Potential Effects of Autonomous Vehicles on the Insurance Industry

Zachery Trump

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____
David Schweitzer, Ph.D.
Thesis Chair

____
Daniel Joseph, Ph.D.
Committee Member

____
James H. Nutter, D.A.
Honors Director

____
Date

Abstract

The implementation of autonomous vehicles, or self-driving cars, promises to radically change much of the normal way of life. While it may seem inconsequential to start small with a vehicle of relatively low level of automation, there are many factors to consider. Some of these factors include security, moral dilemmas, and even the insurance field. One can look back at previous implementations of new technology, such as air bags, and see that it can be difficult to predict consequences and adapt. However, actuaries have been suggesting solutions to make autonomous vehicles a safe reality. While the solutions may vary, one thing is clear: communication between the vehicle and the insurance field is imperative.

Potential Effects of Autonomous Vehicles on the Insurance Industry

As technology continues to improve, people seek out ways to meet needs and desires in society. They look at where comfort can be increased, dangerous situations can be mitigated, and boredom can be eliminated. It does not take long to reach the conclusion that autonomous vehicles would dramatically benefit society. Instead of driving for hours in a vehicle every week, imagine a world where the “driver” can turn around and have quality family time or catch up on work. The current driving system is also clearly dangerous. Globally, car accidents cause 1.24 million deaths every year and is the main cause of death for young people (Mohammed et al., 2019). Many of these accidents are due to driving error, which includes being under the influence of alcohol or drugs, poor driving skills, and distractions. Autonomous vehicles also promise added benefits. Reduced payments for damages to vehicles, automobile insurance, and purchasing new cars could save consumers money. Fagnant and Kockelman (2015) suggest autonomous vehicles could also reduce traffic congestion and fuel consumption. Drivers would also enjoy reduced stress and increased productivity. Clearly, autonomous vehicles could greatly improve the world.

While the end result is tempting, creating and implementing an autonomous vehicle system is complicated. It would cause ripples into many aspects of the economy. One field that will be greatly affected is the insurance industry. Pricing insurance on autonomous vehicles, communicating with car manufacturers, and determining who is liable for unique scenarios are just a few of the changes the industry will have to go through. In fact, the entire system of how an insurance company functions might have to change. While these ripples are difficult to predict, there is insight to gain by studying the history of autonomous vehicles and the history of other automobile-related advancements. Overall, this thesis hopes to get a clearer picture of the challenges that insurance companies will soon face and study a couple possible solutions that have been suggested.

Autonomous Vehicle Background Information

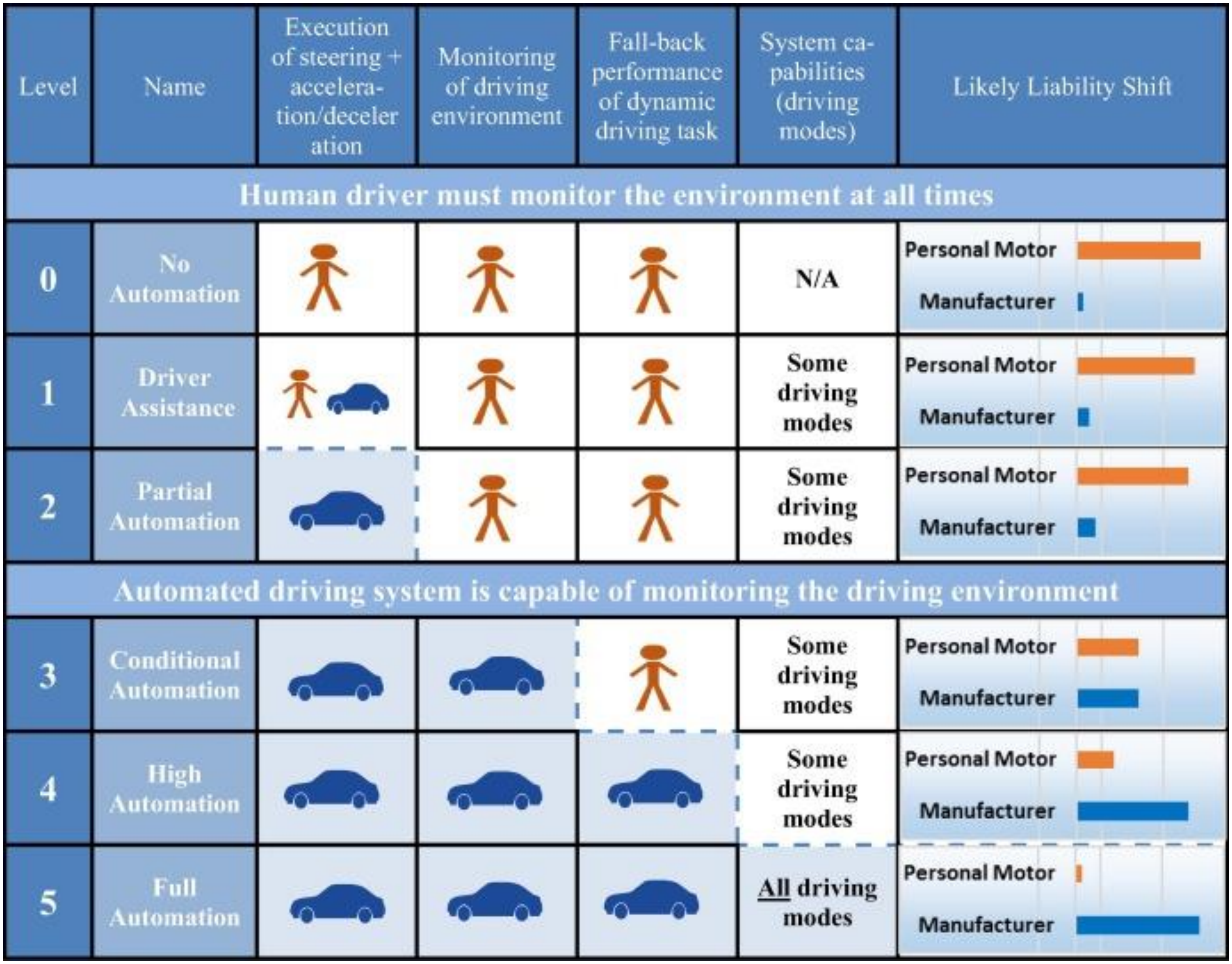
Defining Terms

The term “autonomous vehicle” represents a broad range of ideas. The general definition is a car that is able to operate using an autonomous system instead of a manual driver. To define autonomous systems, Hancock (2019) states, “Autonomous systems are generative and learn, evolve, and permanently change their functional capacities as a result of the input of operational and contextual information” (Clarifying nomenclature section). When we apply these definitions to the current world, the results are not binary. Instead of something being autonomous or not autonomous, there is a range of autonomy.

Levels of autonomy are used to describe where a vehicle fits on the range of autonomy. In 2003, the U.S. Departments of Commerce, Defense, Energy, and Transportation met to create a formal framework for Autonomy Levels For Unmanned Systems, or ALFUS (Huang et al., 2005). This comprehensive model included ten levels of autonomy that the government was able to apply to various fields, such as Mars rovers. However, SAE International (previously known as the Society of Automotive Engineers) released a condensed model with only six levels. This model has become more popular in autonomous conversations and will be used throughout this paper. Figure 1 provides clear distinctions between each level.

Figure 1

Levels of Autonomy



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As levels increase, the amount of responsibility that is given to the automobile increases. At Level 0 there is no autonomy at all, and at Level 5 the car is fully autonomous. The six levels are split in half by whether a human must monitor the driving environment or if a vehicle is capable of doing so. Essentially, Level 2 and Level 3 are separated by who is in control most of the time. Is there a driver employing autonomous techniques or is there a vehicle that occasionally requires human action? Levels 1 and 4 add a couple more autonomous features than the previous levels, such as lane keep assist for Level 1 or adapting to weather conditions for Level 4. Currently progress is limited by technology, and Levels 2 and 3 are the closest to implementation. As a result, this paper will focus mainly on these two levels as challenges and potential solutions are discussed.

History

The genesis of driverless vehicles can be traced back to the 1920s. It began with remote-controlled cars, and it would not escalate to computer-driven self-driving cars for another 60 years (Takács et al., 2018). In 1987, six European countries collaborated in a project called Prometheus (Programme for a European Traffic with Highest Efficiency and Unlimited Safety). Prometheus spanned eight years and was the most funded research project in the world of automated vehicles at that time. As its name suggests, the project's goal was to explore strategies to make traveling on the road safer and the traffic system more efficient. Researchers worked on a communication network between the vehicle and a computer, as well as widening the area of "sight" for the vehicle. This research and experimentation resulted in features we use today, including automated intelligent cruise control and lane keeping (Williams, 1988).

The growth of automation technology began to get attention, especially in the industrial world. Businesses like Amazon were quick to invest in and even incorporate automation onto their shop floors. The next leap in the autonomous vehicle industry resulted from the challenges initiated by the U.S. Defense Advanced Research Projects Agency (DARPA). DARPA hosted competitions during the 2000s in which specialized autonomous vehicles were tested for quality and performance. Through competition, advances were made that pushed the limits of automation further and further. In 2007, six cars that were entered were able to function through various scenarios, involving obeying traffic rules and avoiding obstacles (Fagnant and Kockelman, 2015). These events would eventually attract the attention of the rising company, Google. After six years of research and engineering, Google's efforts led to the first driverless car on public roads in 2015 (Takács et al., 2018). Currently, the number of companies that use autonomous vehicle technology are growing rapidly. A few companies even have experimental Level 5 vehicles similar to Google. It is worth noting that this achievement and the conversations being had today are only possible due to companies like Amazon and Google seeing the potential of automation and investing in its future. While this technology has not found its way to the average person's home, these investments sparked the competitive race to put driverless cars on the market.

Previous Impacts of Technology on Insurance

One strategy to predict the future is to study the past. If the goal is to get a better picture of what the implementation of autonomous vehicles into the market would look like, studying similar prior implementations could be beneficial. The following pages will consist of brief analyses of various automobile and autonomous innovations, including airbags, ABS brakes, drones, and Uber. This will reveal that putting new technology on the market can be a bumpy road that requires persistence and many adaptations. The final impact of the product could be wildly different than the original intent.

Airbags

Airbags were introduced to the market in the 1970s (Kalra, 2017). However, airbags themselves had been invented 20 years prior. Airbags were considered as a possible substitute to wearing a seatbelt, which made them even more attractive. In the 1970's, the use of seatbelts was more of a suggestion than a mandate. As airbags grew in popularity, confidence in their ability to keep people safe grew as well. In 1991, NHTSA (National Highway Traffic Safety Administration) made airbags mandatory in newer car models (Kalra, 2017). This was controversial to car manufacturers because they believed airbags inhibited their ability to sell vehicles. NHTSA's reasoning was based on their prediction that airbags would save 9,000 lives every year (Peterson, 2018). This reasoning would turn out to be very inaccurate. While airbags consistently save many lives, even today, the actual number tends to be closer to the 2,000-3,000 range (Kalra, 2017). Additionally, air bags caused multiple deaths in the initial years of its implementation; though it is worth noting that the number of lives saved dwarfed the losses that they caused.

A few notable lessons can be learned from the history of airbags. One item of interest is the amount of time it took to get airbags into the market. It took 20 years for airbags (a much simpler product than an autonomous vehicle) to scratch the surface of the market. It took even longer to get fully integrated. Therefore, it should not be surprising that it may take some time for autonomous vehicles to be ready to be sold, and even more to be fully integrated. Another key takeaway is that the original idea for airbags was to be a substitute for seatbelts instead of an additional safety measure like it is today. It is important to keep in mind that the role of new technology could fluctuate as time progresses. The intent of autonomous vehicles could look very different after years of use. Next, initial predictions of the effectiveness of new technology can be extremely inaccurate. This is a big problem for insurance companies that require these predictions to price. It is evident that predictions should be tentatively accepted and able to be quickly adapted when necessary. Finally, there is an ethical concern associated with implementing new safety technology. While many were saved, some were killed as a direct result of airbags. This also occurred during the implementation of ABS brakes.

ABS Brakes

Anti-lock Braking System (ABS) brakes were first used in 1945 on airplanes, rather than cars (Aly et al., 2011). They helped the planes' tires to avoid spinning out and losing control. ABS brakes would not be introduced into the automobile market until the 1960s, and it took another 20 years for ABS brakes to be implemented into most cars (Aly et al., 2011). ABS brakes were applied to automobiles in hopes of increasing safety and decreasing accidents. However, it was found that the implementation initially caused more accidents (Peterson, 2012). This occurred because drivers either did not understand how to operate the new brakes, or they gave the new system too much trust. Some drivers were unfamiliar with the way ABS brakes affected their vehicles. When the new system was activated, drivers panicked and reacted erratically, causing an accident. Other drivers gained a false sense of security due to the new invention and drove dangerously as a result. Eventually, drivers became comfortable with ABS brakes, and the positive effects were impressive.

Similarly to airbags, ABS brakes reveal how people could react to autonomous vehicles. One aspect is that the technology could be used for different fields or modes of transportation. Another feature that was also apparent in airbags was that it also took 20 years to expand to the average person's market. Perhaps 20 years is a solid estimate for a new automobile technology to be widely distributed, despite its complexity. Again, there was an initial rise in accidents as a result of new technology. Autonomous vehicle experts and insurance agencies could foresee similar results. People misusing autonomous vehicles will have to be accounted for, as well as clear instructions given on safely operating an autonomous vehicle. It is probably not completely preventable, but it is worth spending effort to diminish the initial problems. Looking from an insurer's perspective, it is difficult to navigate liability in situations of misuse. In a scenario of misuse, a judge might have to decide if it was the driver's error, the product manufacturer's error, or somewhere in between.

Drones

Another good product to examine is drones. Insuring drones is difficult because there are liability issues. When submitting a claim, one must prove that his or her product was defective. In the United States, the term "defective" is defined by each state individually (Beyer, 2014). Some states only consider the consumer expectation test, which decides if a product is abnormally dangerous for the average consumer to consider (Beyer, 2014). Others also consider the risk utility test, which questions if the manufacturer could easily make the product safer (Beyer, 2014). Drone insurance gets even more complicated when cybersecurity, privacy, and the safety of civilians are factored in. For example, drone cybersecurity insurance deals with how data is shared, the importance of the data, the security of the data, and much more. Currently, most insurance companies are hesitant to enter the drone insurance market, due to the complexity. However, larger insurance companies have begun to insure big companies that use drones because they can afford the risk. In the case that insurance companies agree to insure drones, they write specialized packages based on the drone's manufacturing. In other words, insurance companies do not typically have a general drone package. They insure on a case-by-case basis.

Drones are applicable to autonomous vehicles because they are also becoming autonomous. Companies have already begun developing and testing autonomous drones for the market and military use. It would not be surprising if insurers used similar liability definitions for autonomous vehicles. Having the precedent of battles between drone owners and drone manufactures could be useful. Because autonomous vehicles match drones in complexity, it is plausible that the future could look like large insurance companies insuring large companies that use autonomous vehicles. These would also probably work on a case-by-case basis.

Uber

One more invention that can be studied is Uber. Uber is a company that connects people who need a ride to one of their many drivers. It is a taxi service that employs privately owned vehicles. When a driver accepts a job and logs into the Uber app, the driver's personal auto insurance is paused for the remainder of the job (Lynch, 2016). While Uber is the most popular brand of this kind of taxi service, there are other similar companies as well. This form of ridesharing could cause people to buy fewer cars and lower insurance premiums in the future (Lynch, 2016).

Uber is notable because it is a foreshadowing of what a system of autonomous vehicles could look like in the future. In Level 2 and Level 3 vehicles, personal auto insurance could switch on and off as the driver trades control with the vehicle. Certainly, some aspects of liability insurance will have to be activated when a driver takes over, if not the entire package. Another way Uber is preparing the way for autonomous driving is the reduction of personal vehicle use. It makes sense that the ridesharing industry would grow since autonomous vehicles negate the need for human employees. It is also possible that eventually vehicles could entirely become a form of public transportation. If people aren't physically driving, there could be a loss of a need to own a vehicle.

Challenges of Implementing Autonomous Vehicles

Bold, new products can dramatically change the way people operate, even on a daily basis. Implementing autonomous vehicles is an entire system rather than one product. The end goal is to bring about a completely new system of daily transportation. The integration could cause ripples in areas that may be unpredictable. To make this system possible, the many challenges that can be foreseen have to be overcome or at least their severity diminished. While not all of these issues explicitly impact the insurance industry, they will all need to be taken into account when interacting with customers and manufacturers, as well as figuring out liabilities and pricing.

Implicit Challenges

Autonomous vehicles are currently inhibited by technological challenges. An automated vehicle has many factors to safely navigate. Litman (2020) states, "Operating a vehicle on public roads is complex due to the frequency of interactions with other, often-unpredictable objects including vehicles, pedestrians, cyclists, animals and potholes. Because of these interactions, autonomous vehicles will require orders of magnitude more complex software then [sic] aircraft" (p. 24). Programming for a large variety of possible scenarios takes time and a robust system. Additionally, autonomous vehicles will require state-of-the-art equipment. High-tech radar, powerful computers, and quality cameras have to be perfect. Any imperfections could result in fatalities. Another technological risk is cyber security. A system of automated vehicles could leave America vulnerable to terrorist attacks. Imagine a situation where terrorists release a computer virus that causes every car to speed up to 90 miles an hour and disables the brakes.

Even the situation of hacking into one automobile has to be guarded against. While the technology might be available to do so, ensuring that the defense is impregnable takes time. One more hurdle that developers have is creating a traffic system that allows autonomous vehicles to safely navigate, whether independently or in a connected network. Bagloee (2016), who notably presents a model as a solution, states, “The complexity of the AVs navigation rests on the fact that the AVs must share road space with non-AVs, resulting in mixed traffic patterns” (AV navigation model section). At least initially, the road will have to be shared between automated vehicles and manual drivers. It will have to be decided if they are to be segregated into their own respective zones or if they can function in harmony with our current system.

The insurance industry will have to deal with each of these challenges on some level. Each situation will have to be accounted for in liability plans or generalized for simplicity. All the expensive technology will have to be insured in the (ideally unlikely) case of an accident. Individuals will most likely have cybersecurity included in new automobile insurance plans. As mentioned earlier, insuring cybersecurity can be a complex venture, considering the many factors involved. Overall, technological failure and upkeep will still affect the insurance industry and its operations.

The human aspect of an autonomous driving system also complicates the integration process. In order to have a successful autonomous system, humans have to have trust and reliance on the system to function. If people don’t believe autonomous driving is safer than manual driving, no one will purchase an autonomous vehicle. Walker (2018) performed a study on Taiwanese workers who have never interacted with a Level 2 automated vehicle to measure trust. The study measured how much faith people had in various aspects of the Level 2 vehicle before “driving”, immediately afterwards, and 2 weeks later. While trust improved in some aspects, such as lane keeping ability, 8 other attributes showed a decrease in trust. Although this seems pessimistic at first glance, Kerschbaum brings up the first-failure effect, which indicates that humans typically have temporary trust issues when machines first make a mistake (Kerschbaum et al., 2015). Not only does distrust in the product hurt the market, but it also increases the probability of misuse. This could inhibit autonomous vehicles from reaching their full potential and create dangerous situations.

Another challenge is the take-over process. This manual override gives drivers the opportunity to take back the wheel. However, this implies the need for monitoring. Would people watch the road for reasons to take-over, or would they relax? Hancock (2019) answers the question as such, "…if you build vehicles where drivers are rarely required to respond, then they will rarely respond when required" (The take-over delusion section). Even if drivers do respond, drivers have a high probability of having an error in judgment. After a long period of not driving, it makes sense that a driving error is more likely to occur. This situation is even more serious after considering the long-term effects of automated vehicles on an individual's driving ability. Kerschbaum broke down the components of the takeover process into four main phases: the attention shift, the interpretation of the situation, the choice of action, and the completion of the action (Kerschbaum et al., 2015). He also emphasized the need for further study in the area.

The insurance industry will have to deal with these human-centered issues. Insurance companies' forecasts and decisions will have to adapt to the rising and falling of the market due to the trust of consumers. The take-over process will be a huge aspect of insurance packages. Giving drivers the option to take control comes with responsibility. This makes drivers more liable for accidents and damages. It will be interesting to see how insurance agencies deal with the problem of failure to act. Will people refuse to take-over to avoid liability? How will age affect the reflexes needed to make the right decisions in a take-over scenario? These issues are complicated and will probably grow in complexity as the system is implemented.

Challenges Inside the Insurance Industry

There is no doubt that insurance companies will have to work around these issues. However, the insurance industry also has additional internal reformations that have to occur. In a survey, the top three Taiwanese insurance agencies were questioned, and the most popular response was that automated vehicles would change the way insurance companies do business (Fan & Xu, 2019). Everything from how insurance companies interact with customers to how they interact with manufacturing companies could look radically different after the switch.

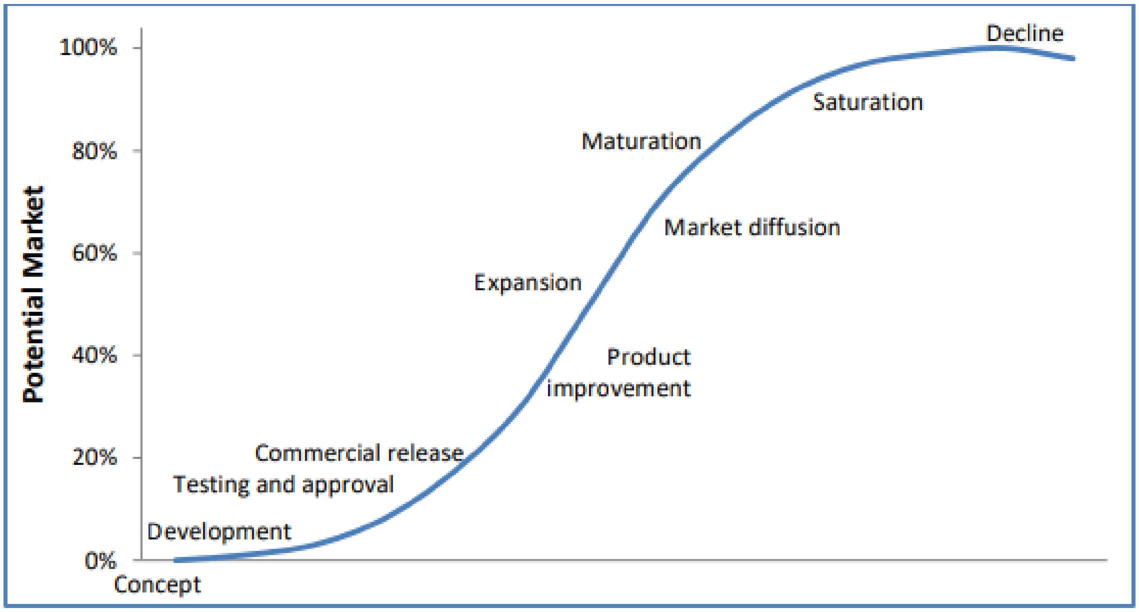
One challenge actuaries would face is the large amount of complex data that would need sorting. To price premiums, actuaries would need to search for the predictive variables through the network of data given (Lynch, 2014). Of course, to do this, actuaries would first need access to the data itself. This would lead to constant, close interactions between third parties, such as insurance companies and car manufacturing companies. Because each company is different, insurance companies would require separate dealings with each car manufacturing company that puts an autonomous vehicle on the market. Another third party that could cause problems is regulators. State governments have regulations on insurance companies that could affect how business is done. In an actuarial review, Lynch (2014) describes one of these regulations already in place: “California, for example, has mandatory rating factors that insurers must use, such as driving record or number of years as a driver” (para. 9) Another change that could come about is liability. Navigating who is to blame for accidents is an entire frontier in discussions of automated vehicles. Do drivers get blamed for not taking over or being attentive, or do car manufacturers get blamed for a glitch in the system?

If the promises of significantly reducing accidents are found to be accurate, the entire insurance industry could be downsized. In fact, a KPMG report stated, “A decline in accident frequency due to safer vehicles and the adoption of autonomous vehicles could shrink the U.S. personal auto insurance sector by 60 percent within 25 years” (Fan & Xu, 2019, p. 15). However, there could also be a rise in product liability insurance, due to how expensive the new technology could be. Another KPMG report highlighted the possibility of a large increase in product liability insurance to 57% of total auto losses by 2050 (Fan & Xu, 2019). While this could diminish the overall downsizing, it is likely that the shrinking of the other aspects of personal auto insurance sector will have a much larger effect, especially if drivers are relieved of liability.

These questions and more must be addressed before a system of insuring automated vehicles can be created. It is evident that a lot of adaptation will be required. However, even more will be necessary as the market gets more automated. The change in the vehicle world will be gradual, so insurance companies will have to deal with problems at each level of automation as the percentage of automated vehicles in the market increases. Figure 2 displays the phases typically gone through by new products. However, each phase may take longer with automated vehicles. Litman (2020) reasons, “Because autonomous vehicle technologies are more complex and costly than these technologies, their market acceptance and penetration are likely to take longer” (p. 27).

Figure 2

Innovation S-Curve



Note. From *Innovation S-Curve* by T. Litman, 2020, Autonomous vehicle implementation predictions: Implications for transport planning. https://www.vtpi.org/avip.pdf. Used with permission.

Applying Autonomous Vehicles to Insurance

Bayesian Networks

Before discussing a possible solution to pricing automated vehicle insurance, it is important to understand the basic concept of a Bayesian Network. First, the statistical distribution of an event must be identified. For example, if the probability of an event follows a Poisson distribution (a reasonable assumption) then the probability of some number of events, x, happening is given by Equation 1.

$$P(x) = \frac{\lambda^x e^{-\lambda}}{x!} \quad (1)$$

The Greek letter, λ, represents the expected value, or average number of events in the time interval in question. Next, consider joint probabilities of the Poisson distribution, or the probability of two or more events occurring together at the same time. One representation of the joint probability of two events is shown as Equation 2.

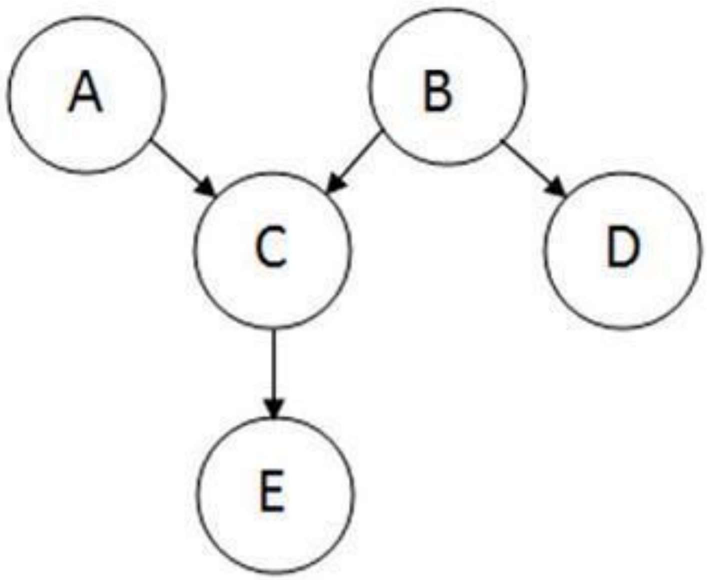
$$P(x_1, x_2) = P(x_1)\, P(x_2|x_1) \qquad (2)$$

The product in Equation 2 includes a term indicating a conditional probability, which is the probability of x_2 given the occurrence of x_1. The joint probability formula can be extended to include more than two events. After finding all the joint probabilities of all the events, a diagram can be created that links all the events. This diagram is called a Bayesian Network (BN).

The goal of a Bayesian Network is to display conditional probability and connect variables that are related to each other. BNs are classified as directed acyclic graphs (Woolf, 2020). This is because a BN guides its reader from event to event in a forward movement. If a BN were to be cyclic, there would be events that would eventually cause themselves. A Bayesian Network consists of nodes and arcs. A node represents a random variable or event. This is usually designated as a circle. The arcs show dependence from one node to another. An arc is displayed as an arrow pointing from one node to the next. A lack of an arrow connecting two nodes implies that the nodes are independent of each other. An example of a Bayesian Network can be examined in Figure 3. It can be seen that C and E are dependent of A and B, but D and C are independent (Woolf, 2020).

Figure 3

Bayesian Network Example



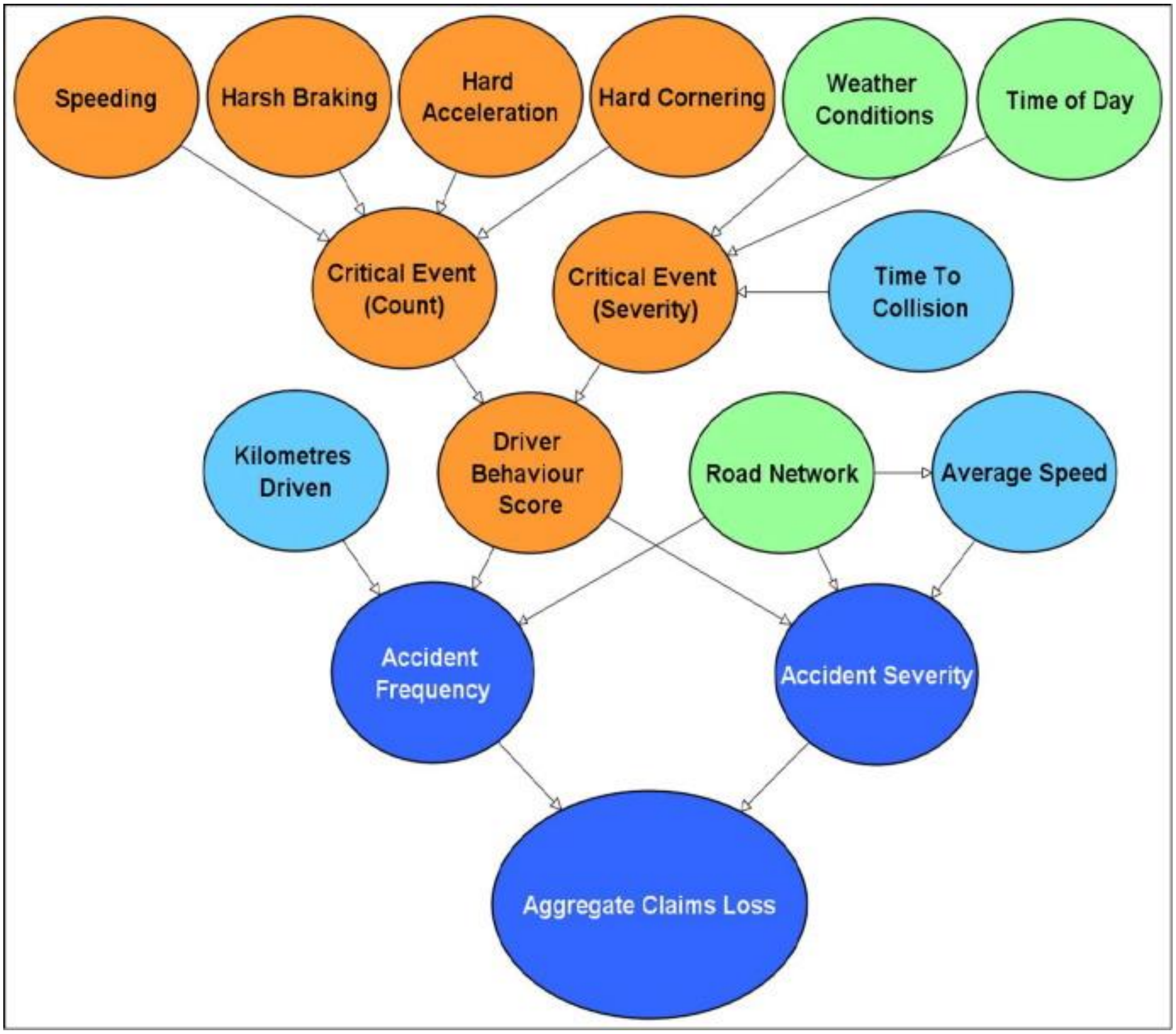
Note. By P. Woolf, 2020, Chemical Process Dynamics and Controls (13.5: Bayesian Network Theory - Engineering LibreTexts). CC BY-NC-SA 3.0.

Bayesian Networks are chosen due to their ability to show all the causal relationships between a wide range of variables. The simple display makes it easy to spot which variables are dependent on other variables. Bayesian Networks also allow for a large number of variables to be present. This is attractive because the problem at hand employs many variables (including future unknown variables) that are interconnected in complicated ways. One more benefit is the ability to be updated when new data arises. Bayesian Networks are famous for being able to work with incomplete data. However, the main concern with BNs is the difficulty of calculation required to construct the network (Woolf, 2020). These characteristics of Bayesian Networks make the model a compelling choice to the automated automobile insurance problem because data tends to be insufficient and actuaries are well-equipped to handle tough calculations. Additionally, Bayesian Networks are adaptable to many industries. They have been applied successfully across a variety of different fields of work, including finance, medicine, law, and even driving behavior (Sheehan et al., 2017).

Insurance is priced based on the expected number of claims and the expected severity of the claims. To find the expected claims loss per driver of a Level 3 semi-autonomous vehicle, a Bayesian Network was created (Sheehan et al., 2017). This process involved using basic actuarial strategies, such as the types of risk factors to apply. Because the traditional risk factors were implemented, the traditional distributions associated were also implemented. For example, accident frequency was modeled as Poisson, and accident severity was modeled as lognormal (Sheehan et al., 2017). In total, 16 variables were chosen with 5 different types of variables (continuous, discrete, integer interval, Boolean, and ranked). These variables were grouped into 4 categories: query, behavioral, situational: environment and road, and situational: individual (Sheehan et al., 2017). These are designated by specific colors as seen in Figure 4.

Figure 4

Bayesian Network for Aggregate Claims Loss Estimation



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This model was tested using a scenario with a driver in control and the automated vehicle in control. To score driving behavior, an existing method was adopted, in which participants start with the top score that diminishes after faults. To collect the data, the team used pre-existing approaches from insurance agencies that already use telematics to price insurance, specifically Pay-As-You-Drive (PAYD) and Pay-How-You-Drive (PHYD) (Sheehan et al., 2017). The results turned out as predicted. The driver had a higher expected aggregate claims loss than when the automated vehicle was in control. One factor that led to this was that automated cars would not speed, which reduces potential loss significantly. Other perks of automated vehicles impact the potential loss similarly, and the final loss was about a tenth of the driver's loss (Sheehan et al., 2017).

This Bayesian Network functions well as a potential solution because of the characteristics of BNs combined with the use of strategies used today by actuaries and insurance agencies. This model can be expanded as needed because Bayesian Networks allow additional factors (such as alcohol use and vehicle type) to be easily incorporated. One potential downside is the large amount of communication necessary between insurance agencies and car manufacturers. Without the telematics, the Bayesian Network would not be possible. However, this possible solution paints a good picture of how the insurance industry might react to the adoption of automated vehicles.

Deep Learning

Another possible solution to the future actuarial challenges mentioned is to automate the insurance industry to keep up with automated vehicles. Instead of manually creating a system to price insurance (such as the Bayesian method above), insurance could be priced instantly by machines communicating with the automated vehicles. Balasubramanian et al. (2018) predicts a world in 2030 where underwriting is completely automated. In the case of an accident, automated vehicles (presumably Level 5) could automatically submit the claim to an insurance program, which would calculate the loss and settle it. In this automated insurance world, insurance would be an instantaneous process with limited human interaction and waiting periods. Although this may seem too convenient or even unrealistic at first, the technology to create this world has almost arrived.

The technology needed to automate the insurance industry revolves around the usage of machine learning and deep learning. Richardson defines machine learning as "…an approach taken within the field of artificial intelligence (AI) whereby AI systems are allowed to build knowledge by extracting patterns from data and has been defined as the field concerned with the study of algorithms that allow computer programs to automatically improve through experience" (Richardson, 2018, p. 2). While machine learning has advanced and proved capable of solving problems, it still falls short in areas that require a more human touch like image recognition or decision making. A newer branch of machine learning called deep learning functions like brain neural networks. As its name suggests, deep learning is the more in-depth version of machine learning that takes it to a new level. Software receives inputs, analyzes them, and makes determinations or decisions based on the data. Deep learning has already been successfully applied to various other fields including speech and audio recognition and, more notably, machine vision. These kinds of learning can be classified as supervised, unsupervised, or semi-supervised depending on the amount of human interaction as the machine "learns."

Due to their nature, machine and deep learning techniques can only be applied to actuarial problems that are expressed as a regression (Richardson, 2018). Regression is a statistical process that measures the relationship between variables, specifically between a dependent variable and at least one independent variable. Equation 3 represents the equation for a multi-variable regression model using β_0 as the intercept, β_i's being the slope terms associated with the independent variables (X_i's), and ϵ representing the error term.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_k X_k + \epsilon \quad (3)$$

Regression is commonly used to predict what the future will look like given past information. Machine and deep learning can take that information and build on it, allowing actuarial work to be done. A program could then adapt and use previous knowledge to apply it to new scenarios like pricing automated vehicles. Short-term pricing, the Mack chain-ladder model, hierarchal IBNR models, mortality forecasting, and life valuation approximation are a few examples of some actuarial problems that use regression (Richardson, 2018). Figuring out ways to link these problems to autonomous vehicle problems or link autonomous vehicle problems to regression will require work.

Actuaries perform difficult work that requires a lot of learning to perform. To solve problems, they choose from an array of methods associated with the task, or they adapt a technique from a different set of methods. While this is currently tough to program, progress is being made to program deep learning systems to acquire actuarial knowledge and apply it (Richardson, 2018). As time passes and this technology develops, less human interaction will be required to specify what is known and what is the logical next step with that knowledge. These methods of deep and machine learning have already been successfully tested in actuarial work. In 2018, the pricing of non-life insurance, IBNR Reserving, and the analysis of telematics data were all completed with the help of machine and deep learning (Richardson, 2018).

Although there are a lot of advantages in the autonomous insurance industry, there are some negative consequences as well. The primary disadvantage is the loss of jobs. As more artificial intelligence replaces human intelligence, the demand for workers in the field will decrease. Realistically, the role of deep learning in the near future will serve to assist actuaries rather than replace them. It will be important to have people in the industry that understand the process, ensure the results are logical, and to present the information clearly. However, it would not be surprising to see actuaries be forced to study artificial intelligence to stay relevant as they prepare for the future. Another disadvantage of this system is the amount of artificial intelligence in the entire mechanism- from the autonomous vehicle to the insurance industry. Some could find it unsettling that artificial intelligence would be “in charge” of people’s physical and financial health. As discussed previously, cybersecurity is also an issue whenever artificial intelligence is introduced. Despite these disadvantages, it seems that applying deep learning to actuarial work could be a viable solution to deal with the challenges of implementing autonomous vehicles.

Conclusion

The world of autonomous vehicles is approaching. Technology will continue to progress as each year goes by. Instead of calling an Uber, a worker might get picked up at the normal time by his or her public transportation autonomous vehicle. Instead of waiting months for an insurance company to send a check, the new insurance program could update your account minutes after the rare case of an accident. While some consumers eagerly await these benefits, insurance companies still have to tackle the challenges accompanied by them. Some of these challenges have been tackled before in similar inventions, such as liability scenarios from drones. Others are brand new and will require creativity, like navigating the takeover process. In this paper, two possible solutions were presented. The Bayesian Network method takes previously established actuarial methods and applies them to the new problem. It is capable of being added to as new problems arise, and some of the processes involved are familiar to people in the industry. This could initially solve the pricing problem and become the foundation of the future insurance system. The deep learning method is a new frontier that uses autonomy to deal with autonomy. Letting computers use regression to calculate many scenarios and quickly settle claims could be the future. This would radically transform the insurance industry and would solve most of the problems insurers face. Both methods have their advantages and disadvantages. Whichever road the insurance industry goes down, it and the people involved will have to continuously adapt as the world around them changes.

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