To Trust or Not to Trust?
A Simulation-based Experimental Paradigm

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Michael Knodler Jr., Ph.D.
Associate Professor
Department of Civil & Environmental Engineering
University of Massachusetts, Amherst

Foroogh Hajiseyedjavadi
Graduate Research Assistant
Department of Civil & Environmental Engineering
University of Massachusetts, Amherst

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Michael Knodler Jr., PhD, PI
Associate Professor
Department of Civil and Environmental Engineering
University of Massachusetts, Amherst
https://orcid.org/0000-0002-6517-4066

Eleni Christofa, PhD
Assistant Professor
Department of Civil and Environmental Engineering
University of Massachusetts, Amherst
https://orcid.org/0000-0002-8740-5558

Foroogh Hajiseyedjavadi
Graduate Research Assistant
Department of Civil and Environmental Engineering
University of Massachusetts, Amherst
https://orcid.org/0000-0003-3448-1239

Francis Tainter
Graduate Research Assistant
Department of Civil and Environmental Engineering
University of Massachusetts, Amherst
https://orcid.org/0000-0003-0180-6113

Nicholas Campbell
Graduate Research Assistant
Department of Civil and Environmental Engineering
University of Massachusetts, Amherst
https://orcid.org/0000-0001-7076-6835

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Abstract

The automated driving system is expected to enhance traffic safety and flow; however, the system will not be as effective if users do not accept it or do not utilize it appropriately [1]. Appropriate acceptance and use of technology depends on attributes such as perceived risk, mental workload, self-confidence, and appropriate level of trust that matches system performance. An inappropriate level of trust in the technology, whether it is over-trust or under-trust, would negatively affect the benefits of that technology. Based on the literature, trust is a dynamic construct that consists of an initial or dispositional trust that is shaped before experiencing the system performance and a history-based trust that constantly changes with user experience of the system. This study first reviews the history of research on humans' trust in automation and the factors that are correlated with trust. It also provides a brief overview of some previous models of trust in automation. Then, based on the gaps in the literature, a simulator-based experiment is proposed to further study the factors affecting initial or dispositioned trust and history-based trust. The results of this study are expected to help better understand drivers' trust in automated vehicles and help enhance human-automation interaction models.

1 Introduction

1.1 Overview of Trust

Advancements in technology have been leading to the automation of manual tasks in different fields, including manufacturing, aviation, maritime operations, and most recently the vehicle industry. Because of the varying definitions of automation across disciplines, it is important to note that the definition used in this study is derived from the work of Parasuraman et al. [2], which defines automation as the execution of one or multiple functions that were previously carried out by a human operator [1, 3].

Automation can, to some extent, cover for human errors, which can increase the safety and performance of the systems; however, in most cases, a human operator is still needed to interact with the system to execute the remaining tasks, monitor the automated system, or assume control when necessary. It should be noted that automated systems do not replace human activities completely; a human is still needed most of the time, but the automation allows the human to perform different tasks while the automation operates [2].

In addition to the technical capabilities, a person's behavior and interaction with the system should be considered as a main parameter in the design of the automated vehicles. Automation technology will not be as effective if drivers do not accept the technology or if they fail to utilize it appropriately. Unlike automation studies in fields like aviation and process operation, there are few articles focused on human trust in automated vehicles [2, 4]. Studies of human-machine interaction in different areas (e.g., aviation, maritime operations, processing, and transportation) can facilitate an understanding of human behavior with automation in general and can be useful for the design of automated vehicle studies.

Appropriate acceptance and use of technology depend on the interaction of different social and individual variables such as subjective norms, perceived risk, mental workload, and self-confidence, as well as an appropriate level of trust that matches system performance [1, 3, 5]. One tool that links those variables to measure acceptance of a technology is the Technology Acceptance Model (TAM). TAM was initially developed by IBM Canada Ltd. in the mid-1980s based on the Theory of Reasoned Action (TRA) developed by Fishbein and Ajzen [6] and Davis and Venkatesh [7] (see Figure 1.1).

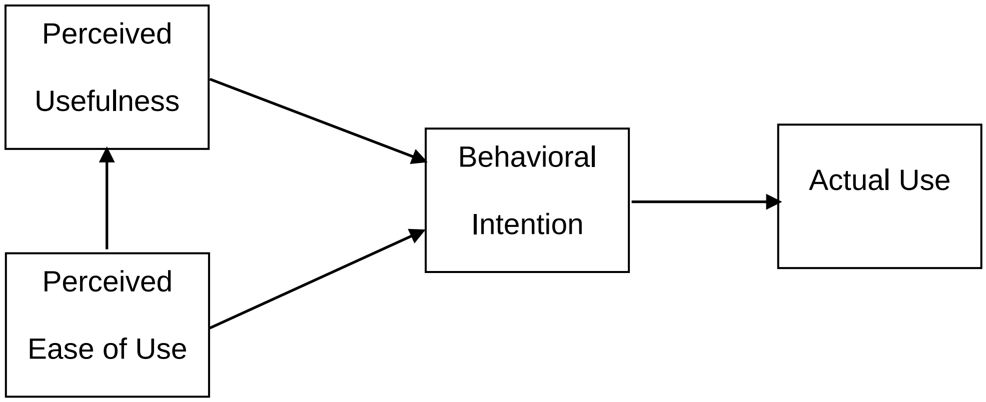

Figure 1.1 - Technology Acceptance Model developed by IBM Canada in the 1980s

However, TAM application in automated driving systems is relatively new and under development. Studies have shown that the level of trust in the system significantly affects reliance on the system and system acceptance [8, 9]. Ghazizadeh et al. [10] proposed a modified TAM for on-board monitoring systems (OBMS) in vehicles and considers trust in the system as a component affecting behavioral intention. *Behavioral intention* is defined as the subjective probability that a person will display or be prepared to perform a particular behavior. The model proposed by Ghazizadeh et al. [10] is provided in Figure 1.2; however, the current study considers that there might be some overlap between perceived usefulness of the system and trust in the system. An inappropriate level of trust in automation, whether it is over-trust or under-trust, would negatively impact the benefits of that technology [1-3].

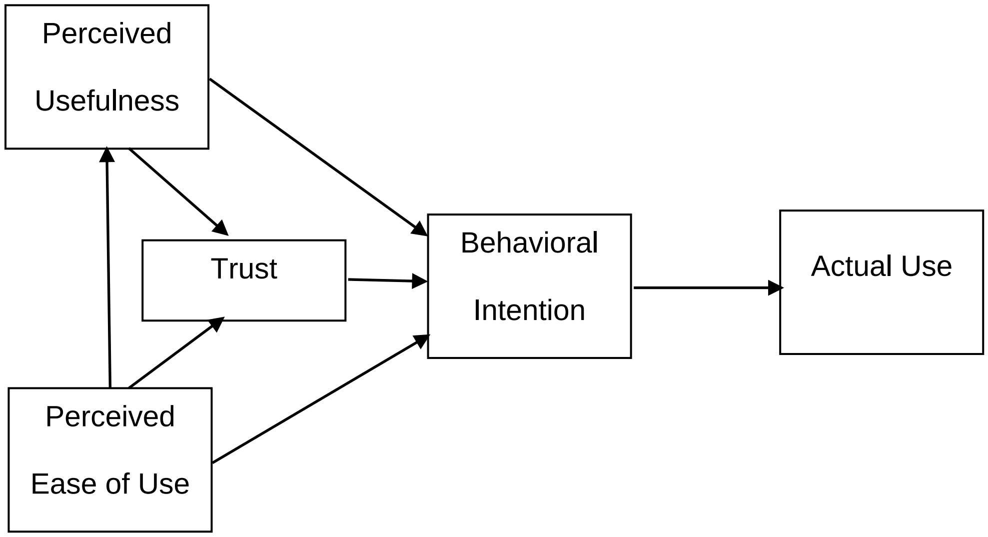

Figure 1.2 – Modified TAM model by Ghazizadeh et al. (2012)

1.2 Background

As discussed earlier, almost every definition of trust across different disciplines considers an element of risk or uncertainty associated with the performance of the trustee [1, 11]. It is important that the level of trust and users' expectancy matches the actual performance of the system.

An inappropriate level of trust that does not match system performance, whether it is mistrust or distrust of the system, can defeat the benefits of automation. Muir [11] introduced the concept of trust calibration as the "process of adjusting trust to correspond to an objective measure of trustworthiness." Mistrust and distrust are two cases of poor trust calibration: mistrust occurs when a subject's trust in the system is higher than its trustworthiness, and distrust occurs when the subjective person's level of trust in the system is less than the trustworthiness of the system [8]. The factors affecting trust can be classified into three categories: (a) machine performance, (b) user-related factors, and (c) environment-related factors [12]. Learning how each of these factors affects trust can help to manipulate individuals' level of trust to match the capabilities of the system. The initial investigation of the effect of system performance and, more importantly, users' subjective opinion about the system performance on their level of trust is the concern of this chapter.

The effect of poor performance of the automated system on users' trust might vary with different characteristics of the automated system as well as the characteristics of the failure. The characteristics of the system include type of automation, which can be (1) the information acquisition system, (2) the warning system, (3) the partial control system, or (4) the full control system. The characteristics of the failure include type of failure, which can be a false alarm or miss, risk associated with the failure, or frequency of failure. To be more accurate, it is the user's subjective opinion on items (2), (3), and (4), rather than the actual state of those items, that changes the user's trust in the system. As mentioned by Merritt and Ilgen [13], perception mediates the effect of system performance on trust. Considering that, users' perception of the system performance, and not only the actual performance of the system, should be studied when designing an automated system.

A user's characteristics and personal traits affect how system failure changes one's trust [13]. In human-human interaction studies, it is also argued that highly trusting individuals usually acquire a more appropriate level of trust in the other party [1]. Merritt and Ilgen [13] showed that trust degradation as a result of observing system failure is more severe for people with higher trust propensity than people with low trust propensity. Their data also show that the individual's perception of trust accounts for 52% of trust variance above the variance caused by the actual trustworthiness of the system.

1.3 Objectives

The main objective of this study was to gain a better understanding of how individual differences and the performance of the system affect one's trust in the system.

1.4 Hypotheses

The following hypotheses were tested in the simulated environment:

a) Glance behavior changes as an individual's trust in the system changes [11]. Horizontal glance distribution, monitoring rate, and blink rate have an inverse correlation with trust in the system.

b) Physiological measures vary with subjects' level of trust in the system.

c) Individual differences affect subjects' initial and history-based trust. The effect of system failure on trust varies across subjects with different levels of propensity to trust [13].

d) The type of hazard in failure conditions and the frequency of failures affect subjects' trust fall.

2 Methods

2.1 Apparatus

This study considers the effect of system failure on subjects' trust in the system when driving with an automated vehicle. A total of 80 subjects aged 20-30 years participated in this study. All participants were recruited from the University of Massachusetts Amherst and the local area and were compensated for their time. All the participants had a U.S. driving license with a minimum of two years of driving experience.

Multiple questionnaires, a physiological sensor, an eye-tracker, and vehicle data were used to capture participants' initial level of trust in automated systems in general as well as in automated vehicles, their subjective and objective driving skills, their driving history, their interaction with automated vehicles with different levels of system performance, and their subjective and objective levels of trust after interacting with the automated system. A SensoMotoric Instruments (SMI) head-mounted eye tracker was used to gather eye behavior during the simulated drives. Vehicle behaviors were automatically recorded by the Realtime Technologies Inc. (RTI) driving simulator. In addition, a chest-band physiological sensor collected subjects' physiological data as they were driving the scenarios. The driving simulator is a fixed-base RTI full cab with 6 screens surrounding it that subtend to 330 degrees of horizontal field of view and 30 degrees of vertical field of view. The SMI head-mounted eye-tracking system tracked and recorded drivers' eye movements during the experiment. The eye-tracking system has three cameras, one facing the scene and two facing the participant's eyes. Each camera records video at 60 frames per second.

The study was a mixed design with five different levels of system performance across groups and eight scenarios within each group. All the subjects drove the same set of scenarios once in the manual driving mode and once in the fully automated driving mode, experiencing one of the five system performance levels to capture their manual driving skill and their interaction with the automated system. The automated vehicle in this experiment was of level 2 automation, in which the automated system is completely in charge of driving tasks; however, the subject still needs to monitor the system and is responsible for the fallbacks.

Each subject was assigned to one of the five groups of system performance: 100% performance, 88% performance with pedestrian interaction failure (i.e., one failure in interaction with pedestrian out of eight total interactions), 75% performance with pedestrian interaction failure (i.e., two failures in interaction with pedestrian out of eight total interactions), 88% performance with stop sign failure (i.e., one failure in interaction with a stop-controlled intersection out of eight total interactions), and 75% performance with stop sign failure (i.e., two failures in interaction with a stop-controlled intersection out of eight total interactions). For the high mental workload experiment, subjects were asked to conduct a hands-free secondary task while completing both manual and automated driving tasks.

2.2 Physiological Measures

Subjects' physiological measures including heart rate (HR) and heart rate variability (HRV) were collected using a BioHarness chest strap sensor. Heart rate variability is the change in the time intervals between consecutive heartbeats. Multiple studies have shown that HRV might be affected by physiological, psychological, and environmental conditions. As an example, Morales et al. [15] showed that HRV is affected by the level of anxiety in athletes. Some works have used HRV as a measure of drivers' psychological conditions while driving [16]. Multiple works in the driver behavior domain used HRVs as a measure of drives' mental state. Wintersberger and Riener [16] showed HRV changes in different driving environments, such as tunnels versus open roads, indicating drivers' levels of anxiety. Knowing the potential impacts on HRV, this paper investigated the potential correlation with drivers' stress caused by failure of the automated vehicle and their subjective level of trust of the system with their disengagement of automation.

Some of the well-known methods to evaluate HRV include time-domain methods, frequency-domain methods, and a method based on the non-linear dynamics of HR [17, 18]. A time-domain method was used for the analysis in this paper. The list of accepted time-domain measures includes standard deviation of NN (SDNN), standard deviation of RR (SDRR), standard deviation of the average NN (SDANN), standard deviation for all NN intervals (SDNNI), Pnn50, HR Max-HR Min, RMSSD, HRV triangular index, and Triangular Interpolation of the NN (TINN) [18]. An algorithm developed by BioH calculates a rolling 300 heartbeat SDNN HRV value. This is updated once per second. For the first 300 beats of a log, an invalid value is reported.

Heart rate variability data often contain false beats due to either physiological or technical conditions [17]. The BioH uses an algorithm that considers a worn detection indication and the signal-to-noise ratio of the ECG signal to establish HR confidence. The HR confidence is between 0-100% and above 20% indicates a reliable heart rate.

2.3 Psychological Measures

Participants were encouraged to use automation as much as possible during automated drives. Subjects were instructed that they were responsible for any behavior of the vehicle and that automation could be disengaged if it felt unsafe or uncomfortable to allow the vehicle to conduct the driving task. Automation could be disengaged either by pressing the brake pedal or by pressing the prescribed button on the steering wheel. The disengagement methods were explained to participants before they completed the practice drive, allowing them to use the disengagement methods outside of the experimental scenarios. If participants disengaged automation from 500 feet before the hazard to about 160 feet after the hazard, the disengagement was scored as 1 for that subject for that scenario. The sum of the disengagement scores for each scenario was calculated across subjects and was divided by the total number of interactions.

2.4 Driver Measures

Subjects' hand and feet movements were recorded using two video cameras. The steering camera was mounted outside the car and was pointed towards the steering wheel through the front passenger window, and the pedal camera was mounted beneath the dash facing the pedals. Recorded streams were synced with the simulator data based on the time stamps in the data outputs using a signal sent at the start of each drive during the experiments. The signal was a beep triggered at the start of the simulator run. The videos were then scored manually to capture hand and foot movements, hereafter referred to as events. The notes reported by the scorers were categorized based on keywords and were either placed into one of the defined categories or discarded as unknown or unrelated events.

2.5 Experimental Design and Procedure

A between-subjects design was used in this study. Each subject was assigned to one of the system performance groups and drove through the eight scenarios once in a manual mode in which the subject was completely in charge of the driving tasks and once in a fully automated mode in which the automated system was in control of the driving tasks. The subject was required to monitor the system and was in charge of the safety redundancies during the automated drives (Level 2 automation as described in SAE International [17]). The order of presenting manual and automated drives was completely randomized. Participants were pseudo-randomly assigned to one of the five groups that interact with an automated system that was either 100% reliable, 88% reliable with pedestrian or stop control failure, or 75% reliable with pedestrian or stop control failure. The 100%, 88%, and 75% reliability levels, as explained earlier, had 0, 1, or 2 failures, respectively, out of the total of eight scenarios.

Each participant provided a written informed consent to participate in the experiment. Participants then completed a demographic and driving history questionnaire, a personality questionnaire, and a pre-experiment trust questionnaire. Following this, participants were outfitted with a physiological sensor around their chests using a chest band and a head-mounted eye-tracker. Complementary instructions were provided before starting the first drive and at the start of each subsequent drive. Two practice drives, one in a completely manual mode and one in a fully automated mode, were provided to the subjects to familiarize them with the controls of the simulator, the simulated environment, and the automated driving system.

In the automated drives, subjects were instructed that they may disengage automation and take over control of the vehicle using a hard button assigned to the automation on the steering wheel or by pressing the brake pedal, and participants were advised to do so if the simulation felt unsafe. Participants were instructed that they could reengage automation if they felt safe doing so by using the same button. Subjects were encouraged to use automation as much as possible throughout the simulation. Subjects were asked to fill out the NASA-TLX questionnaire to measure the level of workload after each of the four drives. They were also asked to answer six trust-related questions after each automated drive. After completing all the driving tasks, subjects were given a post-study trust questionnaire, which was the same as the pre-study trust questionnaire that was completed before the driving simulated scenarios to capture the effect of system performance on their subjective level of trust.

2.6 Scenarios and Drives

Eight scenarios were used in this experiment. The eight scenarios were presented to the subject twice, once in a manual driving task and once in a fully automated driving task. The eight scenarios included four pedestrian scenarios and four stop-sign-controlled intersections. In each of the pedestrian scenarios, a mid-block crosswalk was placed in the subject's path and a pedestrian crossing either from the right side or the left side of the road was presented to the subject. The roads in all the scenarios were four-lane, two-way roadways in a suburban environment. The sequence of the eight scenarios presented to the subjects was fully counterbalanced using the balanced Latin-square method.

The failure of the pedestrian scenario happened when the automated vehicle did not yield to the pedestrian entering the crosswalk. There was no crash between the subject vehicle and the pedestrian since the pedestrian always stopped crossing the road before entering the subjects' travel path if the subject vehicle did not yield. The failure of the stop-controlled intersection scenario happened when the automated vehicle did not stop at the stop bar before entering the intersection. There was no other vehicle at the intersection and there were not any crashes in these scenarios. An example of the scenarios can be seen in Table 2.1.

Table 2.1 - Sample of simulator evaluation scenarios

Sample Pedestrian Scenarios		
Sample Intersection Scenarios		

3 Results and Discussion

3.1 Physiological Results

The physiological data from the sensor and the driving data from the simulator were synced after the experiment using their time stamps. The frequencies of the data collected from the simulator and the physiological sensor were 60 Hz and 1 HZ, respectively. To sync the two datasets, the simulator data was sampled down to 1 Hz. Since the collected measures including HR and HRV were interpolated, an alternative approach would be to interpolate physiological data to match the 60 Hz data points using the linear or cubic spline interpolation method.

A descriptive analysis of the HRV across groups was conducted and is presented in the following graphs. The presented scenarios are flagged with the order in which they were presented to the participants relative to the failure scenario(s). For example, if the scenario was presented right before the failure scenario, its relative order was flagged as -1, and if it was presented right after the failure, its relative order was flagged as 1. The black lines on the top and bottom of the average line represent the standard error of the mean (SEM) for each order. The average of the HRV across subjects in each group is presented for each order in the following figures. Based on the literature on physiological measures, a lower level of HRV is usually correlated with a higher level of anxiety [15]. The sequence of scenarios for the four groups is shown in Figures 1.3-1.6.

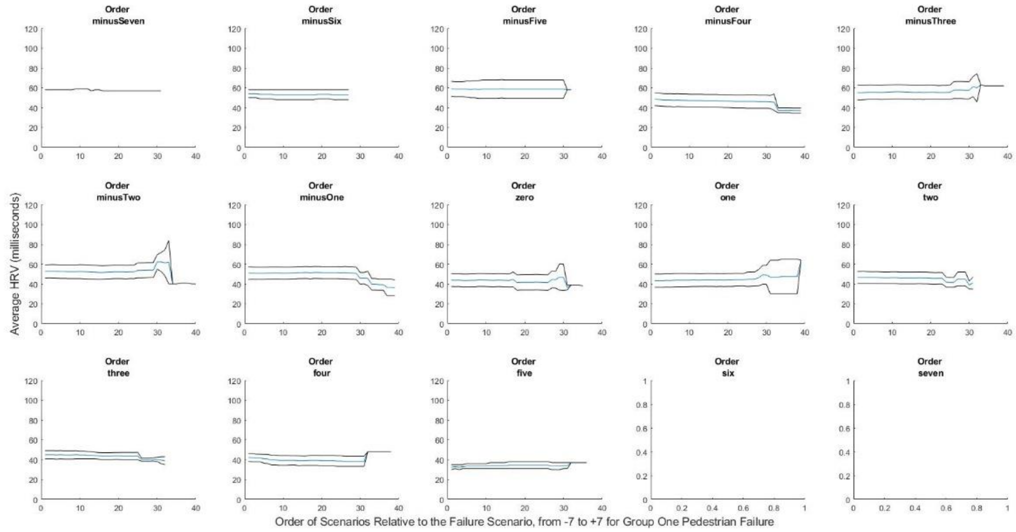

Figure 3.1 - Order of scenarios for Group One, pedestrian failure

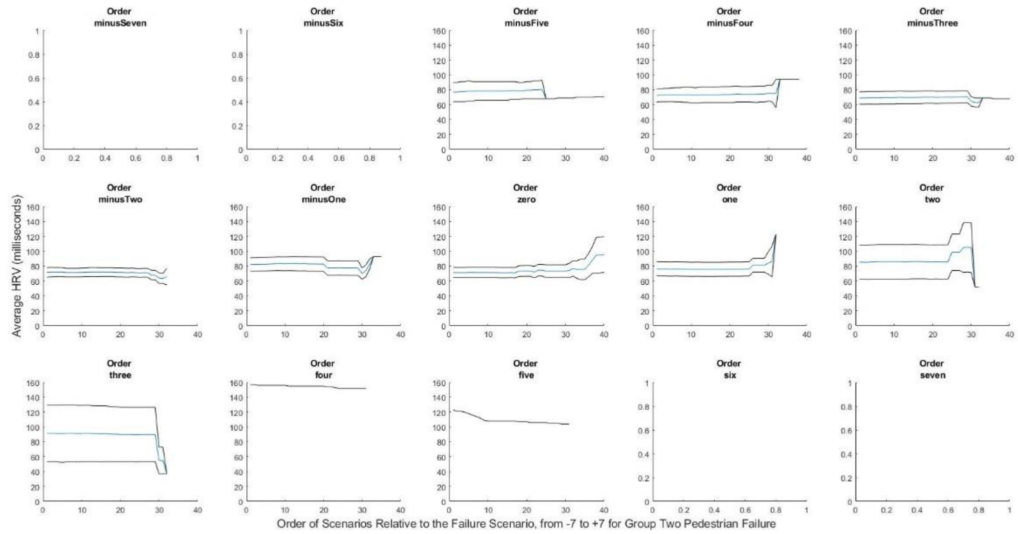

Figure 3.2 - Order of scenarios for Group Two, pedestrian failure

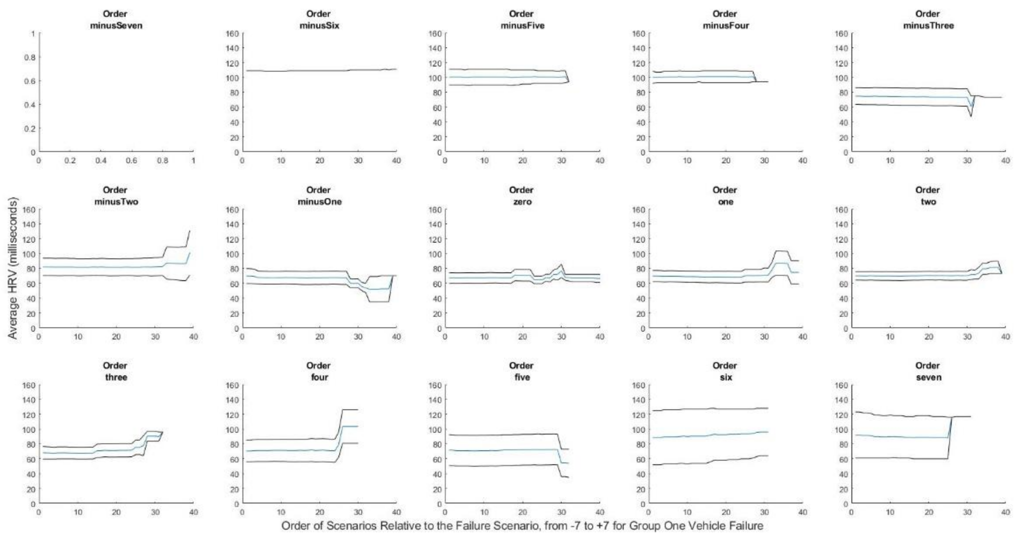

Figure 3.3 - Order of scenarios for Group One, vehicle failure

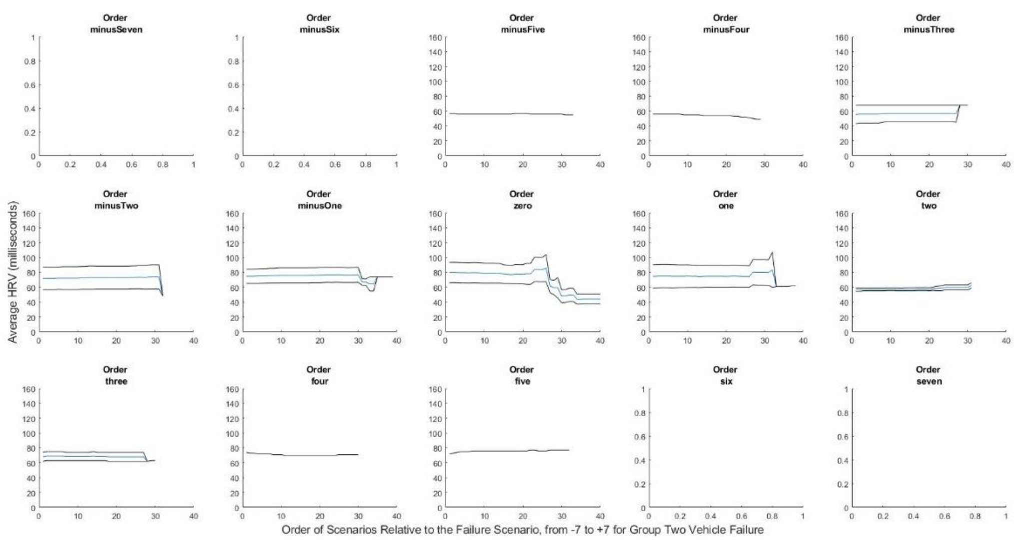

Figure 3.4 - Order of scenarios for Group Two, vehicle failures

To quantify the differences between HRV for scenario orders before and after the failure scenario, an ANOVA test was conducted. The number of observations per order is not the same for all the orders due to the design of the experiment, subject drop outs, or technical limitations with the BioH, the simulator, or the synchronization of the two. Considering this variation in the number of observations, the design was considered unbalanced, and an N-way ANOVA was used to quantify the differences between HRV of multiple orders.

The Kolmogorov-Smirnov normality test showed that HRV data across all the groups and orders follow the normal distribution. The one-way ANOVA was conducted to compare the effect of orders -1 and 1 on HRV across four groups. The results show a significant effect of order on HRV at the $p<0.05$ level across the two orders for the one-pedestrian failure [$F(1, 511) = 13.83$, $p = 0.002$] and the one-vehicle failure [$F(1, 660) = 4.86$, $p = 0.03$] groups. The same analysis on orders -1 and 3 across four groups shows that the effect of order on HRV is significant for the one-pedestrian failure [$F(1, 413) = 21.23$, $p <0.0001$], one-vehicle failure [$F(1, 450) =4.95$, $p <0.05$], and two-vehicle failures [$F(1, 222) = 7.49$, $p <0.002$] groups.

3.2 Psychological Results

A look at the automation usage shows that drivers who have experienced any level or type of system failure are more probable to disengage the automated system in situations where the system is appropriately responding to the environment. In other words, any type or level of system failure that is introduced in this study significantly increases the probability of unnecessary disengagement when the system's response is appropriate. The following Figure 3.5 compares the disengagement rates for the control group (presented as 0 failure) and the rest of the groups that experienced some type of failure.

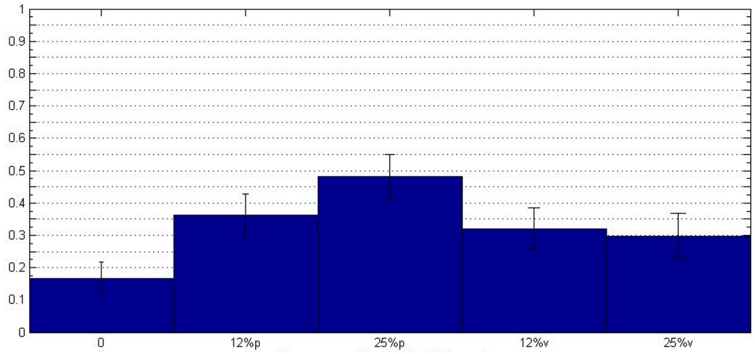

Figure 3.5 - Disengagement rate for no-fail scenarios

Breaking down the disengagement rates across different types of failures (pedestrian interaction and intersection interaction) shows that the disengagement rates are significantly higher for the intersection scenarios than for the pedestrian scenarios for all failure groups (see Figure 3.6). The control group still shows a similar trend; however, the difference between the two scenario types (i.e., pedestrian and intersection types) are not statistically significant for this group.

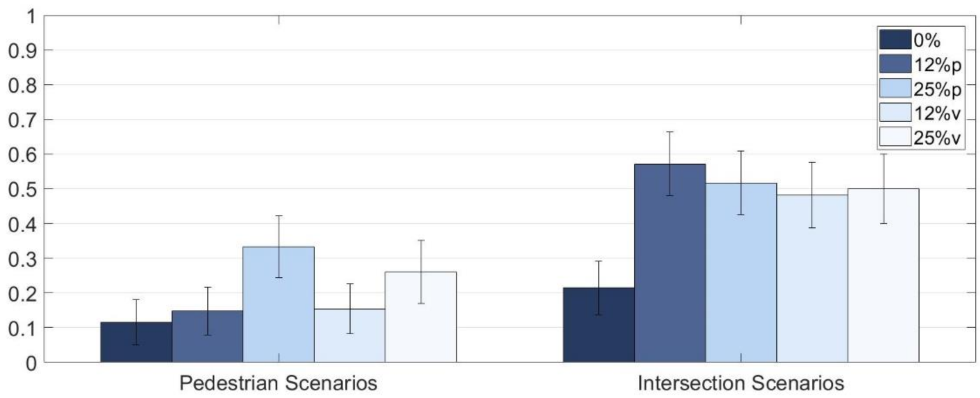

Figure 3.6 - Disengagement rates across different types of failure

The graph shows that any type or level of system failure that is introduced in this study significantly increases the probability of unnecessary disengagement during intersection interactions when the system's response is appropriate.

3.3 Driver Measures

Hand movements were categorized into four groups: (1) engage automation, (2) disengage automation, (3) hands toward steering wheel, and (4) hands away from steering wheel. The average number of events for each of the four categories and the average number of all the events combined were calculated and plotted across subjects in each of the failure groups (Figure 3.7, Figure 3.8, Figure 3.9, Figure 3.10). The average number of events were calculated for scenarios that had been presented to the drivers anywhere between the third scenario before the failure scenario and the third scenario after the failure scenario.

Based on the experimental design, the number of data points would decrease significantly for relative orders more distant than three scenarios from the failure scenario. The trends show an increase in the average number of hand events in the failure scenarios, which is expected since the subject should notice the failure and take control of the driving task. The average might increase for the scenario right after the failure scenario, but in most cases, it will decrease as the subject proceeds through more scenarios afterward.

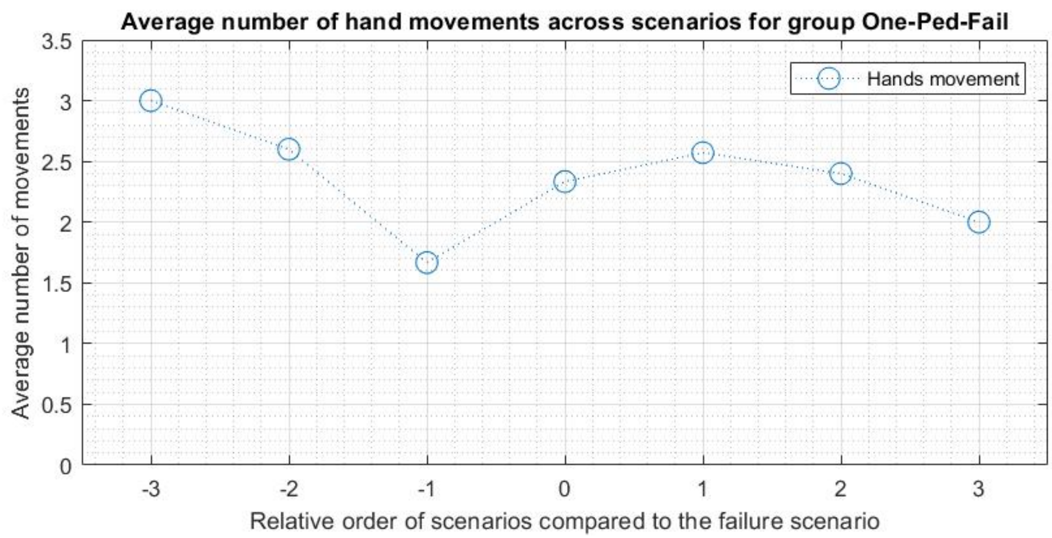

Figure 3.7 - Average number of movements across relative sequences of scenarios for the group with one pedestrian failure

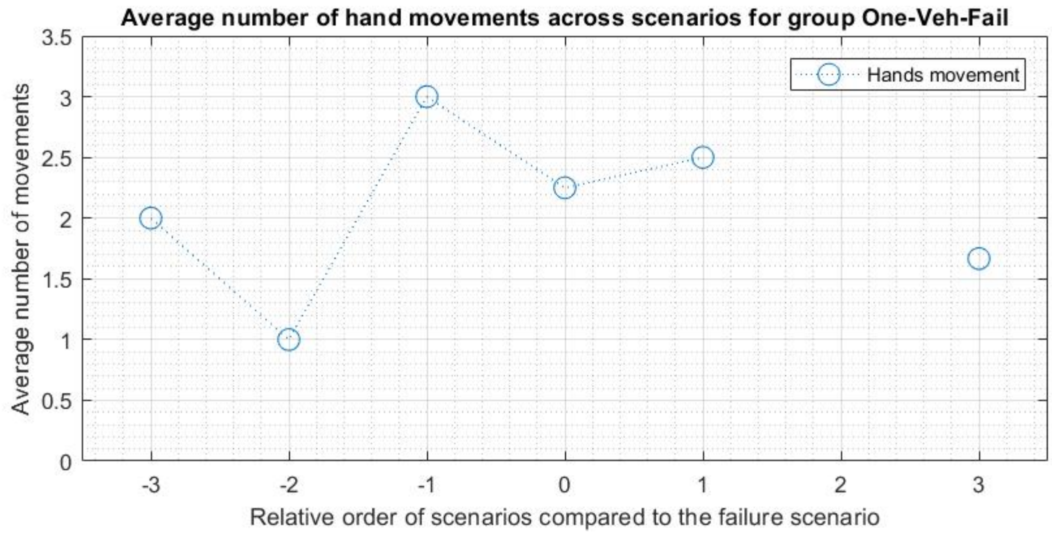

Figure 3.8 – Average number of movements across relative sequences of scenarios for the group with one vehicle failure

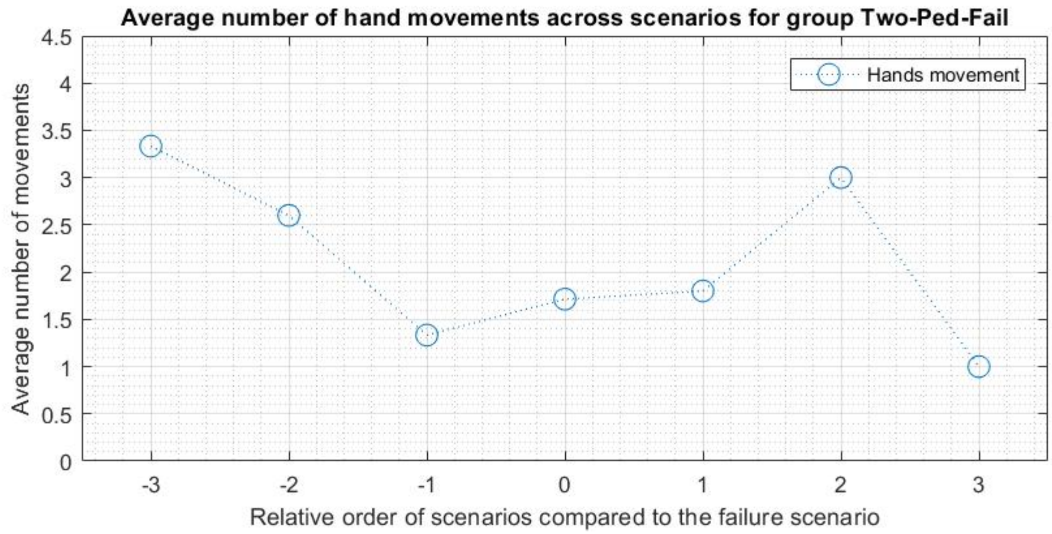

Figure 3.9 – Average number of movements across relative sequences of scenarios for the group with two pedestrian failures

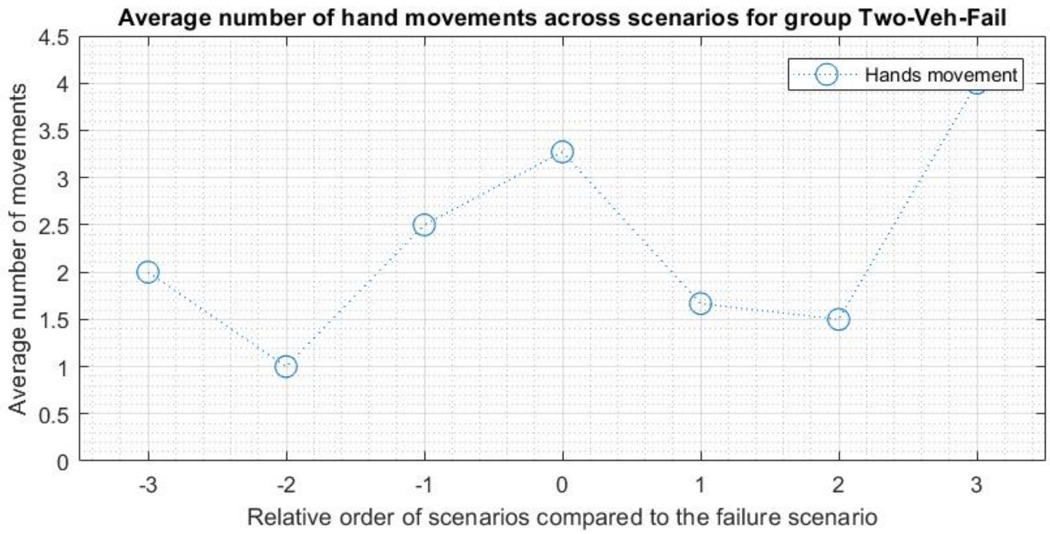

Figure 3.10 – Average number of movements across relative sequences of scenarios for the group with two vehicle failures

Subjects' feet movements near pedals were captured using video cameras during the experiments and scored manually afterward. The events are categorized into 6 groups: (1) foot moves away from pedals completely, (2) brake, (3) foot moves toward brake, (4) foot moves away from bake/release brake, (5) press gas and, (6) foot moves away from gas/release gas. The average occurrences of each event as well as all events combined are calculated across subjects in each of the four failure groups. The averages are calculated for scenarios that have been presented to the drivers anywhere between the third scenario before the failure scenario and the third scenario after the failure scenario. The average of all events combined is plotted for each of the failure groups (Figure 3.11, Figure 3.12, Figure 3.13, Figure 3.14).

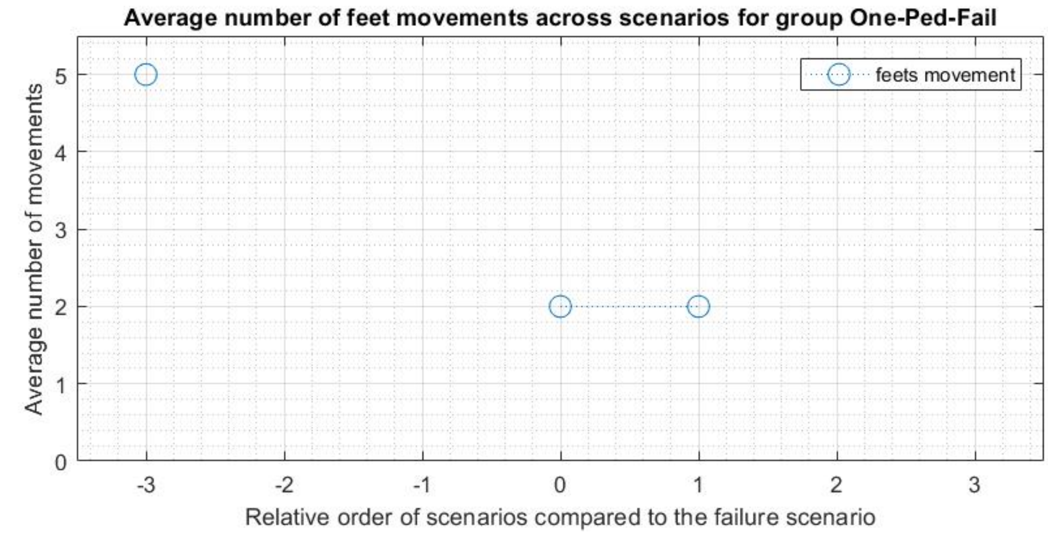

Figure 3.11 – Average number of foot movements across relative sequences of scenarios for the group with one pedestrian failure

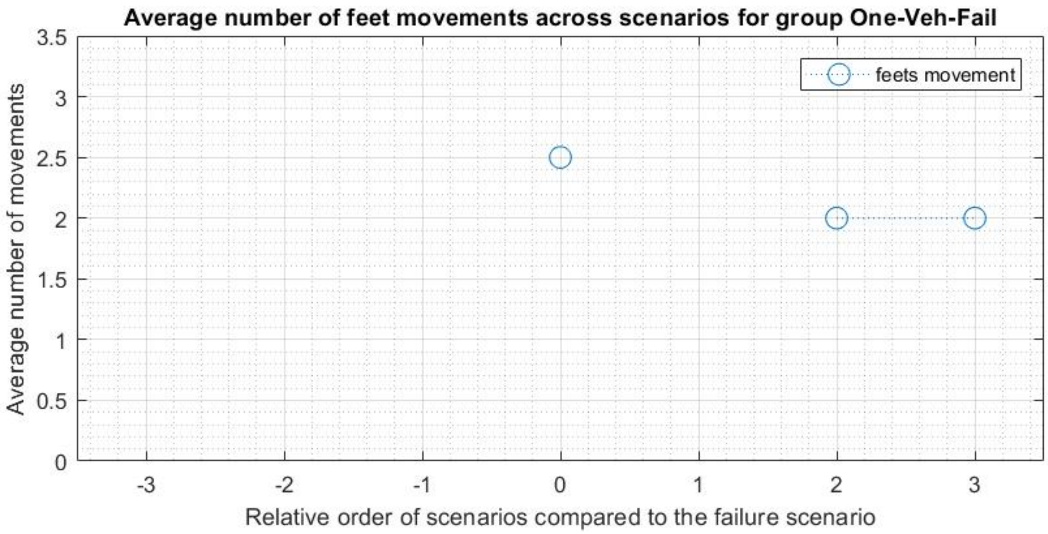

Figure 3.12 – Average number of foot movements across relative sequences of scenarios for the group with one vehicle failure

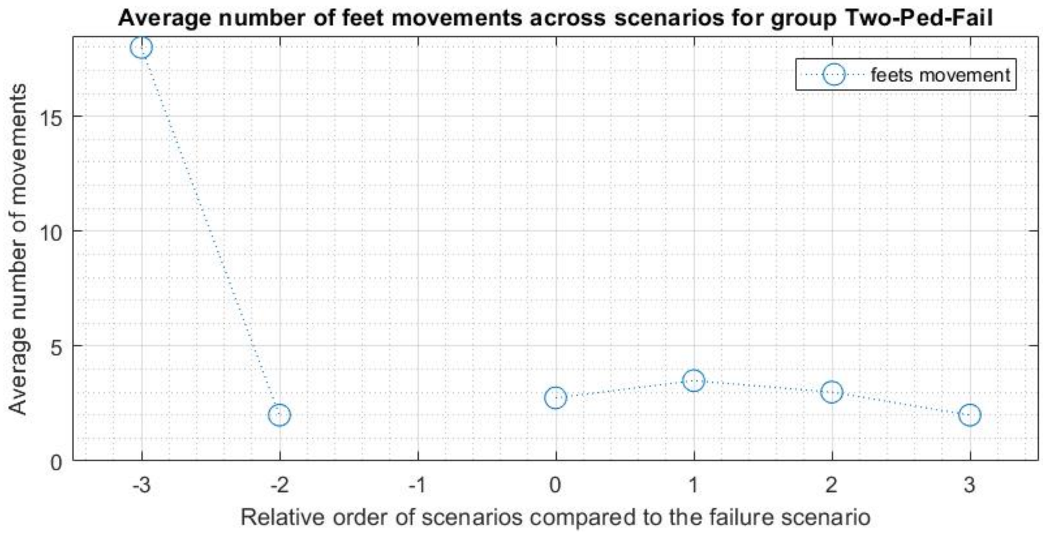

Figure 3.13 – Average number of foot movements across relative sequences of scenarios for the group with two pedestrian failures

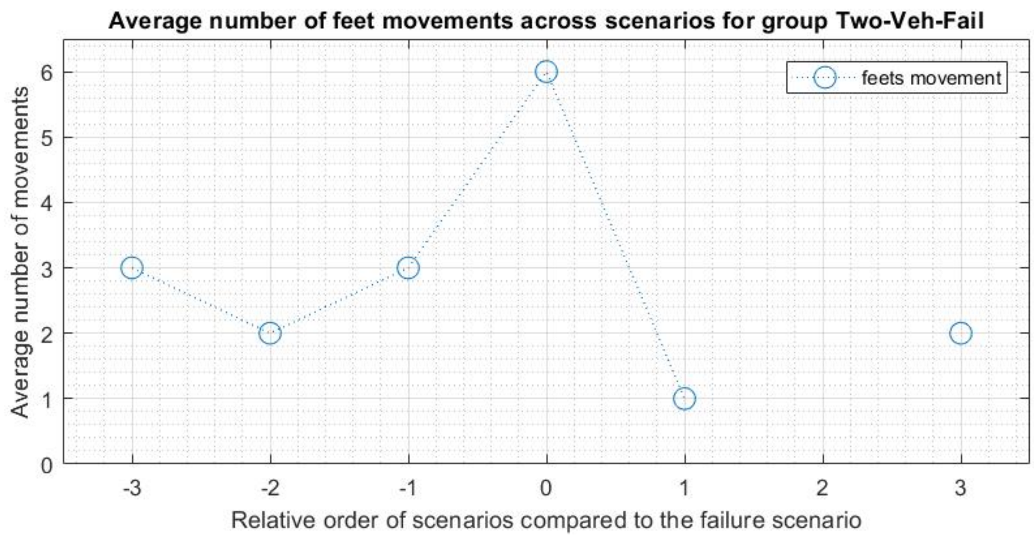

Figure 3.14 – Average number of foot movements across relative sequence of scenarios for the group with two vehicle failures

4 Conclusion

The overall objective of this study was to gain a better understanding of how individual differences and the performance of the system affects one's trust in the system. The conclusions from this driving simulator study were as follows:

- The disengagement rates are significantly higher for the intersection scenarios than for the pedestrian scenarios for all the failure groups; however, the difference between the two scenario types are not statistically significant for the control group
- There was a statistically significant increase in the probability of unnecessary disengagement at intersection interactions when there was any type or level of system failure, even though the system's response was appropriate.
- There was an increased average of hand events in the scenarios with system failure, which remains constant with the hypothesized expectations.
- There was a significantly higher average number of foot movements in the scenarios with two pedestrian failures than in the scenarios with two vehicle failures.

While the results from this simulator study present findings from drivers interacting firsthand with automated vehicles, it is important to note that these highly automated vehicles do not yet exist on the market. More so, the vehicles that exist on the market employing lower levels of automation are not experienced by the majority of drivers. Therefore, the majority of drivers do not possess the preexisting knowledge of automated vehicle operations and they are expected to be unfamiliar with the automated vehicle driving experience. The results from this study are significant in furthering the understanding of the physiological and physiological impacts of drivers' interactions with automation.

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