Changing Driving Styles Using OBD Data: A New Interactive Digital Storytelling Method

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Abstract

Driving is an activity where people become comfortable enough to multitask and lose mindfulness. Some people can even fall into a trance-like state as evidenced by the term "highway hypnosis." People usually only become aware of their driving traits when road interactions demand attention such as being honked at, making an error, weather conditions, etc. OBD ports in cars allow everyday drivers access to information about their driving traits through a Bluetooth connection with a smartphone and data transfer to the cloud. Up until now, insurance companies have used OBD driving data to provide fluctuating car insurance rates to their customers. If the customer drives less, spends less time driving under a certain speed, applies less hard brakes and hard accelerations, then their rates will be lower. In this quantitative research study I propose a method for using OBD port driving data to interact with a dynamically structured audiobook. I use two-years of driving data from my own car and OBD port to determine significant relationships between data points tracked by the Automatic Pro OBD sensor and application. I use SPSS to run correlations, sample t-tests, ANOVAs, and more to discover natural changes in my driving style according to time of day, length of trip, weekend, and more. The expected outcome of this study is a new way to experience digital narrative storytelling and a new way to become more mindful of yourself and your own driving style.

Introduction

Many options exist for consuming text through media. With the advent of smartphones, many people began listening to audiobooks throughout their day. One environment where audiobooks are consumed is in the car. The average audiobook available through an application like Audible is passive and does not require or allow the listener to interact other than choosing chapters and playback speed. The HCI area of interactive digital storytelling explores ways to present narratives to listeners that are interactive rather than passive. The purpose of my quantitative research study is to determine how driving data can be used as an interaction method for digital storytelling through audiobooks. If driving data can be used as an interaction method, then many opportunities arise for behavior change while driving and narrative exploration.

Most changes in driving behavior are related to safety and lowering monthly insurance premiums. Creating narrative based rewards linked to changes in driving behavior may be another method to make roads safer. This study also contributes the potential for new types of learning while driving. One of the problems with listening to audio of text rather than reading it off a page is there are no physical landmarks like left or right page and number of pages left to read to help provide context for remembering information. Pairing informational or literary texts with specific driving data points as people make their daily commute may help people who attempt to use their time behind the wheel for studying learn and recall more (like the author of this paper, a PhD student).

Another contribution of this study is to the driving styles of autonomous cars. If the data from this study reveals driving style changes based on time of day, day of week, duration of trips, etc., then autonomous car designers should incorporate these shifts into autonomous driving styles as it will make the passenger experience more natural. Making a person aware of their own driving style and unconscious tendencies behind the wheel will help people maintain mindfulness and lessen the chance for road rage incidents. Having a narrative that can only be accessed by driving will also create a new way to experience literature and may result in more driving. This may seem more dangerous as Liu et al. (2017) state vehicle mileage is positively related to driving risk and "the greater the mileage traveled by the same vehicle during the insurance year, the greater the likelihood of an accident." But if interactive digital narratives can inspire less hard braking and hard accelerations, their driving will be 2.5 times less likely to cause an accident (Liu et al., 2017).

Literature Review

I reviewed research literature in three areas: Car Insurance Ratings, Driving Styles, and Ergodic Literature. All three of these areas contribute to informing this quantitative study.

Car Insurance Ratings

Many insurance companies have experimented with using OBD data to determine pricing for their customers. This model is referred to as Usage Based Insurance (UBI) and has been categorized into three pricing models by Liu et al. 2017. The pricing models are per-mile premiums (PMP), GPS-based pricing, and mileage rate factors (MRF). MRF can also be used for drive behavior rate factors (DBRF) where speed, mileage, time of day, and others are used to adjust insurance rates (Liu et al., 2017). Progressive insurance used an OBD device called Snapshot to monitor driving behaviors and determine discount rates in 2009 (Cheng et al., 2018). Allstate insurance currently used an OBD program called DriveWise to calculate pricing discounts based on time spent driving over 80 mph, number of sudden brakes, and others (Cheng et al., 2018). State Farm is another insurance company that currently uses Drive Safe to monitor quick acceleration, hard braking, fast cornering, speeding, and distracted driving.

Cheng et. al (2018) used driving records and data of accidents from 120 vehicle OBD ports from the year 2015. They used SPSS to analyze the data and found that the data "the driving time during nights, the driving time during weekends, the proportion of driving time at the speed of 80km/h – 120km/h, the proportion of driving time over 120km/h, driving distance monthly, times of rapid acceleration, times of deceleration, the number of sharp turns taken" all had a significant relationship with the amount of accidents (Cheng et al., 2018). The researchers built a safe driving scoring system which used the EW-AHP (Entropy Weight-Analytic Hierarchy Process) model because it lowers the impact of subjective and objective weighting methods.

Cheng et. al (2018) created three categories that contributed to the safe driving score: driving overspeed and distances, special driving periods, and emergency situations. Driving overspeed and distances consisted of the amount of time driving from 80-120kmh (49.7-74.5mph), amount of time over 120kmh (74.5mph), and total driving distance monthly. Special driving periods consisted of driving time during nights and driving time during weekends. The emergency situations category consisted of times of rapid acceleration, times of rapid deceleration, and number of sharp turns. Cheng et. al (2018) found that driving at over 120kmh (74.5 mph) had the biggest influence on safe driving and received a weighted score of .6 in EW-AHP.

Liu et al. (2017) also used the EW-AHP (Entropy Weight-Analytic Hierarchy Process) to investigate calculating insurance pricing of usage-based insurance models drawn from OBD data. The researchers note that there was no uniform definition for driving behavior as of 2017. Liu et al. (2017) chose ten factors to examine for driver behavior scoring and split them into three categories. The first category was mileage and time and included monthly total mileage, weekday peak time, night driving time, and weekend driving time. The second category was speeding time rate and included 80-120kmh (49.7-74.5mph) and over 120kmh (74.5mph). The third category was different driving condition times and included acceleration times, hard deceleration times, swerve maneuver times, and violation times (Liu et al., 2017).

Liu et al. (2017) developed a scoring model for all the variables after using the EW-AHP method to calculate the weight of each index. An example of the scoring is weekend driving time being 4 if the total monthly time was 0-5 hours, 3 if the time was 5-10 hours, 2 if the time was 10-15 hours, 1 if the time was 15-20 hours, and 0 if the time was anything over 20 hours. Liu et al. (2017) scored the driving data of 100 drivers and ran a correlational analysis between the score and the number of accidents. The researchers found a negative correlation with a score of -0.504. The researchers performed a statistical analysis of the subtotal scores of driving behavior with y=mean accident times and x=scores and found the best fitting function was a quadratic function model (R2=0.998). Liu et al. (2017) found that drive behavior rate factors (DBRF) "can provide a basis for individual insurance rate so as to improve automobile insurance pricing model[s] and to optimize the rate structure."

Driving Styles

As mentioned above, Liu et al. (2017) note that there was no uniform definition for driving behavior as of 2017. One of the gaps identified in research is that many driving style studies have been conducted using questionnaires rather than ODB data such as Van Huysduynen et al. (2015). Many recent studies have been conducted seeking to discover what type of driving passengers prefer while in autonomous cars. Basu et al. (2017) reviewed several attempts at determining a driving style and developed a method investigating the style in which passengers in autonomous cars prefer to be driven. Basu et al. (2017) determined driving style by obtaining data from participants in a driving simulator for degree of defensiveness, which they determined through an aggregate of the following driving features and scenarios: mean distance to lead car, mean time headway, time headway during lane change, and distance headway, braking distance from the intersection, average speed for 20 meters before intersection, time to stop, speed at the intersection, and maximum turn speed. Basu et al. (2017) found 9 out of 15 participants preferred a different driving style to their own. 80% of participants preferred a style they thought was their own, but really it was more defensive than their own style. This shows that people think they drive safer than they really do,

Sagberg et al. (2015) conducted a literature review of research on driving styles and road safety. The researchers split their review into two categories: self-report instruments and behavior recording. The self-report instruments category contained 11 different methods consisting of 4 questionnaires, 3 inventories, 2 inventories, and 2 indexes. The behavior recording category contained 5 different methods including observation by in-vehicle observer, site-based traffic observation, simulator study, controlled field study with instrumented vehicle, and naturalistic driving observation (Sagberg et al. 2015). In the table below taken from the literature review by Sagberg et al. (2015), various definitions for driving style can be seen. A common theme across all the different definitions of driving style is it is developed through habit and changeable, which supports the research of this paper. Sagberg et al. (2015) also classify three main driving styles: calm, careful, and aggressive. This mirrors the competent, overcautious, and reckless definitions I developed and hope to use to shape my narrative.

Definition	Reference
"Driving style concerns individual driving habits—that is, the way a driver chooses to drive"	Lajunen & Özkan, 2011
"Driving style concerns the way individuals choose to drive, or driving habits that have become established over a period of years"	Elander, West, & French, 1993
"An attitude, orientation and a way of thinking for daily driving"	Ishibashi, Okuwa, Doi, & Akamatsu, 2007
"Driving style is concerned with decision making aspects of driving, that is, the manner in which people choose to drive or driving habits that have developed over time"	Deery, 1999
"Driving style is defined as a set of activities and steps that an operator uses when driving an engine powered vehicle, according to his personal judgment, experience and skills"	Rafael, Sanchez, Mucino, Cervantes, & Lozano, 2006
"Driving style is the way in which a driver chooses to drive and is governed by a combination of social, neurobehavioral, and biological mechanisms"	de Groot, Centeno Ricote, & de Winter, 2012
"Driving style is described as a relatively stable characteristic of the driver, which typifies his/her personal way of driving, the way he/she chooses to drive"	Saad, 2004
"Dynamic behaviour of a driver on the road"	Murphey, Milton, & Kiliaris, 2009
"One's preferred way of driving that, over time, develops into driving habits"	Kleisen, 2011

Table taken from Sagberg, F., Selpi, Bianchi Piccinini, G. F., & Engström, J. (2015). A Review of Research on Driving Styles and Road Safety. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *57*(7), 1248–1275. https://doi.org/10.1177/0018720815591313

Ergodic Literature

Reading can be active or passive. Everyday literature, written to be read in a manner requiring trivial movements of the reader's eyes and hands, is considered to be nonergodic and passive. In ergodic literature, reading is more active because "nontrivial effort is required to allow the reader to traverse the text." (Aarseth, 1997). This active effort can range from flipping the book upside down and reading in the opposite direction every eight pages, as required in *Only Revolutions* by Mark Danielewski (2006), to making the reader choose their own path through a Borgesian labyrinth. In interactive digital storytelling through an OBD port, ergodic effort is required by adapting your driving style to access the audio of the novel.

Interactive storytelling through the OBD in a car can also reshape the way writers write. The Oulipo is a group of French writers and mathematicians who began developing constrained writing techniques in the 1960s. OuLiPo is an acronym for Ouvroir de Littérature Potentielle, or Workshop for Potential Literature (Becker, 2012). An example of an Oulipian work is *A Void* by Georges Perec, a 2005 novel for which the constraints were to write 300 pages without using the letter "e." In writing for audiobook interaction through the OBD port, authors will need to consider how to structure their text in a dynamic way to make events occur based on driving statistics. Writers will have to create multiple possibilities for the narrative to go, almost like crafting a choose-your-own-adventure story.

Aims and Objectives

The purpose of my quantitative research study is to determine how driving data can be used as an interaction method for digital storytelling through audiobooks. To determine this, I will have to show that driving data changes enough on a day-to-day basis for the variables to be incorporated into the structuring of a dynamic narrative. I am interested in providing the driver/listener with enough reward to cause a change in driving behavior. Just as the insurance agencies have incentivized safer driving data from OBD ports to lower monthly premiums, I hope to provide a way to incentivize safer driving behavior to unlock new experiences and narrative pathways of an audiobook.

Research Questions

The overall theme of my quantitative research study is to determine how driving data can be used as an interaction method for digital storytelling through audiobooks. I plan to address this theme by answering the following research questions:

1. What factors tracked by the OBD port cause significant changes in driving styles?
2. Can categories be created for three types of driving styles (Competent, Overcautious, and Reckless) that fit the data?

In order to answer the research questions, I hope to find answers to some of the following questions about my own driving style and data:

- Are there more hard brakes or hard accelerations during a certain time of the day?
- Do I drive differently if I am on a shorter or longer car trip?

- Does MPG correlate to more hard brakes or more hard accelerations?
- Does a change in starting destination longitude/latitude result in a different driving style?

Descriptive Analysis

The data was taken from a Google Sheet that was filled in by the application IFTTT using the Automatic Pro OBD's data from a 2010 Toyota Rav 4 driving in the Baltimore City, Maryland area from March 22, 2018 to March 27, 2020. Drives occurred in all calendar months of the year and on all days of the week. The average start time of the trips were between 1-2PM and the average end time of the trips was between 2-3PM. The trips averaged a duration of 21 minutes. 30 trips were less than one minute and registered as .00 on the spreadsheet. The longest trip was 1 hour and 40 minutes. No more than 4 hard acceleration or 5 hard brakes occurred on any trip. The minimum distance of a trip was .010 miles and the maximum distance was 70.35 miles. The average miles driven per trip was 12.708. The minimum times spent driving over 70, 75, and 80 were all 0. The most time spent driving over 70 was 1,402 seconds or 23.36 minutes. The longest time spent driving over 75 mph was 425 seconds or 7.08 minutes. The longest time spent driving over 80 was 69 seconds or just over 1 minute.

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean	Std. Deviation
TimeTripStarted	1478	23.40	.13	23.53	13.9233	3.71845
TimeTripEnded	1478	23.49	.02	23.51	14.1958	3.75226
Duration	1478	1.40	.00	1.40	.2148	.18636
DistanceMiles	1478	70.340	.010	70.350	12.70806	13.495522
AverageMPG	1478	32.70	2.35	35.05	22.2530	6.54029
FuelCost	1478	5.16	.00	5.16	1.3012	1.27550
FuelUsageGallons	1478	2.22	.00	2.22	.4785	.44817
HardBrakes	1478	5	0	5	.43	.694
HardAccelerations	1478	4	0	4	.41	.683
Over70	1478	1402	0	1402	56.25	141.672
Over75	1478	425	0	425	4.47	21.554
Over80	1478	69	0	69	.16	2.773
TripOfTheDayOrder	1478	8	1	9	2.29	1.267
TripsPerDay	1478	7	1	8	2.59	1.356
TypeOfTrip	1478	4	1	5	2.09	.963
LotComingFrom	1478	7	1	8	3.53	1.850
LotHeadedTo	1477	7	1	8	3.53	1.850
Valid N (listwise)	1477					

I dove deeper into the data to provide more insight into the initial idea of the project. The table in Appendix A is sorted into driving events per hour of the day starting at midnight and going through 11PM. The most brakes and accelerations occurred in the 9-10AM hour and the 3-

4PM hour. In those two spans, hard brakes were applied 76 and 65 times respectively. There were 33 events in the 9-10AM hour and 24 events in the 3-4PM hour where hard brakes and hard accelerations were applied during the same trip. No hard brake or hard acceleration events occurred in the hours between 1AM and 6AM. A total of 486 trips featured hard brakes equaling 32.48% of the total amount of trips. A total of 486 trips featured hard accelerations equaling 31.28% of the total amount of trips. A total of 272 trips featured hard brakes and no hard accelerations equaling 18.18% of total trips. A total of 254 trips featured hard accelerations and no hard brakes totaling 16.87% of total trips. A total of 214 trips featured both hard brakes and hard accelerations equaling 14.3% of total trips.

Methods

I used an on-board diagnostic sensor (OBD) called Automatic Pro to relay my driving data to a Google Sheet over two years for 1,496 total trips. The two-year period was between March 22, 2019 and March 27, 2020. The data collection ended at that time because the company that produced my OBD sensor went out of business. The data collection ended at an appropriate time as my driving habits radically changed in the days following because of the worldwide COVID-19 pandemic. The data was first relayed to the Automatic Pro app that accompanied the OBD sensor. I was able to export that data to a google sheet using the application IFTTT (If This, Then That) to relay the data to a Google sheet when the car was cut off and on.

The ODB sensor collected 16 data points consisting of start and stop time of trips, trip distance in miles, trip duration, average MPG, fuel cost, fuel usage in gallons, number of hard brakes, number of hard accelerations, duration over 70 MPH, duration over 75 MPH, Duration over 80 MPH, and starting and ending locations in longitude and latitude. In my analysis I extracted extra data such as day of week and added 24-hour military style time to easily convert to decimals in SPSS. I changed the name of months to their representative numbers and changed the day of the weeks to numbers 1-7 starting with Sunday as 1.

After going through the data carefully when analyzing the type of parking lot I was coming from and headed to for each trip, I realized some of the very short trips that took place (1 minute or less) happened while my car was in the shop without me driving. This resulted in me deleting 18 vehicle trips overall bringing the total driving trips down to 1,478. I also found and deleted 1 more duplicate in the data that was not recognized in SPSS because 1 digit in the latitude was different. To find significant relationships to base a digital interactive narrative audiobook on, I created 6 new variables out of the dataset. The additional variables and brief descriptions can be seen in Table 1 below. To help with getting statistically significant relationships, I also scored 6 of the original data points into groupings that could also be related to driving style. The variables that received scoring can be seen below in Table 2.

I used the statistics software IBM SPSS Version 29.0.2.0 to analyze my dataset for connections between driving variables. I ran a correlation between all the variables to determine if the Pearson Correlation significance number showed a significant relationship. I ran a T-test of the data from 2018 and 2019 to determine if there was a change in driving styles with the change in year. I also ran a T-test between the data from when I lived in the suburbs and the data when I moved to Baltimore City to determine if there was a change in driving style when I changed residences. I also ran independent samples t-tests and ANOVAs. Results from these analyses are listed in the Findings section below and analysis of the findings in regard to driving style can be found in the Discussion section.

Table 1: New Variables Created for Statistical Analysis

	New Variables	How New Variable Was Created
1	Week of Trip (105 total weeks)	Looked at 2018 and 2019 calendars to set weeks.
2	Type of Trip (1-5)	1 – From home to destination 2 – from destination to home 3 – from destination to destination 4 – move car at home 5 –move car at destination
3	Driving Trips per Day (1-8)	1 - 1 trip day 2 - 2 trip day 3 - 3 trip day 4 - 4 trip day
4	Days Since Last Drive (1-11)	1 - drove the day before 2 - one day off 3 - two days off 4 - three days off 5 - four days off
5	Type of Lot Coming From	Residential, Retail, Port and Terminal, urban, city street, institutional, services, gas
6	Type of Lot Headed to	

Table 2: Scored Variables List

	Scored Variable	How New Variable Was Created
1	Season (1,2,3,4)	Grouping 3 months together in sequence.
2	Weekday or Weekend (1,2)	Separating weekdays and weekends in dataset
3	Day Trip Started	Numbered 1-7 based on day of week
4	Day Trip Ended	Numbered 1-7 based on day of week
5	Time of Day (1,2,3)	Morning, Afternoon, Evening
6	Duration Score (1-4)	1 – 0 – 15 mins 2 – 16 – 30 mins 3 – 31 – 45 mins 4 – 46 onward

Findings

The correlation test between all variables revealed some interesting significant relationships (full table is split into two in Appendix B and C). As one might expect, the Distance in Miles, Duration, Duration Score, Average MPG, Fuel Cost, and Fuel Usage in Gallons variables were all very closely related with a Pearson score of .625 and up. Interestingly, the Time Spent Over 70MPH variable was also significantly related to all the previous listed variables except for Average MPG with Pearson scores of .553 and up. Time Spent Over 75MPH and Time Spent Over 80MPH were not significantly related to the Distance in Miles, Duration, Duration Score, Average MPG, Fuel Cost, and Fuel Usage in Gallons variables. Also as one might expect, Time Spent Over 70MPH was significantly related to Time Spent Over 75MPH at .574, as Time Spent Over 75MPH was significantly related to Time Spent Over 80MPH at .714.

	DistanceMiles	Duration	DurSCORE	AverageMPG	FuelCost	FuelUsageGallons	HardBrakes	HardAccelerations	Over70	Over75	Over80
DistanceMiles	1	.882**	.912**	.716**	.989**	.993**	.292**	.145**	.722**	.362**	.080**
Duration	.882**	1	.891**	.625**	.886**	.896**	.313**	.199**	.553**	.278**	0.050
DurSCORE	.912**	.891**	1	.644**	.922**	.928**	.325**	.187**	.589**	.303**	.068**
AverageMPG	.716**	.625**	.644**	1	.695**	.702**	.251**	.139**	.393**	.177**	0.023
FuelCost	.989**	.886**	.922**	.695**	1	.989**	.307**	.162**	.696**	.358**	.084**
FuelUsageGallons	.993**	.896**	.928**	.702**	.989**	1	.311**	.164**	.720**	.381**	.104**
HardBrakes	.292**	.313**	.325**	.251**	.307**	.311**	1	.186**	.195**	.156**	0.043
HardAccelerations	.145**	.199**	.187**	.139**	.162**	.164**	.186**	1	.084**	.084**	0.047
Over70	.722**	.553**	.589**	.393**	.696**	.720**	.195**	.084**	1	.574**	.211**
Over75	.362**	.278**	.303**	.177**	.358**	.381**	.156**	.084**	.574**	1	.714**
Over80	.080**	0.050	.068**	0.023	.084**	.104**	0.043	0.047	.211**	.714**	1

The variables I was hoping to find significant relationships with to determine driving styles did not produce any strong significant results. The number of Hard Brakes per Drive had a low positive correlation with Duration, Duration Score, Fuel Cost, and Fuel Usage in Gallons. Hard Accelerations per drive had negligible correlations to all variables we have discussed so far. Hard Brakes and Hard Accelerations were not significant to each other as well with only a negligible .186 Pearson score.

There were also interesting results with some of the scored variables and new variables I created from the data. The new variable Trip of the Day Order was significantly related to Time Trip Started and Time Trip Started Score at .612 and .597 respectively. Trip of the Day Order was also significantly related to Trips Per Day with a Pearson score of .544. Trip of the Day order also was significantly related to Time Trip Ended with a score of .572. Interestingly, Trip of the Day Order also had a moderate positive significant relationship with the Type of Trip variable with a score of .425 and a low positive significance with the Type of Lot Coming From variable with a score of .349.

	TripOfTheDayOrder	TripsPerDay	TypeOfTrip	LotComingFrom	LotHeadedTo
TimeTripStarted	.612**	.121**	.358**	.353**	-.484**
TimeStartedSCORE	.597**	.104**	.359**	.377**	-.478**
DaysSinceLastTrip	-0.017	-0.025	0.020	-0.039	-0.030
TripOfTheDayOrder	1	.544**	.425**	.349**	-.409**
TripsPerDay	.544**	1	.293**	.077**	.065*
TypeOfTrip	.425**	.293**	1	.521**	-.183**
LotComingFrom	.349**	.077**	.521**	1	-.296**
LotHeadedTo	-.409**	.065*	-.183**	-.296**	1
MonthTripEnded	.070**	.132**	0.018	0.035	0.038
SMTWTFSended	-.054*	-.090**	-.052*	0.008	0.004
DayTripEnded	-0.048	-.087**	-0.015	0.005	0.001
YearTripEnded	-0.006	-0.017	0.019	.072**	.075**
TimeTripEnded	.572**	.110**	.341**	.340**	-.452**

There were also low positive correlations Type of Trip and Time Trip Started , Time Trip Started Score, and Time Trip Ended. There was a moderate positive correlation between Type of Trip and the Type of Parking Lot Coming From. There were low negative correlations between the Type of Parking Lot Headed to and the Time Trip Started, Time Trip Started Score, Trip of the Day Order, and Time Trip Ended.

I ran an Independent Samples T-test on Hard Brakes, Hard Brakes Scored, Hard Acceleration, and Hard Accelerations Scored compared to the data collected in 2018 and 2019 to see if year affected driving style. The results of the group statistics can be seen in the table below with 2018 showing slightly higher braking and acceleration in all variables. I ran an Independent Samples T-test on Trips that started in the AM hours and PM hours compared to the Hard Barkes, Hard Accelerations, Average MPG, Over 70MPH, Over 75MPH, Over 80MPH, and Duration Variables and found everything but Hard Brake Score, and Hard Brakes were significant. (Table can be found in Appendix D). I ran an ANOVA to determine if Hard Acceleration were related to the Type of Trip, Trip of the Day Order, Trips Per Day, Duration, And MPG and found that Type of Trip, Duration, and MPG score were significantly related to Hard Accelerations. I ran the same ANOVA but with Hard Brakes and found that all variables were significantly related. These results are significant because the p value is smaller than the significance level of .05 and the null hypothesis which assumes no significant relationship between the variables is rejected.

Group Statistics

	YearSCORE	N	Mean	Std. Deviation	Std. Error Mean
HardBrakeSCORE	1	555	1.46	.650	.028
	2	754	1.39	.635	.023
HardBrakes	1	555	.49	.744	.032
	2	754	.40	.675	.025
HardAccelSCORE	1	555	1.41	.633	.027
	2	754	1.38	.605	.022
HardAccelerations	1	555	.42	.660	.028
	2	754	.40	.689	.025

Hard Acceleration ANOVA

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
TypeOfTrip	Between Groups	29.939	4	7.485	8.235	<.001
	Within Groups	1338.730	1473	.909		
	Total	1368.669	1477			
TripOfTheDayOrder	Between Groups	13.013	4	3.253	2.033	.087
	Within Groups	2356.625	1473	1.600		
	Total	2369.638	1477			
TripsPerDay	Between Groups	15.354	4	3.838	2.093	.079
	Within Groups	2700.887	1473	1.834		
	Total	2716.241	1477			
Duration	Between Groups	2.249	4	.562	16.884	<.001
	Within Groups	49.045	1473	.033		
	Total	51.294	1477			
MPGscore	Between Groups	13.366	4	3.342	6.246	<.001
	Within Groups	788.096	1473	.535		
	Total	801.462	1477			

Hard Brakes ANOVA

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
TypeOfTrip	Between Groups	48.726	5	9.745	10.868	<.001
	Within Groups	1319.943	1472	.897		
	Total	1368.669	1477			
TripOfTheDayOrder	Between Groups	34.041	5	6.808	4.291	<.001
	Within Groups	2335.597	1472	1.587		
	Total	2369.638	1477			
TripsPerDay	Between Groups	32.653	5	6.531	3.582	.003
	Within Groups	2683.588	1472	1.823		
	Total	2716.241	1477			
Duration	Between Groups	5.548	5	1.110	35.705	<.001
	Within Groups	45.746	1472	.031		
	Total	51.294	1477			
MPGscore	Between Groups	49.239	5	9.848	19.271	<.001
	Within Groups	752.223	1472	.511		
	Total	801.462	1477			

Discussion

The results of the correlation were not as strong as I would have liked. I was expecting that a driving style could be determined through correlations using the Hard Brakes and Hard Acceleration variables. Instead, I only had low positive correlations that were not significant between Hard Brakes and Distance, Duration, MPG, Fuel Cost, and Fuel Usage. These are not surprising results as the longer one is in a car the more chances they will have to use hard brakes. In attempt to find significance I created many new variables which I had forecasted in the novel that I thought might influence driving style subconsciously, such as the type of parking lot you were driving to or from. These variables only showed significant results with the Type of Trip Variable. This means that driving from home to a destination, from a destination to a destination, or from a destination back home were significantly related. But this too is to be expected as you usually leave your house to go to the same places most days, so you are traveling from the same type of lots. The other new variable with significant results was the Trip of the Day order which correlated to Time Trip Started, Days Since Last Trip, and Trips Per Day. These results also were unsurprising as people usually make the same trips each day, and any additional trips would be tacked on after going to work or school, leading to a significant relationship in number of trips and time of day etc.

The results of the t-tests and ANOVAs show that there are significant relationships between many of the variables, but they are not strong enough to show as correlations. I was not able to determine traits that could be used to determine driving style based on my driving data. Maybe with a wider sample size of multiple drivers I may be able to identify the right driving style traits. Also, an upgraded OBD sensor that captures more data points like sharp turns and weather used in many of the driving trials done in the literature review might help. The data confirmed that I make many of the same trips and have the same habits of where I go and how I drive. I think incorporated a schedule into the interactive audiobook I am planning that accounts for Type of Trip and Number of Trip Per Day may be beneficial for structuring playback of the novel. Instead of Driving Style, type of driving day could be programmed to be tracked, so the audiobook would know based on GPS where you were headed and what trip of the day it was. In these calculations could be plot points related to mood and decision fatigue as the days go on and the longer the drives are. This probably would result in a safer interaction method as well when not incorporating rapid accelerations and braking as well as time spent over a certain MPH. Making a schedule based instead of driving style based interactive audiobook will be my new path.

Research Justification

This study introduces novel interaction methods into the field of transportation and human-centered computing. It also can contribute ideas to the Quantified Self movement as ways everyday data can be interacted with and reshaped. The study is also partially autoethnographic as I used my own driving data over two years as my data set. Because I do not know how I was feeling those days or what caused the hard brakes or hard accelerations, this study cannot be an autoethnography. In the future, I hope to keep a driving journal to the data of each trip and see how my awareness changes based on what characteristics I recognize in the data. Thinking about driving in a different way may help benefit society as more people are becoming passengers of autonomous cars and ride share services like Uber and Lyft. There is something important about driving and how it is identified with American spirit that I hope to also uncover with further research. I see some of the American population rebelling against autonomous cars as another way their freedom is being taken away from them. Having a new way to drive that is not just for the enjoyment of the drive and the scenery, but also to experience new aspects of your self as you change your driving style to access new parts of a narrative may lead to a better future.

Description of Original Dynamic Narrative to Fit to Data

My novel is about the impulse purchases that result from the advent of autonomous cars. In the novel, autonomous cars are introduced to the public in the late 1990s. The reader follows the developments at a local retail grocery lot as parking experiences of customers begin to change. This flashes forward to a first-person narrator who is an undercover employee of a mega-mall parking garage. The parking garage is shared space, so there are no parking lines or signs of any kind to help the driver navigate. This creates a safer environment because everyone drives slower, but it also increases decision fatigue in the driver from the extra awareness, resulting in greater impulse purchases and returns of purchases.

The undercover employees at the mega-mall parking garage call themselves "mediators," as they employ certain parking situations either behind the wheel (like honking) or as a pedestrian (like appearing out of nowhere) to specific driving demographics built from a foundation of the data that was collected by the employees during the local retail grocery lot events in the late 1990s. This demographic details on driving style, impulse purchase activity, associated emotion, etc. is also built from return profiles, where customers return items they impulse purchased and have to divulge more information about themselves. The teenagers working at the retail grocery lot in the 1990s develop an early data analysis system and interaction scheme by setting up tables asking for donations or selling girl scout cookies outside of the grocery.

As a mediator in the parking garage, the main character wants to get out. Mediators are usually unemployable liberal arts grads that have a lot of student debt and are employed by the mega-mall in a debt forgiveness/indentured servitude arrangement. The main character has elaborately shifted the interaction data (and changed his own driving style) to create the results he wants to make an escape. What he doesn't realize is that the data has already been censored and corrupted at multiple other levels and stages. The present-day aspect of the novel takes place in the mega-mall parking garage on the day of a political rally for a "shared space everywhere" platform. The group that owns the garage, former cart boys in the 1990s retail grocery lot, have gone radical and plan to push the safety success of "shared space" parking in all areas, removing stop signs, traffic lights, and speed limits. Part of the main character's plan after escaping the parking garage (as he still has not paid off his student loans) depends on this terrible platform being voted for by the American people. Can the events at the parking garage that day fatigue enough people into making a rash decision? Changing your routine in the correct ways will help you find out!

Conclusion

The overall theme of my quantitative research study was to determine how driving data can be used as an interaction method for digital storytelling through audiobooks. Even though no driving style traits could be determined, I did discover how important schedule and routines were regarding automotive transportation. As a result of these findings, I plan to change the interaction style of my interactive audiobook from being based on driving style to being based on the type of trip a driver is making and the number of the trip throughout the day. These methods result in a less invasive and safer interaction style. It may encourage more trips or more trips in the car which will be an interesting extension of the Dérive art movement where people take unplanned walks through urban landscapes to change their focus (Debord, 1958).

Other things I uncovered from this data are the importance of duration of trips, as that is how many people will be able to experience sections of the audiobook. Somehow connecting the GPS information of the trip being taken could also be used to generate a certain length of audiobook text for the listener to engage with on that specific drive. When looking into these new variables more, I decided to compare my data to the national averages to see how I compare to larger datasets. The table below shows that I averaged more trips per day, less distance driven per day, less minutes driven per day, and higher MPG per day than the average American driver. This would also be another avenue to investigate for interaction, how a particular driver differs from the national average on specific variables and determining a score for within range, below, or above to compute driving style.

I plan to continue to develop this project and have been inspired by many of the statistical methods I investigated during this project. I came up with an interesting performance art extension as well where I attempt to drive (or live through collecting various other quantified self datasets which is my current practice) and calculate which numbers would be significant and then consciously hit those numbers in everyday life to give my life more significance. My next adventure in SPSS will be how to calculate what numbers would be significant to make these relationships and life more important and interesting.

Variable	Average	Me
Trips per Day	2.44	2.59
Average Distance Driven per Day	30.1 miles	12.7 miles
less than 6 miles	59.40%	0.36332882
10 miles or less	75%	0.58930988
Minutes per trip	24.5	21.48
MPG	19	22.253

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Appendix A

Analysis of Driving Data by Time of Day

	12:00 AM	1:00 AM	2:00 AM	3:00 AM	4:00 AM	5:00 AM	6:00 AM	7:00 AM	8:00 AM	9:00 AM	10:00 AM	11:00 AM	12:00 PM	1:00 PM	2:00 PM	3:00 PM	4:00 PM	5:00 PM	6:00 PM	7:00 PM	8:00 PM	9:00 PM	10:00 PM	11:00 PM	TOTAL
Hard Brakes	1	0	0	0	0	0	0	4	27	76	35	25	38	41	43	65	32	19	19	27	13	8	9	4	486
Just Brake	0	0	0	0	0	0	0	0	16	43	18	10	19	20	24	41	20	14	11	20	5	3	7	1	272
Hard Acc	2	0	0	0	0	0	1	7	19	64	31	27	40	48	39	57	31	18	21	23	14	14	7	5	468
Just Acc	1	0	0	0	0	0	1	3	8	31	14	12	21	27	20	33	19	13	13	16	6	9	5	2	254
Acc and brake	1	0	0	0	0	0	0	4	11	33	17	15	19	21	19	24	12	5	8	7	8	5	2	3	214
Over 70 Brake	0	0	0	0	0	0	0	2	18	53	15	15	25	25	21	21	15	3	8	11	1	3	4	1	241
Over 75 Brake	0	0	0	0	0	0	0	2	13	10	8	7	12	12	6	10	7	1	3	3	0	1	0	0	95
Over 80 Brake	0	0	0	0	0	0	0	1	3	0	1	1	1	2	0	1	0	0	0	0	0	0	0	0	10
Over 70 Acc	0	0	0	0	0	0	1	3	14	41	11	13	15	21	11	18	12	4	7	6	2	3	3	2	187
Over 75 Acc	0	0	0	0	0	0	1	2	7	10	5	7	7	10	4	8	5	1	3	2	0	1	2	0	75
Over 80 Acc	0	0	0	0	0	0	1	1	5	0	1	1	1	2	0	0	0	0	0	0	0	0	0	0	12

Drives Per Day of Week

Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
110	269	238	246	276	171	186

Drives per Month

Jan	February	March	April	May	June	July	August	September	October	November	December
102	136	132	130	139	91	84	71	122	173	165	151

Appendix B – First Half of Correlation Table

	DistanceMiles	Duration	DurSCORE	AverageMPG	FuelCost	FuelUsageGallons	HardBrakes	HardAccelerations	Over70	Over75	Over80	Chronological	MonthTripStarted	SeasonScore	Weekday1Weekend2	SMTWTFSstarted
DistanceMiles	1	.882**	.912**	.716**	.989**	.993**	.292**	.145**	.722**	.362**	.080**	-.282**	-0.009	-0.012	.119**	.102**
Duration	.882**	1	.891**	.625**	.886**	.896**	.313**	.199**	.553**	.278**	0.050	-.217**	0.004	0.001	.110**	.101**
DurSCORE	.912**	.891**	1	.644**	.922**	.928**	.325**	.187**	.589**	.303**	.068**	-.227**	-0.021	-0.024	.121**	.113**
AverageMPG	.716**	.625**	.644**	1	.695**	.702**	.251**	.139**	.393**	.177**	0.023	-.262**	0.005	0.007	.057*	.069**
FuelCost	.989**	.886**	.922**	.695**	1	.989**	.307**	.162**	.696**	.358**	.084**	-.300**	-0.002	-0.004	.123**	.109**
FuelUsageGallons	.993**	.896**	.928**	.702**	.989**	1	.311**	.164**	.720**	.381**	.104**	-.250**	-0.010	-0.014	.123**	.106**
HardBrakes	.292**	.313**	.325**	.251**	.307**	.311**	1	.186**	.195**	.156**	0.043	-.085**	0.026	0.030	0.023	0.023
HardAccelerations	.145**	.199**	.187**	.139**	.162**	.164**	.186**	1	.084**	.084**	0.047	-0.018	0.012	0.016	.069**	0.032
Over70	.722**	.553**	.589**	.393**	.696**	.720**	.195**	.084**	1	.574**	.211**	-.143**	-0.028	-0.028	.103**	.065*
Over75	.362**	.278**	.303**	.177**	.358**	.381**	.156**	.084**	.574**	1	.714**	0.034	-0.011	-0.012	.098**	.052*
Over80	.080**	0.050	.068**	0.023	.084**	.104**	0.043	0.047	.211**	.714**	1	.071**	-0.031	-0.032	.056*	0.031
Chronological	-.282**	-.217**	-.227**	-.262**	-.300**	-.250**	-.085**	-0.018	-.143**	0.034	.071**	1	-.069**	-.077**	-.090**	-.064*
MonthTripStarted	-0.009	0.004	-0.021	0.005	-0.002	-0.010	0.026	0.012	-0.028	-0.011	-0.031	-.069**	1	.975**	0.007	-0.048
SeasonScore	-0.012	0.001	-0.024	0.007	-0.004	-0.014	0.030	0.016	-0.028	-0.012	-0.032	-.077**	.975**	1	-0.005	-.054*
Weekday1Weekend2	.119**	.110**	.121**	.057*	.123**	.123**	0.023	.069**	.103**	.098**	.056*	-.090**	0.007	-0.005	1	.763**
SMTWTFSstarted	.102**	.101**	.113**	.069**	.109**	.106**	0.023	0.032	.065*	.052*	0.031	-.064*	-0.048	-.054*	.763**	1
DayTripStarted	0.002	0.029	0.024	-0.005	0.014	0.004	0.009	-0.042	-0.041	-0.028	-0.021	0.026	0.014	0.027	-0.021	0.013
YearTripStarted	-.239**	-.189**	-.187**	-.228**	-.258**	-.211**	-.085**	-0.020	-.106**	0.037	.076**	.896**	-.501**	-.496**	-.080**	-0.034
TimeTripStarted	-.134**	-.078**	-.132**	-.108**	-.119**	-.147**	-0.020	-0.024	-.118**	-.118**	-.067**	-.135**	0.035	0.041	-.085**	-.100**
TimeStartedSCORE	-.100**	-.064*	-.123**	-.057*	-.091**	-.117**	-0.032	-0.020	-.087**	-.091**	-.064*	-.138**	.057*	.063*	-0.039	-.053*
DaysSinceLastTrip	.064*	0.029	.065*	-0.022	.073**	.056*	-0.033	-0.040	0.046	0.028	0.025	-0.049	-.109**	-.104**	-.110**	-.199**
TripOfTheDayOrder	-.213**	-.181**	-.238**	-.185**	-.221**	-.240**	-.111**	-.066*	-.127**	-.094**	-.053*	0.029	.070**	.069**	-0.040	-.054*
TripsPerDay	-.128**	-.134**	-.163**	-.095**	-.148**	-.146**	-.107**	-.063*	-.059*	-0.049	0.013	0.045	.132**	.130**	-.061*	-.091**
TypeOfTrip	-.194**	-.195**	-.241**	-.173**	-.212**	-.233**	-.152**	-.123**	-.149**	-.107**	-.057*	0.032	0.018	0.013	-0.047	-.052*
LotComingFrom	-0.044	-0.041	-.078**	.152**	-.057*	-.065*	-0.019	-0.037	-.089**	-.070**	-0.039	.099**	0.035	0.037	-0.050	0.007
LotHeadedTo	.062*	0.022	0.043	.151**	.058*	.078**	-0.018	-0.017	0.040	.062*	.083**	.103**	0.039	0.043	-0.050	0.003
MonthTripEnded	-0.008	0.004	-0.021	0.006	-0.002	-0.010	0.026	0.013	-0.028	-0.011	-0.031	-.070**	1.000**	.975**	0.007	-0.048
SMTWTFSended	.103**	.101**	.113**	.069**	.109**	.107**	0.018	0.027	.065*	.053*	0.031	-.062*	-0.048	-.053*	.758**	.996**
DayTripEnded	0.002	0.028	0.021	-0.006	0.013	0.004	0.004	-0.047	-0.040	-0.028	-0.021	0.028	0.015	0.028	-0.025	0.009
YearTripEnded	-.239**	-.189**	-.187**	-.228**	-.258**	-.211**	-.085**	-0.020	-.106**	0.037	.076**	.896**	-.501**	-.496**	-.080**	-0.034
TimeTripEnded	-.091**	-0.031	-.094**	-.076**	-.076**	-.104**	-0.015	-0.022	-.070**	-.093**	-.063*	-.131**	0.035	0.042	-.085**	-.096**
StartLong	-.255**	-.193**	-.177**	-.240**	-.276**	-.219**	-.131**	-.102**	-.136**	-0.045	0.033	.452**	0.004	-0.002	-.127**	-0.033
StartLat	-.216**	-.171**	-.147**	-.164**	-.229**	-.184**	-.112**	-.114**	-.120**	-0.034	0.029	.396**	-0.012	-0.016	-.126**	-0.022
EndLong	-.239**	-.162**	-.172**	-.158**	-.261**	-.246**	-.126**	-.061*	-.170**	-.077**	-0.040	.446**	0.003	-0.002	-.154**	-.068**
EndLat	-.193**	-.141**	-.150**	-.117**	-.215**	-.198**	-.108**	-.064*	-.129**	-.056*	-0.027	.396**	-0.018	-0.022	-.159**	-.065*

Appendix C– Second Half of Correlation Table

	DayTripStarted	YearTripStarted	TimeTripStarted	TimeStartedSCORE	DaysSinceLastTrip	TripOfTheDayOrder	TripsPerDay	TypeOfTrip	LotComingFrom	LotHeadedTo	MonthTripEnded	SMTWTFSended	DayTripEnded	YearTripEnded	TimeTripEnded	StartLong	StartLat	EndLong	EndLat
DistanceMiles	0.002	-.239**	-.134**	-.100**	.064*	-.213**	-.128**	-.194**	-0.044	.062*	-0.008	.103**	0.002	-.239**	-.091**	-.255**	-.216**	-.239**	-.193**
Duration	0.029	-.189**	-.078**	-.064*	0.029	-.181**	-.134**	-.195**	-0.041	0.022	0.004	.101**	0.028	-.189**	-0.031	-.193**	-.171**	-.162**	-.141**
DurSCORE	0.024	-.187**	-.132**	-.123**	.065*	-.238**	-.163**	-.241**	-.078**	0.043	-0.021	.113**	0.021	-.187**	-.094**	-.177**	-.147**	-.172**	-.150**
AverageMPG	-0.005	-.228**	-.108**	-.057*	-0.022	-.185**	-.095**	-.173**	.152**	.151**	0.006	.069**	-0.006	-.228**	-.076**	-.240**	-.164**	-.158**	-.117**
FuelCost	0.014	-.258**	-.119**	-.091**	.073**	-.221**	-.148**	-.212**	-.057*	.058*	-0.002	.109**	0.013	-.258**	-.076**	-.276**	-.229**	-.261**	-.215**
FuelUsageGallons	0.004	-.211**	-.147**	-.117**	.056*	-.240**	-.146**	-.233**	-.065*	.078**	-0.010	.107**	0.004	-.211**	-.104**	-.219**	-.184**	-.246**	-.198**
HardBrakes	0.009	-.085**	-0.020	-0.032	-0.033	-.111**	-.107**	-.152**	-0.019	-0.018	0.026	0.018	0.004	-.085**	-0.015	-.131**	-.112**	-.126**	-.108**
HardAccelerations	-0.042	-0.020	-0.024	-0.020	-0.040	-.066*	-.063*	-.123**	-0.037	-0.017	0.013	0.027	-0.047	-0.020	-0.022	-.102**	-.114**	-.061*	-.064*
Over70	-0.041	-.106**	-.118**	-.087**	0.046	-.127**	-.059*	-.149**	-.089**	0.040	-0.028	.065*	-0.040	-.106**	-.070**	-.136**	-.120**	-.170**	-.129**
Over75	-0.028	0.037	-.118**	-.091**	0.028	-.094**	-0.049	-.107**	-.070**	.062*	-0.011	.053*	-0.028	0.037	-.093**	-0.045	-0.034	-.077**	-.056*
Over80	-0.021	.076**	-.067**	-.064*	0.025	-.053*	0.013	-.057*	-0.039	.083**	-0.031	0.031	-0.021	.076**	-.063*	0.033	0.029	-0.040	-0.027
Chronological	0.026	.896**	-.135**	-.138**	-0.049	0.029	0.045	0.032	.099**	.103**	-.070**	-.062*	0.028	.896**	-.131**	.452**	.396**	.446**	.396**
MonthTripStarted	0.014	-.501**	0.035	.057*	-.109**	.070**	.132**	0.018	0.035	0.039	1.000**	-0.048	0.015	-.501**	0.035	0.004	-0.012	0.003	-0.018
SeasonScore	0.027	-.496**	0.041	.063*	-.104**	.069**	.130**	0.013	0.037	0.043	.975**	-.053*	0.028	-.496**	0.042	-0.002	-0.016	-0.002	-0.022
Weekday1Weekend2	-0.021	-.080**	-.085**	-0.039	-.110**	-0.040	-.061*	-0.047	-0.050	-0.050	0.007	.758**	-0.025	-.080**	-.085**	-.127**	-.126**	-.154**	-.159**
SMTWTFSstarted	0.013	-0.034	-.100**	-.053*	-.199**	-.054*	-.091**	-.052*	0.007	0.003	-0.048	.996**	0.009	-0.034	-.096**	-0.033	-0.022	-.068**	-.065*
DayTripStarted	1	-0.019	-0.014	-0.020	.089**	-0.047	-.088**	-0.015	0.004	-0.002	0.014	0.010	.996**	-0.019	-0.028	0.016	0.032	0.024	0.030
YearTripStarted	-0.019	1	-.135**	-.144**	0.005	-0.006	-0.017	0.019	.072**	.075**	-.501**	-0.033	-0.017	1.000**	-.130**	.391**	.349**	.387**	.353**
TimeTripStarted	-0.014	-.135**	1	.917**	.067**	.612**	.121**	.358**	.353**	-.484**	0.035	-.102**	-0.019	-.135**	.930**	-.067*	-.070**	-.075**	-.123**
TimeStartedSCORE	-0.020	-.144**	.917**	1	0.047	.597**	.104**	.359**	.377**	-.478**	.057*	-.054*	-0.023	-.144**	.866**	-.086**	-.092**	-.087**	-.136**
DaysSinceLastTrip	.089**	0.005	.067**	0.047	1	-0.017	-0.025	0.020	-0.039	-0.030	-.109**	-.196**	.090**	0.005	0.049	-.060*	-.073**	-0.051	-.069**
TripOfTheDayOrder	-0.047	-0.006	.612**	.597**	-0.017	1	.544**	.425**	.349**	-.409**	.070**	-.054*	-0.048	-0.006	.572**	.059*	0.013	.074**	0.034
TripsPerDay	-.088**	-0.017	.121**	.104**	-0.025	.544**	1	.293**	.077**	.065*	.132**	-.090**	-.087**	-0.017	.110**	0.022	-0.008	0.026	-0.002
TypeOfTrip	-0.015	0.019	.358**	.359**	0.020	.425**	.293**	1	.521**	-.183**	0.018	-.052*	-0.015	0.019	.341**	.068**	.079**	.098**	.078**
LotComingFrom	0.004	.072**	.353**	.377**	-0.039	.349**	.077**	.521**	1	-.296**	0.035	0.008	0.005	.072**	.340**	.151**	.169**	.134**	.124**
LotHeadedTo	-0.002	.075**	-.484**	-.478**	-0.030	-.409**	.065*	-.183**	-.296**	1	0.038	0.004	0.001	.075**	-.452**	.077**	.110**	.151**	.169**
MonthTripEnded	0.014	-.501**	0.035	.057*	-.109**	.070**	.132**	0.018	0.035	0.038	1	-0.048	0.014	-.501**	0.035	0.004	-0.013	0.003	-0.018
SMTWTFSended	0.010	-0.033	-.102**	-.054*	-.196**	-.054*	-.090**	-.052*	0.008	0.004	-0.048	1	0.014	-0.033	-.093**	-0.032	-0.019	-.066*	-.063*
DayTripEnded	.996**	-0.017	-0.019	-0.023	.090**	-0.048	-.087**	-0.015	0.005	0.001	0.014	0.014	1	-0.017	-0.021	0.018	0.038	0.028	0.033
YearTripEnded	-0.019	1.000**	-.135**	-.144**	0.005	-0.006	-0.017	0.019	.072**	.075**	-.501**	-0.033	-0.017	1	-.130**	.391**	.349**	.387**	.353**
TimeTripEnded	-0.028	-.130**	.930**	.866**	0.049	.572**	.110**	.341**	.340**	-.452**	0.035	-.093**	-0.021	-.130**	1	-.065*	-0.038	-.057*	-.108**
StartLong	0.016	.391**	-.067*	-.086**	-.060*	.059*	0.022	.068**	.151**	.077**	0.004	-0.032	0.018	.391**	-.065*	1	.896**	.581**	.580**
StartLat	0.032	.349**	-.070**	-.092**	-.073**	0.013	-0.008	.079**	.169**	.110**	-0.013	-0.019	0.038	.349**	-0.038	.896**	1	.547**	.580**
EndLong	0.024	.387**	-.075**	-.087**	-0.051	.074**	0.026	.098**	.134**	.151**	0.003	-.066*	0.028	.387**	-.057*	.581**	.547**	1	.928**
EndLat	0.030	.353**	-.123**	-.136**	-.069**	0.034	-0.002	.078**	.124**	.169**	-0.018	-.063*	0.033	.353**	-.108**	.580**	.580**	.928**	1

Appendix D - Independent Samples T-test on Trips that started in the AM hours and PM hours

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p			Lower	Upper
HardBrakeSCORE	Equal variances assumed	1.840	.175	1.495	1476	.068	.135	.053	.036	-.017	.123
	Equal variances not assumed			1.491	874.478	.068	.136	.053	.036	-.017	.123
HardBrakes	Equal variances assumed	1.115	.291	1.385	1476	.083	.166	.054	.039	-.022	.131
	Equal variances not assumed			1.379	869.815	.084	.168	.054	.039	-.023	.131
HardAccelSCORE	Equal variances assumed	10.667	.001	1.991	1476	.023	.047	.069	.035	.001	.137
	Equal variances not assumed			1.930	818.614	.027	.054	.069	.036	-.001	.139
HardAccelerations	Equal variances assumed	4.099	.043	1.216	1476	.112	.224	.047	.038	-.029	.122
	Equal variances not assumed			1.175	811.785	.120	.240	.047	.040	-.031	.125
AverageMPG	Equal variances assumed	60.636	<.001	3.962	1476	<.001	<.001	1.45037	.36606	.73232	2.16843
	Equal variances not assumed			4.190	1009.997	<.001	<.001	1.45037	.34617	.77109	2.12966
Over70	Equal variances assumed	63.735	<.001	4.980	1476	<.001	<.001	39.365	7.905	23.858	54.872
	Equal variances not assumed			4.422	681.394	<.001	<.001	39.365	8.902	21.887	56.843
Over75	Equal variances assumed	37.286	<.001	3.432	1476	<.001	<.001	4.146	1.208	1.776	6.515
	Equal variances not assumed			2.636	537.346	.004	.009	4.146	1.573	1.056	7.236
Over80	Equal variances assumed	32.242	<.001	2.855	1476	.002	.004	.444	.156	.139	.749
	Equal variances not assumed			1.917	458.060	.028	.056	.444	.232	-.011	.900
Duration	Equal variances assumed	17.458	<.001	2.957	1476	.002	.003	.03091	.01045	.01040	.05142
	Equal variances not assumed			3.256	1119.455	<.001	.001	.03091	.00949	.01228	.04954
DurSCORE	Equal variances assumed	26.511	<.001	5.803	1476	<.001	<.001	.310	.053	.205	.415
	Equal variances not assumed			6.061	978.967	<.001	<.001	.310	.051	.210	.410