crashes likely prevented) according to whether it was a lane departure crash and whether the vehicle had relevant lane departure technologies, for each technology package (A–D). The next four rows include multipliers that were used to reduce the likely effectiveness of the technology given a variety of hazardous conditions. The final row provides estimates for technology use (i.e., whether or not the technology was turned on).

For each estimate, there is an Initial value (i.e., assumed effectiveness in 2017) and a Final value, representing the research team's assumptions regarding the potential improvement in the technology by 2050. Values in intermediate years were estimated using an S-shaped curve to estimate technological maturity and improvement between these Initial and Final values.

__Table A2.__ ADAS Technology Effectiveness and Use Parameters Included in Model to Produce the Results Presented in This Report.

	Package A: **FCW. LDW, BM, and PD**	**Package B:** **ACC + Package A**	**Package C:** **AEB, ESA, and LKA + Package B**	**Package D:** **DDA + Package C**
Base Effectiveness				
Non-lane-departure crashes[a]	Initial / Final[d] With LDW: 0.10 / 0.20 Without LDW: 0.10 / 0.20 Potential for crash mitigation is limited because warnings do not directly prevent crashes. Values same for "With LDW" and "Without LDW" because effectiveness in preventing non-lane-departure crashes is assumed independent of LDW.	Initial / Final[d] With LDW: 0.30 / 0.70 Without LDW: 0.30 / 0.70 Although intended as a convenience technology, ACC may help to prevent some crashes by reducing the driver's cognitive load. There is room for considerable technological maturation with respect to performance in urban stop-and-go traffic.	Initial / Final[d] With LKA: 0.40 / 0.90 Without LKA: 0.50 / 0.90 LKA may reduce the risk of some crashes that were preceded by a lane departure but which were not classified as lane-departure or road-departure crashes (e.g., a rear-end crash or sideswipe that was preceded by an unintentional lane departure).	Initial / Final[d] With LKA: 0.70 / 0.95 Without LKA: 0.70 / 0.95 Same values used with and without LKA because DDA centers the vehicle in its lane when the system is active.
Lane-departure crashes[a]	Initial / Final With LDW: 1.00 / 1.00 Without LDW: 0.1 / 0.15 Majority of lane-departure crashes would not be prevented if lane-keeping features are deactivated, however, use of FCW and BSM may prevent some lane departures from resulting in collisions.	Initial / Final With LDW: 1.00 / 1.00 Without LDW: 0.1 / 0.15 Majority of lane-departure crashes would not be prevented if LDW is turned off, however, use of FCW and BSM may prevent some lane departures from leading to crashes. Addition of ACC is not expected to meaningfully increase probability of avoiding lane departure crashes.	Initial / Final With LKA: 1.00 / 1.00 Without LKA: 0.1 / 0.15 Majority of lane-departure crashes would not be prevented if LKA features are deactivated, however, use of AEB may prevent some lane departures from resulting in collisions.	Initial / Final With LKA: 1.00 / 1.00 Without LKA: 0.1 / 0.15 Deactivating LKA features would functionally deactivate DDA, thus values for lower packages (without DDA) apply when LKA is deactivated.
Reduction in Effectiveness				
Low-visibility conditions (e.g., rain)[b]	Modifiers to Initial / Final With LDW: 0.75 / 0.95 Without LDW: 0.75 / 0.95 Some reduction in effectiveness is low visibility is anticipated initially. This is expected to improve over time as new sensing modalities are used.	Modifiers to Initial / Final With LDW: 0.90 / 0.95 Without LDW: 0.90 / 0.95 Performance of ACC is not reduced substantially by low visibility; however, use of longer-range sensors in the future is anticipated to reduce performance decrement associated with low visibility.	Modifiers to Initial / Final With LKA: 0.85 / 0.95 Without LKA: 0.85 / 0.95 Collision intervention systems are primarily designed for low warning time collisions, which is a major vector of low visibility fatalities. Radar-based systems should not be affected significantly by low-visibility conditions such as rain.	Modifiers to Initial / Final With LKA: 0.90 / 0.98 Without LKA: 0.90 / 0.98 Depending on visibility conditions and type of sensors used, current DDA systems may automatically deactivate. It is possible that future DDA may mitigate the risks of low visibility driving by selecting routes that avoid major hazards.

	Package A:	Package B:	Package C:	Package D:
Adverse surface conditions (e.g., ice)[b]	Modifiers to Initial / Final With LDW: 0.30 / 0.40 Without LDW: 0.30 / 0.40 Alerting is judged to be of little value in the types of crashes most common in adverse surface conditions as driver is assumed to be engaged in the driving task due to challenging conditions, thus the warnings are expected to be relatively less beneficial, with limited potential to improve with technological maturation.	Modifiers to Initial / Final With LDW: 0.75 / 0.85 Without LDW: 0.75 / 0.85 Alerting is judged to be of little value in the types of crashes most common in adverse surface conditions as driver is assumed to be engaged in the driving task due to challenging conditions, thus the warnings are expected to be relatively less beneficial, with limited potential to improve with technological maturation.	Modifiers to Initial / Final With LKA: 0.85 / 0.90 Without LKA: 0.70 / 0.90 Note these values only apply to crashes not preceded by loss of control/traction. Loss of control/loss of traction crashes were deemed not preventable by ADAS. Adverse surface conditions are expected to reduce system performance though not greatly in situations with no loss of traction; and there is room for improvement with technological maturation.	Modifiers to Initial / Final With LKA: 0.90 / 0.95 Without LKA: 0.90 / 0.95 Depending on visibility conditions and type of sensors used, current DDA systems may automatically deactivate. It is possible that future DDA may mitigate the risks of adverse surface conditions driving by selecting routes that avoid major hazards.
Darkness[b]	Modifiers to Initial / Final With LDW: 0.90 / 0.95 Without LDW: 0.50 / 0.70 Most warning systems are not severely impaired by dim lighting or darkness. Since driver fatigue plays a major role in crashes occurring in darkness, alerts are particularly important in this scenario, potentially offsetting any decrement in the performance of the warning system itself.	Modifiers to Initial / Final With LDW: 0.90 / 0.95 Without LDW: 0.50 / 0.70 Most warning systems are not severely impaired by dim lighting or darkness. Since driver fatigue plays a major role in crashes occurring in darkness, alerts are particularly important in this scenario, potentially offsetting any decrement in the performance of the warning system itself	Modifiers to Initial / Final With LKA: 0.75 / 0.95 Without LKA: 0.70 / 0.90 Research has shown that some collision intervention systems perform less well in certain crash types in darkness (e.g., AEB in crashes with pedestrians). There is opportunity for improvement with technological maturity. LKA is of minimal relevance to non-lane-departure crashes in dim lighting but may help to avoid some other crash types that were preceded by an unintended lane departure.	Modifiers to Initial / Final With LKA: 0.80 / 0.95 Without LKA: 0.80 / 0.95 Deactivating lane-keeping features would functionally deactivate DDA, thus values for lower packages (without DDA) apply when LKA is deactivated.
Work Zones[b]	Modifiers to Initial / Final With LDW: 0.50 / 0.80 Without LDW: 0.50 / 0.80 Warning systems may issue false warnings or fail to activate in the presence of ad hoc changes to traffic patterns (e.g., lane shifts) or fail to activate if the visual environment is excessively complex. Ad hoc nature of road construction may limit the ability to overcome limitations with technological maturity.	Modifiers to Initial / Final With LDW: 0.70 / 0.90 Without LDW: 0.70 / 0.90 Warning systems may issue false warnings or fail to activate in the presence of ad hoc changes to traffic patterns (e.g., lane shifts) or fail to activate if the visual environment is excessively complex. Ad hoc nature of road construction may limit the ability to overcome limitations with technological maturity. ACC may help avoid rear-end crashes in stop-and-go traffic in work zone.	Modifiers to Initial / Final With LKA: 0.75 / 0.95 Without LKA: 0.75 / 0.95 AEB may be beneficial in work zones and its performance should not be reduced greatly. LKA is greatly limited by temporary lane markings, lane shifts, etc.	Modifiers to Initial / Final With LKA: 0.80 / 0.98 Without LKA: 0.80 / 0.98 Current systems often struggle in work zones, but there is opportunity for improvement with technological maturity.

	Package A:	Package B:	Package C:	Package D:
Probability of system use[c]				
	Initial / Final LDW: 0.20 / 0.90 All others: 0.80 / 0.90 Will vary by warning system. Research has shown that many drivers deactivate LDW but keep other warning systems active.	Initial / Final LDW: 0.05 / 0.90 All others: 0.20 / 0.90 ACC is likely to be used most frequently on long highway drives but infrequently in other contexts. Future systems may be used in a wider array of driving contexts as the technology matures.	Initial / Final LKA: 0.40 / 0.90 All others: 0.80 / 0.90 Research has shown that many drivers deactivate LKA but keep other collision intervention systems active. Also, many vehicles retain last setting for lane-keeping features but default AEB to on after every ignition on-off cycle, increasing probability that LKA will be deactivated but AEB will remain activated. Probability of use likely to increase with technological maturity.	Initial / Final LKA: 0.10 / 0.90 All others: 0.20 / 0.90 DDA is likely to be used most frequently on long highway drives but infrequently in other contexts. Future systems may be used in a wider array of driving contexts as the technology matures. Also note that these values include misuse and abuse of system, e.g., by using system outside of operational design domain.

FCW: forward collision warning; LDW: lane departure warning; BM: blindspot monitoring; PD: pedestrian detection; ACC: adaptive cruise control; ABE: automatic emergency braking; LKA: lane keeping assistance; ESA: emergency steering assistance; DDA: dynamic driving assistance (i.e. simultaneous operation of ACC and LKA)

a. Base effectiveness indicates proportion of crashes prevented by technology shown in column, assuming ideal conditions (absence of hazards that reduce system effectiveness). Lane-departure crashes and non-lane-departure crashes considered separately due to research indicating that consumers are more likely to deactivate lane departure warning and lane keeping assistance systems than other systems.
b. Reduction in effectiveness of technology shown in column in the presence of the hazard indicated. When the hazard is present, the system effectiveness is multiplied by the value shown. A value of 1 indicates no reduction in effectiveness for the hazard listed; 0 indicates that the system has no effectiveness when the hazard is present. Lane-departure and non-lane-departure crashes considered separately.
c. For ACC and DDA, probability of system use denotes the probability that the technology is engaged at any given time. For collision intervention systems (AEB, LKA), this represents probability that the system is turned on (not deactivated). For warning systems, this represents the probability that the system is turned on and that the driver is responsive to warnings. Probability of system use was modeled in a "step-down" approach such that if systems within a higher package were not in use, the effectiveness and probability of use of next lower system would apply. Within each package, lane-keeping features were considered separately from other features where applicable due to research indicating lower probability of use of lane-keeping features.
d. Initial value represents value assumed in base year (2017). The final value represents value assumed in 2050 given anticipated technological maturity. Values in intermediate years were modeled as an "S-shaped" curve between initial value in the base year and final value in 2050.
Effectiveness estimates were determined through literature reviews and discussions within the research team. The table briefly includes the research team's collaborative thinking under each estimate. These data points represent best estimates at the time of this study; however, additional research is needed to refine these estimates, given the dearth of information on many of these technologies under these specific scenarios.

Appendix B. Parameter values used to model best estimate, high uptake & use, and low uptake & use scenarios.

Parameter	Best Estimate	High Uptake & Use	Low Uptake & Use
Attractiveness weight	0.5	0.7	0.3
Industry learning effectiveness	0.5	0.7	0.3
Learning speed	0.1	0.5	0.02
Initial perceived safety relative to actual safety	0.2	0.5	0.00
Technology usage modifier	1	1.5	0.5