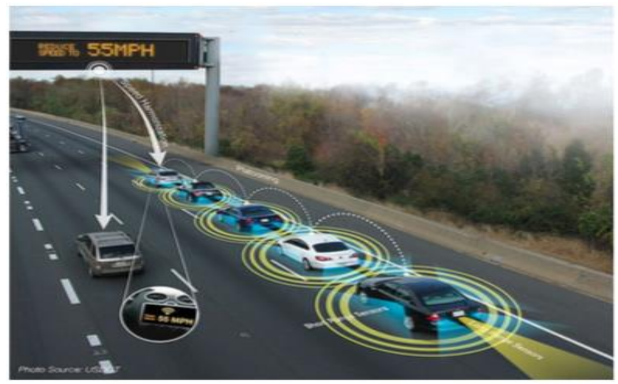
Integrating Human Behavior toward the Development of Safer Cooperative Automated Transportation: Implementation of SHRP2 Naturalistic Driving Study



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1. Problem Statement

The emergence of innovative transportation technologies comprises vehicle connectivity, autonomy, and personal mobility are accelerated by the rapid advancement in communication and information technologies along with advanced artificial intelligence on a large scale. Among the most comprehensively researched innovative technologies, Cooperative Automated Transportation (CAT), which includes Connected Vehicles (CV), Autonomous Vehicles (AV), and Connected and Automated Vehicles (CAV) received remarkable interest in recent years and recognized as “game-changer” in the current transportation system. CV technology refers to a system that includes different advanced wireless communication technologies to allow vehicles to share real-time transportation information with vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications (Intelligent Transportation Systems Joint Program Office (ITSJPO), 2020). AV comprises several technologies including video cameras, radar sensors, light detection, etc. that integrate directly into the vehicle infrastructure to enable vehicles to control themselves partially or fully at different hierarchy levels (Anderson et al., 2016). The CAV incorporates the technologies of CV and AV to operate with any level of connectivity and/or automation ability, as illustrated in Figure 1. The continuing development of automotive technology suggests that Automated Driving Systems (ADS) equipped vehicles will be a reality in the near future and therefore, have been considered the key future research importance, as stated by the National Highway Traffic Safety Administration (NHTSA) and the Society of Automotive Engineers (SAE) (NHTSA, 2018; SAE International, 2018). It is anticipated that the introduction of CAT will enhance the people’s quality of life in many aspects compared to the traditional human-driven vehicles (HV). Utilizing vehicle automation and connectivity-aided communication, CAT offers unprecedented opportunities to resolve various longstanding transportation problems. The potential benefits of CAT include but not limited to improve traffic safety by reducing the number of crashes resulted from human errors; alleviate congestion by controlling the behavior of specific vehicles in the platoon when introduced in a mixed traffic stream, thus improve traffic operations; enhance human productivity by providing better driver/passenger travel experience and increase environmental benefits to the transportation system by reducing vehicle emissions (Martínez-Díaz et al., 2019; Stern et al., 2018; Talebpour and Mahmassani, 2016).

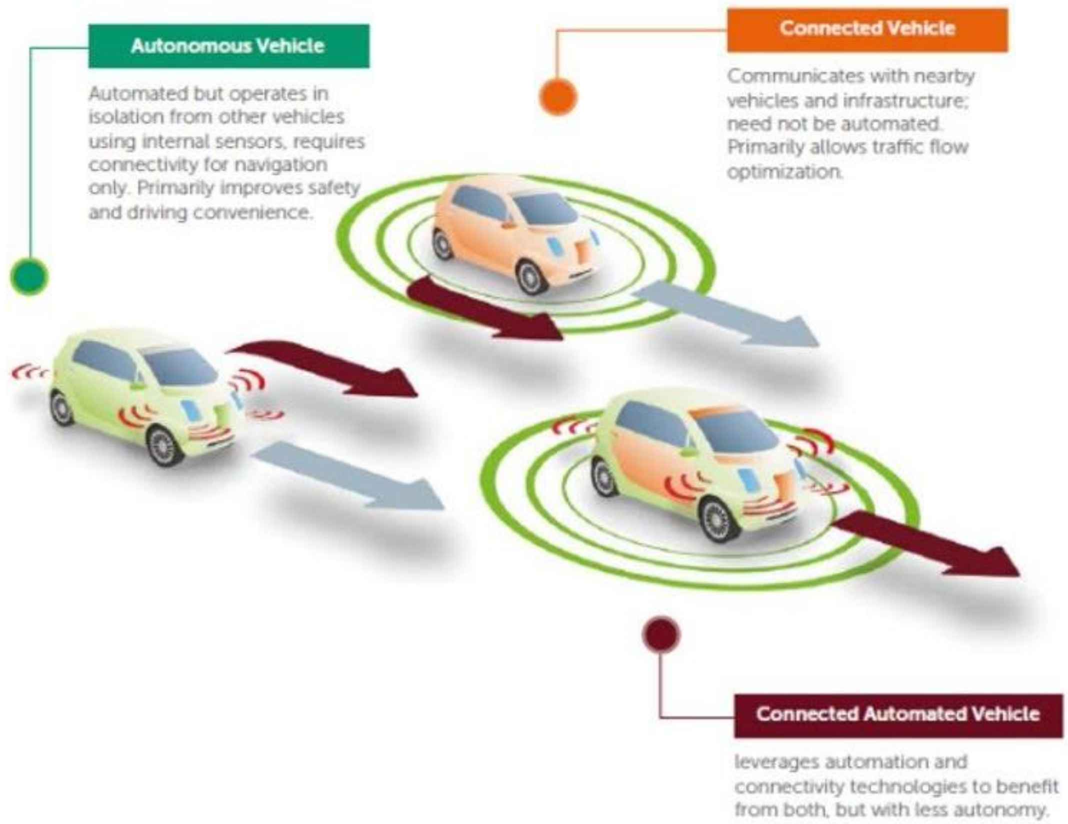

Figure 1: Cooperative Automated Transportation (Source: iCAVE2 Project at University at Buffalo (University at Buffalo, 2016)**)**

With the blooming of high-performance mobile processors, affordable and robust sensors/ cameras, and high-speed connectivity, such as 5G technologies, CAT will likely emerge sooner than anticipated on the roadways. However, 100 percent market penetration rates (MPR) of CAT might not be achieved before long because it will be challenging to integrate CAT technologies into all the existing vehicles and roadway facilities. Despite the potential benefits of CAT, there is an increasing concern regarding the transition era of CAT where both CAT and HV will be interacting and sharing the same roadways in a mixed traffic environment. In terms of AV, we are far from level 5 implementation. Many automobile manufacturers are experimenting with level 3 & 4 automation (e.g., partial/conditional automation), which frequently requires human override, continuous attention of the drivers, and might not work as intended due to poor visibility, especially in adverse weather when lane markings and the surroundings are not properly visible. In such extreme conditions, many autonomous car manufacturers, including Tesla®, are using the lead vehicle as a guide for automation. Tesla® owner's manual mentioned that "*Autopilot is a hands-on driver assistance system that is intended to be used only with a fully attentive driver. It does not turn a Tesla® into a self-driving car nor does it make a car autonomous. Before enabling Autopilot, drivers must agree to keep their hands on the steering wheel at all times and to always maintain control and responsibility for your car* (Tesla, 2020)." Therefore, CAT could introduce a variety of traffic problems caused by the complex behavior of human driving. If CAT is not appropriately integrated and tested with human behavior in mind, it might generate unexpected consequences.

In order to overcome these limitations, automated vehicles should mimic human driving to reduce variability and to ensure more harmonious traffic flow. However, mimicking human drivers requires driver behavior cloning, which is a popular approach where human behavior could be integrated into CAT so that it imitates the actions of human drivers. The next challenge is to determine the percentage of behavior cloning required for proper CAT implementation. It is expected that at lower MPRs of CAT, more behavior cloning is required and with the increase of MRP, the requirement for behavior cloning will be reduced. When 100 percent MPR and level 5 automation will be achieved, there will be no need for behavior cloning of CAT. However, at low MRP of CAT, it is crucial to determine the appropriate level of behavior cloning of CAT equipped vehicle for ensuring proper safety and operation.

Although behavior cloning is necessary for proper CAT deployment, it is extremely difficult to achieve due to the unpredictability and peculiar nature of individual human behaviors (Aoude et al., 2012). In order to integrate heterogeneous nature of human behavior through behavior cloning approach, real-time trajectory-level naturalistic driving data is essential. Therefore, this study will utilize the data from the Second Strategic Highway Research Program (SHRP2) Naturalistic Driving Study (NDS), which is the most comprehensive naturalistic study in the US. Naturalistic driving data could be leveraged to gather fundamental information on how people drive; how they avoid crashes, navigate, maintain speed; stay within their lane; control the vehicle; and how these vary according to age, experience, and other roadway and environmental factors (Regan et al., 2013). All this information then could be used to clone driver behavior.

Considering the research gaps and current limitations of CAT deployment, the primary objectives of this research is to leverage the SHRP2 NDS data to gather an in-depth understanding of human behavior for achieving proper behavior cloning and to integrate the findings toward the development of an effective CAT. The research objectives will be achieved by investigating the following two research questions:

1. Can SHRP2 NDS data be effectively utilized for cloning human behavior in a Cooperative Automated Transportation (CAT) environment?
2. To what degree we should integrate behavior cloning into CAT to ensure proper safety and operations at different Market Penetration Rates (MPRs)?

2. Preliminary Literature Review

2.1 Behavior Cloning

Driving involves interacting with a wide variety of environmental, traffic, and roadway conditions. Modeling CAT with each possible representative driving scenario is impractical. Behavior cloning, in contrast, could be an approach to mimic the full spectrum of driving behavior into CAT. Behavior cloning is a process in which human skills and abilities could be captured and replicated through a computer program via machine learning and deep learning algorithms. In this process, actions of human performing the driving task (e.g., how they perform while changing lanes/ following cars, how they control vehicles from deviation, how they avoid crash situations, etc.) are recorded with particular conditions, which have generated the corresponding actions. In case of CAT, the driving task could be reconstructed using the recorded actions that are preserved in an organized way through learning algorithms to imitate the performed human behavior (Codevilla et al., 2019; Patachi et al., 2019; Sumanth et al., 2020). Three different human actions, namely driving pattern leading to crashes/ near-crashes, deviation from normal driving, and kinematics profiling could be implemented into CAT through the behavior cloning approach, as shown in Figure 2. The human actions required for behavior cloning have been discussed in the following sections.

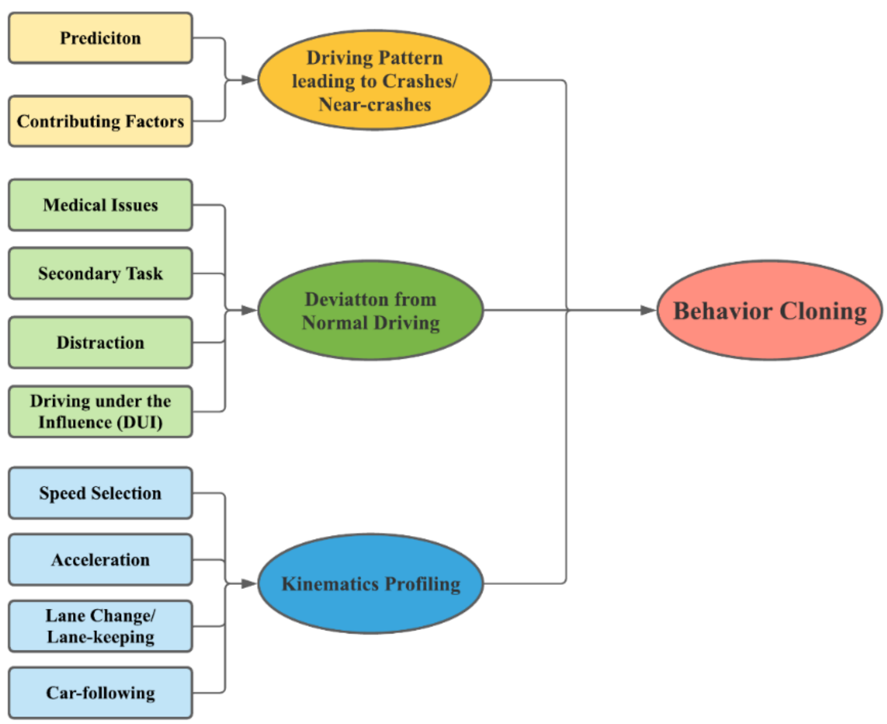

Figure 2 Driving Actions for Behavior Cloning

Prediction of crashes/ near crashes requires the detection of micro-level fluctuations in driving behavior and performances. With the availability of naturalistic driving data, researchers have been experimenting with various traditional and advanced methodologies to gain proper insights about the crash risks associated with driving behavior. Using the 100-Car NDS data, many studies have used "near-crashes" as a crash surrogate and found many interesting conclusions associated with crash occurrence (Guo et al., 2010; Jonasson and Rootzén, 2014; Jovanis et al., 2011). These studies stated that lateral and longitudinal acceleration, critical incident button, forward TTC, rear TTC, yaw rate, driver demographic, physiological factors, and event attributes can increase the accuracy of near-crash estimation. Studies based on more advanced SHRP2 NDS data also utilized similar vehicle kinematics variables to detect/predict near-crashes (Ali et al., 2019; Osman et al., 2019a) with impressive performance. In a CAT environment, the findings from these studies can be utilized to continuously monitor micro-level driver behavior in real-time and can be integrated through behavior cloning, which is crucial for developing effective CAT. In addition, previous studies investigated the contributing factors that could potentially lead to crashes by analyzing microscopic driving behavior and performance coupled with other roadway/environmental factors at the trajectory level using naturalistic driving data. For instance, the studies of Papazikou et al. showed that type, speed, acceleration of vehicles, and time within the crash sequence are important factors that could significantly reduce Time-To-Collision (TTC) below critical values and could increase the likelihood of motor vehicle crashes. More importantly, these studies suggested that timestamps with abrupt TTC reduction could be accurately identified using NDS data, which could be very beneficial in developing Advanced Driver Assistance Systems (ADAS) (Papazikou et al., 2019, 2017). Utilizing behavior cloning process, such findings could be incorporated into CAT to develop effective ADAS that could detect and prevent early deviation from normal driving in a CAT environment.

Driver distraction has become a major concern worldwide for traffic safety analysts for the past several decades mainly due to the recent advancement in mobile devices. However, identifying distracted driving and analyzing its association with crash risk has always been a challenging task. NDSs revealed that driver distraction, especially cell phone use (e.g. texting, dialing, browsing, and reaching for or answering the phone), could significantly increase crash involvement and crash severity (Justin M Owens et al., 2018; Justin M. Owens et al., 2018). Using in-vehicle video feeds from the SHRP2 NDS, researchers have managed to create a unique dataset, named Naturalistic Engagement in Secondary Tasks (NEST), which consists of an array of secondary tasks in naturalistic trips and its association with crash/near-crash. Many insightful studies have been conducted based on this dataset, such as development of a distraction index for measuring crash risk based on eye glance behavior (Bakhit et al., 2019), investigating the combined effect of multiple secondary tasks on crash involvement (Risteska et al., 2018), and examining the influence of weather and traffic-related factors on secondary task involvement in naturalistic trips (Domeyer et al., 2016). With the help of facial recognition algorithms, other similar studies have also used SHRP2 NDS video feeds to detect face, head pose, attention (Paone et al., 2015), and secondary task involvement including cell phone usage (Seshadri et al., 2015). The continuous time-series data form NDSs combined with advanced machine/deep learning techniques have also been effectively utilized to detect driver distraction and analyze its effect on motor vehicle crashes (Osman et al., 2019b; Osman and Rakha, 2020). Detecting and analyzing distracted driving under naturalistic settings could be implemented into CAT via behavior cloning, which has numerous real-time safety implications such as, monitoring driver alertness and providing appropriate warnings, identifying safe and risky driving maneuvers, etc.

Investigating driver behavior is a very challenging task due to the unpredictability and peculiar nature of individual human behaviors. In an attempt to evaluate some core driving behavior, such as speed selection, acceleration, lane change, lane keeping, and car-following behavior, many studies have successfully used naturalistic driving data. For instance, studies suggested that drivers varied their speeds with regard to roadway alignment and weather conditions. Drivers increased speeds on segments with constant speed limits and with limited access points, and reduced their speeds under congested traffic, inclement weather, and along horizontal curves. In addition, younger drivers were found to increase their speeds while traveling (Hallmark et al., 2015; Hamzeie, 2018). Considering lane-keeping behavior, a study utilizing naturalistic driving data suggested that roadway type, driver age, vehicle speed, and lane width significantly affected driver lane-keeping ability. More importantly, eyes-off roads significantly reduced drivers' ability to maintain lanes properly (Peng et al., 2013). However, another study considered naturalistic data from Shanghai Naturalistic Driving Study (SH-NDS) to investigate lane change behavior and implied that lane change duration was substantially influenced by traffic and lighting conditions, lag gap, relative speed, and acceleration of the following vehicle as well as the lane change vehicle (Yang et al., 2019). In addition, considerable efforts have been provided using naturalistic driving data to investigate car-following behavior through calibration and validation of car-following models in an attempt to develop better intelligent vehicles, similar to CAT (Sun et al., 2019; Wang and Zhu, 2018). The insightful findings from these studies could be adopted and trained to the CAT using behavior cloning to reconstruct human driving behavior.

2.2 Integration of Behavior Cloning into CAT

Considering the potentiality of CAT in solving various transportation problems, many studies focused on integrating human driving behavior through behavior cloning into CAT. Papadoulis et al. evaluated the safety impacts of CAV on motorways by developing a decision-making CAV control algorithm in VISSIM microsimulation platform. To simulate human driving behavior in CAV, they utilized the External Driver Model Application Programming Interface (API) of VISSIM to adjust driver behavior related to longitudinal and lateral movement (Papadoulis et al., 2019). Similarly, Liu and Fan developed Intelligent Driver Model (IDM) using External Driver Model in VISSIM and used it as a Car-following model for CAV (Liu and Fan, 2020). Another study evaluated safety assessment of CAV using microsimulation modeling approach where they integrated acceleration, lane changing, and gap acceptance behavior into CAV using VISSIM microsimulation software (Virdi et al., 2019). The study of Morando et al. investigated the safety impacts of AV using a simulation-based surrogate safety measure approach. The default parameters of VISSIM's Wiedemann 99 car-following model were modified to model the behaviors of AV with level 4 automation (Morando et al., 2017). Using microsimulation techniques, Asadi et al. investigated the potential transportation impacts of CAV where longitudinal movement (i.e., car-following model with longitudinal spacing of vehicles and their acceleration and deceleration behavior) and lateral movement (i.e., gap acceptance model including lane change, merging, and diverging) were adjusted to replicate driving behavior of CAV(Asadi et al., 2019).

3. Previous Human Factor and CAT Studies by the Research Team

The research team has previously utilized SHRP2 NDS data, driving simulator, and VISSIM microsimulation to conduct extensive research related to driver behavior investigation and CAT applications, as summarized in Table 1.

Table 1 Previous Related Studies by the Research Team

Topics/ Area	**Methods**	**Key Findings**	**References**
Speed/ Headway selection behavior	Ordered Logistic Regression, Association Rules Mining, Machine Learning,	• Significant speed reduction in adverse weather • Speed follows Weibull distribution in adverse weather	(Khan et al., 2020), (Khan et al., 2018), (Ghasemzadeh and Ahmed, 2019a), (Ghasemzadeh et al., 2018), (Ahmed and Ghasemzadeh, 2018)
Lane - keeping/Lane-changing behavior	Ordered Logistic Regression, Association Rules Mining, Clustering Analysis, MARS	• Adverse weather can significantly increase the standard deviation of lane position • Driver age and experience have significant effects on driver lane-keeping ability • Mean lane-changing durations in heavy fog were significantly higher than clear weather under mixed-flow condition	(Das et al., 2019a), (Das et al., 2019b), (Ghasemzadeh and Ahmed, 2018), (Das and Ahmed, 2019), (Das et al., 2020a)
Car following behavior	Microsimulation in VISSIM software	• Intra-driver car-following behavior is heterogeneous • Car-following behavior is a function of the driving environment	(Berthaume et al., 2018), (James et al., 2019)
Lane change prediction/detection	Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN), and eXtrem Gradient Boosting (XGBoost)	• 95.9 percent detection accuracy • 73 percent prediction accuracy • Incorporating weather could improve the accuracy of lane change detection	(Das et al., 2020b)
Trajectory level weather detection	Image Processing, Machine Learning, Deep Learning, Neural Network	• Weather can be detected using in-vehicle video cameras • Incorporating vehicle kinematics improves accuracy • 96 percent accuracy in snow detection • 98 percent accuracy in fog detection	(Khan and Ahmed, 2020), (Khan and Ahmed, 2019), (Elhashemi et al., 2019)
Crash/ near-crash detection/prediction	Logistic Regression, Decision Tree, K-Nearest Neighbors (K-NN), Deep Learning	• Warning message 5 to 23 seconds before the event could reduce crash risk • Decision Tree and Deep Learning provided higher detection accuracy of near-crashes	(Ali et al., 2019)

Topics/ Area	Methods	Key Findings	References
Crash investigation	Logistic Regression, Hamiltonian Monte Carlo Markov Chain Bayesian inference	• Traffic control device and lighting conditions can affect crash occurrence • 30 percent of the unobserved heterogeneity arises from variation in summer and winter crashes	(Irfan Ahmed et al., 2020), (Ghasemzadeh and Ahmed, 2019b), (Ghasemzadeh and Ahmed, 2016)
Risky driving pattern identification	Machine Learning, Clustering Analysis, Trajectory Analysis	• Machine learning algorithm can detect risky driving pattern • Trajectory analysis helped in better discriminating driving patterns during a specific event	(Ali et al., 2020)
Real-time risk assessment	Black-box graphical tools, Accumulated Local Effect (ALE), Partial Dependence Plot (PDP)	• 90 percent accuracy in clustering crash versus non-crash cases with a high level of sensitivity • ALE provides a more reliable interpretation than PDP	(Khoda Bakhshi and Ahmed, 2020)
Driver distraction	SEM, Driving Simulator	• In-vehicle distractions had a high effect on the crash likelihood • Dangerous driving behavior had a direct effect on the crash risk probability • CV Human Machine Interface (HMI) tended to introduce additional visual workload	(Shaaban et al., 2020), (Yang et al., 2020b)
Evaluating CV applications	Driving Simulator, VISSIM, Microsimulation Modeling	• CV weather notifications did not invoke any notable workload • The reductions in conflicts displayed a decreasing trend with the increase of CV penetration rates • The maximum reduction in conflicts was 85 percent when all trucks were equipped with CV technology	(Yang et al., 2020b), (Raddaoui and Ahmed, 2020), (Yang et al., 2020a)

4. Study Benefits

Cooperative Automated Transportation (CAT) implementation on the roadways is generating new challenges for transportation practitioners and policymakers. Therefore, a thorough understanding of the impacts of CAT on highways is extremely essential to the DOTs, including WYDOT, especially at the early stage of CAT implementation where human-driven vehicles (HV) will interact with CAT. This interaction might increase crash risks and create unsafe scenarios, which may potentially surpass the safety benefits of CAT due to the fact that driving pattern and performance of CAT-equipped vehicles are not similar to HV. This shortcoming of CAT implementation might be mitigated by integrating driver behavior into CAT so that it can imitate the behavior of HV, which will reduce the speed variability and conflicts, as well as will ensure harmonious traffic flow. At the initial stage of CAT implementation, integration of human behavior into CAT is crucial; however, at the final stage where the majority of the vehicles will be

CAT, the level of behavior integration could be minimal. This study will provide appropriate levels of human behavior integration at every step of CAT deployment, which will help DOTs, including WYDOT, to proactively assess the risk of CAT implementation in various scenarios based on different weather, traffic, and facility types. In addition, the study will support WYDOT to safely and efficiently facilitate CAT integration into the road network in Wyoming. The research findings will also benefit the scientific community, practitioners, and authorities responsible for traffic safety and decision making, and will be a key to ensure proper safety and operations of the emerging CAT technologies.

5. Statement of Work

The proposed research will concentrate on utilizing the SHRP2 NDS data to understand the complex nature of human behavior, incorporate the behavior for the development of Cooperative Automated Transportation (CAT) and investigate the CAT capacity at different levels of Market Penetration Rates (MPR). Eleven tasks under two phases will be conducted to fulfill the main objective of this research. The primary phase will employ the SHRP2 NDS data to investigate different driving actions for behavior cloning; then, based on the behavior cloning, the second phase will focus on integrating the human behavior into CAT and evaluate the CAT capability. An overview of the proposed research tasks is illustrated in Figure 3 below; detailed descriptions of each task are presented in the following sections.

Task 1: Literature Review

A thorough review of literature will be carried out regarding the Naturalistic Driving Study (NDS) and lessons learned from various SHRP2 safety research throughout the world. The review of literature will also include the potentiality of NDS data for real-word CAT implementation, methodologies, and testing.

Task 2: Data Acquisition

SHRP2 NDS data for freeways of six US states (Florida, Indiana, New York, North Carolina, Pennsylvania, and Washington) will be collected from the Virginia Tech Transportation Institute (VTTI). NDS trips that contained crash or near-crash events in all weather conditions and occurred on freeways will also be requested from VTTI. Additional baseline normal driving trips will be acquired considering the same driver, same vehicle, and same traversed route to compare a matched “control group” condition against driving epochs occurring in crash/ near-crash events with a ratio of 2:1 or 4:1. Moreover, roadway geometric data will be acquired from the SHRP2 Roadway Information Database (RID) that contains a comprehensive description of roadway characteristics for the six NDS states.

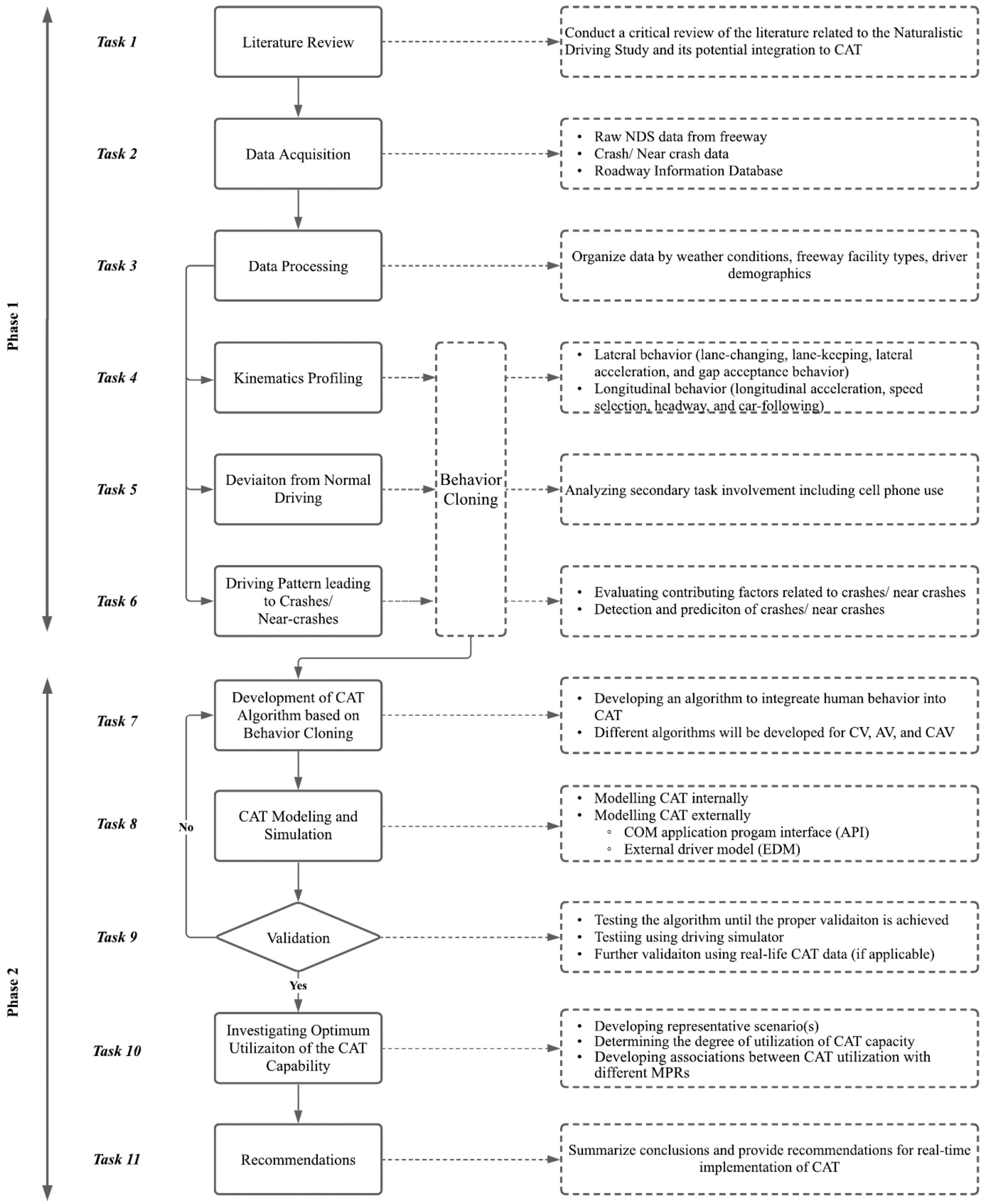

Figure 3 Overview of the Proposed Research Tasks

Task 3: Data Processing

The collected NDS data will be processed and reduced, and the data will be checked for erroneous values and inaccuracies. The reduced NDS data will be further verified by the Wyoming NDS Visualization and Visibility Identification Tool (Ahmed et al., 2018). Crash/near-crash events will be verified, and video data will be processed and reduced. To verify near-crash events and match them with normal driving trips, latitude, and longitude data along with video records will be used in the GIS and the visualization tool. The final verified NDS trips will be organized by weather conditions, freeway facility types, and driver demographics. All the verified time-series data will be aggregated through applying spatial and temporal segmentation using suitable fixed time and distance windows, such as half-minute, one-minute, half-mile, one-mile, etc. In addition, the RID data will be processed, reduced, using GIS and aerial and street view images from Google maps and linked to the NDS data.

Task 4: Kinematics Profiling

Once NDS trips are identified and data are reduced, lateral behavior (lane-changing, lane-keeping, lateral acceleration, and gap acceptance behavior) and longitudinal behavior (longitudinal acceleration, speed selection, headway, and car-following) will be analyzed with regard to weather conditions, facility types, locations, roadway geometry, and driver characteristics. This step will facilitate modeling and analysis including but not limited to parametric (e.g., multivariate logistic regression, generalized estimating equations (GEE), etc.) and non-parametric approaches (e.g., association rules, Classification And Regression Trees (CART), Multivariate Adaptive Regression Splines (MARS), etc.). Other advanced modeling techniques such as Machine Learning and Deep Learning techniques will also be utilized.

Task 5: Deviation from Normal Driving

The focus of this task will be to detect deviation from normal driving due to driver's involvement in secondary tasks or distraction. Using in-vehicle video cameras, this will be identified through drivers's eye-tracking movement via image processing and advanced Deep Learning (e.g., Convolutional Neural Network (CNN)) algorithms. When distracted drivers are identified, their driving pattern will be analyzed from the change of vehicle kinematics.

Task 6: Driving Pattern leading to Crashes/ Near-crashes

The task will be focused on quantifying driver characteristics and performance preceding crashes and near-crashes based on different weather conditions and facility types. A set of contributing factors associated with crashes/ near-crashes using hierarchical Bayesian approach and machine learning techniques will be evaluated. Utilizing the SHRP2 NDS and RID datasets, micro-level fluctuations of vehicle performance and driver behavior with roadway geometric characteristics are now possible to detect, which can provide valuable insights to detect risky vehicles through prediction of crashes/ near-crashes. Driving pattern leading to crashes/near-crashes will then be identified.

The findings of Task 4, Task 5, and Task 6 will be used for behavior cloning, which will then be considered as inputs for the second phase to develop human-like CAT implementation.

Task 7: Development of CAT Algorithm based on Behavior Cloning

The research team will develop CAT algorithms based on the in-depth findings from the Behavior Cloning. The development will be achieved in three steps in an attempt to create a robust system that can be readily implemented based on the available technologies on roadways. The first step will only focus on AV algorithms and the subsequent steps will focus on CV and CAV algorithms, respectively. The primary objective of this task will be the development of algorithms that will enable CAT equipped vehicles to mimic the trajectory of human driving.

Task 8: CAT Modeling and Simulation

This step will mainly focus on modeling CATs, based on the algorithms developed in task 7, in the microsimulation platform using PTV VISSIM software. The default VISSIM parameters (e.g., car-following, lane-changing, desire speed distribution, etc.) will be updated based on the findings from the Behavior Cloning. However, modeling CAT algorithms will be mainly achieved externally with the help of COM Application Programming Interface (API). It is worth mentioning that COM API can access and manipulate all simulation elements in VISSIM. In addition, External Driver Model (EDM) will be developed in C++/Python programming platform in an attempt to replace the VISSIM default driver model. The CAT modeling in VISSIM is illustrated in Figure 4.

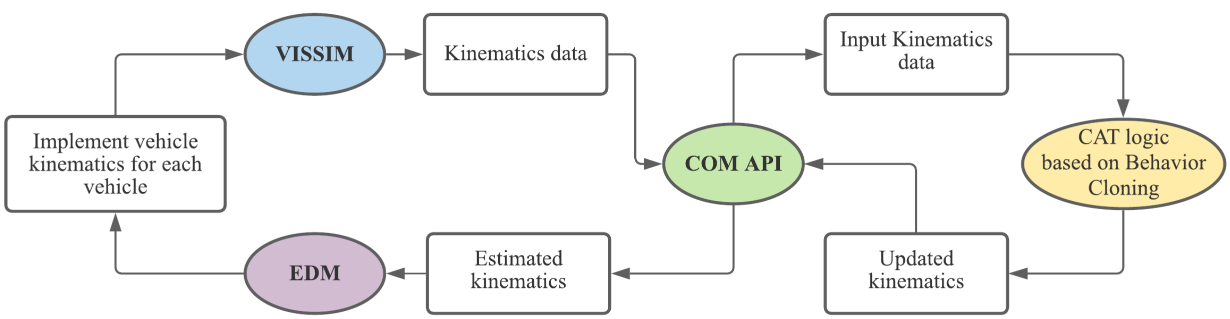

Figure 4 CAT Modeling and Simulation (API: Application Programming Interface, CAT: Cooperative Automated Transportation, EDM: External Driver Model)

Task 9: Testing and Validation

The testing and validation of CAT algorithms will be performed in microsimulation. Different scenarios will be developed and compared with the baseline models. The CAT algorithms will be updated until proper validation is achieved. By leveraging driving simulator, the scenarios will also be recreated to test the applicability of the CAT algorithms. Further validation will also be performed if real-life CAT data are available.

Task 10: Investigating Optimum utilization of CAT Capacity

This task will mainly investigate the degree of behavior cloning required into CAT equipped vehicles for optimum performance in terms of operation and safety. In order to find the optimum utilization of CAT capacity, different scenarios will be developed and tested in the microsimulation platform under various market penetration rates (MPR). For instance, the merging of CAT equipped vehicles while entering freeways will be tested at different MPR. The same CAT modeling framework, as described in task 8, will be utilized. A sensitivity analysis will be conducted by incrementing MPR at 5 percent intervals and for each MPR the appropriate degree of behavior cloning into CAT equipped vehicles will be determined. The CAT algorithms, as mentioned in task 7, will also be updated to account for the appropriate degree of behavior cloning. In order to reduce variability and ensure harmonious traffic flow, it is expected that with the increase of MRR, the requirement for behavior cloning of CAT equipped vehicles will be reduced.

Task 11: Recommendations

This research will recommend the most promising and appropriate CAT control logics to DOTs, agencies, and car manufacturers throughout the real-world implementation of CAT. It is worth mentioning that the appropriate CAT control logics will be based on optimum behavior cloning at different MPR. The recommendations will include detailed descriptions of the CAT algorithms and implementation steps.

6. Work Plan and Implementation Process

6.1 Project Kickoff Meeting

A kick-off meeting shall be scheduled to occur within the first 30 days of execution by the University of Wyoming. The preferred method for the kick-off meeting is via teleconference or video conference. At minimum, the project manager and the principal investigator will attend. The WYDOT Research Center staff must be advised of the meeting and given the option to attend. Other parties such as the office of Safety R&D at Turner Fairbank Highway Research Center may be invited, as appropriate. The subject of the meeting will be to review and discuss the project's tasks, schedule, milestones, deliverables, reporting requirements, and deployment plan. A summary of the kick-off meeting shall be included in the first progress report.

6.2 Deliverables

Quarterly progress reports will be submitted. In addition, any major achievement, i.e., the completion of tasks will be reported to the project managers. Draft final report and a final report incorporating the project managers' comments and corrections will be submitted at the end of the project.

6.2.1 Progress Reports

The University of Wyoming research team will submit quarterly progress reports to the WYDOT Research Center. The first report will cover the activity that occurred in the 90 days following the issuance of the task work order.

6.2.2 Draft Final Report

The Draft Final Report is due 90 days prior to the end date of the task work order. The draft final report will be submitted to the WYDOT Research Center. It should be edited for technical accuracy, grammar, clarity, organization, and format prior to submission to the WYDOT Research Center for technical approval.

6.2.3 Final Report

Once the draft final report has been approved, the University of Wyoming research team shall prepare the final report. The UW research team will email the final report in PDF as well as MS Word format.

6.2.4 Project Closeout Presentations

The findings of this study will be presented to the WYDOT Research Center at the conclusion of the project.

7. Timeline and Budget

The study will be performed in 24 months after the Notice to Proceed (NTP). The project will be led and supervised by Dr. Ahmed and two PhD candidates. In addition, 2 graduate students will be assigned to different tasks throughout the project. As shown in Table 2, the total cost of the project is $177,917. The total cost will cover all tasks listed above and illustrated in Table 3 including the literature review, travel/ virtual conference registration, SHRP2 data acquisition from VTTI as well as technology transfer. Additionally, the total 2 years cost will cover the salaries of 2 full-time PhD candidates for 1 year, total 6-month salary for 2 postdocs, and 2-month salary for one faculty members over the two years. The PIs will be submitting a proposal to Mountain-Plains Consortium (MPC) for additional funds for this study.

Table 2: Project Budget

2 Year Budget : 2021-2023		
SHRP2 Human Behavior for CAT Applications		
CATEGORY	Budgeted Amount from WYDOT	Total
Faculty Salaries	$20,208	2-month salary for 1 Co-PI
Administrative Staff Salaries	$0	
Other Staff Salaries (Engineers/ Postdocs)	$29,000	6-month PI/Postdocs salary
Student Salaries	$45,720	2 PhD students - 1 Year
Staff Benefits	$26,822.59	
Total Salaries and Benefits	**$121,751**	
Student Support Other Than Salaries	$18,816	Tuition/No indirect
SHRP2 Data Acquirement	$10,000	VTTI Data Acquisition
Expendable Property, Supplies, and Services	$500	
Domestic Travel/ Virtual Conference Registeration	$2,000	
Foreign Travel	$0	
Other Direct Costs (specify)	$0	
Total Other Direct Costs	**$31,316**	
F&A (Indirect) Costs	$24,850	20% WYDOT
TOTAL COSTS	**$177,917**	

Table 3: *Project Schedule*

	Research Task	**Month**																							
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Phase 1	**Task 1**																								
	Literature Review																								
	Task 2																								
	Data Acquisition																								
	Task 3																								
	Data Processing																								
	Task 4																								
	Kinematics Profiling																								
	Task 5																								
	Deviation from Normal Driving																								
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	Driving Pattern leading to Crashes/ Near-crashes																								
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	Development of CAT Algorithm based on Behavior Cloning																								
Phase 2	**Task 8**																								
	CAT Modeling and Simulation																								
	Task 9																								
	Testing and Validation																								
	Task 10																								
	Investigating Optimum Utilization of the CAT Capacity																								
	Task 11																								
	Recommendations																								
	Documentation and Deliverables Schedule																								

Quarter Reports Draft Final Report Final Report

8. Technology Transfer

The research results will be disseminated through technical paper publications and presentations in academic venues and press releases using media outlets. The technology transfer activities in this project will benefit both the scientific community and authorities responsible for decision-making. The research team will seek input from other interested parties to improve upon the study design and methodology. WYDOT staffs will be involved in all phases of the research.

9. Data Management Plan

A Data Management Plan (DMP) is attached to this proposal. The plan provides a description of the nature, scope, and scale of data that will be collected during the course of the project. The plan provides information on how the data will be collected, shared, where the data will be housed, who will have access to the data, and any backup strategies that will be implemented.

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