MSC. HUMAN FACTORS AND ENGINEERING PSYCHOLOGY

LEARNING EFFECT IN DRIVING SIMULATORS – ONLINE DRIVING SIMULATORS AND DRIVING SIMULATORS LEARNING CURVES ANALYSIS.

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ABSTRACT

Objective: This study has for objective to identify if it is possible to calculate learning curves from data sets obtained from driving simulators and if there is transfer from online driving simulators to on the road driving. Proving transfer will demonstrate learning effectiveness of online simulators, enabling a safer and more cost effective driving learning experience.

Method: This study was divided into three parts, in which data sets from different experiments were analyzed and learning curves were calculated. The first data set included results from students that performed the online driving simulator lessons from the company Green Dino, this was an uncontrolled data set. The second data set contained semi-controlled data set and it was taken from van Wijk's (2020) research project performed in an online driving simulator. Finally, the controlled data set was taken from the Voskes experiment (2020), which consisted of participants performing trials on a physical driving simulator. A learning curve model was created and the results were analyzed according to the variables that each data set contained.

Results: Learning curves from physical and online driving simulators from semi-controlled and controlled experiments data sets can be observed, including transfer from experienced drivers. In this particular study, there was no success in calculating learning curves from an uncontrolled data set, however, recommendations for better data acquisition were made.

Conclusion: The learning curve model used in this study showed that it is possible to show learning outcomes from driving simulators under specific conditions. These conditions can be used for a large-scale experiment to validate the best way to obtain quality data from driving simulators.

Keywords: driving simulators, online driving simulators, learning curves, learning transfer.

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2 GENERAL INTRODUCTION

Road traffic injury is increasingly recognised as a major health concern, particularly for adolescents and young adults (Winston, et al., 2014; Alver, et al., 2014). The possibility of being involved in a crash in the first six months after receiving a driving license for this group of drivers, in the Netherlands, is 4.5 times higher than for older drivers (SWOV, 2021). Higher risk can be associated to the absence of experience, lack of education, and risky driving behaviour (Clarke, et al., 2002). In a country such as the Netherlands, the amount of driving licenses emitted to young people has been increasing in the last few years, every year over 48 percent of young adult drivers are trained and certified to operate a device that put this population in risk (Trend in the Netherlands , 2018). Working towards improving driving learning methods for new drivers is, therefore, an urgent need.

Driving demands both procedural skills and higher-order cognitive skills (Beanland, et. al, 2013). Procedural skills involve executing a sequence of actions, which may become automated with extensive practice (Schendel & Hagman, 1982). These skills are best learned by following a sequenced and stepped approach to teaching, either a simple or complex task (Burgess, et. al, 2020). Higher-order cognitive skills involve situation monitoring, assessment, response planning, and execution (Pollatsek, et. al, 2011). Gaining early driving experience is a major protective factor for the reduction of crash risk in young novice drivers and this is mainly because it enables the improvement of high-level driving-related cognitive skills (Kinnear, et al., 2013).

Pre-license training involves teaching basic driving skills to learners before they obtain a driver's licence, which is mandatory in most of the European countries, Canada and the US (Deppermann, 2018). The acquisition of driving skills was limited to on the road training until alternatives such as simulators and online driving simulators (ODSs) became available. Using a simulator to develop driving skills is safer and more cost-effective. Additionally, it can provide objective and repeatable measures of driver performance and allow complete control of the driving environment (Allen R. &., 2011). Not to leave behind the fact it can be easily administrated in a laboratory setting, which can benefit driving research.

Although there are multiple advantages of using simulators, there isn´t enough scientific evidence of the efficacy of ODSs. Since we do not want to go on this journey without a target destination, we should be able to assess if skills are learned and transferred to on-road driving. Learning curves (LCs) provide a mathematical representation of the learning process that takes place as task repetition occurs (Anzanello & Fogliatto, 2011). LCs were formally introduced by T.P Wright while studying the productivity trends of the production of aircraft (Wright, 1936). Nowadays LCs are not only used to assess productivity in manufacturing environments but they can also be used in the medical area, to estimate learning of the surgical skills needed in procedures such as laparoscopy (Huijser, 2015; Weimer, 2019). LCs are not limited to calculating past learning events, they are also a powerful tool that can act as a forecast engine, predicting future learning performance (Schmettow, 2021). Therefore, it is of great interest of this study to evaluate the data from an ODS using learning curves and to evaluate the feasibility of using them as part of a hybrid training, together with driving simulators and on the road training. The previously mentioned assessment of analysing the transfer of skills could determine if ODSs can provide young drivers with driving experience during the first months, in a more cost efficient way.

For the first section of this thesis, Green Dino, a company that produces driving simulators and that is a pioneer in ODSs, provided a data set with the information of the students that performed online driving lessons using their ODS. The training consisted of nine fifteen-minute training modules and which were primarily developed to respond the need of online lessons during the coronavirus pandemic (Green Dino, 2021). The analysis of online lessons data will lead to a set of recommendations, that will serve as a guideline for a future experiment that has the intention to improve the design of online driving simulators at Green Dino.

The study will also include a section that will analyse a data set from a semi-controlled environment, using records from an experiment that consisted of investigating performance after a driver training method in an online driving simulator using a speed episode (van Wijk, 2020). The data set from a very controlled environment, which consisted of a data set from a driving simulator that examined the potentials of simulator-based driving training, with a specific focus on the use of speed-episodes and differences between experience levels of the drivers, will also be analysed (Voskes, 2020). Both data sets analysis mainly consist of the visualization of the data with the different predictors and the calculation of learning curves. Following the data analysis of the different data sets, recommendations for the previously mentioned experiment will be proposed. The recommendations will include all the lessons learned during the data analysis process and will focus on the acquisition of the right data for learning curves calculations. If we are able to gather the correct information to asses learning, skill transfer from OSs could also be proved.

2.1 Simulators and Learning

2.1.1 Learning with driving Simulators

The use of simulators as an assessment and intervention tool for driving is an emerging field (Devos, et al., 2016). Supplying adequate simulator training can learn important higher-order cognitive skills such as eye scanning without exposing drivers to hazardous driving situations (Triggs & Regan, 1998). It is environmentally friendly, flexible, and can train driver learners in different road traffic environments (Sætren, et al., 2018). In addition, simulators make it possible to study hazard anticipation and perception in an ethical way (Underwood, et al., 2011). Driving simulators offer the opportunity for feedback and instruction that is not easily achieved in real vehicles. For example, it is possible to freeze, reset, or replay a scenario (Vlakveld, 2005). and in the particular case of Green Dino's simulators, the type of feedback is adaptive, regulated in three different levels based on student´s performance. Green Dino’s physical simulators have shown a decrease in the involvement in accidents and the total number of driving lessons on the road. Students´ percentage of passing the first exam increases with the use of the simulator training, additionally the cost of the training decreases for the student and the profit for the driving school increases (Kuipers, 2016).

Contrary to the already mentioned advantages, it is claimed that the fact that trainees are not exposed to real danger and consequences of actions, can lead to a false sense of safety, responsibility, or competence (Kappler W. , 1993). Low-fidelity simulators may evoke unrealistic driving behaviour and therefore produce invalid research outcomes (de Winter, et al., 2012). However, a growing body of evidence indicates that driving-simulator measures are predictive for on-the-road driving performance (Shechtman, et al., 2009).

2.1.2 Learning with online driving simulators

Many countries in the world are now participants in the biggest unplanned experiment that education has ever seen, migrating to fully online learning methods. On the potential upside, the new forced reliance on technology in education may accelerate some changes that had already started (Thomas & Rogers, 2020). Online driving simulators allow users to experience as much of the actual driving. The ODSs can include 3D simulation, virtual reality and digital twin.

Complex online virtual simulation (OVS) learning experiences, can increase student knowledge, exposure, and engagement with the diagnostic reasoning process in medical areas (Duff, et. al, 2016). An experiment using eye movement showed that a PC-based risk awareness and perception training can successfully help novice drivers to identify where potential risks are located and what information should be attended to (Pollatsek, et. al, 2006). In a further study, Pollatsek and his research team found that young drivers who followed a PC based hazard anticipation training increased their scanning behaviour and were more likely to gaze at areas of the roadway with relevant information about potential risks than the untrained drivers (Pradhan, et al., 2009). The previous findings can be indicators that online driving simulators could also have the same benefits.

In order to evaluate the learning impact from ODSs, we need to investigate further the results that the already available ODSs have achieved so far, for this purpose, Green Dino provided a data set with the information of their students. Green Dino BV is specialized in automated driver behaviour assessment. The company focuses on relative validity. Driver behaviour in virtual environments should be reliable and predictive for on-road driving. According to the creators of the online simulator, the absolute validity of driving simulators is of minor importance and in most cases too expensive (Green Dino Driving Simulator, 2011). Their simulator offers an affordable solution for those who want to learn how to drive. A broad range of parameters can be observed, analysed, and stored in their software solution. Their driving simulation software is built upon a unique architecture based on driving tasks. Driving tasks are complex procedures used for the assessment of the driver's behaviour controlling the traffic. For driving style assessment and driver training, a virtual instruction module is available with an adaptive feedback system and road safety assessment (Green Dino Driving Simulator, 2011). The reports obtained from Green Dino´s simulator could provide a helpful insight into how driving skills can or cannot be acquired.

2.2 Assessing learning

2.2.1 Learning curves

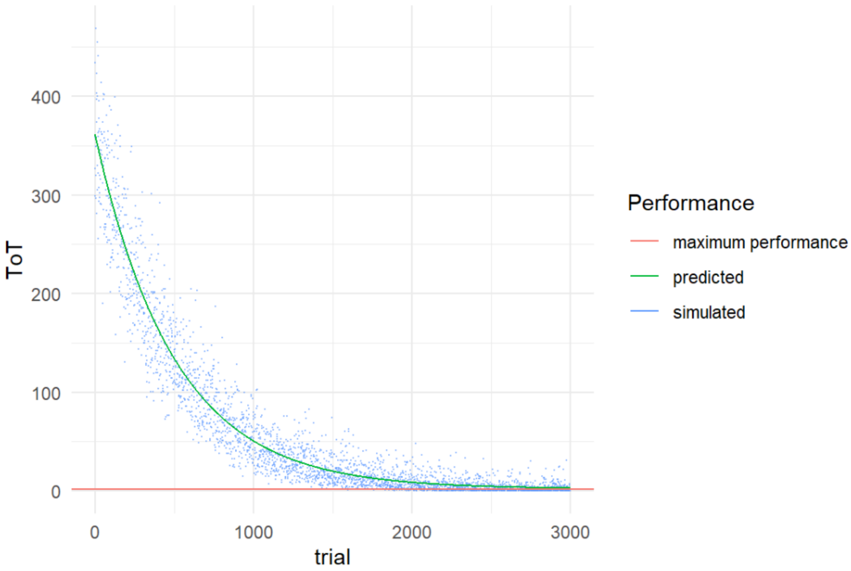
A practical way to understand how learning happens is by referring to Schmettow´s (2021) learning phases. The first phase of learning is task knowledge, this happens when the learner can generate an action plan based on the understood words. This knowledge has more or less a discrete learning function, which jumps from 0 to 1 at the exact moment the instructions are understood (Schmettow, 2021). According to Schmettow (2021), once there is comprehension, it won't go away. The second phase of learning is building skills. The initial action plan is mostly just a general plan, leading to a not so good performance. Building skills is a long running, continuous process of refining the action plan. These refinements are tweaks like short-cuts, parallel execution out-of-loop execution, etc. Building skills can be ascribed as the process of finding possible tweaks (Schmettow, 2021). These phases could be adapted to the process in which driving students are involved, each participant creates an action plan about how to perform certain tasks while driving based on the previous knowledge they have, then after performing a lesson, tweaks can be discovered producing learning outcomes.

The notion that human learning follows a smooth power law of diminishing gains is well-established in psychology (Donner & Hardy, 2015). There is a point of maximum performance, which is reached asymptotically, but never crossed and the process is non-linear, such that the net effect diminishes over time (Schmettow, 2021). A learning curve can be used to monitor development progress, predict growth patterns, and plan programs for reliability improvement (Duane, 1964). The parameter Asymptote means the level of maximum performance which is reached asymptotically with continued practice. The Amplitude parameter describes the amount of improvement. It shows the difference between the performance before the first trial and the Asymptote. The last parameter is the Rate parameter which displays the overall speed of learning (Heathcot, et al., 2000).

When all the refinements (or tweaks as previously explained), are found and applied, the learning organism has reached its level of maximum performance. Maximum performance usually is a person-specific parameter that is always finite and never zero, because some parts of the organism cannot be tweaked, such as the travel time in nerve cells and the inertia of limbs (Schmettow, 2021). A crucial aspect is the notion that learning continues, more slowly among those with greater task experience. Performance will improve with practice, becoming more accurate, reliable, and less prone to disruption (Groeger & Banks, 2007). If we refer back to the driving learners, the number of tweaks found in the simulator lessons at the beginning for the inexperienced drivers should be higher at the beginning since there are more tweaks to discover and then dimmish after certain trials when there are not many tweaks left to discover.

An example of how a learning curve can behave is shown in Figure 1 (Schmettow, 2021). In this image, you can see how the ToT (time on task), has a high amplitude, and after some trials, this starts to decrease until it reaches the maximum performance which in the case of ToT would be the lowest time required for every trial.

FIGURE 1 LEARNING CURVE SIMULATION



The formula to calculate learning curves consists of an amplitude, catch rate, and asymptote (Pt=Asym+Ampl×Survt) (Schmettow, 2021). If a model is run with the Stan engine, all parameters need to run without boundaries and this is done by converting the parameters using the log/exp and logit/inv_logit. Amp and Asym need conversion from non-negative to unbound and Surv needs double-bound to unbound conversion. (Schmettow, 2021). The reparametrization gives the following formula (Pt=expAsym+expAmpl×logit−1Survt) (Schmettow, 2021). The previous formula will be used for the calculation of the learning curve models in the different chapters.

Learning curves have already been used to assess learning in simulators, more specifically, in laparoscopy simulators (Weimer, 2019). In Weimer's experiment, for each of the participants, three individual learning curves were designed based on time-on-task and three based on damage. Each learning curve contained three parameters, namely Asymptote, Rate, and Previous experience. The asymptote parameter reflected the predicted maximum performance of an individual in the long run. The way learning was assessed in laparoscopy simulators could also be used to calculate learning curves in driving simulators if we replace the parameter damage for the number of errors or lane departures for example.

2.2.2 Learning Transfer

The ultimate goal of training is for the trainee to transfer what was learned in training to the actual real world. Transfer of training refers to the process of applying knowledge, skills and abilities learned from training programs to real-world situations and the maintenance of them over time (Liu, et al., 2008). Bi-directional online transfer learning uses knowledge learnt in each online domain to aid predictions in others (McKay, et al., 2020), this allows us to make predictions about driving performance from one scenario to another one. Transfer can be positive, when an individual correctly applies knowledge skills and abilities learned in one environment (e.g. a driving simulator) to a different setting (e.g. on-road driving) (Liu, et al., 2008). Negative transfer on the other side occurs when existing knowledge and skills obstruct proper performance in a different task or setting, or that the trainee reacts to the transfer stimulus correctly as he or she has practiced and was trained, but incorrectly in relation to the real world (Liu, et al., 2008).

Basic skills can be identified using the reverse transfer technique. According to Gopher (1989), a complex task such as flying can be decomposed into simple subtasks. The skills that are learned during a simple situation, like flying straight ahead, can then build up to be implemented in a complex situation like a low altitude flight (Kappler W. , 2008). The aim is to speed up learning by transferring from simple situations at the start to subsequent situations which increase in difficulty. It is not known yet if certain tasks like the ones performed during gaming that involve visual, spatial, and motor coordination skills (Adams, et.al, 2012) , could be then transferred to a more complex situation like driving in a simulator. It would also be interesting to analyse if experienced drivers could transfer the skills gained on the road to online simulators.

2.3 Research question

In order to provide hybrid driving training including online driving simulators, we need to know if skills are developed during the online lessons and if they are transferable. If this information is available we could max out the possibilities that online simulators provide, without facing the risk of over-trusting them.

- Can learning curves be observed after performing online driving simulator lessons?
- Is there transfer from on-the-road driving experience to simulator driving performance? If so, can we expect transfer from simulator driving skills to on the road performance?

3 DRIVING SIMULATORS DATA EXPLORATION DATA

The enormous amounts of data that result from driving simulator experiments must be reduced into meaningful information that provides insight into driver behaviour. According to Reyes and Lee (2011) in order to get good quality data, researchers should plan how the software code will be written and tested, use the plan to create the data reduction software using good coding practices, and test the code during the writing process using visualization techniques to verify that it is performing the functions required to reduce and transform the data as intended. If planning occurs throughout the Project, rather than doing it until the data have been collected, adjustments and changes can be made to the other phases if needed (Reyes & Lee, 2011). The reality is that it is not always possible to plan the data gathering and sometimes unstructured data, or as some authors refer to "big data jungle" (Yan, 2017) needs to be analysed, then detecting quality in large unstructured data sets becomes very complex and computational building block approaches for data clustering can help (Dresp-Langley, et al., 2019). Even if there are already some developments being done that will help analyse data from the wild (Dresp-Langley, et al., 2019), this study aims to focus on quality data gathering. The journey of going from uncontrolled data to controlled data set analysis will allow us to evaluate the feasability of the calculation of learning curves in a controlled environmet and evaluate if it is posible to see learning curves in wild data so we can prove that the online driving simulator is effective for learning purposes. If learning curves cannot be observed we can come up with recommendations for an experiment that can gather quality data in order to answer our research question about the possibility of having learning curves and transfer in simulators based on our results in more controlled data sets.

3.1 Exploring "wild" data.

During this phase, we want to explore the possibility of finding learning outcomes in a non-controlled dataset from an online driving simulator report. The data acquisition was not planned to serve for learning curve model analysis, participants had the freedom to perform the lessons at any time and in any order they preferred and there was no formal monitoring for the completion of the training. The information from 403 students that participated in the online driving simulator training at Green Dino was used. The data provided by the driving simulators company contained a lot of participants that only performed a few lessons or only did some exams, these made it difficult to see the development of certain skills or improvements within lessons. Therefore, a sample of 17 participants that completed 2000 or more trials was created in order to measure individual learning effects on specific tasks or lessons.

The online driving simulator environment was provided by Green Dino (Green Dino, 2021). Participants could log in on their own computer via an internet portal to download the software on their computer. This was only compatible with the Windows operating system, and a computer mouse had to be used in order to control the car in the game. Moving the mouse forward resulted in acceleration, moving the mouse down in deceleration, and left and right controlled the steering wheel direction The left and right arrows, or the z and c keys were used to open a viewport which displayed the mirrors and a view to the left and right of the car. Green Dino offers driving simulators with automated feedback for training and assessment of learner and experienced drivers. The automated feedback system works with driving tasks and instruction levels (Victor, the Virtual Driving Instructor).

The student driver had a particular level for each of the driving tasks distinguished by the simulator. This is the degree to which the student has mastered the driving task. The simulator distinguished the following levels, in ascending order of learning: 1. Deliberate (Acting on instructions) 2. Semi-automatic (Acting with the need for fewer instructions) 3. Automatic (Acting without the need for instructions). Level of instructions change depending on the students performance. The level of learning is the most important means of assessment within the operator program (The Dutch Driving Simulator Operator Manual V20, 2007).

3.1.1 Data exploration

The online lessons data set consisted of a document with different and after the data exploration, the most relevant variables resulted in the following:

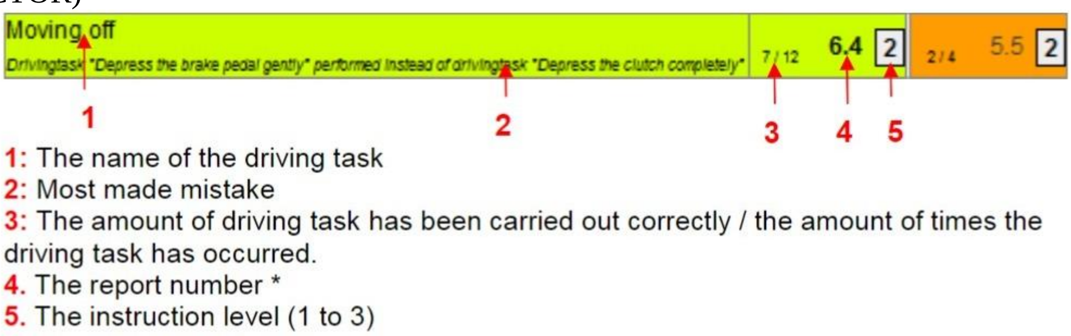
Independent variables

- Trial: A continuous variable was added which cumulatively counted the task performance within the different lessons for each individual (amount of training).
- Student ID: Categorization for participant-level learning curves analysis.
- Lesson ID: Number that identified the lesson that was then used to categorize lessons in clusters.
- Category level: Variable created for analysis purposes. The level was assigned to each cluster of lessons being, beginner, advanced, specialized, exam, and NA.

Dependent variable

- OverallTaskScore: The Strength & Weakness report shows task scores as explained in Figure 1Figure 2 and the analysis was done using the number identified with 4 (Victor, the Virtual Driving Instructor).
- Taks Score: Is the amount of driving task that has been performed correctly over the amount of times the driving task has occurred as shown in Figure 2 in section 3.

FIGURE 2 DESCRIPTION OF TASK SCORE (VICTOR, THE VIRTUAL DRIVING INSTRUCTOR)



The sample selection was done using Tableau and the data analysis in Rstudio. The data set with the initial variables were used to explore the information about all participants and possible visualization of the data. After discovering that there were many internal users

(Green Dino accounts) these were eliminated in order to have only data from students. Personal information from students was also removed for privacy reasons. In order to have a continuous variable that will allow a learning curve calculation, an extra variable which was named trial, was created. The trial variable is based on the end date and time. The visualizations were made based on the overall task score see Figure 3 and Figure 4.

FIGURE 3 OVERALL TASK SCORE TRIAL AND PARTICIPANTS

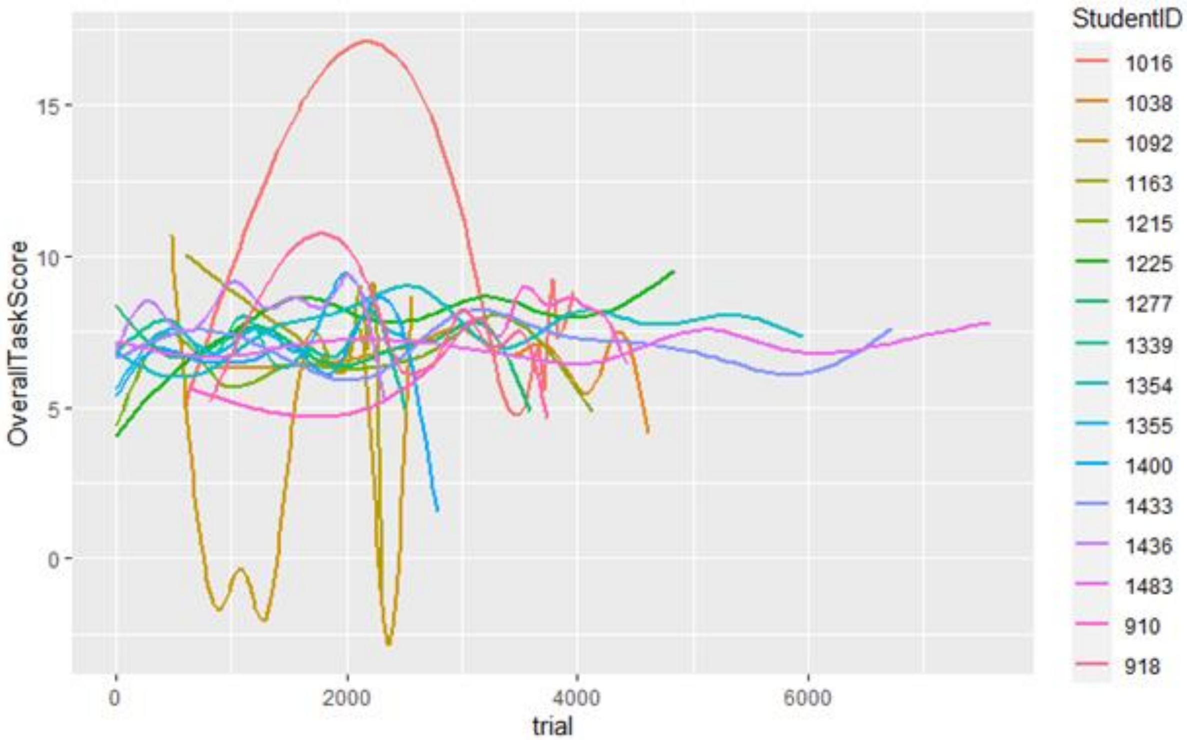
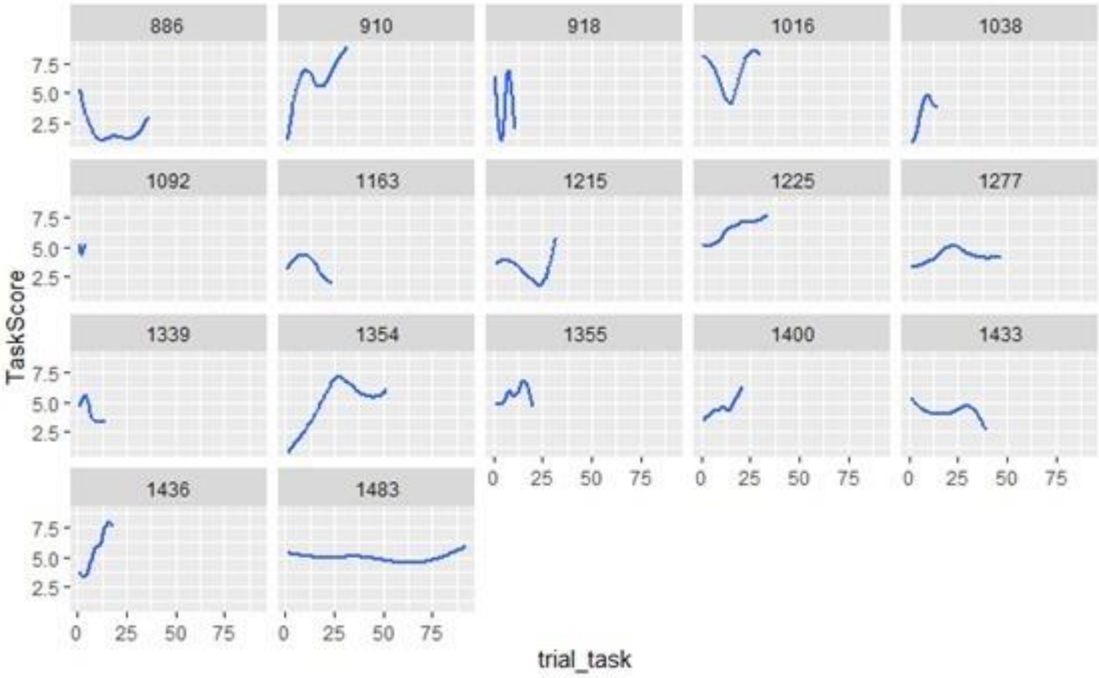


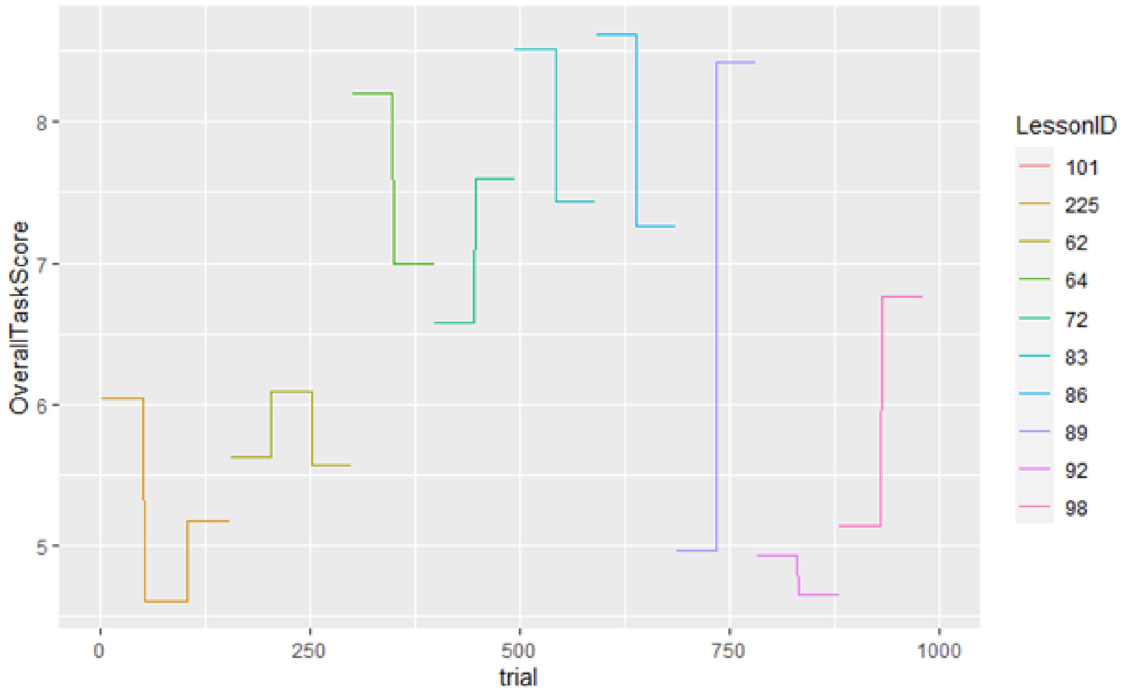
FIGURE 4 OVERALL TASK SCORE AND TRIAL TASK



Lessons were clustered in different categories and levels based on the level determined in the online driving program, the categories were beginner, specialist, or advanced and an exam category was also included. Also, the variable trial_lesson was created to see the development within a lesson and a variable that counted the trials for each task specifically. So no matter what lesson the task was encountered in, it was counted cumulatively. Individual learning curves were explored for specific during their entire training process, but also specific lessons or just the general learning process.

In the wobbling curves performed in the exploratory phase, there was a drop in most of the curves. An individual file of the data was created for two participants (1016, 1215), to be able to explain the graphs and see where the lower scores appear and what might cause this drop. Figure 5 shows the development of the OverallTaskScore of participant 1215, indicating a decrease in performance from trial 1 to 600. The individual file shows that this low score is caused more than 5 lessons. The explanation for the decrease is that the trials represented different parts of a lesson which were ordered alphabetically in the data set and not in the order that were performed. Therefore no accurate conclusions on learning effects could be obtained from these visualisations.

FIGURE 5 PART. 1215 OVERALL TASK SCORE



3.1.2 Results

With the data from the online simulator, it is not possible to plot the learning curve of the participants, therefore the answer to our research question is that no learning curves can be obtained from an uncontrolled data set from an online driving simulator. Different steps were followed to make the data useful for learning curve analysis, such as cleaning the data, clustering the tasks in categories, defining levels for the lessons, and implementing a trial variable, however it was not possible to conclude any learning outcome. The following recommendations are proposed for better data acquisition,

- The system should only enable a lesson if the previous lessons are already completed. This does not have to be limited to performing the lesson, a test could also replace certain lessons.
- Lessons that were not taken and just passed with a test should be identifiable.
- Start time and end time per task should be available, in order to analyze the time on task (ToT).

- The report should contain the chronological number of tasks performed.
- There should be individual task scores, additional to the averaged ones.
- There should be a classification that divides students with previous experience and students without it. If possible, there should be a pre-assessment of the student´s level prior to the course, that can later be retrieved in the report from the system.
- Ideally, the type of feedback from the system should remain consistent during a lesson. This is only for the calculation of the curve purposes since the adaptive system can be beneficial for learning purposes.
- In order to assess fatigue and re-learning, the time that the person spent driving in the same log-in should be available.

3.1.3 Discussion

The enthusiasm for "big data" encourages the use of larger datasets with massive numbers of measured variables (Kaplan, et. al., 2014). Although having a large data set may be very attractive, due to the almost unlimited possibilities for analysis, positive outcomes are not always the case. In this chapter, the aim was to prove that learning curves could be plotted from a data set that included the results of students that performed driving lessons with Green Dino's online simulator, which was not possible due to the conditions of the data set. Green Dino designed their system based on their particular needs of data acquisition at the time of implementation and although their report works for assessing students by comparing them between each other, the data obtained is not that flexible for other analysis purposes, such as learning curves calculation.

Ideally, systems should be enabled with high flexibility such that the system is adaptive to complex analytical applications (Xiong, et. al., 2010). Green Dino´s system design could include the recommendations discussed in the results section so that in addition to the current valuable features they provide, individual learning curves could also be obtained. An experiment to test if performing lessons in order from low complexity to high complexity could work, additionally to having the ToT and individual scores for each task could result in learning curves from their students.

If the results from the experiment including all the recommendations turn out to be favourable, a new feature in their assessment system could be added. Instead of analysing the data posterior to the lessons, the learning curve model from (Schmettow, 2021) could be integrated and therefore provide with the calculation of the learning curves at the moment, and not only that, it could also predict the learning rate for each participant. This could be an additional feature offered by the simulator system in which it can predict the amount of training time needed individually.

3.2 Analysing semi-controlled data

During phase 2 of the data analysis, we want to discover if it is possible to plot learning curves from a semi-controlled experiment. The data obtained for this chapter is from a thesis project which was performed using a Green Dino online driving simulator and which is detailly explained in van Wijk´s (2020) thesis. This experiment examined performance after training in an online driving simulator using a speed episode. This episode is a block of trials performed in between blocks of trials focused on accuracy, where participants aim to finish the task as fast as possible instead of error-free. The objective was to discover whether the speed episode effect was also observable in an online driving simulator and to investigate if the skills learned in a simulator could be retained after a week. According to van Wijk´s (2020) research, there is evidence that procedural skills in simulators are hardly forgotten. Participants were divided into two groups, one of them performed the speed episode and the other one was the control group, doing only accuracy blocks. Van Wijk (2020) was interested in the level of skill retention, therefore her study consisted of two driving sessions with a week of no driving in between. Participants drove 2 kilometres per trial, in 4 blocks of 8 trials, divided into 2 sessions. The blocks and sessions were performed as shown in Table 1 (van Wijk, 2020).

TABLE 1 BLOCKS AND TRIALS SET UP

Session	Block	Accuracy condition	Speed condition
1	1	Accuracy *8 trials*	Accuracy *8 trials*
	2	Accuracy *8 trials*	Speed *8 trials*
	3	Accuracy *8 trials*	Accuracy *8 trials*
2	4	Accuracy *10 trials*	Accuracy *10 trials*

For the purpose of the analysis in this chapter, only the participants from the accuracy group will be taken into consideration. Therefore the impact of the speed episode will not be looked into and only learning curves from the accuracy group will be analysed, together with the level of retention after a week and not the impact of speed episodes.

All of the sessions took place remotely with online support, the screen from the participant was shared with the experimenter and a video call took place for guidance during the experiment. Participants did not have the freedom to choose which lessons to perform and for how long they wanted to do it. Nevertheless, there was no control of the environment in which the participant performed the experiment, such as light conditions, internet speed, or size of the screen, that is why it is considered a semi-controlled experiment.

The data set from the study contained the variables participant, training, ToT, crashes, speed, and steer. The variables that were included in the analysis were the following:

Independent variables

- Trial: A variable that cumulatively counts the task performance within the different lessons for each individual.

- Participant: This categorization will for the participant level analysis, making individual learning curves)
- Training: The type of training that the participants performed was identified, this could be accuracy training or speed training. The analysis was done just for the accuracy group, due to the ToT variability.

Dependent variables

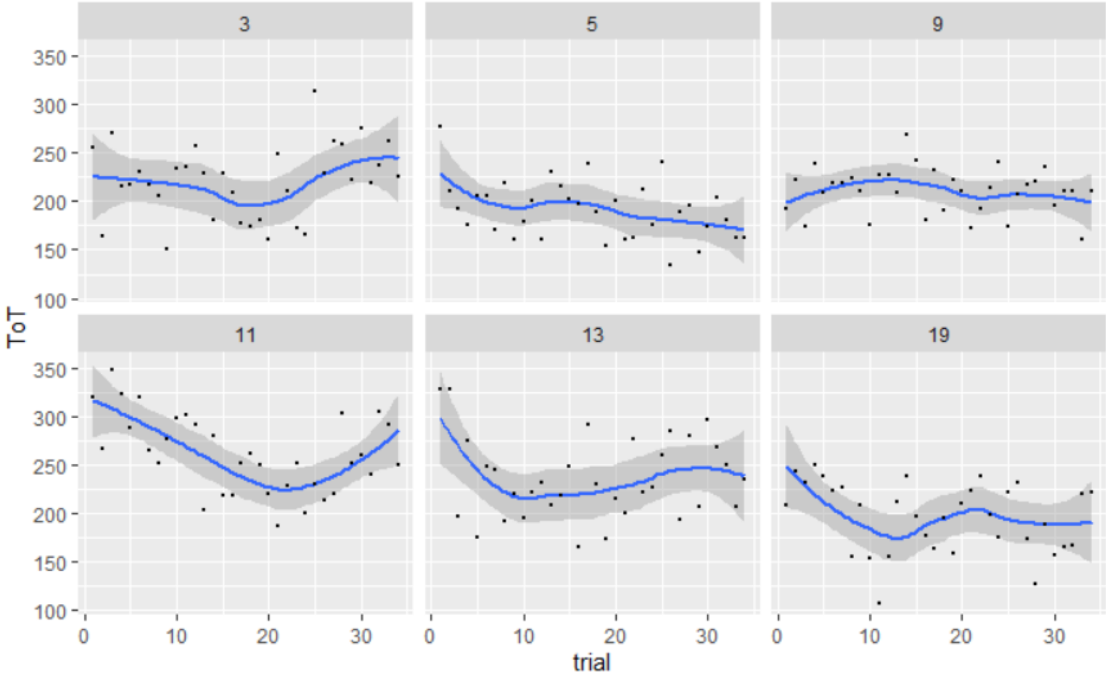
- ToT: Time on task. Time that the participant took to complete the task.

The analysis was performed using R studio and the code can be found in appendix 6.1.

3.2.1 Data exploration

The data visualization was done using the ToT variable. The participants that were analysed belong to the accuracy group. It is important to mention that after trial 24 there was a one-week break. We can already observe from the data visualization made prior to the model, that participants 3, 11 that the amplitude increases after the break which could imply learning-forgetting or a readaptation phase. Participants 13 and 19 start showing this increase even from trials before the break which could be derived from fatigue (Figure 6).

FIGURE 6 TOT ACCURACY GROUP

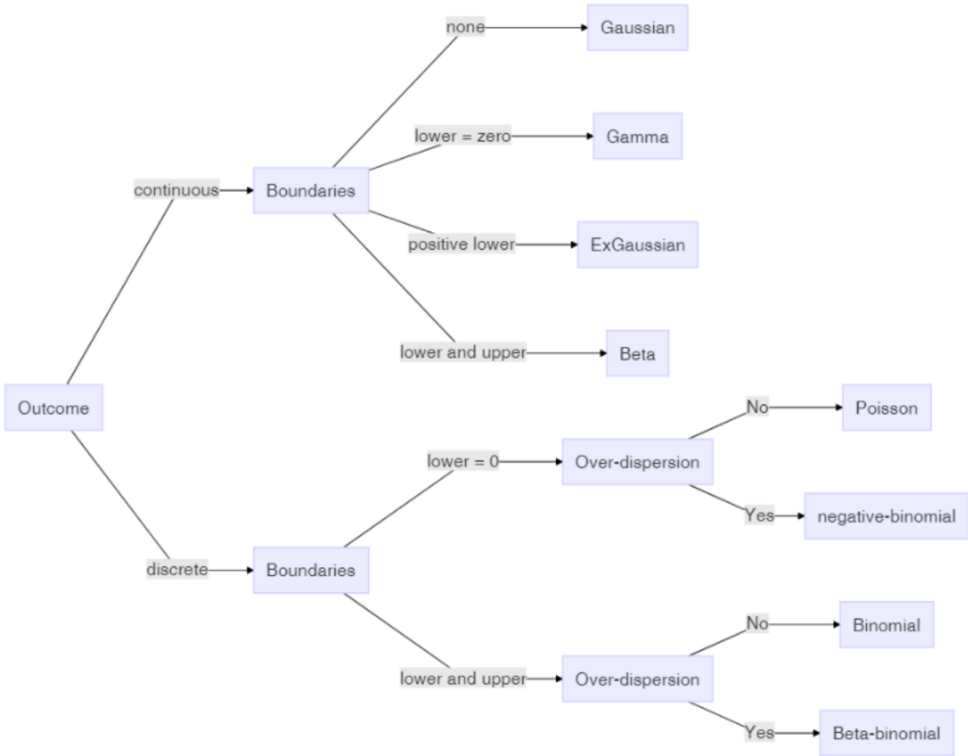


MODEL ESTIMATION

A statistical model was built, following the LACY model **(**Pt = expAsym+ expAmpl× logit−1(1−Ctch)t) from Schmettow (2021). In the previous formula, the parameters have been converted. The amplitude and the asymptote were converted from non-negative to unbound and the catch rate was converted from double bound to unbound. The previous conversion was done because we have random effects and these require normal distribution, which is unbound, this removes the difficult assumption of constant variance (Schmettow, 2021).

The model was built to analyse the ToT at a participant level for the accuracy group. The GAMMA family was used because our variable is continuous and has cero as a lower boundary.

FIGURE 7 SCHMETTOW´S DECISION CHART FOR GENERALIZED LINEAR MODELS



The formula used was (*ToT = exp Asym + exp Ampl + logit*$^{-1}$ *(1-Ctch)*^{t}) (Schmettow, 2021). Priors, which are estimations of the lower and upper values made by the researcher had to be used (Schmettow, 2021). For linear models such as learning curves, Brms (used in the models presented in this thesis) do not have an automatic choice of weak priors (Schmettow, 2021), that is why they were estimated. The R code with the details of the model can be found in appendix 6.1.

3.2.2 Results

The model outcome is shown in Figure 8 and fitted responses can be found in Table 2. The amplitude shown is not large, we can see in the coefficients table that the reduction of ToT was around one minute. These results could be a consequence of a poor model fit, therefore we included LOESS to assess the model fit (Figure 9).

FIGURE 8 TOT ACCURACY GROUP

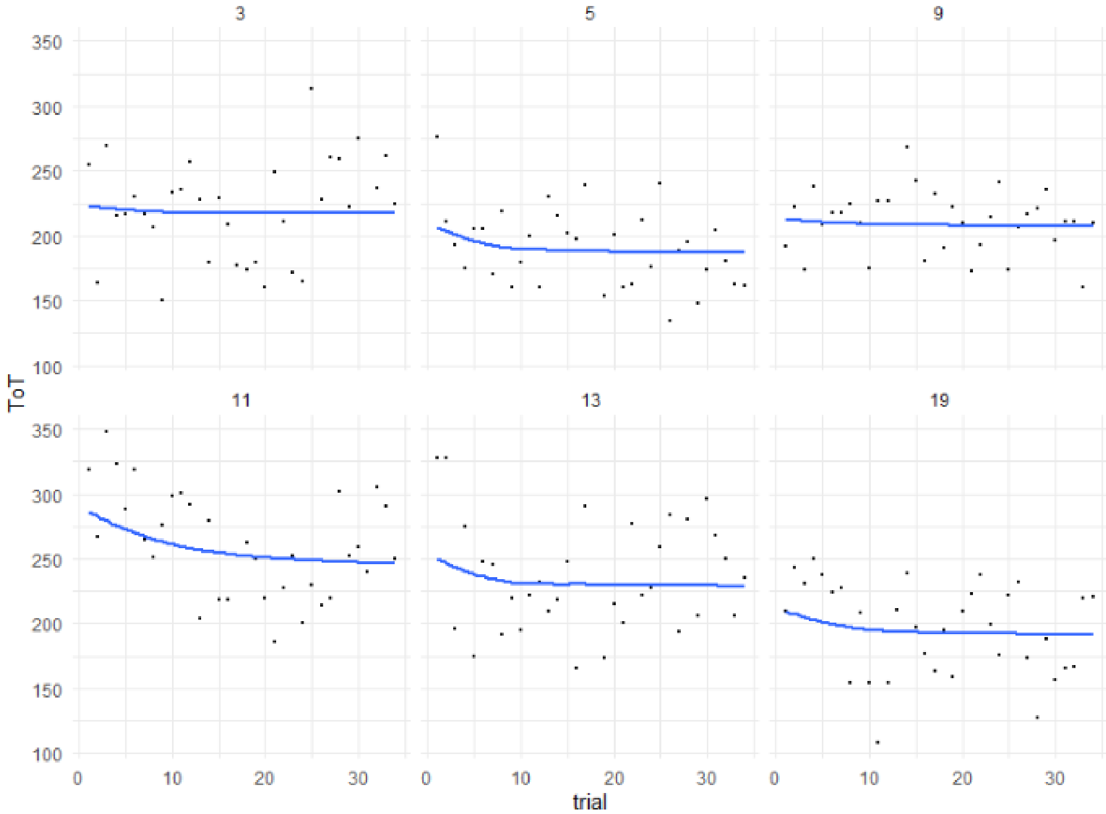
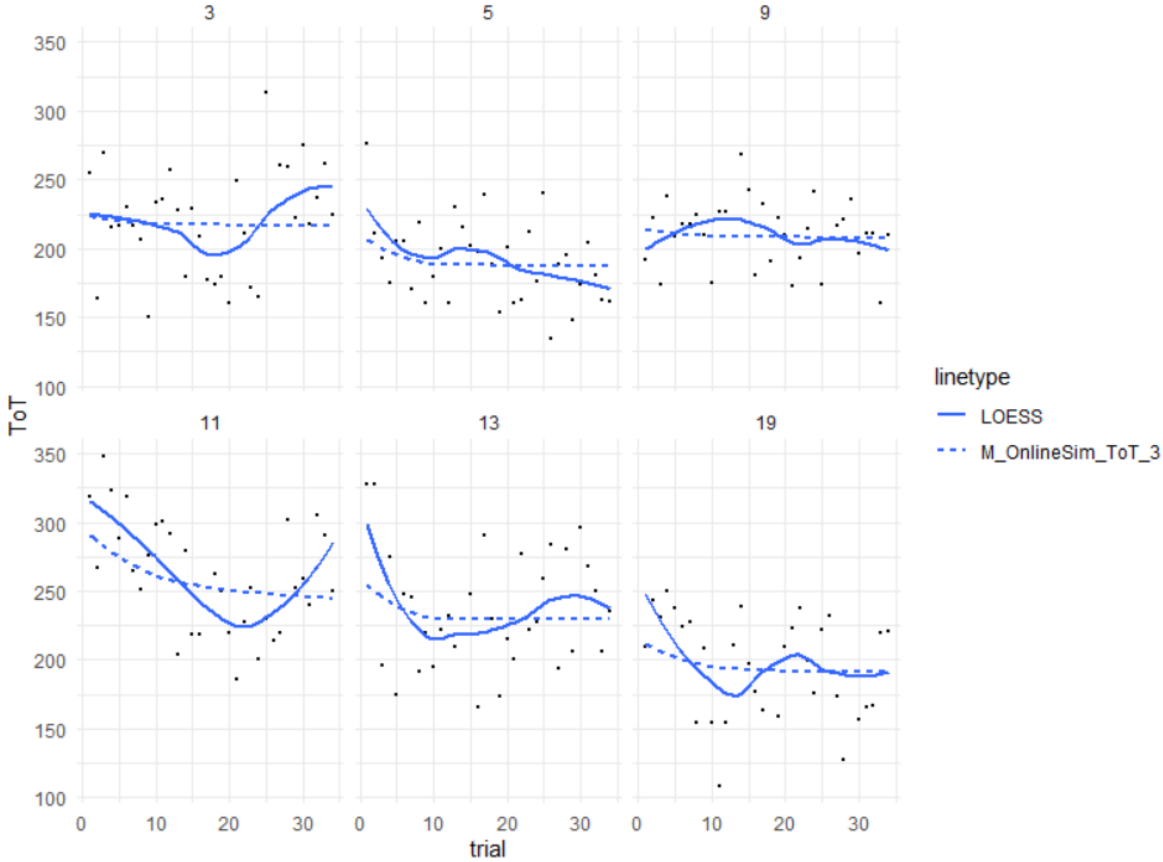


TABLE 2 PARAMETER COEFFICIENT TABLE TOT

Coefficient estimates with 95% credibility limits

Parameter	Center	Lower	Upper
Amplitude	66.8187102	5.1387683	7.561582e+02
Catch rate	0.2712452	0.0025894	5.998450e+00
Asymptote	206.7272108	5.4560123	2.424027e+02

FIGURE 9 MODEL FIT LOESS



The poor model fit shown in Figure 9 outcome could be because of the fatigue factor which participants showed during the last trials of the first session and also because of the forgetting factor or re adaption to the first trials of session 2.

3.2.3 Discussion

From this chapter we can conclude that the research question regarding the possibility of showing learning curves from online driving simulators data analysis is feasible, however, the model fit was not good. From the results section, we can remember that the amplitude dropped after certain trials and then increased again. This can have its origins in two different factors, fatigue or forgetting. Learning curves from trials that were taken on the same day can show that performance starts declining at a certain point and this is caused by fatigue (Schmettow, 2021). Task repetitiveness can reduce a person's physical and cognitive resources and ultimately lead to fatigue (Asadayoobi, et. al., 2021).

In the learning field, forgetting occurs in any of the following situations: (1) when encoding confitions are not similar and retention of material learned, (2) when old learning interferes with new learning, and (3) when there is an interruption in the learning process for a period of time (Jaber, 2006). For this particular case, forgetting may have been caused by the one-week break included in the experiment, and shorter breaks may be recommended. However, there were not enough trials to estimate if the amplitude decreased over time during session 2. If we were able to see more trials we could say that rather than forgetting, the amplitude increase was due to an adaptation phase from the participants.

From this chapter, we can conclude that in order to have accurate data acquisition, too many trials on the same day, together with long breaks, such as one week, could have an impact on the variation of the amplitude of the learning curves. In van Wijk´s experiment (2020), each trial consisted in driving 2 kilometres and each block included 8 trials. Most of the participants show an amplitude increase in the third block which can give us a guide that participants should drive approximately 30 kilometres and then take a short break. For future studies a model that takes into consideration fatigue and learning-forgetting relationship will be a better fit, so the assumptions found in this analysis become more clear.

Although the characteristics of the participants were mentioned in van Wijk´s experiment (2020), it could have been useful to include a category in the data set with the driving experience that each participant had. In the thesis project, it is also mentioned that participants reported feeling exhausted after session 1, however, no formal assessment of workload was done. For the future experiment, a questionnaire including driving experience and workload could serve as good predictors in the analysis. Another limitation of this data set was that there was no performance measure other than ToT that could be analysed. The number of crashes was either 0 or 1, and for analysis purposes, we need a continuous variable.

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3.3 Analysing controlled data

During phase 3 we want to learn if there is a learning outcome that can be plotted in a learning curve from lessons in a driving simulator and if driving experience is transferred to driving simulator performance. The information from 37 participants that performed the driving lessons included in the experiment from the effect of speed episodes on acquiring driving skills study, were analysed. The data obtained for this chapter is from a thesis project which was performed in the BMS laboratory of the University of Twente in a very controlled environment. It took place with a physical driving simulator and not an online driving simulator like in the rest of the chapters in this thesis. The participants performed the trials under the same conditions that were provided by the BMS lab and under the supervision of the experimenters (Voskes, 2020). This experiment consisted of 3 blocks of 12 trials, with a duration of 1.5 minutes approximately. The track was fixed for all trials and there were no other road users, to reduce complexity. All participants started with an accuracy block, then the experimental group did a speed training block in which they were told that the objective was to finish as fast as possible and that making mistakes was not important. The control group did a second accuracy training block. The last block consisted of an accuracy training for both groups (Voskes, 2020).

The data set from the study contained the variables, participant, training, driving experience, ToT, number of lane departures, number of collisions, and trial. For this phase the information about driving experience was available and it was used as a predictor. The variables were analysed as follows:

Independent variables

- Trial: Amount of training.
- Participant: Classification of participants that allowed plotting participant-level learning curves.
- Training: The type of training that the participants performed was identified, this could be accuracy training or speed training.

Predictor

- Experience: Whether participants had driving experience or not was identified in the data set.

Dependent variables

- ToT: Time on task. Time that the participant took to complete the task.
- Number of lane departures: This variable counted the number of errors made on staying on the lane.

3.3.1 Data exploration

The analysis was done only for the participants that performed the accuracy training, since the focus of this study is not the effect of speed episodes. The variables ToT (Figure 10) and number of lane departures (Figure 11) were analysed for the predictor experience. The expectation is that experienced drivers would already start with a lower amplitude in both dependent variables, ToT and number of lane departures. The number of collisions is not included because it was very low, almost none of the participants had collisions and if they did, they would only have one.

FIGURE 10 TOT EXPERIENCED VS INEXPERIENCED ACCURACY GROUP

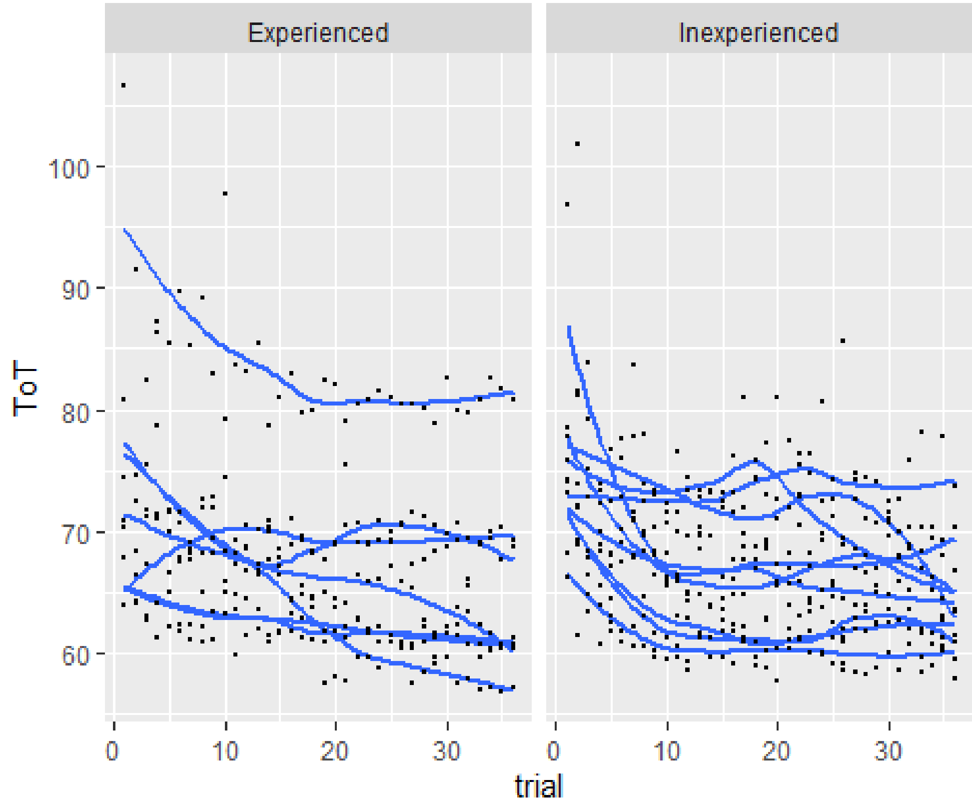
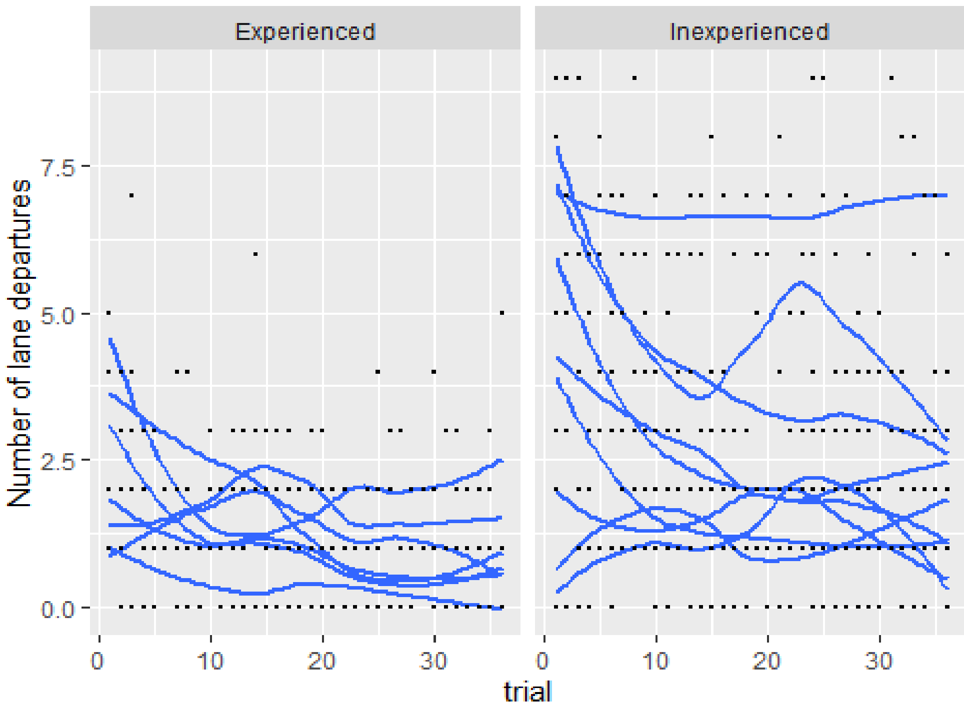


FIGURE 11 NUMBER OF LANE DEPARTURES EXPERIENCED VS INEXPERIENCED ACCURACY GROUP



MODEL ESTIMATION

The analysis was performed using R studio and the code can be found in appendix 6.2. Two statistical multilevel models were built, following the LACY model **(**Pt = expAsym+ expAmpl× logit−1(1−Ctch)t) from Schmettow chapter 9 (2021).

In the previous formula, the parameters have been converted as in model from chapter 3.2.1. The previous conversion was done because it is required for normal distributed random effects (Schmettow, 2021). Priors had to be estimated as in the model from section 3.2.1.

The first model was built to analyse the ToT on participant level, with the predictor experience. The model was built using a GAMMA family, based on the decision chart for generalized linear models (Figure 7) (Schmettow, 2021) and the Lacy formula, from Chapter 9 (Schmettow, 2021). The R code can be consulted in Appendix 6.2

The second model was built to analyse the number of lane departures on participant level, for the predictor experience. The model was built using a Poisson family because we used a discrete measure with no upper boundary (Figure 7) (Schmettow, 2021) and the formula is the same as the one in the previous model, also including experience as a predictor.

3.3.2 Results

Participant level learning curves according to experience, concerning the variable ToT, can be observed in Figure 12. It can be noted how inexperienced participants 5, 12, 20, 24, and 27 start with higher amplitude in ToT, and over the different trials, the amplitude decreases. If we see the differences in amplitude from experience in Table 3, where coefficients are shown we can see that the difference in upper and lower limits is very high and that participant 20 starts as high as 91 seconds. Experienced participants such as 3, 30, 33, and 35 start with a low amplitude, which may be an indicator of transfer from on-the-road driving skills.

FIGURE 12 LEARNING CURVES TOT EXPERIENCED AND INEXPERIENCED ACCURACY TRAINING

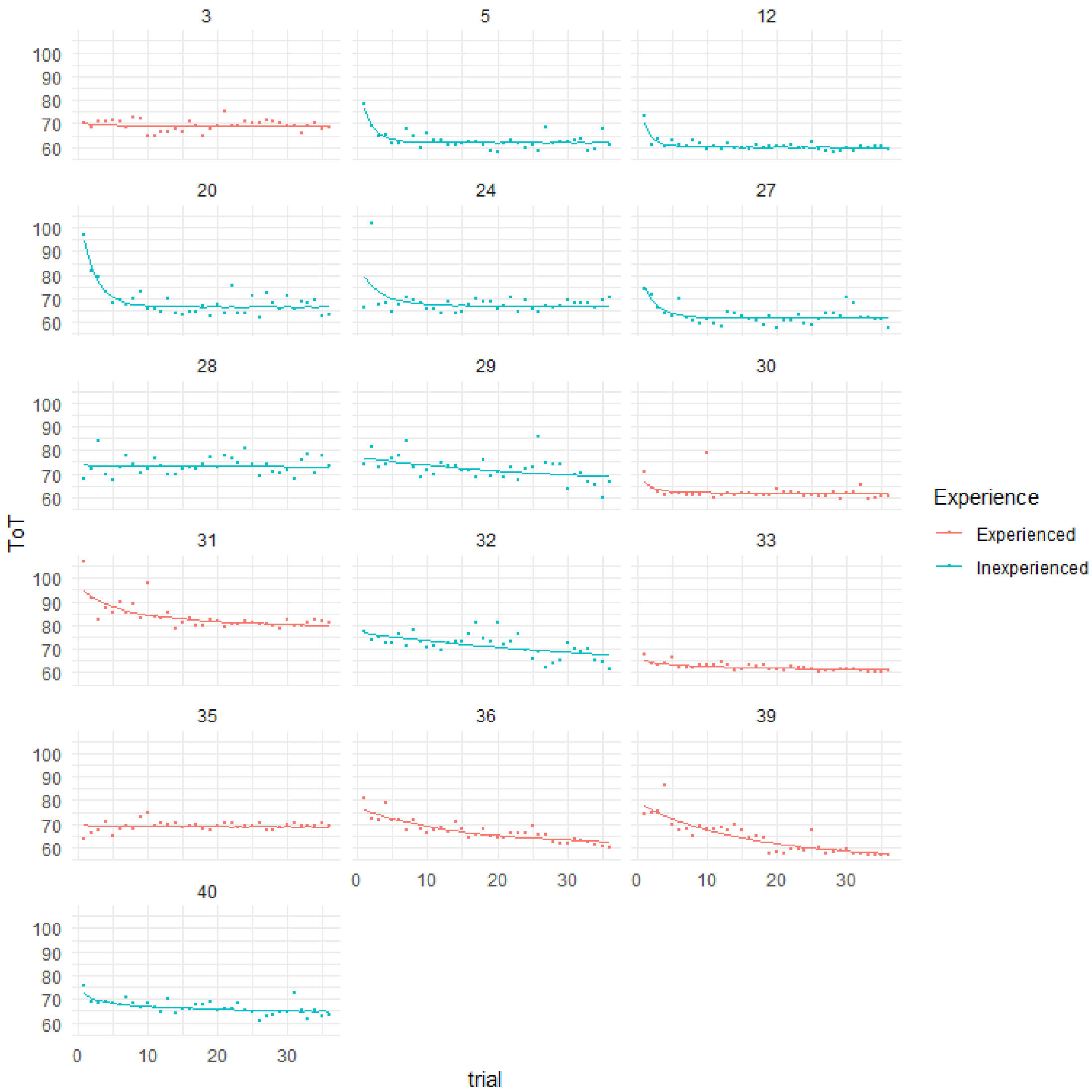


TABLE 3 PARAMETER COEFFICIENT TABLE TOT

Coefficient estimates with 95% credibility limits

Parameter	Center	Lower	Upper
Amplitude	10.1135023	3.9140782	24.0846282
Amplitude Experience	3.6231893	1.2941236	91.6300502
Catch rate	0.4558779	0.0696004	2.1563626
Asymptote	63.0992493	58.6956680	66.8753854

For the second model which included the number of lane departures and the predictor experience, the results in a participant level can be observed in Figure 13 and the coefficients in Table 4. The amplitude difference between experienced and inexperienced participants is not as high as for the model that analysed ToT but there is a difference from the experienced group that shows possible transfer from on the road driving skills.

We can observe close to a flat line in participants 20, 27, 30, 3, 39, and 40, this can be an indicator that tweaks have already been found. The interesting part is that participants that presented this phenomenon are not exclusive to the experienced group which can indicate that there is an overlap of the skills acquired in a simpler task, these skills could have been learned in a simpler task (Gopher & Siegel, 1989). Gaming experience could be a predictor for this skill overlap and it will be interesting to include it in the large-scale experiment.

The data analysis from this data set can give us a good approximation about the model that needs to be used to calculate the learning curves, using the predictors established in the research question like gaming experience, driving experience, and skill level for the experiment. It also shows a difference between experienced drivers and inexperienced drivers in ToT which can also show that there is a transfer from experienced drivers into driving simulators. The previous statement can indicate that there might also be a transfer to online driving simulators.

FIGURE 13 LEARNING CURVES NUMBER OF LANE DEPARTURES EXPERIENCED AND INEXPERIENCED ACCURACY TRAINING

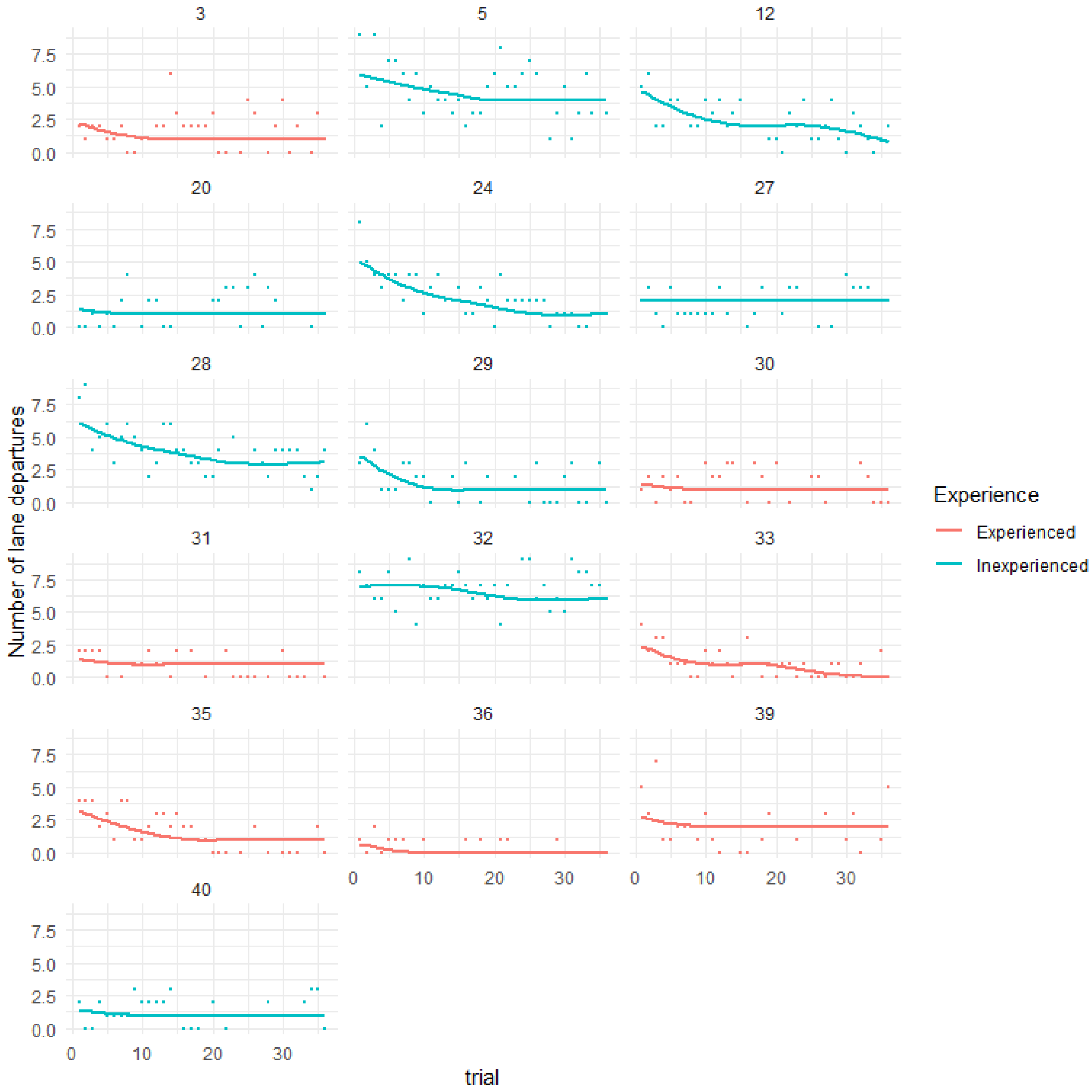


TABLE 4 PARAMETER COEFFICIENT TABLE NUMBER OF LANE DEP.

Coefficient estimates with 95% credibility limits

Parameter	Center	Lower	Upper
Amplitude	2.5318383	0.9921394	5.1191386
Amplitude Experience	1.9859707	0.9251256	5.9198259
Catch rate	1.0038568	0.1599318	5.7525477
Asymptote	1.3281985	0.8608116	2.2932144

3.3.3 Discussion

If we refer back to the research question section where we speculated whether or not learning curves can be observed after performing online driving simulator lessons, this chapter´s analysis provides us with evidence that the learning curve models work in a controlled driving simulator environment. Although this chapter did not include an ODS, rather a physical driving simulator, the formula used showed that there is evidence of learning outcomes and a food fit of the LACY model. This analysis method can be then used in future experiments with ODS. It is important to highlight that for this chapter we had a performance measure which was lane departure, in addition to ToT, and that it is recommended to include these measures for the future experiment. Additionally, driver experience from participants was distinguishable in the data set and this served as a predictor for skill transfer from one scenario to a different one. From all the advantages mentioned, we can conclude that a controlled experiment is preferred for learning curve analysis. However, if we evaluate the bigger picture, performing this kind of experiments is not the most practical approach. Ideally, a controlled experiment could be done in order to test the best way to improve flexibility in Green Dino's system and the rest of the learning analysis could be done with the report obtained from Green Dino´s system updated. This data could have the benefit of having more trials and also a bigger sample for deeper analysis.

Regarding transfer, experienced drivers, in general, showed a lower amplitude in both ToT and number of lane departures. We could say there was a positive transfer shown in this experiment. Positive transfer happens when a person correctly applies knowledge skills and abilities learned in one environment, in this case, on the road driving to a different setting like the simulator (Liu, et al., 2008). In most of the cases, the transfer is expected reversely, happening from the training environment to the real-life situation however this chapter showed us that it can also be the other way. This opens possibilities to explore different scenarios from which drivers can transfer skills from their everyday life to driving performance. For the future experiment using gaming experience, which is an activity that involves visual, spatial, and motor coordination skills (Adams, et. al, 2012) should be considered as a predictor. Research has already shown that there is a positive impact on laparoscopic skills using a Wii console for psychomotor skills (Kulkarni, et. al., 2020), driving skills could also be benefited from this transfer.

Regarding the number of trials, in this experiment, there were 3 blocks of 12 trials, with a duration of 1.5 minutes approximately. Although the driven distance is not measured we can use the driven time to assess the ideal duration per session for the future experiment. In this chapter, there was no clear evidence of fatigue after the completion of all the trials, which leads us to the conclusion that the time spent performing the task was a better fit than the previous chapter. From chapter Analysing semi-controlled data3.2 we concluded that around 30 was the maximum number of trials performed, before reaching fatigue, and if we divide the average time that participants took for the entire session 1, this would be around 45 minutes. Therefore the experiment should aim for sessions of 45 minutes to 1 hour driving before a break. These findings show the importance of having the start time and end time of each log-in session in the Green Dino simulator system.

4 GENERAL DISCUSSION

This study analysed the data from three different scenarios and the results of each analysis helped answer the research question presented in section 2.3. It is possible to get learning curves from a controlled experiment using a driving simulator and there is transfer from experienced drivers from on the road to a simulator which gives us an indication that reverse transfer could also happen (Liu, et al., 2008). Additional to answering the research question this study provided us with guidelines for a future large-scale experiment design for calculating learning curves from online driving simulators, the findings are described in the discussion section of each chapter, however, a summary is presented in Table 5.

TABLE 5 COMPARISON 3 DATA SETS SUMMARY

	Advantages	**Limitations**	**Proposal exp.**
Uncontrolled data set	Large sample. More trials available. Variety of lessons ranging from low complexity to high complexity. Real representation of a course. Learner freedom to select what to learn and for how long to learn it.	Data report not suitable for learning curve analysis. No control over lessons performed. No control of driving time per session.	Lessons should follow a certain order. Availability of ToT. Availability of individual task scores. Availability of time per log-in.
Semi controlled data set	Performance of the same trials in the same order according to group. Remote monitoring, without the need for a laboratory environment.	No predictors available. Experiment took too long in the first session causing fatigue. One-week break with possible learning-forgetting. Not enough trials.	Driving sessions should not be longer than an hour. The break between one session and another should be established. Include workload assessment.

Controlled data set	Performance measure included (number of lane departures). Driving experience information available	A not practical approach for large samples.	Include predictors such as driving or gaming experience.

Simulators have shown that it is possible to replace a certain amount of training in the medical areas such as the performance of bronchoscopy operations, in which students in one hour of training basic bronchoscopy and familiarity with airway anatomy were effectively taught (Blum, et al., 2004). Similar results have been shown in laparoscopy training simulator studies in which speed episodes were used and time pressure improved the performance in simulator-based training (Weimer, 2019). Driving simulators show similar results, and this can be observed in the results of chapter 3.3.2, in which not only learning curves can be observed, the transfer from experienced drivers is also visible.

There have not been many studies that look into the learning effect of ODS training, however, it is thought that low-fidelity simulators or simulators that intentionally alter the driving experience may be more effective than those that focus on a more precise representation of the driving setting and vehicle dynamics (Lee J. , 2004). In this study a low fidelity simulator did not show to be more effective than a driving simulator, however, this may have been due to the poor model fit. The future experiment should focus on addressing the analysis of learning curves from ODS and identify the skills that can be transferred. Even the most sophisticated driving simulators do not deliver all of the visual, vestibular, and proprioceptive changes that occur when the steering wheel is turned and the vehicle changes course (Charles, 2003), therefore a hybrid model proposal will be preferred for future new drivers.

According to Gopher (1989), a complex task can be decomposed into simple subtasks. The skills that are learned during a simple situation, can then be implemented in a more complex situation (Kappler W., 2008). In other words, tweaks can be trained separately

(Schmettow, 2021). This was the possible reason for the observations made in section 3.3.2 where there were no more tweaks found but the performance was good. This leads us to think that not only driving experience can be transferred as shown in section 3.3.2 but skills learned in a different environment such as gaming could be transferable. The assessment of gaming experience in the large-scale experiment could contribute to proving this idea.

Learning measurement tends to be retrospective as if measuring should be done only after a training program is completed rather than using measurement data to achieve a successful training program (Spitzer, 2005). If the large-scale experiment results successful, and data can be acquired including all the recommendations made in this thesis then the measurement can be done at the moment of the training performance, since measuring is most powerful when used early and often (Spitzer, 2005). As mentioned in section 3.1.3, learning curves can not only be used for measurement, but they can predict future performance, giving us the possibility to predict the learning rate at a participant level (Schmettow, 2021).

Following the prediction proposal made for the learning rate, it could also be useful to predict the number of kilometres driven before fatigue at an individual level. In section 3.2.2, we discovered that the performance declined after an hour and that this could be linked to fatigue. Since the main purpose of this study is to improve driving performance in young drivers, developments can be made so that fatigue can be tracked and participants get a report of the number of kilometres they can drive safely without being affected by fatigue. Since mental fatigue onset is seen to have variable patterns amongst the subjects performing the same task and under the same conditions (Wang, et al., 2018), this could be analysed individually, tracking their performance. This way online driving simulators could offer two additional features to the already provided which would be estimating the time each student will take to complete the training on an individual level and the driving safe distance before fatigue so that participants know their limits.

CONCLUSION

Learning curves from a controlled experiment data set can be calculated. There is transfer from experienced drivers to driving simulators and there might also be transfer from other activities such as gaming. A larger-scale experiment with the lessons learned in this study should be implemented to demonstrate that learning curves can be calculated from online driving simulators too.

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6 APPENDIX

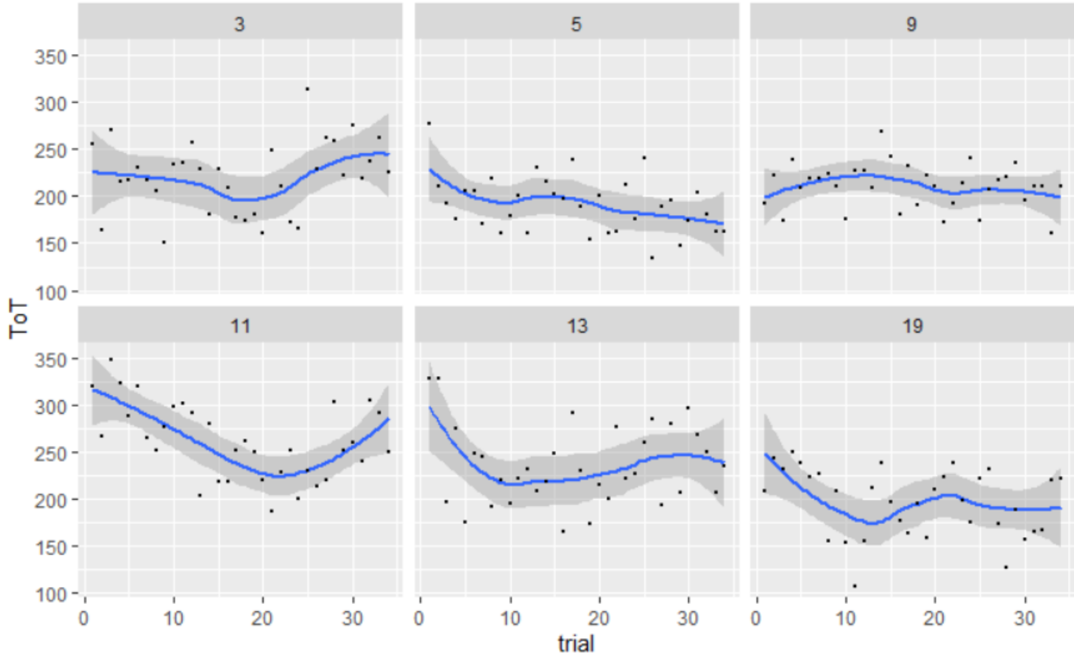
6.1 R code analysis phase 2

OnlineSimulator_Thesis

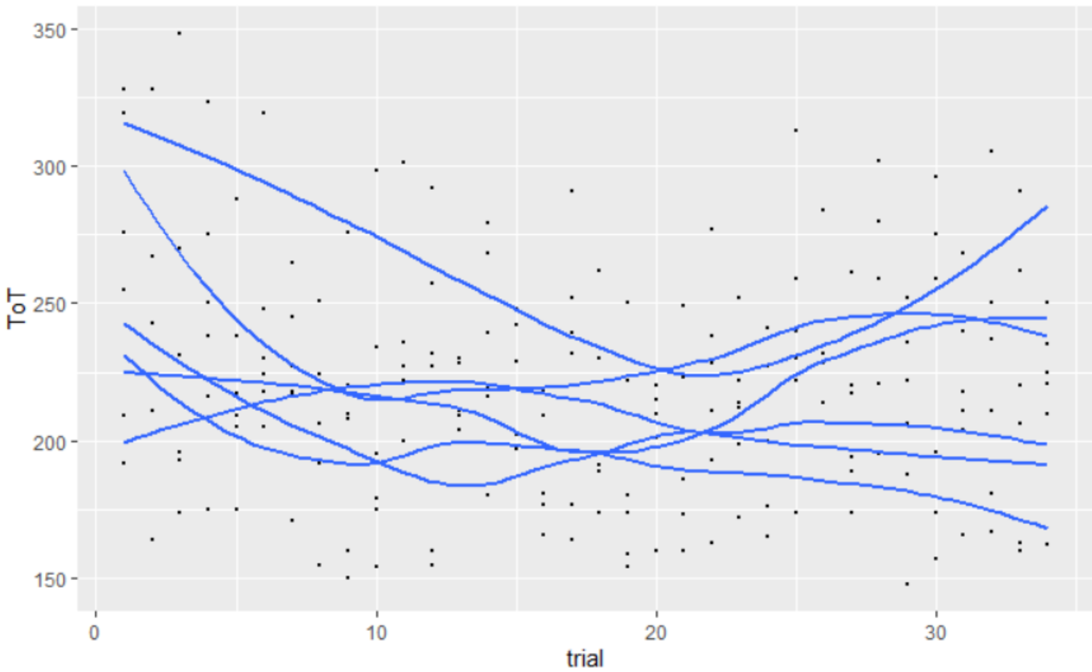
Estefania Villalobos

15-12-2021

```
D_OST <- read_csv("~/HFE/Thesis/Data Online Simulator Lara/AH_1SECONDS_
1.csv")

##
## -- Column specification --------------------------------------------
------------
## cols(
##   Part = col_double(),
##   Training = col_character(),
##   Block = col_double(),
##   block = col_double(),
##   Blk_type = col_character(),
##   trial = col_double(),
##   crashes = col_double(),
##   speed = col_double(),
##   steer = col_double(),
##   ToT = col_double()
## )

D_OST_ACC <- D_OST %>%
  filter(Training == "Accuracy")

D_OST_ACC %>%
    ggplot(aes(x = trial, y = ToT)) +
    geom_smooth(se = F, scale = "free_y") +
  geom_smooth() +
  geom_point( size= .2)+
    facet_wrap(~Part)

## Warning: Ignoring unknown parameters: scale

## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```




```
D_OST_ACC %>%
  filter(ToT> 140) %>%
    ggplot(aes(x = trial, y = ToT, group = Part)) +
    geom_smooth(se = F)   +
geom_point(size = .2)+

## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



```
D_OST_ACC <-
D_OST%>%
filter(Training == "Accuracy")

D_OST_ACC %>% sample_n(10)
```

Part	Training	Block	block	Blk_type	trial	crashes	speed	steer	ToT
11	Accuracy	4	4	Accuracy	27	0	9.423522	-0.021820	220
11	Accuracy	2	2	Accuracy	10	0	6.662972	0.005643	298
9	Accuracy	4	4	Accuracy	26	0	9.707790	0.013384	207
3	Accuracy	4	4	Accuracy	34	0	9.006537	0.004862	225
11	Accuracy	1	1	Accuracy	8	0	7.997299	-0.015800	251
13	Accuracy	1	1	Accuracy	2	0	6.099343	0.019383	328
11	Accuracy	2	2	Accuracy	13	0	9.810690	-0.019190	204
3	Accuracy	1	1	Accuracy	5	0	9.370382	-0.010060	217
11	Accuracy	3	3	Accuracy	17	0	8.026260	-0.003210	252
13	Accuracy	1	1	Accuracy	4	0	9.361368	0.007796	275

```
F_lacy_prior <- c(set_prior("normal(5.25, 0.576)", nlpar = "ampl"),
set_prior("normal(-2.76, 2.07)", nlpar = "ctch"),
set_prior("normal(1.84, 0.576)", nlpar = "asym"))

F_lacy <- formula(ToT ~ exp(asym) + exp(ampl) * inv_logit((1-ctch))^trial)
```

```
F_lacy_ef_ToT <- list(formula(ampl ~ 1|Part),
              formula(ctch ~ 1|Part),
              formula(asym ~ 1|Part))

F_lacy_prior_1 <- c(set_prior("normal(5.25, 0.875)", nlpar = "ampl"),
set_prior("normal(-2.76, 2.07)", nlpar = "ctch"),
set_prior("normal(1.84, 0.576)", nlpar = "asym"))


F_lacy_prior_3 <- c(set_prior("normal(5.25, 1.05)", nlpar = "ampl"),
set_prior("normal(-2.76, 2.07)", nlpar = "ctch"),
set_prior("normal(1.84, 0.875)", nlpar = "asym"))


F_lacy_prior_4 <- c(set_prior("normal(5.25, 1.43)", nlpar = "ampl"),
set_prior("normal(-2.76, 2.07)", nlpar = "ctch"),
set_prior("normal(1.84, 1.05)", nlpar = "asym"))


F_lacy_prior_5 <- c(set_prior("normal(5.25, 1.76)", nlpar = "ampl"),
set_prior("normal(-2.76, 2.07)", nlpar = "ctch"),
set_prior("normal(1.84, 1.43)", nlpar = "asym"))


M_OnlineSim_ToT_3 <-
D_OST_ACC %>%
brm(bf(F_lacy,
flist = F_lacy_ef_ToT,
nl = T),
prior = F_lacy_prior_5,
family = Gamma(link = identity), iter = 4000,
data = .)

## Compiling Stan program...

## Start sampling

## Warning: There were 771 divergent transitions after warmup. See
## http://mc-stan.org/misc/warnings.html#divergent-transitions-after-wa
rmup
## to find out why this is a problem and how to eliminate them.

## Warning: There were 8 transitions after warmup that exceeded the max
imum treedepth. Increase max_treedepth above 10. See
## http://mc-stan.org/misc/warnings.html#maximum-treedepth-exceeded

## Warning: Examine the pairs() plot to diagnose sampling problems

## Warning: Bulk Effective Samples Size (ESS) is too low, indicating po
sterior means and medians may be unreliable.
```

```
## Running the chains for more iterations may help. See
## http://mc-stan.org/misc/warnings.html#bulk-ess

## Warning: Tail Effective Samples Size (ESS) is too low, indicating po
sterior variances and tail quantiles may be unreliable.
## Running the chains for more iterations may help. See
## http://mc-stan.org/misc/warnings.html#tail-ess

coef(M_OnlineSim_ToT_3, mean.func = exp)

## Warning: `funs()` was deprecated in dplyr 0.8.0.
## Please use a list of either functions or lambdas:
##
##   # Simple named list:
##   list(mean = mean, median = median)
##
##   # Auto named with `tibble::lst()`:
##   tibble::lst(mean, median)
##
##   # Using lambdas
##   list(~ mean(., trim = .2), ~ median(., na.rm = TRUE))
```

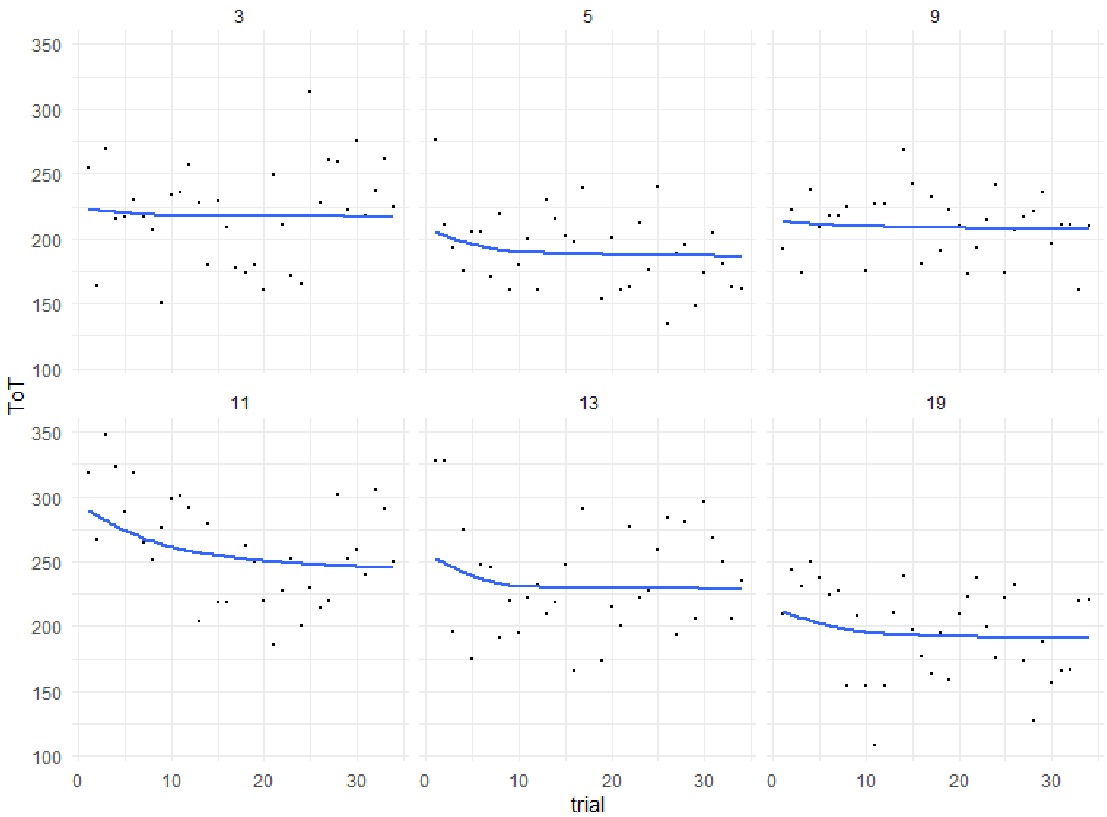
Coefficient estimates with 95% credibility limits

parameter	type	nonlin	re_factor	re_entity	center	lower	upper
b_ampl_Intercept	fixef	ampl	NA	NA	66.8187102	5.1387683	7.561582e+02
b_ctch_Intercept	fixef	ctch	NA	NA	0.2712452	0.0025894	5.998450e+00
b_asym_Intercept	fixef	asym	NA	NA	206.7272108	5.4560123	2.424027e+02
r_Part__ampl[3,Intercept]	ranef	ampl	Part	3	0.6884716	0.0000000	6.902572e+01
r_Part__ampl[5,Intercept]	ranef	ampl	Part	5	0.9771514	0.0000000	3.966559e+03
r_Part__ampl[9,Intercept]	ranef	ampl	Part	9	0.6306424	0.0000000	5.588153e+01
r_Part__ampl[11,Intercept]	ranef	ampl	Part	11	1.0974194	0.0000000	2.815917e+01
r_Part__ampl[13,Intercept]	ranef	ampl	Part	13	1.0588502	0.0000000	5.774518e+01

r_Part__ampl[19,Intercept]	ranef	ampl	Part	19	0.8737899	0.0000000	4.363443e+01
r_Part__ctch[3,Intercept]	ranef	ctch	Part	3	1.8018768	0.0000000	4.466409e+24
r_Part__ctch[5,Intercept]	ranef	ctch	Part	5	2.7228652	0.0000000	1.762075e+28
r_Part__ctch[9,Intercept]	ranef	ctch	Part	9	1.5139795	0.0000000	3.497092e+24
r_Part__ctch[11,Intercept]	ranef	ctch	Part	11	0.6194926	0.0000000	1.591017e+19
r_Part__ctch[13,Intercept]	ranef	ctch	Part	13	2.1170238	0.0000000	7.155064e+21
r_Part__ctch[19,Intercept]	ranef	ctch	Part	19	1.6958534	0.0000000	5.115972e+25
r_Part__asym[3,Intercept]	ranef	asym	Part	3	1.0348680	0.5996326	1.370932e+00
r_Part__asym[5,Intercept]	ranef	asym	Part	5	0.9033279	0.3785957	1.119912e+00
r_Part__asym[9,Intercept]	ranef	asym	Part	9	0.9863194	0.4377972	1.248524e+00
r_Part__asym[11,Intercept]	ranef	asym	Part	11	1.1462921	0.8476568	2.766312e+00
r_Part__asym[13,Intercept]	ranef	asym	Part	13	1.0942734	0.7394181	1.675209e+00
r_Part__asym[19,Intercept]	ranef	asym	Part	19	0.9223117	0.3134455	1.152089e+00

```
P_M_OnlineSim_ToT_3 <- posterior(M_OnlineSim_ToT_3)
PP_M_OnlineSim_ToT_3 <- post_pred(M_OnlineSim_ToT_3)

T_pred_M_OnlineSim_ToT_3 <- PP_M_OnlineSim_ToT_3 %>%
  group_by(Obs) %>%
  summarize(center = median(value))

D_OST_ACC$M_OnlineSim_ToT_3 <- T_pred_M_OnlineSim_ToT_3$center
D_OST_ACC$M_OnlineSim_ToT_3_resid <- D_OST_ACC$ToT - D_OST_ACC$M_Online
Sim_ToT_3

D_M_OnlineSim_ToT_3 <-
  as_tibble(M_OnlineSim_ToT_3$data) %>%
  mutate(M_OnlineSim_ToT_3 = T_pred_M_OnlineSim_ToT_3$center)

D_OST_ACC %>%
  ggplot(aes(x = trial, y = ToT)) +
```

```
  facet_wrap(~ Part) +
  geom_point(size = .2) +
  geom_smooth(aes(y = M_OnlineSim_ToT_3), se = F) +
  theme_minimal()

## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



6.2 R code analysis phase 3

Voskes thesis data

Estefania Villalobos

16-12-2021

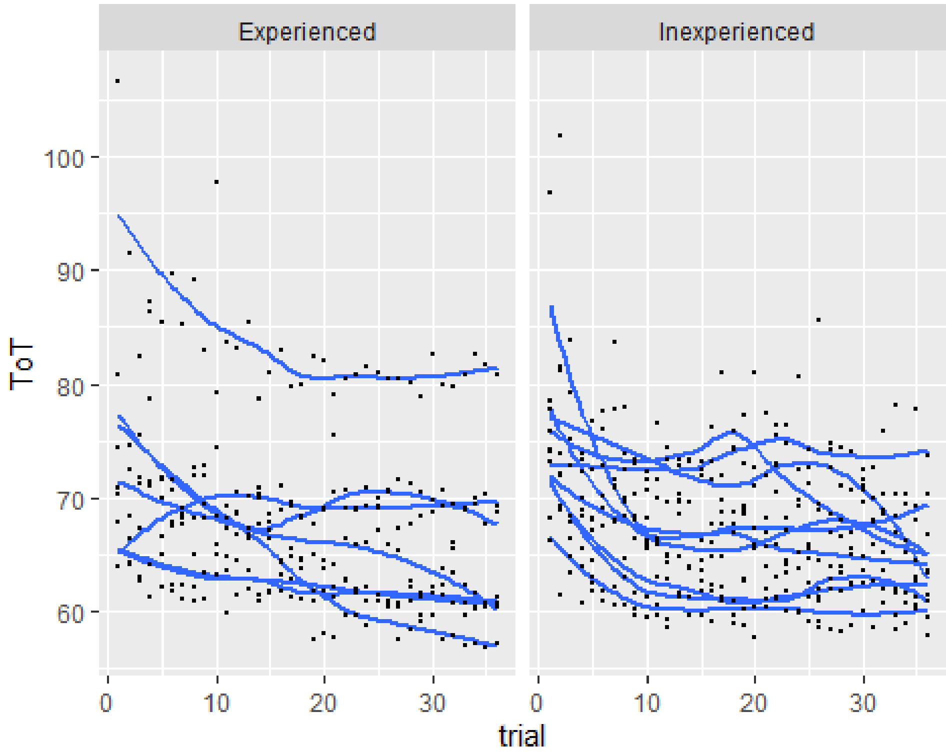
```
D_SimPar <- read_csv("~/HFE/Thesis/Data Driving Simulator/Data_Bachelor
_Master.csv")

##
## -- Column specification ------------------------------------------
------------
## cols(
##   Participant = col_double(),
##   ToT = col_double(),
##   Nld = col_double(),
```

```
##   Nc = col_double(),
##   trial = col_double(),
##   Training = col_character(),
##   Experience = col_character()
## )
D_SimPar %>% sample_n(10)
```

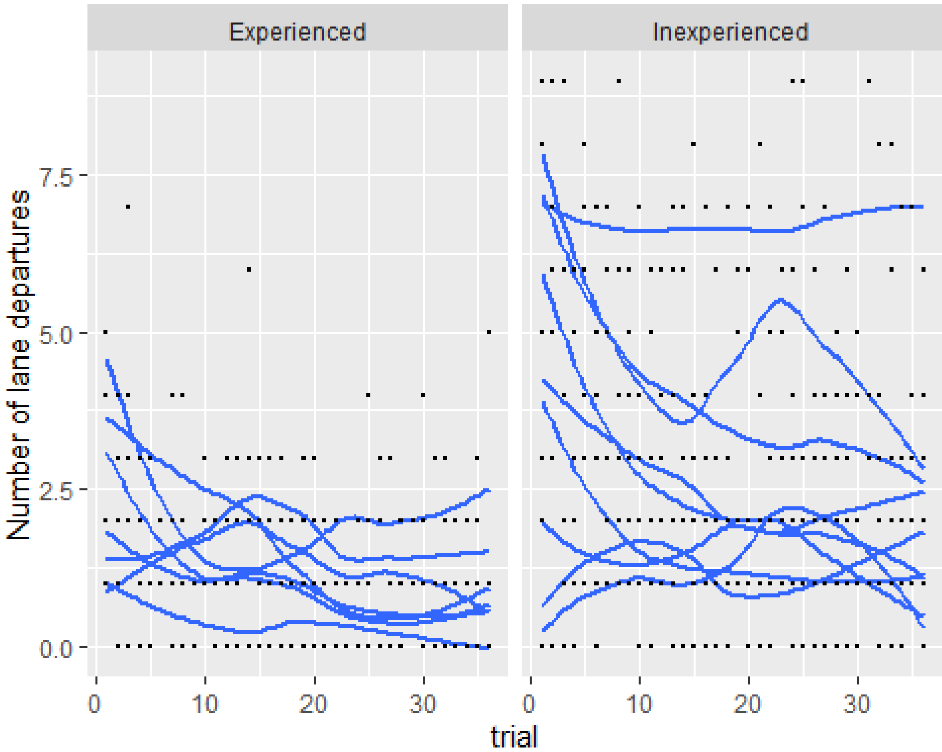
Participant	ToT	Nld	Nc	trial	Training	Experience
18	51.21	NA	NA	16	Speed	Experienced
9	47.69	NA	NA	17	Speed	Inexperienced
18	48.00	NA	NA	23	Speed	Experienced
33	60.42	0	0	26	Accuracy	Experienced
12	61.49	2	0	13	Accuracy	Inexperienced
32	72.90	4	0	9	Accuracy	Inexperienced
36	62.31	0	0	33	Accuracy	Experienced
20	72.61	0	0	27	Accuracy	Inexperienced
18	50.39	NA	NA	22	Speed	Experienced
17	100.93	0	0	1	Speed	Experienced

```
D_SimPar %>%
    filter(Training == "Accuracy") %>%
    ggplot(aes(x = trial, y = ToT, group = Participant)) +
    geom_smooth(se = F) +
  geom_point(size = .2) +
    facet_wrap(~Experience)
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```


Participant	ToT	Nld	Nc	trial	Training	Experience
18	51.21	NA	NA	16	Speed	Experienced
9	47.69	NA	NA	17	Speed	Inexperienced
18	48.00	NA	NA	23	Speed	Experienced
33	60.42	0	0	26	Accuracy	Experienced
12	61.49	2	0	13	Accuracy	Inexperienced
32	72.90	4	0	9	Accuracy	Inexperienced
36	62.31	0	0	33	Accuracy	Experienced
20	72.61	0	0	27	Accuracy	Inexperienced
18	50.39	NA	NA	22	Speed	Experienced
17	100.93	0	0	1	Speed	Experienced




```
D_SimPar %>%
    filter(Training == "Accuracy") %>%
    ggplot(aes(x = trial, y = Nld, group = Participant)) +
    geom_smooth(se = F) +
  geom_point(size = .2) +
  labs(y= "Number of lane departures") +
    facet_wrap(~Experience)

## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```




```
D_SimParAcc <-
  D_SimPar %>%
  filter(Training == "Accuracy")

D_SimParAcc %>% sample_n(10)
```

Participant	ToT	Nld	Nc	trial	Training	Experience
12	63.01	4	0	5	Accuracy	Inexperienced
40	63.40	2	0	28	Accuracy	Inexperienced
31	82.39	2	0	3	Accuracy	Experienced
27	61.97	3	1	33	Accuracy	Inexperienced
33	62.70	1	0	22	Accuracy	Experienced
3	67.58	2	0	19	Accuracy	Experienced
27	57.64	2	1	20	Accuracy	Inexperienced
39	57.01	2	0	34	Accuracy	Experienced
29	74.32	0	0	28	Accuracy	Inexperienced
40	62.58	3	0	35	Accuracy	Inexperienced

MODEL ESTIMATION

```
F_lacy_prior <- c(set_prior("normal(5.25, 0.576)", nlpar = "ampl"),
                  set_prior("normal(-2.76, 2.07)", nlpar = "ctch"),
                  set_prior("normal(1.84, 0.576)", nlpar = "asym"))

F_lacy_prior_1 <- c(set_prior("normal(5.25, 0.875)", nlpar = "ampl"),
                  set_prior("normal(-2.76, 2.07)", nlpar = "ctch"),
                  set_prior("normal(1.84, 0.576)", nlpar = "asym"))
```

```r
F_lacy_prior_2 <- c(set_prior("normal(5.25, 1.05)", nlpar = "ampl"),
                    set_prior("normal(-2.76, 2.07)", nlpar = "ctch"),
                    set_prior("normal(1.84, 0.576)", nlpar = "asym"))

F_lacy <- formula(ToT ~ exp(asym) + exp(ampl) * inv_logit((1-ctch))^tri
al)

F_acy_ef_1 <- list(formula(ampl ~ 1|Participant),
                 formula(ctch ~ 1|Participant),
                 formula(asym ~ 1|Participant))

F_acy_ef_4 <- list(formula(ampl ~ 1 + Experience + (1|Participant)),
                   formula(ctch ~ 1 + (1|Participant)),
                   formula(asym ~ 1 + (1|Participant)))

M_7 <-
  D_SimParAcc %>%
  brm(bf(F_lacy,
         flist = F_acy_ef_4,
         nl = T),
      prior = F_lacy_prior_1,
      family = Gamma(link = identity),
      iter = 4000,
      data = .)

## Compiling Stan program...

## Start sampling

## Warning: There were 323 divergent transitions after warmup. See
## http://mc-stan.org/misc/warnings.html#divergent-transitions-after-wa
rmup
## to find out why this is a problem and how to eliminate them.

## Warning: Examine the pairs() plot to diagnose sampling problems

## Warning: Bulk Effective Samples Size (ESS) is too low, indicating po
sterior means and medians may be unreliable.
## Running the chains for more iterations may help. See
## http://mc-stan.org/misc/warnings.html#bulk-ess

## Warning: Tail Effective Samples Size (ESS) is too low, indicating po
sterior variances and tail quantiles may be unreliable.
## Running the chains for more iterations may help. See
## http://mc-stan.org/misc/warnings.html#tail-ess

coef(M_7, mean.func = exp)

## Warning: `funs()` was deprecated in dplyr 0.8.0.
## Please use a list of either functions or lambdas:
##
##   # Simple named list:
##   list(mean = mean, median = median)
```

```
##
##   # Auto named with `tibble::lst()`:
##   tibble::lst(mean, median)
##
##   # Using lambdas
##   list(~ mean(., trim = .2), ~ median(., na.rm = TRUE))
```

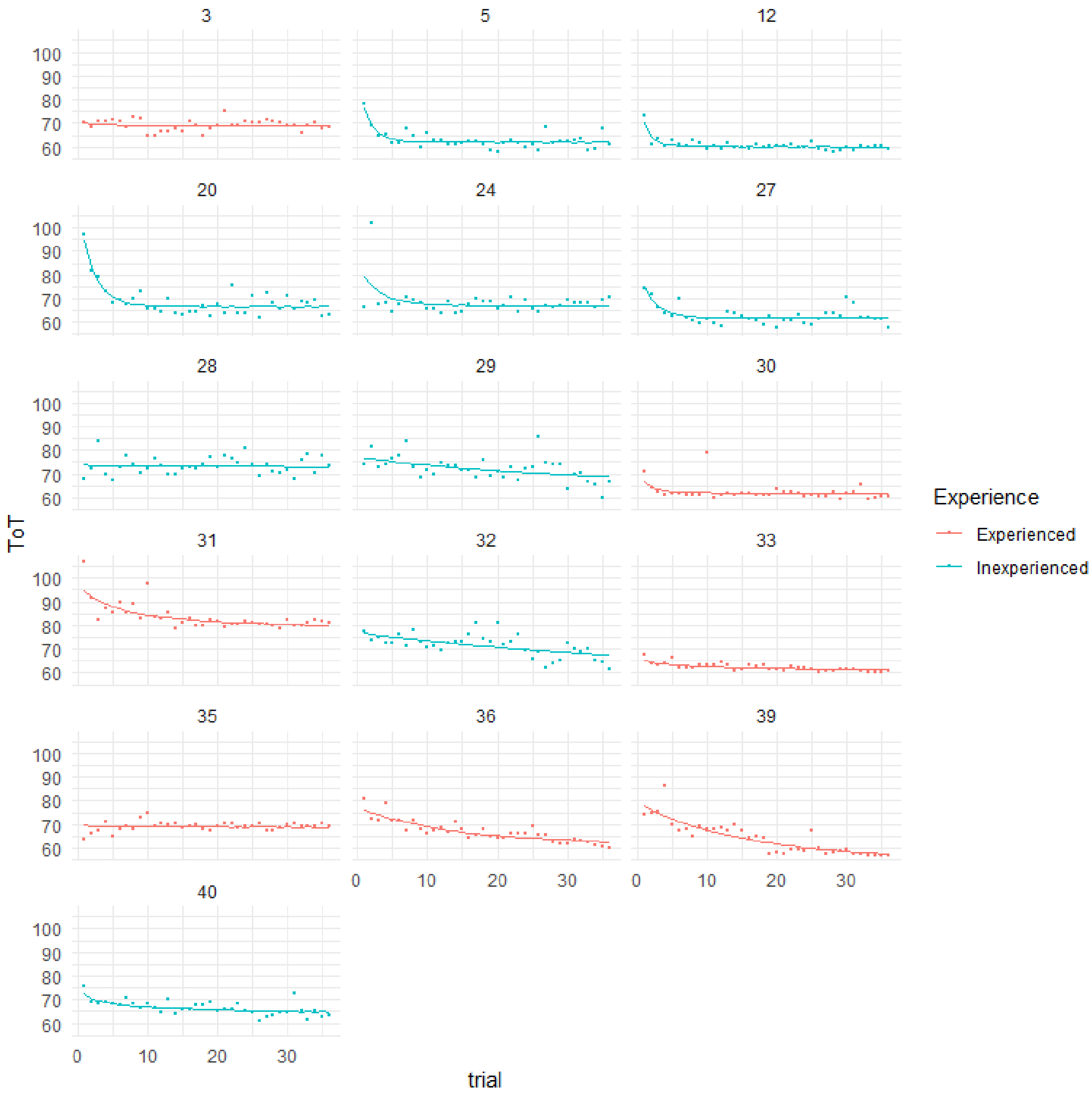
Coefficient estimates with 95% credibility limits

parameter	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
b_ampl_Intercept	fixef	ampl	Intercept	NA	NA	10.1135023	3.9140782	24.0846282
b_ampl_ExperienceInexperienced	fixef	ampl	ExperienceInexperienced	NA	NA	3.6231893	1.2941236	91.6300502
b_ctch_Intercept	fixef	ctch	Intercept	NA	NA	0.4558779	0.0696004	2.15636 26
b_asym_Intercept	fixef	asym	Intercept	NA	NA	63.0992493	58.6956680	66.8753854
r_Participant__ampl[3,Intercept]	ranef	ampl	Intercept	Participant	3	0.5569444	0.0012394	2.2169029
r_Participant__ampl[5,Intercept]	ranef	ampl	Intercept	Participant	5	0.8734891	0.0271452	2.5656400
r_Participant__ampl[12,Intercept]	ranef	ampl	Intercept	Participant	12	0.8223005	0.0070906	3.5950121
r_Participant__ampl[20,Intercept]	ranef	ampl	Intercept	Participant	20	1.3567194	0.0389326	2.8903655
r_Participant__ampl[24,Intercept]	ranef	ampl	Intercept	Participant	24	0.5202453	0.0092983	1.2391477
r_Participant__ampl[27,Intercept]	ranef	ampl	Intercept	Participant	27	0.6243462	0.0087120	1.6014258
r_Participant__ampl[28,Intercept]	ranef	ampl	Intercept	Participant	28	0.3391476	0.0000019	1.6712646
r_Participant__ampl[29,Intercept]	ranef	ampl	Intercept	Participant	29	0.4372827	0.0050622	1.0550676
r_Participant__ampl[30,Intercept]	ranef	ampl	Intercept	Participant	30	0.9981152	0.1550618	5.9293037
r_Participant__ampl[31,Intercept]	ranef	ampl	Intercept	Participant	31	2.0014889	0.7621021	7.3405729
r_Participant__ampl[32,Intercept]	ranef	ampl	Intercept	Participant	32	0.5103622	0.0135565	1.1777595
r_Participant__ampl[33,Intercept]	ranef	ampl	Intercept	Participant	33	0.6510922	0.0136682	2.3244230
r_Participant__ampl[35,Intercept]	ranef	ampl	Intercept	Participant	35	0.4960025	0.0000096	1.9903495
r_Participant__ampl[36,Intercept]	ranef	ampl	Intercept	Participant	36	1.6048091	0.6441812	4.2320839

r_Participant__ampl[39,Intercept]	ranef	ampl	Intercept	Participant	39	2.3956117	1.0032021	6.2293693
r_Participant__ampl[40,Intercept]	ranef	ampl	Intercept	Participant	40	0.3436277	0.0141251	1.4181879
r_Participant__ctch[3,Intercept]	ranef	ctch	Intercept	Participant	3	1.7187571	0.0031952	344.1849064
r_Participant__ctch[5,Intercept]	ranef	ctch	Intercept	Participant	5	6.4794980	0.9511299	55.8508829
r_Participant__ctch[12,Intercept]	ranef	ctch	Intercept	Participant	12	9.6106438	0.9614995	153.4388132
r_Participant__ctch[20,Intercept]	ranef	ctch	Intercept	Participant	20	4.0671348	0.7430735	26.1227039
r_Participant__ctch[24,Intercept]	ranef	ctch	Intercept	Participant	24	2.5644106	0.4847975	19.1116912
r_Participant__ctch[27,Intercept]	ranef	ctch	Intercept	Participant	27	3.7547795	0.6824902	30.1253354
r_Participant__ctch[28,Intercept]	ranef	ctch	Intercept	Participant	28	0.2440474	0.0007559	1179.3348269
r_Participant__ctch[29,Intercept]	ranef	ctch	Intercept	Participant	29	0.1769017	0.0236690	1.1521655
r_Participant__ctch[30,Intercept]	ranef	ctch	Intercept	Participant	30	4.4085407	0.1072467	82.8489901
r_Participant__ctch[31,Intercept]	ranef	ctch	Intercept	Participant	31	0.7542594	0.0718870	17.7982982
r_Participant__ctch[32,Intercept]	ranef	ctch	Intercept	Participant	32	0.1447862	0.0240775	0.9482507
r_Participant__ctch[33,Intercept]	ranef	ctch	Intercept	Participant	33	0.7940507	0.0419092	39.3272529
r_Participant__ctch[35,Intercept]	ranef	ctch	Intercept	Participant	35	0.4946106	0.0010149	669.6269164
r_Participant__ctch[36,Intercept]	ranef	ctch	Intercept	Participant	36	0.4737303	0.0742496	3.2620247
r_Participant__ctch[39,Intercept]	ranef	ctch	Intercept	Participant	39	0.4032781	0.0777637	2.7156924
r_Participant__ctch[40,Intercept]	ranef	ctch	Intercept	Participant	40	0.8927545	0.0529291	40.3678685
r_Participant__asym[3,Intercept]	ranef	asym	Intercept	Participant	3	1.0715803	0.9123291	1.1578676
r_Participant__asym[5,Intercept]	ranef	asym	Intercept	Participant	5	0.9828632	0.9238044	1.0566954
r_Participant__asym[12,Intercept]	ranef	asym	Intercept	Participant	12	0.9525289	0.8964431	1.0251785
r_Participant__asym[20,Intercept]	ranef	asym	Intercept	Participant	20	1.0571516	0.9932321	1.1367424
r_Participant__asym[24,Intercept]	ranef	asym	Intercept	Participant	24	1.0626894	0.9997595	1.1437049

r_Participant__asym[27,Intercept]	ranef	asym	Intercept	Participant	27	0.9806637	0.9223944	1.0547588
r_Participant__asym[28,Intercept]	ranef	asym	Intercept	Participant	28	1.1045078	0.8603339	1.2139537
r_Participant__asym[29,Intercept]	ranef	asym	Intercept	Participant	29	0.9934981	0.8201917	1.1136588
r_Participant__asym[30,Intercept]	ranef	asym	Intercept	Participant	30	0.9746955	0.9005159	1.0486361
r_Participant__asym[31,Intercept]	ranef	asym	Intercept	Participant	31	1.2526204	0.9827914	1.3713493
r_Participant__asym[32,Intercept]	ranef	asym	Intercept	Participant	32	0.9469367	0.7925076	1.0644520
r_Participant__asym[33,Intercept]	ranef	asym	Intercept	Participant	33	0.9629204	0.8529541	1.0335599
r_Participant__asym[35,Intercept]	ranef	asym	Intercept	Participant	35	1.0621637	0.8986669	1.1478716
r_Participant__asym[36,Intercept]	ranef	asym	Intercept	Participant	36	0.9721597	0.8655641	1.0565453
r_Participant__asym[39,Intercept]	ranef	asym	Intercept	Participant	39	0.8743161	0.7815659	0.9495191
r_Participant__asym[40,Intercept]	ranef	asym	Intercept	Participant	40	1.0137866	0.8449957	1.0960737

```
P_M_7 <- posterior(M_7)
PP_M_7 <- post_pred(M_7)

T_pred_M_7 <- PP_M_7 %>%
  group_by(Obs) %>%
  summarize(center = median(value))

D_SimParAcc$M_7 <- T_pred_M_7$center
D_SimParAcc$M_7_resid <- D_SimParAcc$ToT - D_SimParAcc$M_7

D_M_7 <-
  as_tibble(M_7$data) %>%
  mutate(M_7 = T_pred_M_7$center)

D_SimParAcc %>%
  ggplot(aes(x = trial, y = ToT, col = Experience)) +
  facet_wrap(~ Participant, nrow = 7) +
  geom_point(size = .2) +
  geom_line(aes(y = M_7)) +
  theme_minimal()
```



NUMBER OF LANE DEPARTURES

```
F_lacy_Nld <- formula(Nld ~ exp(asym) + exp(ampl) * inv_logit((1-ctch))
^trial)

M_Test_Nld_exp_1 <-
  D_SimParAcc %>%
  brm(bf(F_lacy_Nld,
         flist = F_acy_ef_4,
         nl = T),
      prior = F_lacy_prior_2,
      family = poisson(link = identity), iter = 4000,
      data = .)

## Compiling Stan program...

## Start sampling
```

```
## Warning: There were 20 divergent transitions after warmup. See
## http://mc-stan.org/misc/warnings.html#divergent-transitions-after-wa
rmup
## to find out why this is a problem and how to eliminate them.

## Warning: Examine the pairs() plot to diagnose sampling problems

## Warning: Bulk Effective Samples Size (ESS) is too low, indicating po
sterior means and medians may be unreliable.
## Running the chains for more iterations may help. See
## http://mc-stan.org/misc/warnings.html#bulk-ess

coef(M_Test_Nld_exp_1, mean.func = exp)
```

Coefficient estimates with 95% credibility limits

parameter	type	nonlin	fixef	re_factor	re_entity	center	lower	upper
b_ampl_Intercept	fixef	ampl	Intercept	NA	NA	2.5318383	0.9921394	5.1191386
b_ampl_ExperienceInexperienced	fixef	ampl	ExperienceInexperienced	NA	NA	1.9859707	0.9251256	5.9198259
b_ctch_Intercept	fixef	ctch	Intercept	NA	NA	1.0038568	0.1599318	5.7525477
b_asym_Intercept	fixef	asym	Intercept	NA	NA	1.3281985	0.8608116	2.2932144
r_Participant__ampl[3,Intercept]	ranef	ampl	Intercept	Participant	3	0.9626174	0.1888867	1.7508864
r_Participant__ampl[5,Intercept]	ranef	ampl	Intercept	Participant	5	0.9829819	0.3427158	1.8181901
r_Participant__ampl[12,Intercept]	ranef	ampl	Intercept	Participant	12	0.9362206	0.3169464	1.5574334
r_Participant__ampl[20,Intercept]	ranef	ampl	Intercept	Participant	20	0.9564941	0.0798452	1.7029614
r_Participant__ampl[24,Intercept]	ranef	ampl	Intercept	Participant	24	1.0049230	0.4901218	1.9599544
r_Participant__ampl[27,Intercept]	ranef	ampl	Intercept	Participant	27	0.9696086	0.1187399	1.7628101
r_Participant__ampl[28,Intercept]	ranef	ampl	Intercept	Participant	28	0.9973212	0.4470783	1.9565021
r_Participant__ampl[29,Intercept]	ranef	ampl	Intercept	Participant	29	0.9786545	0.3465035	1.7027345
r_Participant__ampl[30,Intercept]	ranef	ampl	Intercept	Participant	30	0.9567944	0.2037672	1.7515851
r_Participant__ampl[31,Intercept]	ranef	ampl	Intercept	Participant	31	0.9837861	0.3290314	2.1398910
r_Participant__ampl[32,Intercept]	ranef	ampl	Intercept	Participant	32	0.9999215	0.2287249	1.7077046

r_Participant__ampl[33,Intercept]	ranef	ampl	Intercept	Participant	33	1.0325794	0.5835595	2.9540733
r_Participant__ampl[35,Intercept]	ranef	ampl	Intercept	Participant	35	1.1003861	0.7391896	3.7199313
r_Participant__ampl[36,Intercept]	ranef	ampl	Intercept	Participant	36	0.9680142	0.2445338	1.8716992
r_Participant__ampl[39,Intercept]	ranef	ampl	Intercept	Participant	39	1.0200033	0.4393045	3.1536002
r_Participant__ampl[40,Intercept]	ranef	ampl	Intercept	Participant	40	0.9684125	0.1118917	1.8061488
r_Participant__ctch[3,Intercept]	ranef	ctch	Intercept	Participant	3	4.3580413	0.0196181	882.0801387
r_Participant__ctch[5,Intercept]	ranef	ctch	Intercept	Participant	5	0.1709070	0.0075669	7.0176239
r_Participant__ctch[12,Intercept]	ranef	ctch	Intercept	Participant	12	0.3688246	0.0480123	5.2482933
r_Participant__ctch[20,Intercept]	ranef	ctch	Intercept	Participant	20	25.3670256	0.4807860	3545.8395527
r_Participant__ctch[24,Intercept]	ranef	ctch	Intercept	Participant	24	0.2982939	0.0473116	1.9984690
r_Participant__ctch[27,Intercept]	ranef	ctch	Intercept	Participant	27	9.6940830	0.4254393	1248.8086886
r_Participant__ctch[28,Intercept]	ranef	ctch	Intercept	Participant	28	0.2312770	0.0221341	3.0733522
r_Participant__ctch[29,Intercept]	ranef	ctch	Intercept	Participant	29	0.9319742	0.1294430	8.1710964
r_Participant__ctch[30,Intercept]	ranef	ctch	Intercept	Participant	30	4.8104504	0.0466112	1079.1261373
r_Participant__ctch[31,Intercept]	ranef	ctch	Intercept	Participant	31	1.4973534	0.1233544	91.7830965
r_Participant__ctch[32,Intercept]	ranef	ctch	Intercept	Participant	32	0.0317905	0.0001632	37.0183409
r_Participant__ctch[33,Intercept]	ranef	ctch	Intercept	Participant	33	0.7004461	0.0967558	6.5101237
r_Participant__ctch[35,Intercept]	ranef	ctch	Intercept	Participant	35	0.2864665	0.0456773	2.0834181
r_Participant__ctch[36,Intercept]	ranef	ctch	Intercept	Participant	36	3.0877103	0.2880286	689.3526708
r_Participant__ctch[39,Intercept]	ranef	ctch	Intercept	Participant	39	1.0822801	0.0672097	21.3302551
r_Participant__ctch[40,Intercept]	ranef	ctch	Intercept	Participant	40	13.9328861	0.4706522	1701.9857375
r_Participant__asym[3,Intercept]	ranef	asym	Intercept	Participant	3	1.1168272	0.3357467	1.8606953
r_Participant__asym[5,Intercept]	ranef	asym	Intercept	Participant	5	1.6874133	0.3324982	4.0194342

r_Participant__asym[12,Intercept]	ranef	asym	Intercept	Participant	12	1.0143504	0.2519986	2.0045953
r_Participant__asym[20,Intercept]	ranef	asym	Intercept	Participant	20	0.9407372	0.4717568	1.5551584
r_Participant__asym[24,Intercept]	ranef	asym	Intercept	Participant	24	0.7063781	0.1752602	1.4729174
r_Participant__asym[27,Intercept]	ranef	asym	Intercept	Participant	27	1.2860255	0.6646154	2.1063846
r_Participant__asym[28,Intercept]	ranef	asym	Intercept	Participant	28	1.5667853	0.3796386	3.2310652
r_Participant__asym[29,Intercept]	ranef	asym	Intercept	Participant	29	0.8120087	0.3656766	1.4302753
r_Participant__asym[30,Intercept]	ranef	asym	Intercept	Participant	30	0.8898710	0.2857552	1.5040347
r_Participant__asym[31,Intercept]	ranef	asym	Intercept	Participant	31	0.5631080	0.2103368	1.0090855
r_Participant__asym[32,Intercept]	ranef	asym	Intercept	Participant	32	2.0337576	0.4477616	6.0410591
r_Participant__asym[33,Intercept]	ranef	asym	Intercept	Participant	33	0.4874226	0.1714658	0.9292586
r_Participant__asym[35,Intercept]	ranef	asym	Intercept	Participant	35	0.5401307	0.1505070	1.1335716
r_Participant__asym[36,Intercept]	ranef	asym	Intercept	Participant	36	0.2566508	0.0814483	0.5386837
r_Participant__asym[39,Intercept]	ranef	asym	Intercept	Participant	39	1.2682919	0.5836794	2.0819046
r_Participant__asym[40,Intercept]	ranef	asym	Intercept	Participant	40	0.9239805	0.4714661	1.5467309

```
 P_M_Test_Nld_exp_1 <- posterior(M_Test_Nld_exp_1)
PP_M_Test_Nld_exp_1 <- post_pred(M_Test_Nld_exp_1)

T_pred_M_Test_Nld_exp_1 <- PP_M_Test_Nld_exp_1 %>%
  group_by(Obs) %>%
  summarize(center = median(value))

D_SimParAcc$M_Test_Nld_exp_1 <- T_pred_M_Test_Nld_exp_1$center
D_SimParAcc$M_Test_Nld_exp_1_resid <- D_SimParAcc$Nld - D_SimParAcc$M_T
est_Nld_exp_1

D_M_Test_Nld_exp_1 <-
  as_tibble(M_Test_Nld_exp_1$data) %>%
  mutate(M_Test_Nld_exp_1 = T_pred_M_Test_Nld_exp_1$center)

D_SimParAcc %>%
  ggplot(aes(x = trial, y = Nld, col = Experience)) +
  facet_wrap(~ Participant, nrow = 7) +
  geom_point(size = .2) +
  geom_smooth(aes(y = M_Test_Nld_exp_1), se = F) +
```

```
  labs(y= "Number of lane departures") +
  theme_minimal()

## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```