An Integrative Model of Drivers' Take-over Time in Semi-Automated Driving

Master Thesis

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ABSTRACT

Introduction: The take-over process from autonomous to manual driving in semi-automated vehicles introduces a new critical moment for road safety. Although previous work has investigated extensively what factors affect the necessary time for a successful take-over by the driver, less is known about how specific stages within the take-over process are affected by those factors.

Model: An interactive model was developed to investigate how specific factors as reported in the literature (e.g., alert modality, alert onset time) impact four distinct stages of the take-over process. The model uses a database based on previous studies, which can be used to integrate findings across studies. Using an interactive visual interface, the end-user can systematically comb through the database and compare results for different settings of these factors.

Testing: The model was used to study the effect of different factors on the transition of control, which provided valuable insight in the take-over process. For example, the model showed that visual-auditory bi-modal alerts resulted in a faster initial response to the alert than purely visual or purely auditory alerts, and that the timing of the alert has a significant impact on the occurrence of last-second take-overs.

Discussion: The model can help to reveal how different factors affect specific stages of the take-over process. This can aid in the design and testing of new interventions and policies.

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1 INTRODUCTION

The continuous advancements in automated driving technology we currently see gradually shift the driver's role from being fully in control of the vehicle towards more of a monitoring role. This allows the driver to increasingly allocate time to tasks other than driving. A framework commonly used to describe important steps within this shift is given by SAE International [87], which focusses on the amount of tasks allocated to either the vehicle or the driver. Here, the shift is divided into six distinct levels, ranging from level 0 (no automation) to level 5 (full automation). Currently, Alphabet's Waymo [103] shows the highest level of automation, as it can navigate fully automated in a very restricted, predefined area, ranking it at level 4. However, until this or the highest level of automation become widely accessible, a number of legal, ethical and technical issues must be resolved first [32]. Given the current technological state, more realistic candidates for wider accessibility are the semi-automated, level 3 cars. Here, the car is capable of taking over the driving task for a prolonged period of time under specific conditions, but may require the driver to take back control of the vehicle at any time. For example, when the car encounters unfamiliar or difficult conditions.

While semi-automated cars can reduce the time that the driver must allocate to the driving task itself, they are subject to the irony of automation [5]: The driver's behavior may change in new and unforeseeable ways, potentially introducing new and unpredictable problems for road safety. Some behavior can be expected however, and can thus be anticipated. For instance, while the car is driving autonomously, the driver will likely engage in a secondary task using hand-held devices such as smartphones, as a significant number of drivers already do in non-automated cars [1,20]. This engagement with non-driving related tasks (NDRTs) can in turn increase the driver's workload with tasks unrelated to the current traffic condition, thereby affecting their driving performance [59,117]. Level 3 automation gives the driver the possibility to allocate more time to the NDRT while automation is enabled. However, there still remains a critical moment when the car encounters a situation it is unable to navigate through safely and gives control back to the human driver – which will be referred to as *transition of control* in this thesis.

With the safety-critical importance of a timely transition of control in semi-automated driving, research on the factors affecting the time required by the driver is plentiful. A wide range of factors have been investigated, including technical factors such as the modality of the alert [75,113], behavioral factors such as the type of NDRT performed [113], or cognitive factors such as the workload caused by the NDRT [44]. Given the vast amount of potential contributing factors, it is beneficial to have a better understanding about the specific effects these factors have on the transition of control, and how they interact with one another. For this thesis, a model was created that can help to test quantitative theories about the effects these factors have on the transition of control based on the vast amount of literature in the field. In addition to the overall time required for the transition of control, the model focusses on specific stages of the transition of control, and how those are affected by different factors.

In the following sections of this thesis, first the background concerning the stages of the transition of control and possible effects of influencing factors will be discussed. Afterwards, the model will be discussed in more detail, addressing its main components and how it simulates the transition of control process. Then, a number of tests will be discussed that have been performed using the model. Finally, implications of the results from these tests will be addressed in more detail.

2 FRAMEWORK OF THE TRANSITION OF CONTROL

Dividing transition of control into distinct stages allows for a more thorough investigation of the most critical aspects for driver safety. This can be used to pinpoint specific stages in research and can guide design choices for car manufacturers. A framework dividing the transition of control into such stages has been proposed by Janssen et al. [36]. This framework looks at the transition of control as an interruption process and builds on existing frameworks for interruption handling and attention interleaving (e.g. [3,10,11]) and translates it to the domain of transitions of control in semi-automated vehicles. While this framework gives a thorough account of the possible factors influencing the transition time between stages, it does not make quantitative predictions about those transitions. The model introduced in this thesis aims to bridge this gap in order to allow for a better understanding of not only *what* factors influence the transitions, but also *how* they influence the transitions and how those influences accumulate over the stages.

The framework by Janssen et al. [36] divides the transition of control into eleven distinct stages, focusing on both transitions from working on the NDRT (stage 0) to driving manually (stage 6) (i.e., from automated driving to manual driving), and from driving manually back to working on the NDRT (stage 10) (i.e., from manual driving to automated driving). The first transition requires an adequate and timely action from the driver in order to avoid negative consequences for overall road safety, and is extensively studied within the field of (semi)-automated driving [120]. The focus of the model presented in this thesis will thus be on the first transition from working on the NDRT (stage 0) to driving manually (stage 6) (Figure 1). In this section, first these stages will be explained. Afterwards, the factors that that are assumed to play a role in the onset of each stage will be discussed in more detail.

2.1 Stages of the Transition of Control

The framework by Janssen et al. [36] divides the transition from working on the NDRT to driving into six stages: *Work on the NDRT (stage 0), presentation of external alert (stage 1), disengagement (stage 2), orient (stage 3), suspend the NDRT (stage 4), physical transfer of control (stage 5),* and *continue to drive (stage 6).*

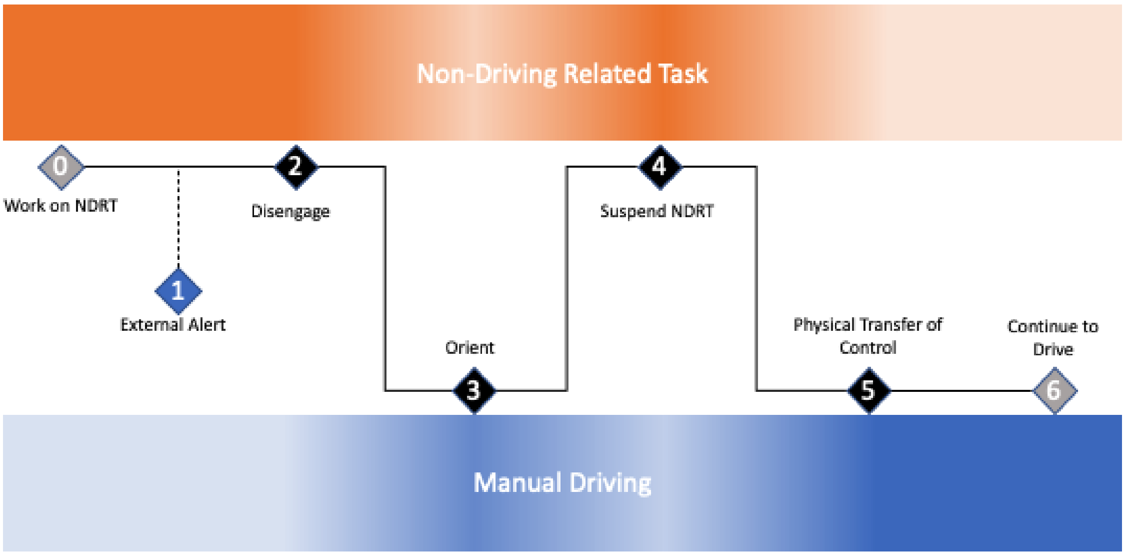


Figure 1: When a semi-automated vehicle encounters a situation that requires the input of the human driver, the driver must eventually transition from working on a non-driving related task (NDRT) (Stage 0) to driving manually (Stage 6). This transition is initiated by an external alert (Stage 1), and followed by a period of interleaving between those two tasks (Stages 2-5). The figure is based on the interruption framework by Janssen et al. [36]*, and adapted to highlight the transition from Stage 0 to Stage 6.*

2.1.1 Stage 0: Work on Non-Driving Related Task

The negative effect that working on NDRTs has on road safety during manual driving has been subject of many reviews (e.g. [20,115]). Despite these known effects, many drivers still report to engage in NDRTs [34], and a significant number of accidents occur due to such distractions [106]. NDRTs that drivers regularly engage in range from purely cognitive tasks (e.g. daydreaming), conversing or listening to music to more complex visual-manual tasks such as texting or searching objects in the car [34].

While automation is enabled in level 3 automated driving [87], drivers are expected to (occasionally) perform NDRTs as well. In fact, next to the safety benefits automation brings along, a major incentive for drivers to purchase (semi)-automated cars is to use their time during commute for tasks other than driving [108]. Since the driver can allocate more time and resources to the NDRTs, they can become more complex (e.g. writing formal e-mails) and time consuming (e.g. reading books, watching movies) than they are during manual driving. The type of NDRT performed during automation may have an effect on later stages of the transition of control. Potential effects will be discussed in more detail in section 'Influencing Factors on Stage Onset Times'.

While automation allows the driver to safely engage even in more complex NDRTs, a new potential risk moment arises when control is handed back to the driver. Since the disengagement from driving may have lasted longer, regaining sufficient situational awareness can require more time. Furthermore, with tasks becoming cognitively more demanding, the take-over time as well as the performance after driving may be negatively affected. However, engaging in a NDRT during automation can also have a positive effect on take-over performance, since it can prevent underload [4], which can have a negative effect on take-over performance as well.

2.1.2 Stage 1: Presentation of the External Alert

When a level 3 automated vehicle approaches a situation that requires assistance from the driver, it must signal the impending transition of control to the driver in an appropriate way. Choosing the proper external alert to initiate the transition of control plays a crucial role in the success of the transition of control. Two aspects of the alert are commonly discussed in the literature [120], and will be further investigated using the model: (1) The alert onset time, and (2) the alert modality. Both factors can have an effect on certain stages of the transition of control. These will be discussed in more detail in section 'Influencing Factors on Stage Onset Times'.

2.1.3 Stage 2: Disengage

In the interruption framework [36], stage 2 describes the first *disengagement* from the NDRT after the alert is presented. In an experimental setting, this stage can for instance be indicated by tracking the first eye-gazes away from the NDRT using an eye-tracking device, or tracking interruptions of button presses during manual tasks. Depending on the alert onset time, the driver may go back to the NDRT after disengaging for the first time (or even after reaching a later stage). Thus, for the remainder of this thesis stage 2 refers only to the first disengagement from the NDRT.

2.1.4 Stage 3: Orient

After the first disengagement from the NDRT, drivers have to *orient* to the driving task in order to regain sufficient situational awareness (e.g., about the complexity of the traffic) for a safe take-over. In an experimental setting, the initiation of stage 3 can for instance be described by the first gaze towards the road/traffic. Similar to the disengagement in stage 2, the driver might go back to the NDRT after orienting to the driving task. Thus, stage 3 refers only to the first orientation during a transition of control.

2.1.5 Stage 4: Suspend Non-Driving Related Task

Before taking back control of the vehicle, the driver must *suspend the NDRT.* Initiation of this stage can objectively be measured using eye-tracking (e.g. measuring the last gaze away from the NDRT), or by measuring performance on the NDRT (e.g. last physical interaction with the device). As discussed in previous sections, the driver might go back and forth between the NDRT and preparing to drive during the transition of control. Thus, stage 4 defines the last suspension of the NDRT before control is taken back by the driver.

2.1.6 Stage 5: Physical Transfer of Control

The last stage of the transition of control investigated with the model is the *physical transfer of control*. This denotes the point in time at which the driver has switched off automation, for instance by deactivating automation manually (e.g. by pressing a button) or by interacting with the steering wheel and/or pedals, and is now in charge of lateral and longitudinal control of the vehicle. Reaching stage 5 on time is critical for traffic safety during the transition of control.

2.1.7 Stage 6: Continue to Drive

After the transition of control is completed, the driver *continues to drive* in stage 6 until the traffic condition is back within the boundaries of the automation. The focus of the model discussed in this thesis is on the transition times between stages up to the physical transfer of control in stage 5. However, some factors can have a negative effect on driving performance after the transition of control is completed, such as cognitively more demanding tasks [88,92]. These negative effects on driving performance can last up to 40 seconds [60], and should also be taken into account when designing systems to facilitate the transition of control in semi-automated vehicles.

2.2 Influencing Factors on Stage Onset Times

The onset times for the stages of the framework [36] previously discussed can be affected by a multitude of factors. For the purpose of this thesis however, the focus lies on three factors: (1) Alert Onset Time, (2) Alert Modality, and (3) Non-Driving Related Task (NDRT)-type. These factors have been selected, because they are expected to have an influence on the stage onset times [36], and have been studied extensively [120]. In addition, they are commonly reported in the study designs of automated driving studies, even if they are not the main focus of the respective study. This allows the model to have access to an extended database to work with for each factor.

2.2.1 Alert Onset Time

Alert onset time refers to the moment when the alert occurs. Typically, it denotes the time budget available to the driver to physically take back control of the vehicle before reaching a critical event (e.g., an obstacle on the road) or the boundaries of the automated driving system (e.g., missing lane markers, system failure). Take-over time appears to be positively correlated with the alert onset time [120]. In the literature, alert onset times of 5 to 8 seconds are oftentimes considered to be the minimum time drivers need to take back control safely (e.g., [24,63]) and are regularly used in empirical studies [120]. However, while most studies report a mean take-over time of under 5 seconds [120], this mean take-over time does not take into account possible outliers (i.e. drivers that need significantly more time than average). Yet, those are the drivers that pose a significant risk to road safety, as they might not take back control in time to respond to the critical event appropriately. It is thus important to not only understand how the alert onset time affects the mean take-over times, but also how it affects the proportion of these outliers.

Depending on the alert onset time, the driver has more or less time to take back control of the vehicle. This allows the driver to continue to work on the NDRT for an extended period of time, if presented with longer alert onset times. Furthermore, people tend to prefer to pause a task at *natural breakpoints* (i.e. the end of a sub-task, such as finishing to write a sentence in an e-mail) [35]. Longer alert onset times would allow the driver to finish more time-consuming (sub)-tasks, or even to start a new one before taking back control of the vehicle. Alert onset times are thus expected to affect the suspension of the NDRT (stage 4), and consequently the subsequent physical transfer of control (stage 5).

2.2.2 Alert Modality

The alert modality refers to how the alert is presented to the driver. The most common modalities used for alerts in autonomous driving are auditory alerts, visual alerts, or a combination of both [120], but other alert formats such as haptic [58] have been studied as well. It should be noted that some alert modalities are more likely to be missed entirely by the driver than others. For instance, visual-only alerts are likely to be overseen when the alert is presented on a device other than the one used for the NDRT [113]. While such occurrences might influence the model indirectly (e.g., if trials with missed alerts are reported with longer take-over times), missed alerts are not simulated by the model directly.

The modality with which an alert is presented can have an effect on the time needed to perceive that alert. For instance, tactile stimuli have been found to result in the shortest initial response times in a general human-machine interface, followed by auditory stimuli and finally visual stimuli [16]. A similar effect can be expected in an automated driving setting, thus influencing how long it takes for the driver to initially perceive and react (i.e., to first disengage in stage 2) to the alert.

Similarly, the alert modality could influence the time it takes the driver to initiate orientation (stage 3). For instance in [75], tactile alerts have resulted in the fastest eyes-on-road times, closely followed by auditory alerts. Visual-only alerts showed significantly slower eyes-on-road time. This type of alert might require the driver to first look at the alert before looking towards the traffic if it is presented on a device other than the one used for the NDRT, thus prolonging the time needed until the eyes fixate on the road.

Finally, the alert modality could affect the initiation of stage 4, depending on the perceived urgency that the alert is evoking. While the perceived urgency is mostly caused by the type of alert regardless of its modality (e.g. comparing different auditory [27,56], or tactile alerts [79]), some studies suggest that perceived urgency is affected differently by different alert modalities. Here, larger differences in perceived urgency are more commonly found in auditory and tactile alerts than in visual alerts [6,49]. With a higher perceived urgency, drivers may be less inclined to begin a new sub-task, thus accelerating the initiation of stage 4. Consequently, the physical transfer of control (stage 5) could be faster if the driver has suspended the NDRT earlier.

2.2.3 NDRT task Modality

The allocation of time and resources to Non-Driving Related Tasks (NDRTs) in (semi)-automated driving plays an important role within the field, as many people see the possibility to work on a NDRT as a major reason to purchase (semi)-automated cars [108]. The types of NDRTs that are likely going to be performed in (semi)-automated vehicles are similar than those already performed as passengers during manual driving today, although some in a higher frequency [76]. A wide range of NDRTs is expected to be performed, including but not limited to: listening to music, watching movies, or writing emails. In order to reduce the large variety of NDRTs, this thesis will focus on the modality required to perform the NDRT (i.e., ‘reading a book’ and ‘watching a silent movie’ are both considered as ‘visual’ NDRTs).

Depending on the modality of the NDRT performed while automation is enabled, disengagement (stage 2) may be delayed. Before disengaging from the NDRT, people may want to reach a natural breakpoint [35]. Depending on the NDRT modality, reaching a natural breakpoint may require more time. For instance, in a bi-modal visual-manual NDRT such as playing a video game, reaching a good moment to look away from the game might take longer than during an auditory task such as conversing with another passenger. In addition, reaching a natural breakpoint can take more time with cognitively demanding NDRTs, as there are less suitable sub-tasks for disengagement due to the higher task complexity.

The NDRT modality can also have an indirect effect on orientation (stage 3). Depending on the modality of the NDRT, the driver may have elicited more or less monitoring behavior while automation was enabled. Higher monitoring behavior while working on the NDRT might in turn lead to a more accurate mental model of the environment, reducing the necessary time to gain sufficient situational awareness when orienting towards the road [116].

Finally, the NDRT modality could have an effect on the suspension of the NDRT (stage 4) as well. The driver could for instance be more tempted to begin a new sub-task if the NDRT is simple and rather monotonous (e.g., filling out a calendar) instead of cognitively more demanding (e.g., playing a game). Depending on the NDRT-modality, identifying a new sub-task that can be completed in the remaining time can also be more or less difficult, thus affecting the driver’s incentive to do so. As was the case for the previously discussed factors, this can consequently affect the onset of the physical transfer of control (stage 5) as well.

While the effect of these factors on overall take-over time has been extensively studied [120], less empirical findings about how they affect specific stages of the transition of control are available. Although some studies report onset times for several stages (e.g., [8,26,40]), it is not consistently done across studies. Furthermore, while there are some factors of the study design that are used more frequently than others (e.g., a bi-modal auditory-visual alert; an alert onset time of 5-8 seconds [120]), they are not used consistently throughout the literature. This divergence improves our understanding of the role these factors play in the transition of control. However, it makes it difficult to adequately compare research findings and to investigate the effects different factors have on take-over time over a wider range of studies. A better understanding of how those factors affect specific stages of the transition of control can help researchers and engineers to pinpoint moments in the take-over process that benefit most from a certain intervention. In order to facilitate the comparison of research findings, a model was created for the purpose of this thesis.

3 THE MODEL

The goal of the model presented in this thesis is to provide a tool that can help to better understand the effect different factors have on the time needed by the driver to go through the stages of the transition of control [36] after an incentive to take back control was given. The model was designed to answer three questions related to the transition of control:

(1) *How does the driver go through the stages of the transition of control discussed by Janssen et al.* [36]*?* The model calculates and visualizes how each stage of the transition of control process is affected by certain combinations of parameters representing specific factors (e.g., alert modality). Based on selected parameter choices, the model combs through its database to create a subset of studies matching the selection. Results from this subset are then combined and used to create a simulation of the transition of control, considering each stage of the process. This allows users to investigate how a specific factor, or a combination of factors, impacts each stage, as well as the transition of control as a whole.

(2) *Are the stages affected differently by some factors than by others?* The model allows the user to create multiple simulations at the same time, each based on a different subset of data (i.e., based on different selected parameter choices). These simulations can conveniently be compared in order to test, how the difference in selected parameter choices affect the resulting simulations in each stage. The model also allows the user to add findings to the included database, making it possible to compare other results (e.g., from new studies) to a larger database of previous studies.

(3) *How likely is the transition of control going to succeed in time for the driver to react to a critical event, and how is the success rate affected by different factors?* The model makes educated guesses about the rate of successful transitions in relation to the critical event onset for each stage, based on the selected parameter choices. For stage 5 (i.e., the physical transfer of control) this functionality is particularly interesting, as it can help to estimate the proportion of drivers unable to take back control in time to react appropriately to a critical event.

An important aspect of the model is that in these visualizations, comparisons, and predictions, it does not only focus on the mean or typical values that are expected. Instead, it provides an expected distribution of results. Therefore, it also allows identification of the extremes of performance, such as the fastest or slowest possible. This is in line with other modeling techniques more common in human-computer interaction (e.g., Card, Moran, and Newell's focus on Fast-man, Middle-man and Slow-man [15]; or the focus on 'bracketing' of a performance range [42]).

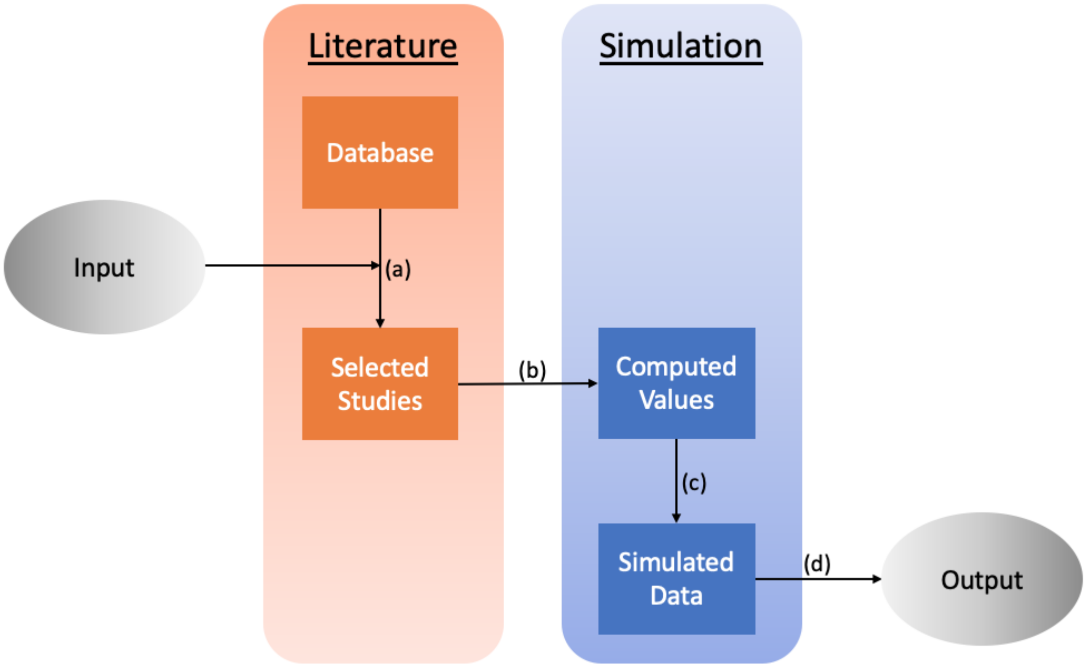


Figure 2: The model works by simulating a number of transitions based on values retrieved from the literature. (a) Based on the input parameters selected by the user, the model filters its database to get a set of selected studies matching the input parameters. (b) From the selected studies, a pooled mean and standard deviation is calculated for each stage of the transition of control. (c) Based on these computed values, a number of transitions are simulated. (d) The resulting simulated data is used to create the model output.

The model (Figure 2) contains an extensive database, consisting of results from 265 experimental groups from 67 level 3 automated driving studies. Based on the parameter choices selected by the user, the model filters through this database to create a subset containing experimental groups matching that selection. From this subset, summary statistics are calculated for each stage. These summary statistics are then used to estimate an underlying distribution of onset times for each stage, based on the selected parameter choices. Then, 10,000 transitions of control are simulated by randomly sampling values from the estimated distributions for each stage, resulting in the simulated distributions for each stage of the transition of control. The model visualizes the resulting distributions in numerous ways, allowing the user to investigate the effect of the parameter selections on the transition of control.

The model was implemented using R Shiny (R version 3.6.1; Shiny version 1.3.2) and can be retrieved from the 'Supplementary Materials'. In the following section, the functionality of the model is explained in more detail. First, the literature search that was conducted to obtain the model's database will be discussed. Afterwards, the model's user interface is explained in more detail, including the input the user can interact with and the output the model returns. Finally, the computations used to create the model's simulations are discussed.

3.1 Literature search

The model relies on findings from previous studies to simulate the transition of control process. In order to provide the model with an extensive database of research findings to work with, a systematic literature search was conducted. In the following section, the process of this literature search and the resulting database are discussed in more detail.

3.1.1 Search strategy

As an initial collection of literature, the meta-analysis by Zhang et al. [120] was used, as it offered an extensive and recent (as of 2019) review of studies investigating the transition of control in level 3 automated driving. Although the authors made their review publicly available, the included literature (129 studies from 119 records) was reexamined for this literature search to collect all data relevant for this project. Specifically, the purpose of Zhang et al. was to investigate overall take-over time, so they did not report information about stages 2-4. If a source was not available online (e.g., unpublished work) and could therefore not be examined, it was excluded from the literature search. This search strategy yielded only few results for stages 2, 3, and 4 (See section 'Resulting Set of Studies'). Therefore, three studies known by the supervisors to discuss at least one of the earlier stages were added to the database. If the reaction times were only reported using plots, the corresponding values were extracted using the WebPlotDigitizer [84].

3.1.2 Eligibility Criteria

Studies had to fulfill the following criteria to be included in the review:

1. The study had to involve the transition of control from automated driving (or the simulation thereof, e.g. using 'Wizard of Oz' [64]) to the human driver (i.e., SAE Level 3 or above).
2. The participant had to be involved in a NDRT while automation was enabled in at least one of the conditions included in the study.
3. The transition of control had to be initiated by an external take-over request (i.e., an alert) to which the subject had to react (i.e., no self-interruptions or driver-initiated transitions of control).
4. The study had to report the mean and standard deviation (or another metric from which the standard deviation could be calculated) for at least one of the stages 2-5.
5. The study had to be written in English, German, Dutch or French.

After collecting all the data from each study matching those criteria, experimental groups were further removed if they did not match all criteria. For example, if a study had two experimental groups ('with NDRT' vs. 'without NDRT'), only results for the 'with NDRT'-group were kept in the database.

3.1.3 Collected Information

A number of variables were extracted from the studies (Table 1). These include information about the study design (e.g. 'alert modality', 'number of participants') as well as the results ('mean' and 'standard deviation' for each stage). In order to group similar NDRTs together,

Variable	Definition	Example (with Source)
Author	The last names of all authors and the year of publication.	Van der Meulen, Kun, Janssen (2016) ([61])
Title	The title of the paper.	Switching Back to Manual Driving: How Does it Compare to Simply Driving Away After Parking? ([61])
Number of Participants	The number of participants in the corresponding experimental condition. If the number of subjects differed between stages (e.g. due to data collection issues), the smaller number was recorded.	16 ([61])
Alert Onset Time	The time budget (seconds) between alert onset and reaching the critical event. If an experimental group perceived a range of alert onset times, the mean alert onset time was recorded. If participants perceived multiple alerts in one trial (e.g., through pre-alerts), the first (pre)-alert onset was recorded.	7 ([61])
Alert Modality	The modality or modalities used for the alert.	Visual-auditory ([61])
NDRT Modality (Input)	The modality or modalities involved to process sensory information relevant for the NDRT.	Visual ([61])
NDRT Modality (Output)	The modality or modalities involved in executing the NDRT.	None ([61])
For stages 2-5:		
Stage mean	Mean RT (milliseconds) from alert onset time to the stage.	2556 (Stage 5) ([61])
Stage SD	The standard deviation (milliseconds) of the RT for the stage.	1158 (Stage 5) ([61])
Stage SE	The standard error (milliseconds) of the RT for the stage. Only included if reported instead of the standard deviation.	102 (Stage 5) ([53])
Stage CI95	The 95% Confidence Interval of the RT for the stage. The reported value equals the difference between the upper and lower limit. Only included if reported instead of the standard deviation.	750 (Stage 5) ([77])
Stage definition	How the stage was defined in the study.	Gas/brake pedal input (Stage 5) ([61])

Table 1: Variables retrieved from the studies during the literature search. For each experimental group the information for all variables was retrieved separately, if the information was available.

the modalities required to perform the NDRT were collected rather than the specific task. To this end, a distinction was made between the *input modalities* and the *output modalities,* loosely based on the *multiple resource theory* [105]. The input modality refers to the modalities involved in processing the necessary sensory information to perform the NDRT (i.e., visual, auditory, tactile). The output modality refers to the modalities necessary to execute the NDRT (i.e. manual, cognitive, vocal). While 'cognitive' is not technically an output modality in the same sense than 'manual' or 'vocal', it was included here as it requires active participation by the participant. This distinction was included to allow for a more precise filtering of experimental conditions, for instance to analyze how interfering or contrasting alert and NDRT input modalities affect transition times differently. The categorization into specific input and output modalities was based on the description of the NDRT in the respective literature. If the NDRT was not explained in more detail, the descriptions from other studies using the same (or a similar) NDRT were considered. For a NDRT to be categorized as requiring a *cognitive* output modality (which – one could argue – any activity does to some degree), it had to be introduced explicitly as such in the study. The collected information was transcribed to an excel-table (See 'Supplementary Materials'). Within the table, rows represent experimental groups and columns represent variables (i.e., columns were formed based on information as listed in Table 1). If a study did not report information for a variable, the corresponding cell reads '-Not Reported-'.

3.1.4 Resulting Set of Studies

The literature search resulted in a database of 265 experimental groups from 67 studies. In total, data from 2591 participants was retrieved. Out of these studies, 64 were found through the meta-analysis by Zhang et al. [120], and 3 were suggested by the supervisors [28,52,114]. Studies included in the database are highlighted with an Asterix (*) in the 'REFERENCES' and can be found in *Appendix A.* A detailed account of values retrieved for each variable, and a review of the information gathered for each stage can be found in Table 2 and Table 3, respectively.

The majority of studies used an alert onset time between 5 and 7 seconds, followed by an alert onset time of 7 to 12 seconds. About two third of experimental groups were exposed to a bi-modal auditory-visual alert, and two third performed a NDRT with a visual input modality. The most commonly required NDRT output modality was manual, followed by cognitive-manual. Although each variable contains one clearly dominant value, at least some of the other values are reported sufficiently frequent to give the model enough data to adequately simulate the influence those values have on the transition of control.

Table 3 shows that the amount of available results differs widely between the stages. While stage 5 (physical transfer of control) is discussed in all but one study, information for other stages is reported less frequently, especially for stage 2 (Disengage), and stage 4 (Suspend NDRT). This discrepancy of reported stages can have several causes. For stages 2 and 3, reporting information requires additional material (i.e., an eye-tracking device). Depending on the research question of a given study and the resources available, including results from an eye-tracker may not be relevant or impractical for the experimenter. Furthermore, a lot of studies including eye-tracking devices in their design were interested in other gaze behavior, such as the monitoring behavior during automation (e.g., [30]), or the proportion of gazes at mirrors after transition (e.g., [93]). While such results give valuable

Variable	Value	N Studies	N Groups
Alert Onset Time			
	$t \leq 3$	4	8
	$3 < t \leq 5$	11	31
	$5 < t \leq 7$	25	104
	$7 < t \leq 12$	19	70
	$12 < t$	4	9
	Not reported:	14	43
Alert Modality			
	Auditory	16	41
	Tactile	6	10
	Visual	4	8
	Auditory-Tactile	4	9
	Auditory-Visual	49	173
	Tactile-Visual	3	7
	Auditory-Tactile-Visual	6	14
	Mixed[1]	1	3
NDRT-Modality (Input)			
	Auditory	11	26
	Tactile	2	4
	Visual	57	179
	Visual-Auditory	11	33
	Mixed[1]	5	21
	None[2]	2	2
NDRT-Modality (Output)			
	Cognitive	2	3
	Manual	37	102
	Vocal	6	15
	Nap/Relax	2	2
	Cognitive-Manual	13	48
	Cognitive-Vocal	7	18
	Mixed[1]	6	22
	None[2]	17	55

Table 2: Prevalence of reported values for each variable by studies and experimental groups. These values are available to the user in the model parameters for the respective variable.

insights in the transition of control process as well, they are not usable for the model presented in this thesis.

Studies about (semi)-automated driving often focus on the performance on the driving task rather than on the NDRT. Instead, the NDRT is seen as a distractor, whose effect on the driving task is of interest to the experimenter. Findings on the NDRT performance (including

[1] If a factor was reported as 'mixed', the reported results were averaged over multiple trials using different modalities for that factor.

[2] If a NDRT modality is reported as 'none', a NDRT was still performed, but did not require either an input or an output modality (e.g., listening to music requires an auditory input modality, but no output modality).

Stage		Definition	N Studies	N Groups
Stage 2				
	Total:		**5**	**17**
	Definitions:	First gaze/saccade away from NDRT	4	14
		First gaze through windshield	1	3
Stage 3				
	Total:		**15**	**62**
	Definitions:	First gaze/fixation on road (center)	14	60
		First gaze at scenery	1	2
Stage 4				
	Total:		**6**	**24**
	Definitions:	First hand movement	3	12
		Hands free	1	3
		Last interaction with NDRT	2	9
Stage 5				
	Total:		**66**	**260**
	Definitions:	Disable automation through button/lever	6	19
		Gas/brake pedal input	6	13
		Hand on wheel	18	82
		Input through steering wheel, pedals or button	5	23
		Steering wheel input	9	24
		Steering wheel or pedal contact	3	13
		Steering wheel or pedal input	17	76
		Not reported:	3	10

Table 3: Number of studies and experimental groups retrieved for each stage, including the prevalence of their definitions. If a study reported results matching multiple definitions for one stage, only the earlier was retrieved (i.e., if a study reported 'hand-on-wheel' time and 'steering wheel input' time, the reported value for 'hand-on-wheel' time was selected for stage 5).

the time until it is suspended) are thus often not relevant for a given study, and are therefore not frequently reported. Furthermore, it is difficult to measure suspension of some NDRTs (i.e., for purely cognitive or purely auditory tasks), limiting the data available for stage 4.

The meta-review by Zhang et al. [120] - through which the majority of studies for this literature search were found – studied the overall take-over time (i.e., from alert onset in stage 1 to the physical transfer of control in stage 5) in particular. By default, the studies included in their meta-review reported information for stage 5, as they would have not been eligible for their review otherwise. Consequently, most studies considered for the current literature search had data available for stage 5. The only exception [28] was one of the studies suggested by the supervisors.

The model creates a subset of results from this database depending on the input given by the user. This subset is then used to calculate the underlying distribution for each stage of the transition of control based on the users input, which is then visualized by the model in multiple ways. The user can interact with the model in the user interface.

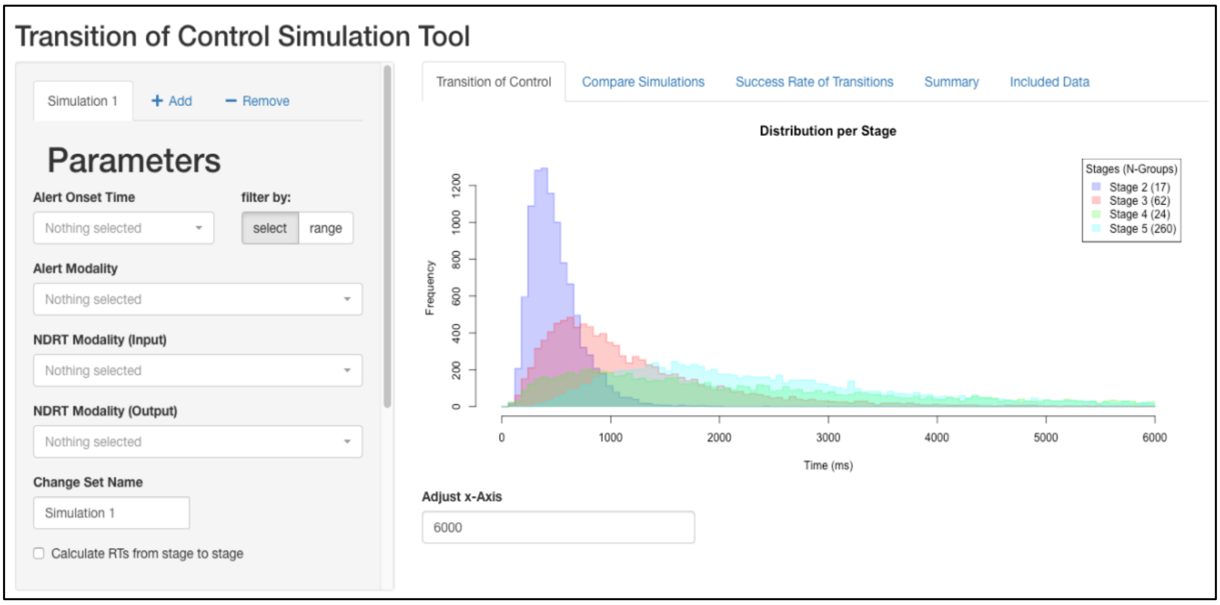


Figure 3: UI at model initiation. The input is presented on the left side of the window and the output on the right side. At initiation, the transition of control considering the entire database is presented.

3.2 User Interface

The model's UI consists of two main panels, which are visualized in Figure 3: The *Input* is presented on the left side, and the *Output* on the right side of the interface.

3.2.1 Input

With the input panel, the user can interact with the model by manipulating the subset of the data considered for the simulations, thereby allowing the user to investigate the desired configuration of factors. On the top of the input panel, the currently selected simulation is presented (Figure 3). At model initiation, one simulation considering the entire database is available. The user can add new simulations, or remove simulations (if at least two are available) using the corresponding buttons. If multiple simulations are present, the user can switch between them. The input and output presented by the model correspond to the currently selected simulation. The input panel can further be divided into two sections. (1) The *Parameter* section, which includes selectors that affect the currently chosen simulation only, and (2) the *Settings* section, which includes selectors that affect all simulations equally.

3.2.1.1 Parameter

The *Parameter* section contains selectors that the user can manipulate in order to filter through the database to create a subset of results that will be considered in the calculations for the simulation. Initially, the *Parameter* section contains four selectors representing the factors discussed in section 'Influencing Factors on Stage Onset Times'.

1. Alert Onset Time: The time between alert onset (i.e., stage 1) and critical event. The user can either select exact value (e.g., an alert onset time of 5 seconds), or a range of values (e.g., an alert onset time between 5 and 8 seconds).

2. Alert Modality: The modality or modalities with which the alert is presented (e.g., visual, auditory, tactile, or a combination of these).
3. NDRT Modality (Input): The modality or modalities involved in receiving relevant information from the NDRT (e.g., visual, auditory, tactile, or a combination of these).
4. NDRT Modality (Output): The modality or modalities required to interact with the NDRT (e.g., manual, cognitive, vocal, or a combination of these).

For each selector, a number of choices are available. Those correspond to the values retrieved for each factor in the literature search (see section 'Resulting Set of Studies'). The user can select multiple choices at once, allowing for an easy grouping of parameter choices. Based on the selected choices for each parameter, the model filters out entries in the database that do not match the selection. For instance, if the user selects 7 seconds for 'Alert Onset Times' and 'visual' & 'visual-auditory' for 'Alert Modality', the model will only consider results from experimental groups for the simulation that were exposed to an alert onset time of 7 seconds, and were presented with either a visual or a visual-auditory alert. Next to the selectors, there are two additional options in the *Parameter* section:

1. *Change Set Name:* Allows the user to rename the currently selected simulation. The new name will then appear at the top of the input panel, and in the model outputs. This functionality is especially useful when comparing multiple simulations. For instance, when comparing simulations considering visual, auditory, and tactile alert modalities, the simulations can be renamed as 'Visual', 'Auditory', and 'Tactile'. These names will then appear in the plot legends, improving the interpretability of the plots.
2. *Calculate RTs from stage to stage*: In the literature, the stage onset times are typically reported in relation to the alert onset (stage 1) rather than to the preceding stage. By default, the model uses the values as reported in the literature to simulate each stage of the transition of control, thus simulating each stage independently. If this tick box is selected however, for each stage the model also takes into account the results from its preceding stage. For example, in order to simulate a value for stage 3, the model estimates a distribution representing the transition from stage 2 to stage 3. Then, it randomly draws a value from that distribution, and adds it to a value randomly drawn from the distribution of stage 2. If no data is available for a certain stage with the selected parameter choices, that stage is skipped (i.e., if no data is available for stage 4, a distribution from stage 3 to stage 5 is estimated to simulate data for stage 5). This functionality can be useful to investigate in more detail how a certain factor affects the transition from one stage to another. However, when this functionality is enabled, the available data from the database is greatly reduced, as for each stage it can only take results from studies into account that also report its preceding stage. This functionality will be discussed in more detail in section 'Transition from Stage to Stage'.

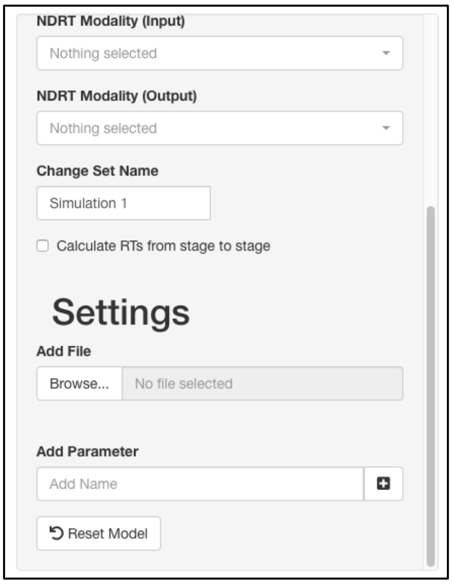


Figure 4: Continuation of the input panel with the 'Settings'-section. The section is reached by scrolling down on the input panel.

3.2.1.2 Settings

The *Settings* section (Figure 4) contains options that affect the database or the model's UI and thus affect all simulations equally. It consists of the following options:

1. *Add File:* Allows the user to add an additional Excel-file containing more study results. For example, future researchers can add new research findings to the database in order to expand it, or to compare those findings to the included database. If a file is added, the available selector choices in the 'parameter' section are updated automatically. For instance, if results from a study using a novel type of visual alert named 'experimental new visual alert' are included in the new file, the selector 'Alert Modality' will have the 'experimental new visual alert' as available choice. After a new file was added to the database, the user can choose if the database should only contain the new data, the initial data, or both. The necessary format and content of an added file is discussed in more detail in the 'Readme'-file (Supplementary Materials).
2. *Add Parameter*: Allows the user to add new selectors to the *Parameter* section. Valid choices are any column names from the excel-table producing the database. New selectors have the same functionality than the initial ones. Adding parameters serves two purposes. First, the user can investigate new factors if they are included in a previously added file. Second, it can help to filter out data more precisely. For example, the user can add the parameter 'Author' in order to only include data from specific studies.
3. *Reset Model*: Resets the model to its initial state. This removes newly added files, parameters and simulations, as well as the selected parameter choices.

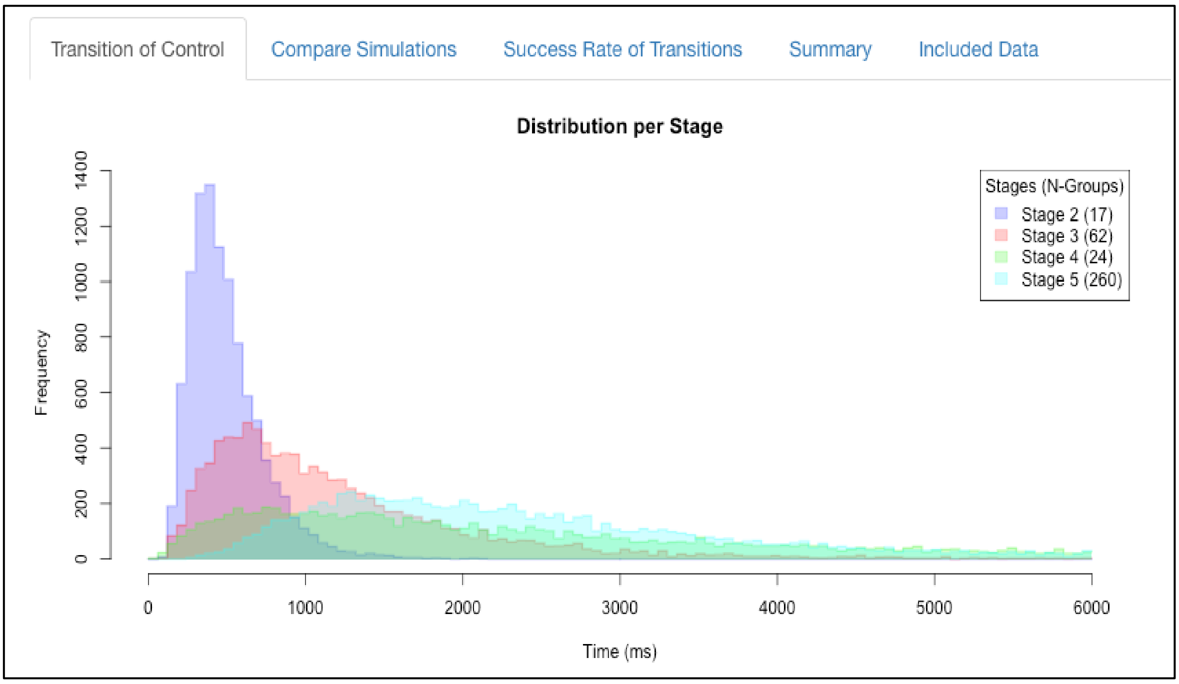


Figure 5: The 'Transition of Control' output panel of the model. This panel shows the distributions for each stage of the currently selected simulation. The simulation shown here considers the entire database and will be discussed in more detail in 'Test 1 – General Patterns in the Distribution of Stage Onset Times'.

3.2.2 Output

On the right side of the UI (Figure 3), the model output is presented. Here, the simulations resulting from the user's selection on the input are visualized in numerous ways, allowing the user to investigate the effects of different parameter configurations on the stages of the transition of control. The output consists of 5 panels: *Transition of Control, Compare Simulations, Success Rate of Transitions, Summary,* and *Included Data.*

3.2.2.1 Transition of Control

In this panel (Figure 5) the entire transition of control for the currently selected simulation is visualized, showing the estimated distribution for each stage in a different color. This panel is presented at model initiation. For each stage, absolute onset times are shown here (i.e., from alert onset in stage 1 to the respective stage). This plot gives the user an overview of the expected transition from stage to stage over time, considering the selected parameter choices of the current simulation. In order to account for large values caused by the skewness of the distribution, the x-axis is cut-off at the 99th percentile of the stage with the highest values. However, the user can adjust the x-axis manually if necessary. In the legend, the number of experimental groups from the database considered in the simulation for each stage can be found. If no data is available for a certain stage given the selected parameter choices, the stage is not visible in the plot.

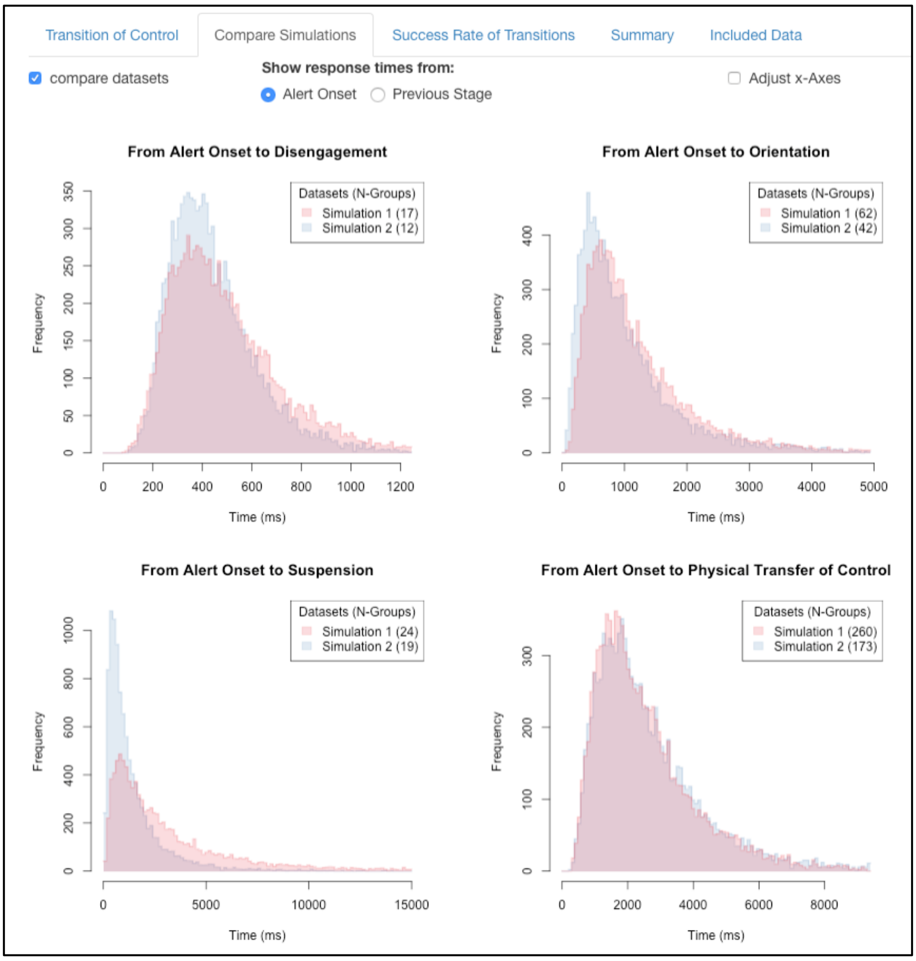
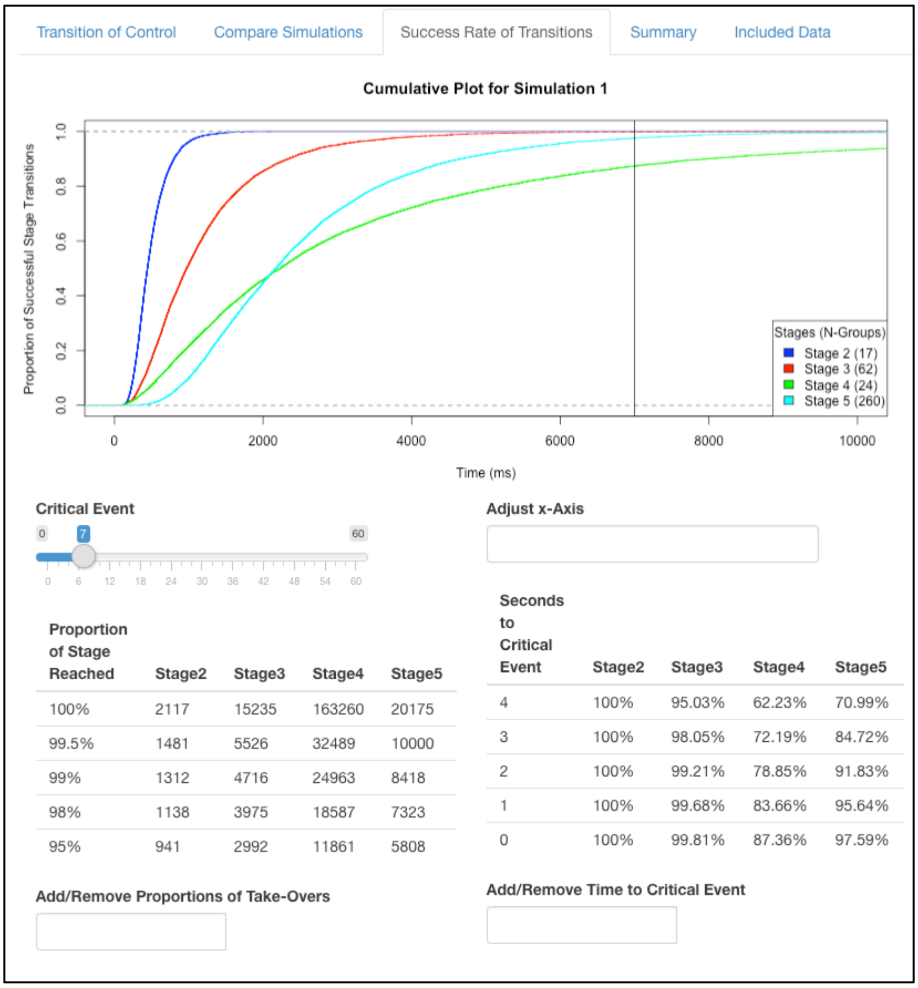


Figure 6: The 'Compare Simulations'-Panel. Each stage is plotted individually, either by absolute times (i.e. form alert onset in stage 1), or from the previous stage. If multiple datasets are currently used, the user can choose to plot them simultaneously here.

3.2.2.2 Compare Simulations

The 'Compare Simulations' panel displays four plots, one for each of the stages 2, 3, 4, and 5 (Figure 6). If multiple simulations have been created, all simulations can be plotted simultaneously in this panel. This allows the user to look at the different effects on stage onset times stemming from distinctive parameter combinations. The user can however choose to only display the currently selected simulation here as well. As for the 'Transition of Control'-panel, the x-axis is cut off at the 99th percentile, but can be adjusted manually if desired.

The stage onset times can either be plotted in relation to the alert onset (stage 1), or in relation to the previous stage (See section 'Transition from Stage to Stage' for how this transition time is estimated). If stages are plotted in relation to the previous stage, in contrast to the 'Calculate RTs from stage to stage'-option in the input panel, stages cannot be skipped if no data is available for them. For example, if data is only available for stage 2 and stage 4, the plot for stage 4 will stay empty, instead of plotting it in relation to stage 2. This was done to avoid a comparison between simulations with different stage transitions. For example, comparing stage onset times in relation to the previous stage for stage 4, if one simulation



Proportion of Stage Reached	Stage2	Stage3	Stage4	Stage5
100%	2117	15235	163260	20175
99.5%	1481	5526	32489	10000
99%	1312	4716	24963	8418
98%	1138	3975	18587	7323
95%	941	2992	11861	5808

Seconds to Critical Event	Stage2	Stage3	Stage4	Stage5
4	100%	95.03%	62.23%	70.99%
3	100%	98.05%	72.19%	84.72%
2	100%	99.21%	78.85%	91.83%
1	100%	99.68%	83.66%	95.64%
0	100%	99.81%	87.36%	97.59%

Figure 7: 'Success Rate of Transitions'-Panel. The panel at the top shows a cumulative plot for each stage in relation to the critical event (vertical line). At the bottom, two tables are shown, one showing the times needed for each stage to reach a certain percentage of successful transitions (left), and one showing the percentage of successful transitions by time in relation to the critical event (right).

has data available for stage 2 and stage 4, while the other simulation has data available for stage 3 and stage 4.

3.2.2.3 Success Rate of Transitions

The 'Success Rate of Transitions' panel (Figure 7) displays information about the rate of successful takeovers in relation to the critical event. At the top of the panel, a cumulative plot is displayed, including each stage of the currently selected simulation, along with a vertical line displaying the critical event. The user can adjust the time of the critical event, as well as the cut-off point of the x-axis. At the bottom, two tables are shown, one showing the time needed for a certain proportion of simulated trials to reach each stage (left), and one showing how many simulated trials have reached each stage at a certain time in relation to the critical event (right). For both tables, the user can add and/or remove rows. This panel gives the user a clearer picture about the rate of successful transitions of control in relation to the time of the critical event. This gives the user valuable insights on the proportion of drivers that are expected to fail to take back control in time in order react appropriately to the critical event.

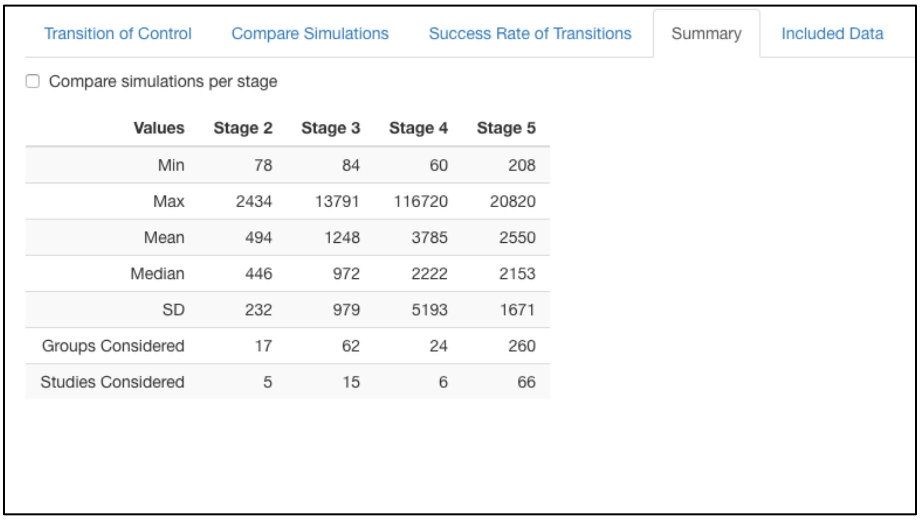


Figure 8: 'Summary'-Panel. Presents several summary statistics for each stage. The user can either choose to get the summary statistics from the currently selected simulation only, or to compare all simulations per stage.

3.2.2.4 Summary

The summary panel (Figure 8) presents a table with summary statistics for each stage included in the simulation. The table displays the smallest and largest values, the mean, the median, and the standard deviation from the simulated distribution for each stage. In addition, it shows from how many experimental groups the results are considered for the simulation and from how many different studies those experimental groups come from.

The user can either choose to show the summary statistics for the currently selected simulation only, or to compare all available simulations by stage. Overall, this panel is designed as a qualitative addition to the previously discussed panels, providing the user with concrete values related to the visualized data in other panels.

3.2.2.5 Included Data

The final panel (Figure 9) shows the subset of the database that has been taken into consideration for the currently selected simulation. By default, the table shows the authors, the value from the initial parameters (see section 'Parameter'), and the reported mean values for each stage of the experimental groups included in the subset. The user can however add or remove columns as desired. Valid columns are equivalent to the columns included in the excel-table from the literature search (see section 'Resulting Set of Studies'). The main purpose of this panel is to give the user an overview of the experimental groups considered in the simulation, thus helping to find common traits and discrepancies between the groups in order to look for new potentially interesting parameter combinations that may be interesting to inspect further. In addition, it can help to quickly find the source of specific results, if the user wishes to look at the corresponding study in more detail.

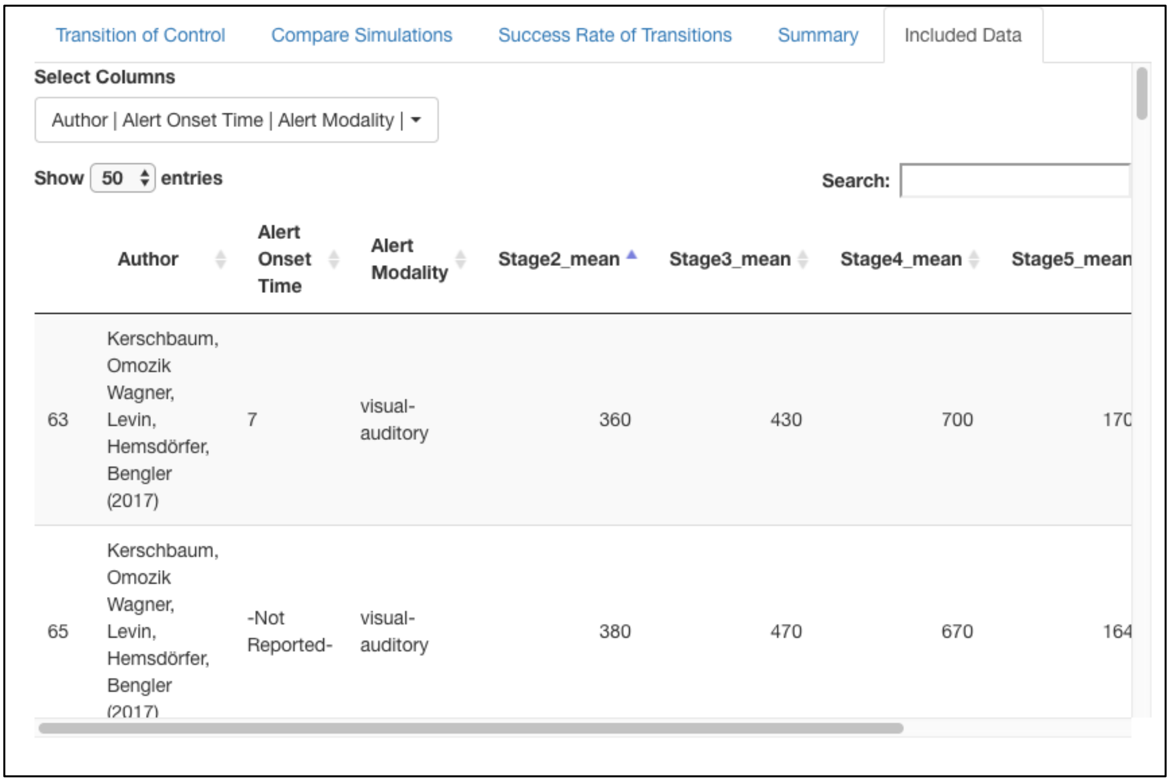


Figure 9: 'Included Data'-panel. Gives the user an overview of the experimental groups considered for the currently selected simulation. The panel contains a search-bar and allows to sort the data in different ways, in order to improve usability.

3.3 Computation

A number of calculations have to be made in order to obtain the outputs discussed in the previous section from the data in the set of studies. These are discussed in more detail in this section.

3.3.1 Retrieve Standard Deviation from Reported Results

In some studies, the standard error of the mean was reported rather than the standard deviation. If this was the case, the standard deviation was calculated using following formula taken from [31]:

$$\sigma = SE \times \sqrt{N}$$

With standard deviation σ, standard error *SE*, and number of participants *N.*

In some other cases, the 95% confidence interval was reported instead of the standard deviation. In this case, the standard deviation was calculated using the formula [31]:

$$\sigma = \sqrt{N} \times \frac{(upper\ limit - lower\ limit)}{2 \times t\ value}$$

With standard deviation σ and number of participants *N*. The t-value was retrieved from a t-value table commonly reported in statistical books (e.g. [2]), using a degree of freedom equal to the number of participants minus 1.

3.3.2 Combined Mean and Standard Deviation per Stage

With the means and standard deviations retrieved from each study in the current dataset, a combined mean and standard deviation is calculated for each available stage in order to approximate the underlying distribution. The combined mean μ_t is calculated using the formula [31]:

$$\mu_t = \frac{N_1\mu_1 + N_2\mu_2 + \cdots + N_k\mu_k}{N_1 + N_2 \ldots + N_k}$$

With mean μ, number of participants *N,* and number of experimental groups *k.* The combined standard deviation σ_t is calculated using the formula [31]:

$$\sigma_t = \sqrt{\frac{(N_1 - 1)\sigma_1^2 + (N_2 - 1)\sigma_2^2 + \frac{N_1 N_2}{N_1 + N_2}(\mu_1^2 + \mu_2^2 - 2\mu_1\mu_2)}{N_1 + N_2 - 1}}$$

With standard deviation σ*,* number of participants *N*, and mean μ. If more than two experimental groups were included, this formula was applied sequentially (i.e. first combining 'Study 1' with 'Study 2', then 'Study 1 & Study 2' with 'Study 3', and so on).

3.3.3 Transition from Stage to Stage

In the literature discussing the transition of control in level 3 automated driving, the mean reaction times and standard deviations for each stage are commonly reported in relation to the alert onset (Stage 1), rather than from the preceding stage. However, investigating how certain combinations of parameters may affect the transition between specific stages can potentially display interesting patterns. In order to allow the user to do so, the mean and standard deviation from stage to stage have to be estimated based on the existing information for each study.

The mean between stages μ_b is calculated as the difference between the means

$$\mu_b = \mu_2 - \mu_1$$

With mean μ_1 being from the stage preceding the stage with mean μ_2.

The standard deviation between stages σ_b is calculated as

$$\sigma_b = \sqrt{\frac{(\sigma_1^2 + \mu_1^2) + (\sigma_2^2 + \mu_2^2)}{2} - \left(\frac{\mu_1 + \mu_2}{2}\right)^2}$$

The derivation of this formula can be found in *Appendix B.*

With the estimations for μ_b and σ_b for each available study, the combined mean and standard deviation are then calculated as discussed in section 'Combined Mean and Standard Deviation per Stage'.

3.3.4 Shape of the Distribution

Although it is difficult to make a precise estimation of the underlying distribution for each stage of the transition of control using only the means and standard deviations generally reported in the literature, two assumptions about the shape of the distribution can be made that are common in reaction time data: (1) The distribution is *positively skewed,* and (2) there are *no negative reaction times.*

(1) Positive skewness is described by a longer tail of the distribution towards higher values on the x-axis and is common in reaction time data [82]. This tail occurs when a small but significant portion of the reaction times are much larger than the average, while very few, if any, are much shorter than average. In the transition of control, this translates to most drivers having similar, relatively short take-over times, while a small number requires much more time to successfully take over control. Although small in numbers, these outliers pose a significant risk to road safety, as they might not take back control in time to avoid the critical event. Considering them in the model is thus especially important, as they play a major role in the success of the alert.

(2) No negative reaction times are expected to occur, as they would suggest that the take-over process was initiated by the driver before the alert onset. While this can happen in practice if the take-over is self-initiated by the driver, the model discussed in this thesis focusses explicitly on the transition of control initiated by an external alert.

Both assumptions are made for the reaction times as reported in the literature (i.e. for each stage in relation to the alert onset), as well as for the transition times between stages as discussed in section 'Transition from Stage to Stage'. For the transition between stages, an additional assumption has to be made to exclude negative values, namely that the stages of the transition of control always occur in the same order. While this is inevitably true between some stages (i.e. the driver cannot orient towards the road (Stage 3) before first disengaging from the NDRT (Stage2)), exceptions to this rule can still occur. For example, in [75] the participants took back control of the vehicle (Stage 5) on average 30ms before orienting towards the road (Stage 3). Such results are however a rare exception.

In order to simulate data that matches the assumptions of (1) positive skewness and (2) no negative reaction times, a log-normal distribution is used as the underlying distribution. Out of the possible distributions adequate to model reaction time data (see [51] for an interactive overview), the log-normal distribution was chosen for a combination of practical and accuracy reasons. A log-normal distribution matches the assumptions (1) and (2), allowing for the simulated data to later match those as well. While other distributions like the ex-Gaussian are generally said to have the best fit for reaction time data [71], estimating adequate values for its parameters requires a lot of information about the data (i.e., raw data is necessary), making it impractical for this model. The parameter values for the log-normal distribution can however be estimated using the sample's mean and standard deviation, which are the most commonly (and oftentimes only) reported statistical results reported in level 3 automated driving studies [120]. The log-normal distribution can be estimated using the expected value $\widehat{\mu}$ and the standard deviation of the natural logarithm $\widehat{\sigma}$, both of which can be calculated using the mean μ_t and the standard deviation σ_t of the set of studies, as computed in Section 'Combined Mean and Standard Deviation per Stage'.

The factor $\widehat{\mu}$ is calculated using the formula *(e.g.* [94]):

$$\widehat{\mu} = \log\left(\frac{\mu_t^2}{\sqrt{\mu_t^2 + \sigma_t^2}}\right)$$

The factor $\widehat{\sigma}$ is calculated using the formula (e.g. [94]):

$$\widehat{\sigma} = \sqrt{\log\left(1 + \frac{\sigma_t^2}{\mu_t^2}\right)}$$

4 TESTING

Next, the functionality of the model was tested. For the scope of this thesis, testing had two main purposes: *(1)* to test the functionality of the model, and *(2)* to reveal interesting patterns in the literature that emerge when combining results that cover different stages of the interruption framework [36], and which can improve our understanding of the effects that different factors have on the transition of control from automated to manual driving.

To do so, 5 tests were performed with the model. First, a simulation was created using the entire database, in order to test some of the model's functionalities and to give a picture of general patterns that describe the literature findings. Second, the effect of a visual-auditory bi-modal alert on the stages of the transition of control is investigated and compared to its uni-modal visual- and auditory counterparts. Third, commonly used non-driving related tasks (NDRTs) are compared by their output modalities to study how they affect the stages of the transition of control. Fourth, a number of simulations are conducted to study how alerts and NDRTs interact with one another if they involve similar or dissimilar modalities. Finally, simulations based on the most commonly reported alert onset times are compared to see how they affect the occurrence of safety-critical last moment transitions of control.

If not stated otherwise, the values for each stage were simulated independently from one another, using the results as reported in the literature as a baseline for the calculations

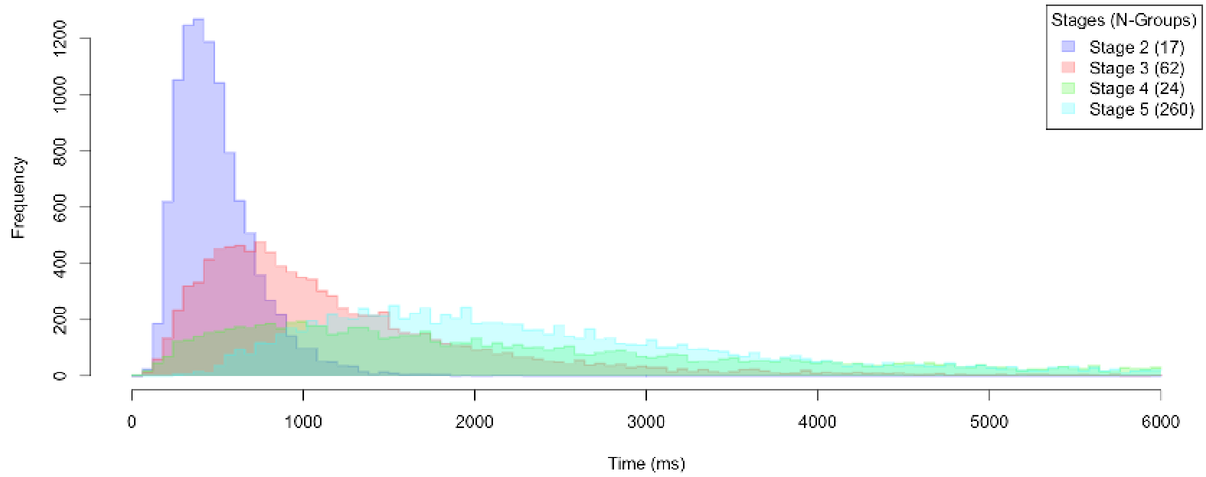


Figure 10: Distribution of the simulated data when taking the entire database into account. For each stage, the simulation is done independently, considering data from all experimental groups for which results for the respective stage was reported. The numbers of experimental groups included for each stage are listed in brackets in the legend.

(i.e. from alert onset to the respective stage). This was done because calculating the values from stage to stage greatly reduces the number of observations from the database included in the calculation, as it can only consider observations that discuss both the current stage and its preceding stage (See section 'Transition from Stage to Stage').

Due to the expected asymmetry of the distribution resulting from its skewness, the standard deviation was not considered a good measure of spread in the data. Instead, the quartile deviation (QD) [45] was calculated using the formula:

$$QD = \frac{(Q_3 - Q_1)}{2}$$

where Q_3 is the simulation 75th percentile and Q_1 the simulation 25th percentile. A higher QD suggests a larger spread of the distribution.

4.1 Test 1 – General Patterns in the Distribution of Stage Onset Times

The goal of the first test was to uncover general patterns in the distribution of stage onset times during the transition of control. In order to do this, a simulation was run with the model considering the entire database for calculations.

4.1.1 Model Performance

The data resulting from this simulation is plotted in Figure 10. The simulation resulted in distinct stage onset time distributions for stage 2 (M = 0.50, QD = 0.13), stage 3 (M = 1.23, QD = 0.47), stage 4 (M = 3.84, QD = 1.67), and stage 5 (M = 2.56, QD = 0.90). With regard to the alert onset times of 5 to 8 seconds oftentimes considered the minimum time required for the driver to take back control safely (e.g., [24,63]), a significant proportion of transitions failed to succeed (i.e., failed to reach stage 5) in time. 7.86% of transitions have not been successful 5 seconds after the onset of the alert. After 8 seconds, still 1.37% of transitions have not yet been terminated. It should be noted however, that some experimental groups considered for this simulation were exposed to longer alert onset times, and may thus distort this result. The

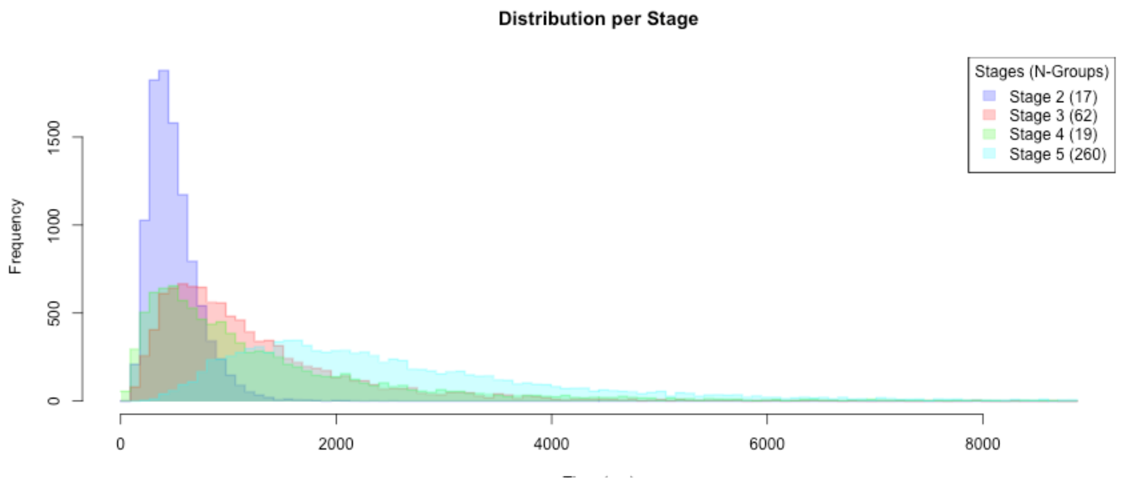


Figure 11: Distribution of the simulated data considering the entire database except for the study contributing to stage 4 with exceptionally large stage onset times. By excluding results from this study, the distribution of stage 4 now resembles the distribution of stage 3. Other stages remain unaffected by the removal.

effect of specific alert onset times on the rate of failed transitions will be investigated in 'Test 5 - Rate of Successful Take-Overs Based on Alert Onset Time'.

4.1.2 Discussion

The long tails in the distribution of stage 5 elicited by the model suggest that a significant portion of transitions may result in an unsuccessful take-over with regard to the commonly reported alert onset times used in the literature. After 8 seconds, 1.37% percent of simulated transitions have not been accomplished. This corresponds to 1 in every 73 drivers failing to take back control in time, if they had 8 seconds to react to a critical event. Considering the negative consequences of a failed take-over, this rate can arguably be considered too high. Thus, while an alert being presented on such short notice might suffice in most cases, the model suggests that it is not sufficient to ensure overall road safety.

Overall, the distributions of the stages resulting from this simulation elicit a specific pattern. Stage 2 shows the shortest mean stage onset time and the smallest spread in the data. The mean and spread of the stages consistently increase through stage 3 and stage 5. This pattern suggests that the stages of the transition of control generally follow the framework by Janssen et al. [36]: Initial stages are handled quickly and consistently, whereas the variation in how quickly a stage is handled increases over time. However, stage 4 does not follow the pattern as clearly as other stages, having a larger mean and spread than stage 5, thus resulting in the highest values overall. A closer look at the database reveals an explanation for the unexpected pattern.

5 of the 24 experimental groups with reported results for stage 4 come from one study that used an alert onset time of 21 seconds (in the form of a pre-alert) [28], all of which eliciting a stage onset time for stage 4 above 8 seconds. This study only reported values for stage 4, thus not equally affecting the simulation of other stages (a comparatively large stage onset time could have been expected at least for stage 5 in this study). By excluding the results of this study for the simulation, another pattern - unexpected in its own way – emerges (Figure 11). The distribution now peaks shortly before stage 3, but elicits a longer tail. Based

on the mean and quartile deviation, stage 4 (*M* = 1.43, *QD* = 0.62) is now located between stage 3 (*M* = 1.23, *QD* = 0.47) and stage 5 (*M* = 2.56, *QD* = 0.90), however being much closer to stage 3. This pattern now suggests that the onset of stage 4 occurs almost in parallel to the onset of stage 3. This may be due to the generally short alert onset times used in the literature comprising the database (see Table 2). Given the limited time participants had to take back control of the vehicle in most of the experimental groups, they may not strive to reach a natural breakpoint in the non-driving task before suspending it. Instead, they might suspend it as soon as the alert was perceived in order to react in time for the critical event. The effect that the results from [28] had on the model's simulation for stage 4 shows however, that an extended alert onset time can have a significant effect on the shape of the transition of control. More research is needed to better understand how these longer alert onset times affect the stages of the transition of control.

This finding has a significant implication for the model's optional functionality to calculate stage onset times in relation to their preceding stage (see section 'Transition from Stage to Stage'), as it is implemented with the assumption that drivers go through the stages consecutively (i.e., the model does not simulate negative stage transitions). Considering that stage 3 and stage 4 seem to occur almost in parallel in Figure 11, it can be expected that stage 4 is reached earlier in time than stage 3 in some transitions. A closer look at the experimental groups of the database shows that this has indeed been observed in multiple experimental groups [8,40]. The estimated distributions from stage to stage may have been oversimplified in the model. These distributions could elicit unique shapes that need to be taken into account for the simulation. However, given the limited data for some stages, and the limited accessibility to raw data, studying the stage transitions in depth was difficult in the scope of this project. The calculation from stage to stage should thus be used with caution, and with proper consideration of the subset of the database considered for the calculations. Users are advised to use the model's default simulation (i.e., simulating each stage in relation to the alert onset), as will be done in the remainder of this thesis. For a clearer view on the stage distributions from this section, Figure 10 and Figure 11 are plotted per stage in *Appendix C.*

4.2 Test 2 – Effect of Different Alert Modalities on the Transition of Control

Next, the effect of alert modality on the take-over process was investigated using the model. In the literature, by far the most commonly used alert is a bi-modal visual-auditory alert with 173 experimental groups in the database (reported in 49 papers) being exposed to it, followed by purely auditory alerts with 41 occurrences (16 papers) in the database. For the purpose of this test, the focus will thus be on the visual-auditory bi-modal alert, and how the distributions of timings for the different stages compare to those for purely visual or purely auditory alerts.

4.2.1 Model Performance

The data resulting from these simulations is plotted per stage in Figure 12. According to the model, alert modality had little effect on overall transition time (i.e., from alert onset to the physical transfer of control in stage 5. Figure 12, bottom right), with all simulations resulting in mostly overlapping distributions. For intermediate stages however, the model resulted in

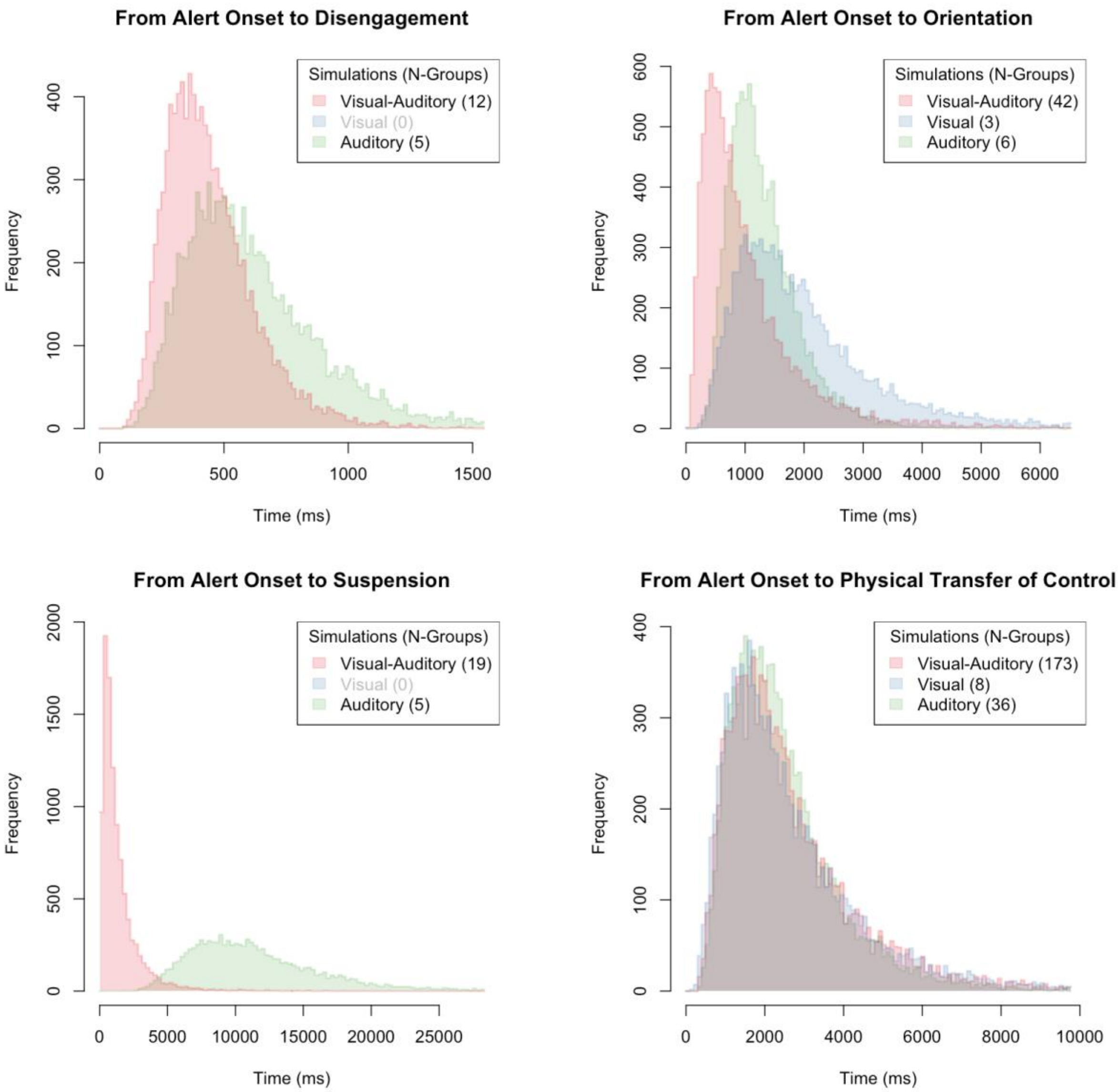


Figure 12: Distribution of the simulated data considering different alert modalities. Overall, the visual-auditory alert (red) resulted in the shortest stage onset times, compared to visual (blue) and auditory (green) alerts. This effect was most prevalent in earlier stages and dissipated in the final stage of the transition of control.

a significant difference in stage onset times between the selected alert modalities. A visual-auditory alert led to the earliest distribution peaks in stage 2 (disengagement), stage 3 (orientation), and stage 4 (suspension of the NDRT), and showed the least spread in data compared to most other distributions in these stages. Only in stage 3 (Orientation) did the visual-auditory alert have a larger spread (QD = 0.42) than the auditory-only alert (QD = 0.36), although not as large as the visual-only alert (QD = 0.68). The largest discrepancy in distributions can be seen in stage 4 (suspension of the NDRT) between visual-auditory alert (M = 0.94, QD = 0.62) and auditory-only alert (M = 10.58, QD = 3.03). It should be noted however, that the experimental groups considered for the auditory-only alert condition in this stage all came from [28], whose impact on stage 4 has been discussed extensively in 'Test 1 – General Patterns in the Distribution of Stage Onset Times'.

4.2.2 Discussion

The data simulated in this test showed an interesting effect of alert modality on the transition of control. While the modality of the alert had a visible effect on earlier stages of the transition, with the fastest stage onset times occurring with a bi-modal visual-auditory alert, this effect dissipates in the last stage of the transition. The minimal effect of alert modality on overall takeover time has also been determined in the meta-review [120] from which most studies comprising the model's database have been gathered. However, incorporating the stages of the interruption framework [36] revealed that the alert modality has an effect on the intermediate stages of the transition, suggesting that drivers take more time to perceive and initially react to uni-modal alerts as compared to bi-modal visual-auditory alerts. The modality used to alert the driver should thus especially be taken into consideration when a quick initial reaction from the driver is desired, for example to provide the driver with information about the current traffic situation in order to prepare them for an upcoming takeover request.

4.3 Test 3 - Effect of NDRT Output Modalities on the Transition of Control

Next, a comparison of the effects of manual and cognitive non-driving related task (NDRT) output modality on stage onset times was conducted. Three simulations were performed with the model:

- *(1) Cognitive:* The first simulation uses results from experimental groups being exposed to a NDRT that required cognitive engagement from the participants for the calculations. Purely cognitive NDRTs were included here as well as NDRTs requiring cognitive modality in combination with another modality (i.e., 'cognitive-vocal', 'cognitive-manual'). A task was said to require cognitive output if it was discussed as such in the respective study (See section 'Collected Information').
- *(2) Manual*: The second simulation uses results from experimental groups being exposed to a manual NDRT for the calculations. As for simulation (1), purely manual NDRTs were included as well as NDRTs requiring manual output in combination with another modality (i.e., 'manual-cognitive'). Note that there is overlap between (1) and (2), as some groups had a cognitive-manual NDRT.
- *(3) Other*: The last simulation used results from experimental groups being exposed to a NDRT that required neither a cognitive nor a manual output from the participant for the calculations. Here, NDRT requiring vocal output were included, as well as NDRT requiring no output from the participant.

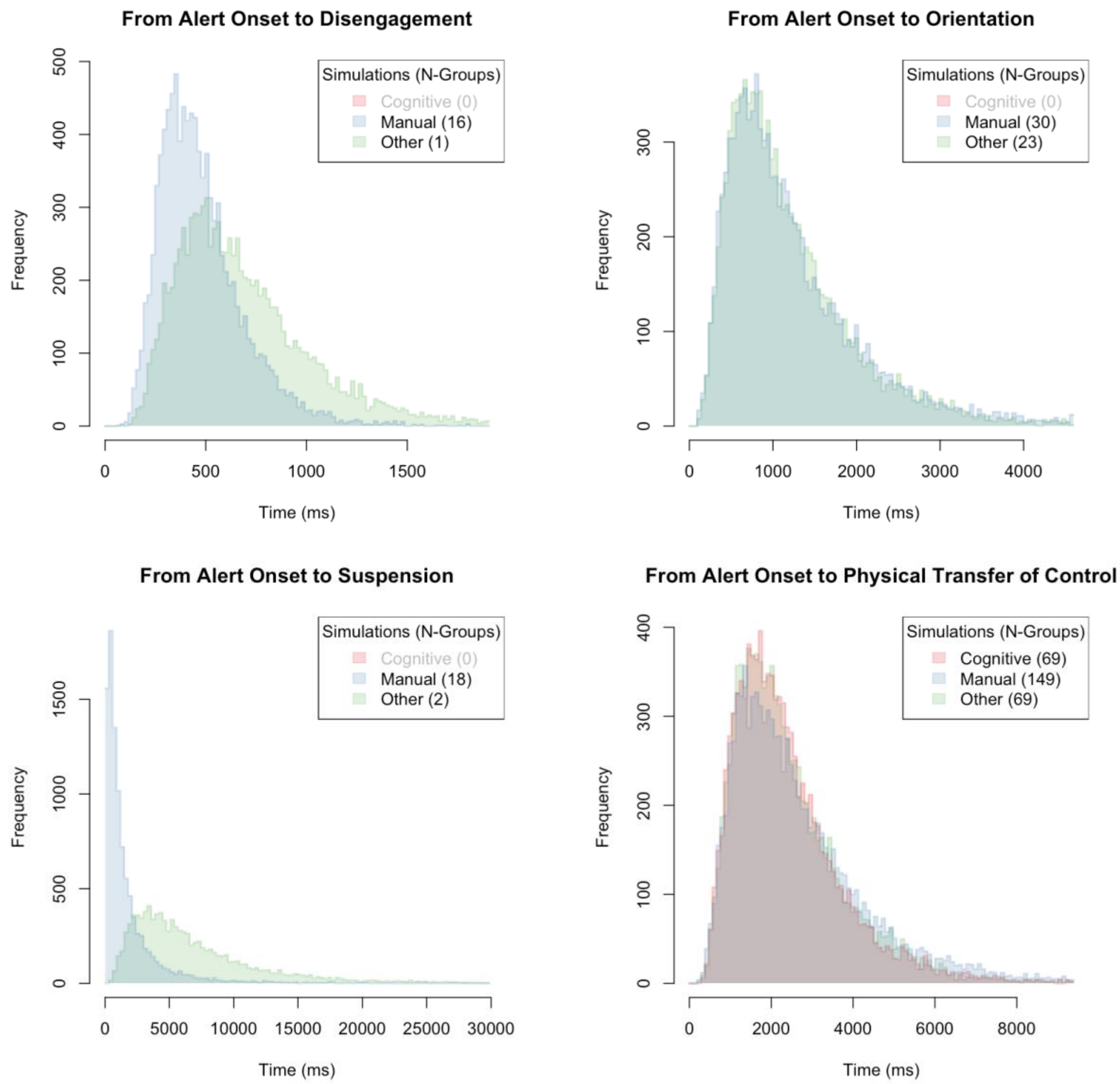


Figure 13: Distribution of the simulated data based on non-driving related task (NDRT) output modality.

4.3.1 Model Performance

The data resulting from these simulations is plotted in Figure 13. While NDRTs requiring a cognitive modality (*M* = 2.10s, *QD* = 0.81) elicited similar overall take-over times than other NDRTs (*M* = 2.10, *QD* = 0.81), a slightly different pattern resulted from manual NDRTs (*M* = 2.20s, *QD* = 0.94) with a more spread out distribution. This resulted in a larger failure rate 8 seconds after onset of the alert for manual (1.94%) compared to cognitive (0.66%) and other (0.82%) NDRTs.

A similar trend was elicited in stage 3, with slightly later stage onset times with manual NDRTs (*M* = 1.01s, *QD* = 0.46) compared to other NDRTs (*M* = 0.98, *QD* = 0.43). However, the difference was much smaller here, and is barely noticeable in the visualization of the results. In stage 2 and stage 4, manual NDRTs resulted in visibly shorter peaks and spread of the distribution than other NDRTs. Here, a comparison should be made with caution though, considering that for other NDRTs, the model only considered 1 and 2 experimental groups for stage 2 and stage 4, respectively.

4.3.2 Discussion

Results from this test suggest that the (output)-modality of the NDRT being performed while automation is enabled has the largest effect on the tail of the distribution in stage 5 (physical transfer of control). Specifically, NDRTs requiring some sort of manual response from the driver resulted in two to three times as many unsuccessful transitions 8 seconds after the alert onset than did cognitive and other NDRTs. The effect of manual NDRTs on stage onset time was not as evident in stage 3 (orientation), suggesting that manual NDRTs affect overall transition time more than the initial reaction to the alert. While results for stage 2 (disengagement) and stage 4 (suspension of the NDRT) suggest an effect in these stages as well, more data is necessary here to ensure that this effect is not caused by secondary factors in the design of the studies considered in the simulation of the other NDRT modality.

Interestingly, a cognitive NDRT modality did not result in a difference in overall take-over times (i.e., stage 5), compared to other NDRTs. Yet, possible effects in the intermediate stages could not be revealed due to a lack of available study results in these stages. However, although the model suggests that cognitively demanding NDRTs do not affect the take-over time itself, previous studies suggest that cognitively demanding NDRTs can affect driving performance [88,92] in general. This should be taken into consideration by future researchers and engineers, as these NDRTs might reduce the quality of driving for some time after the transition of control, even if the take-over time is unaffected.

4.4 Test 4 – Interaction of Alert Modality and NDRT Input Modality

In order to test how the model performs when multiple parameters are manipulated simultaneously, the effect of alert modality combined with different NDRTs for each stage was investigated. Specifically, the focus of this test was to see how stage onset times are affected differently when alert and NDRT modalities are identical, or different. In order to do so, nine simulations were performed, one for each combination of alert modality (visual, auditory, visual-auditory) and NDRT input modality (visual, auditory, visual-auditory).

4.4.1 Model Performance

Figure 14 shows a comparison of the simulated data per stage. In stage 2 (disengagement) and stage 4 (suspension of the NDRT), the visual-auditory bi-modal alert resulted in an earlier peak and less spread in the distribution compared to the auditory alert when a visual NDRT was performed (Figure 14, a, g). In stage 3 (orientation), the visual alert resulted in the latest peak and largest spread in combination with a visual NDRT (Figure 14, d) and a bi-modal NDRT (Figure 14, f). In both cases, the bi-modal alert resulted in the earliest peak. In combination with the visual NDRT, the bi-modal alert resulted in a longer tail than the auditory alert, however. In stage 5 (physical transfer of control), different patterns emerged. In combination with a visual NDRT (Figure 14, j), the bi-modal alert resulted in the earliest peak, while the auditory alert resulted in the latest peak. The visual alert however resulted in the most distinct

Alert Modality	NDRT modality			
	Visual	Auditory	Visual-Auditory	Total
Visual	13.51s	6.65s	4.83s	11.65s
Auditory	9.13s	4.73s	5.69s	8.44s
Visual-Auditory	10.94s	8.90s	11.68s	11.06s
Total	10.76s	7.07s	10.86s	10.02s

Table 4: Time passed (in seconds) until 99.5% of simulated trials reached stage 5 (physical transfer of control) for each simulation. The 'total' values are added for reference and were retrieved from simulations created by manipulating the corresponding parameter only (e.g., the threshold was reached after 11.65s in a simulation using a visual alert and ignoring the NDRT input modality).The threshold of 99.5% was chosen to avoid large variations of values caused by the highest transition times reported by the model.

tail. In combination with an auditory NDRT (Figure 14, k), the visual alert resulted in the latest peak and largest spread. Here, the bi-modal alert resulted in an earlier peak than the auditory alert, but had a larger spread in the distribution and a more distinct tail. In combination with a visual-auditory bi-modal NDRT (Figure 14, l), the auditory alert resulted in the earliest peak, and the bi-modal alert resulted in the largest spread in the distribution.

Table 4 shows how much time passed until 99.5% of simulated trials transitioned to stage 5 (physical transfer of control) with each parameter combination. This was done in order to see how NDRT and alert modality affect the time required for the majority of drivers to take back control in time. Overall, the longest times resulted from the simulation with a visual alert and visual NDRT modality (13.51s), while the shortest times resulted from the simulation with an auditory alert and auditory NDRT modality (4.73s). The alert modality resulting in the longest times regardless of NDRT modality was visual (11.65s), followed by visual-auditory (11.06s), and auditory (8.44s). For the NDRT modality, the longest times regardless of alert modality were caused by visual-auditory (10.86s), followed by visual (10.76s), and auditory (7.07s).

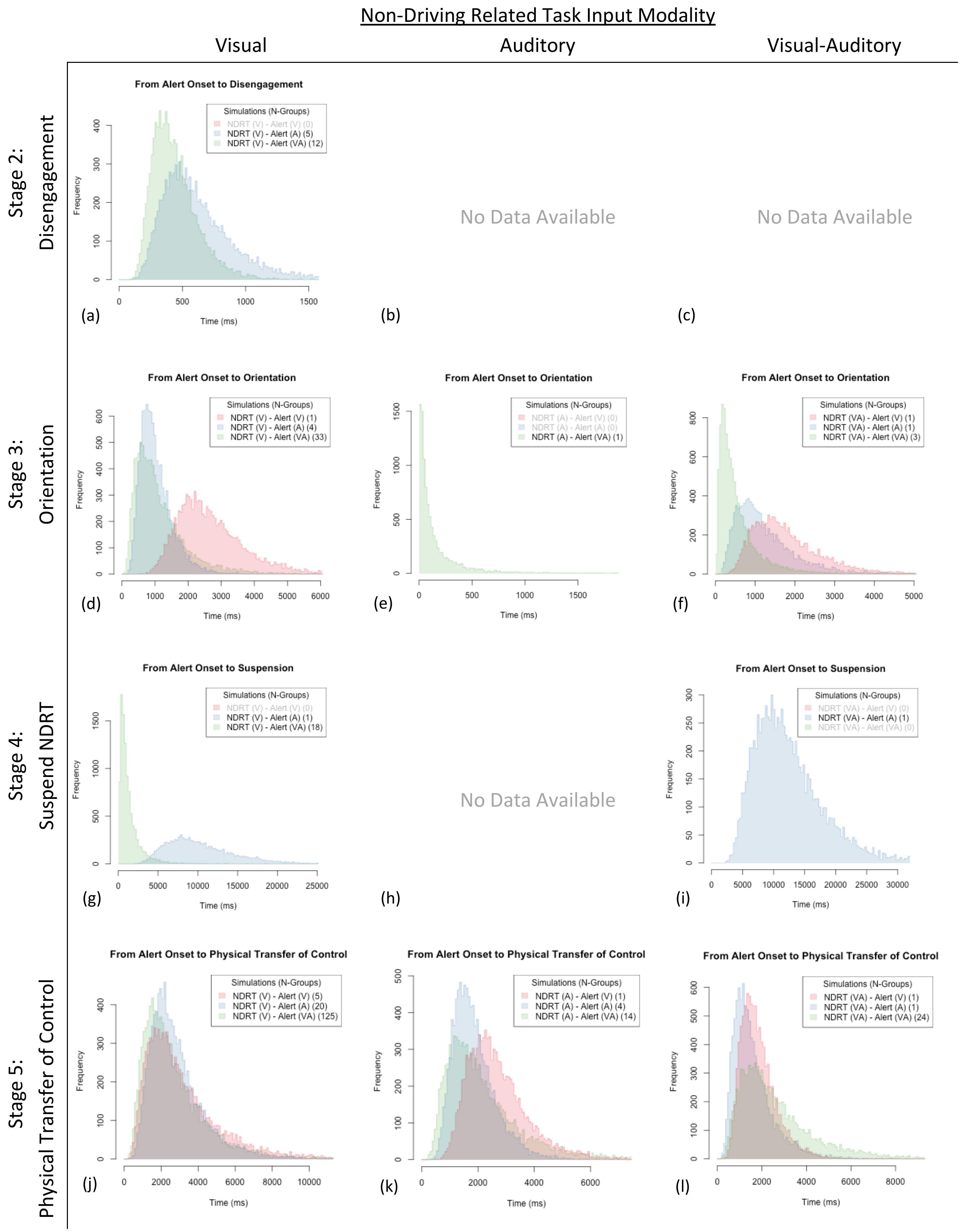


Figure 14: Simulated data per stage for visual (left), auditory (center), and visual-auditory (right) NDRT input-modalities. Each plot contains the distribution from simulations using visual (V), auditory (A), and visual-auditory (VA) alert modalities.

4.4.2 Discussion

The results from this test presented in Figure 14 suggest that the visual-auditory bi-modal alert resulted in the fastest stage onset times in combination with most NDRT input modalities in earlier stages. Drivers appear to react faster to bi-modal alerts compared to purely visual, or purely auditory alerts. The faster response to bi-modal alerts may be caused by a higher probability to perceive the alert initially. While purely visual or purely auditory alerts are more likely to remain unnoticed, especially if the currently performed NDRT presents information in the same modality, bi-modal alerts might overcome this issue by allowing the driver to perceive the alert in different ways. A preference for the bi-modal alert is also prevalent in the literature. In the model's database, 173 out of 265 experimental groups were presented with a bi-modal visual-auditory alert. For the overall transition of control, this advantage seems to dissipate, however.

Looking at the onset times for stage 5 (physical transfer of control), the longest overall transition times appear to result from simulations where alert and NDRT modalities are identical. This was the case for both purely visual (Figure 14, j) and bi-modal visual-auditory (Figure 14, l) modalities. For the bi-modal modality this pattern is surprising, considering that purely visual or purely auditory alerts overlap with the modalities of a bi-modal NDRT as well. Interestingly, the opposite was the case for the auditory modality (Figure 14, k), where the auditory alert led to the shortest overall transition times when presented during an auditory NDRT.

The results from this test suggest that the interaction between alert- and NDRT-modality are more complex, and that there is no clearly advantageous alert modality for all take-over requests. Other aspects of the alert that have not been taken into consideration here might play a significant role as well. For instance, regardless of the modality used, the perceived urgency of the alert might affect the duration of the transition [27,56]. Furthermore, the alert can be more or less disrupting depending on how it presented to the driver (i.e., was the visual alert presented on the same device used for the NDRT? Was the volume of the auditory NDRT turned down when the auditory alert was presented?). It is possible that more disruptive alerts result in different patterns in the transition of control. Due to the more selective inputs used in this test (i.e., experimental groups had to match two factors – alert modality and NDRT input-modality – for their results to be considered for the simulations), most simulations only had limited data available for calculating the underlying distributions. Consequently, these other aspects of the alert presentation (or other differences in the study design) may have affected some of the resulting distributions more than others. Future users of the model can take other alert properties such as perceived urgency or disruptiveness into account to study their effect of the transition of control.

4.5 Test 5 - Rate of Successful Take-Overs Based on Alert Onset Time

For the final test, the model was used to investigate the effect of alert onset time on the rate of successful take-overs. Therefore, a simulation was run for each of the four most commonly used alert onset times: 3.5 seconds (13 experimental groups; 3 studies), 6 seconds (30

	3.5 Seconds	6 Seconds	7 Seconds	10 Seconds
2s before critical event	55.82%	94.97%	99.24%	98.25%
1s before critical event	75.66%	98.24%	99.79%	99.01%
Critical Event	85.16%	99.34%	99.95%	99.45%

Table 5: Percentage of simulated trials having reached stage 5 (physical transfer of control) by alert onset time, in relation to the critical event onset.

experimental groups; 9 studies), 7 seconds (69 experimental groups; 13 studies), and 10 seconds (42 experimental groups; 10 studies). The model's 'Success Rate of Transitions'-panel will be the main focus of this test. Here, the critical event onset will be adjusted to the alert onset time of the respective simulation (i.e., for the alert onset time of 6 seconds, the critical event will be set to 6 seconds in the model).

4.5.1 Model performance

For alert onset times of 6, 7, and 10 seconds, the majority of simulated take-overs led to a successful transition, with over 99% of simulated trials having reached stage 5 (physical transfer of control) at the time of critical event occurrence (Table 5). The highest percentage was yielded using an alert onset time of 7 seconds, with 99.95% of successful take-overs at the time of critical event onset (Figure 15). For the shortest alert onset time (3.5 seconds) however, only 85.16% have reached stage 5 at critical event onset. While almost all simulated trials have reached stage 5 at the critical alert onset with an alert onset time of 6 seconds, 5% have not reached it yet 2 seconds before the critical event onset, suggesting that 1 in 20 take-overs were completed at the last moment.

4.5.2 Discussion

The model's results suggest that alert onset times of 6 seconds and more give most drivers sufficient time to take back control of the vehicle on time to react to a critical event, although an alert onset time of at least 7 seconds is required to avoid last-moment take-overs. These findings correlate well with mean take-over times commonly reported in the literature, which rarely surpass 6 to 7 seconds [120]. The model's results suggest however, that a small but critical fraction of transitions fails to succeed in time to respond to the critical event. This becomes even more apparent when looking at the rate of uncompleted transitions 2 seconds before the critical event, especially for the shorter alert onset times. Here, a little over 5% have not yet taken back control with an alert onset time of 6 seconds. With an alert onset time of 3.5 seconds, the rate of uncompleted transitions even rises to approx. 44%. Avoiding last-moment transitions can be crucial for traffic safety, as it gives the driver more time to react appropriately by steering and/or braking if the critical event requires a change in lateral or longitudinal trajectory.

The success rates reported here refer to driver-readiness (i.e., hands on the steering wheel) and do not necessarily translate to adequate driving performance after take-over, which has been found to be impaired for an extended time after take-over [60]. Furthermore, the database only contains transitions tested in an experimental setting. With longer periods

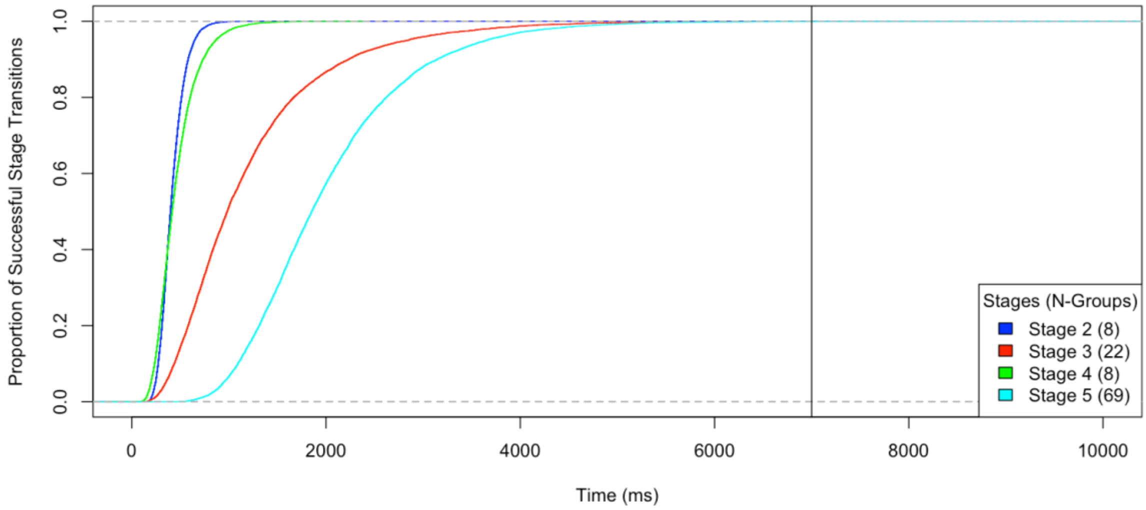


Figure 15: Cumulative plot of successful transitions to each stage for a simulation using an alert onset time of 7 seconds. The vertical line represents the occurrence of the critical event.

of disengagement from the driving task, drivers may become more fatigued [37], and familiarization with the automation over time can lead to a decrease in monitoring behavior during periods of automation [47]. In a real-life scenario, take-over times can thus be quite different, considering that take-over requests may occur less frequently and more unexpected. Considering that the rate of failed transitions may thus be higher in a real-life scenario than in an experimental setting, it is even more important to study not only the average time drivers need to take back control of the vehicle, but to also study the number of drivers that would fail to do so in time. As was done in this test, the model helps to reveal how the rate of successful transitions is affected by certain factors.

5 GENERAL DISCUSSION

The goal of the model presented in this thesis was to create an interactive tool that can help researchers and engineers to study the effects different factors have on the transition of control in semi-automated driving, and how specific stages of that transition, as discussed by Janssen et al. [36], are affected differently by those factors. The model does so by quantifying over results from an extensive database of level 3 automated driving studies in order to determine the underlying distributions of stage onset times based on the parameter selections made by the user of the model. Based on these distributions, the model simulates the transition of control process, and visualizes the simulated data in multiple ways. The model was designed to investigate three questions concerning the transition of control process: *(1) How does the driver go through the stages of the transition of control discussed by Janssen et al.* [36]*? (2) Are these stages affected differently by some factors than by others? (3) How likely is the transition of control going to succeed in time for the driver to react to a critical event, and how is the success rate affected by different factors?*

With the model, a number of tests have been conducted for the purpose of this thesis. These have given valuable insights on the effects of alert onset time, alert modality, and non-driving related task (NDRT)-modality on the overall take-over process, and on the intermediate stages of the transition of control. However, the tests discussed here only represent a few examples of possible parameter combinations that can be studied with the model. Furthermore, due to the interactive design of the model, its functionality can easily be expanded by adding more data to its database, and by including new parameters that represent factors that have not been discussed in this thesis. Readers of this thesis are encouraged to use the model in ways that have not been discussed here, in order to reveal unexpected patterns in the simulated data that can help to improve our understanding of the transition of control in semi-automated driving. In the remainder of this section, first the implications of the findings from the testing section of this thesis will be discussed. Afterwards, some limitations and future work will be addressed.

5.1 The Transition of Control Model: Findings and Implications

The model results discussed in this thesis gave valuable insights on the transition of control process in semi-automated driving. Overall, the model elicited distinct patterns in the stages discussed by Janssen et al. [36]. By comparing simulations resulting from different parameter combinations, the model gave insight on how certain factors affect different moments of the take-over process differently than others. This insight can help future researchers and engineers to target specific moments of the transition process through deliberate design choices, in order to optimize overall take-over time and quality. By simulating not only mean stage onset times, but a distribution of stage onset times instead, the model also shed light on the occurrence of the less frequent - but critical - failed transitions. The findings discussed in this thesis relate to the three aspects of the transition of control the model was designed to shed light on: *(1) How does the driver go through the stages of the transition of control discussed by Janssen et al.* [36]*? (2) Are these stages affected differently by some factors than by others? (3) How likely is the transition of control going to succeed in time for the driver to react to a critical event, and how is the success rate affected by different factors?* The insights for each of these aspects gained with the help of the model, and their implications for our understanding of the transition of control and traffic safety overall will be discussed in more detail now.

With regard to aspect (1), the model's performance in 'Test 1 – General Patterns in the Distribution of Stage Onset Times' suggested that drivers go through the initial stages of the transition of control quickly and more consistently, but that stage onset times become increasingly spread out throughout the subsequent stages. The model highlights the transition from stage to stage nicely, by illustrating how similar and/or distinct the distributions of stage onset times are overall. Here, an interesting pattern emerged with the suspension of the NDRT in stage 4. In some simulations, stage 4 elicited a significant overlap with stage 2 (disengagement) and stage 3 (orientation), which becomes particularly apparent in Figure 11 and Figure 15. In their original discussion of the stages of the transition of control, Janssen et al. [36] argued that such fast or overlapping transitions might occur, for example when the driver self-interrupts to take back control. The model suggests however, that such transitions occur frequently when the transition is initiated by an external take-over request as well. This prevalent overlap might be an artifact of the database. In the literature included in the database, the average alert onset time was 7.8 seconds. On such short notice, drivers may not have sufficient time to go back to the NDRT after the first disengagement or orientation. Considering that people generally need some time to resume a task after an interruption [65], they might just suspend the NDRT right away after an external alert was presented to them instead. Longer alert onset times, for example through pre-alerts as discussed in [28], can result in a different pattern here. The distributions in Figure 12 and Figure 14 (g) highlight this, where the longer alert onset time of 21 seconds used in [28] resulted in a distinctively later peak and larger spread in the distribution of stage 4 compared to other distributions. This shows the need to study longer alert onset times in general, as those appear to have a significant impact on the driver's willingness to resume the NDRT after first disengaging from it. More research is needed to understand how take-over time and quality are affected if drivers have sufficient time to reach a natural breakpoint [35] in their NDRT before taking back control of the vehicle.

Regarding aspect (2), the model showed clear differences in the effect of some factors on the onset times for the stages of the transition of control. For example, 'Test 2 – Effect of Different Alert Modalities on the Transition of Control' revealed that alert modality had little effect on the overall take-over time (i.e., physical transfer of control in stage 5), but affected the initial response to the alert in stage 2 (disengagement) and stage 3 (orientation), with the bi-modal visual-auditory alert resulting in faster stage onset times than purely visual or purely auditory alerts. The minor impact of alert modality is in line with findings from the meta-review by Zhang et al. [120]. Their review did not reveal the alert modalities effect on earlier stages, however. Changes in response time due to alert modality as suggested by the model are in line with findings on general human-machine-interfaces (HMI) [16], suggesting that some connections between alert presentation in semi-automated driving and HMIs can be made. However, while alert modality did not show an effect on stage 5 onset when studied independently, an interactive effect between similar and dissimilar alert- and NDRT-input modalities have been found in 'Test 4 – Interaction of Alert Modality and NDRT Input Modality'. This implies that some aspects affecting the transition of control cannot be studied by looking at isolated factors. The model can help future users here, as it can be used to easily combine different factors in order to uncover their cumulative effects on the take-over process. In contrast to the alert modality, NDRT-output modality appeared to have a larger effect on stage 5 than on stage 3, as was discussed in 'Test 3 - Effect of NDRT Output Modalities on the Transition of Control'. Interestingly, cognitive tasks resulted in a similar distribution in stage 5 than other tasks did, while manual tasks showed a slightly more shifted distribution, resulting in a larger proportion of late transitions. This result was unexpected, considering that cognitively demanding tasks have been found to affect the driver's performance in semi-automated driving in general [88,92]. However, while such tasks may not have an effect on the take-over time, they could still affect the quality of driving after control was successfully taken back by the driver. Overall, the model's results discussed here implyt that the duration of the take-over process can be optimized by targeting certain moments of the transition of control with specific interventions. For example, the choice of modality with which the alert is presented to the driver can accelerate the perception of the alert, while guidelines on NDRTs that the driver can perform while automation is enabled can affect the time needed by the driver to physically take back control of the vehicle. Researchers and engineers can thus benefit from the model, as it can help to reveal the stages of the transition that certain interventions affect most.

Finally, for aspect (3) the model gave valuable insight on the occurrence of longer transition times in semi-automated driving. In most simulations, the majority of transitions succeeded well within the commonly reported alert onset times of 5 to 8 seconds considered to be the minimum time drivers need to take back control safely (e.g., [24,63]) and regularly used in empirical studies [120]. However, most simulations showed a distinct tail in the distribution of take-over times, suggesting that a small but significant number of transitions can take much longer than expected to succeed. Those outliers are critical for traffic safety, since potentially hazardous situations are more likely to be caused by them rather than by the average take-over [33]. The results discussed in 'Test 5 - Rate of Successful Take-Overs Based on Alert Onset Time' show how the alert onset time can affect the occurrence of these outliers. Simulations using an alert onset time above 5 seconds resulted in less than 1% of failed transitions at critical event onset. However, 2 seconds before the critical event onset, the proportion of not (yet) successful take-overs rose to 5% in the simulation using a 6 second alert onset time. Avoiding last moment take-overs may be beneficial, considering that some situations can require the driver to directly steer or brake in order to avoid a collision. This initial response after take-over can take additional time and should be taken into account when studying the transition of control as well. The ratio of late take-overs can also be affected by certain factors. For example, in 'Test 3 - Effect of NDRT Output Modalities on the Transition of Control' a more distinct tail (i.e., more late take-overs) resulted from simulating a manual NDRT compared to other NDRTs. While those differences may be small in an experimental setting, their effect could be more severe in real-life scenarios. When taking part in an automated driving study, participants might anticipate that a critical event is going to occur at any time, increasing their readiness to react accordingly (analogous to *demand characteristics* [70] in psychology studies, where participants can alter their behavior simply because they are currently taking part in a study). By taking into account the occurrence of late take-overs, the model can thus help to reveal what factors can increase the tendency of drivers to take more time for the transition of control. A better understanding of these processes is a valuable insight that can help to improve traffic safety overall by reducing the risk of safety critical situations due to a delayed take-over.

The findings discussed in this thesis only represent a small fraction of possible influences on the take-over time in the transition of control than can be studied using the model. Various other influencing factors have been discussed in the literature, including cognitive load induced by the NDRT [117], fatigue [97], the traffic situation [81], or the monitoring behavior of the driver [109]. Future users are encouraged to study how the transition of control is affected by those factors individually, or in combination with other factors using the model.

5.2 Limitations and Future Work

The model is able to give valuable insight on the effects different factors have on the transition of control process in automated driving. However, there are some limitations to the functionality of the model. These limitations, and how they can be addressed in the future will be discussed here.

In some cases, the model was unable to simulate certain stages of the transition of control, especially for stage 2 (disengagement) and stage 4 (suspension of the NDRT). This becomes particularly apparent when combining multiple parameters, thus limiting the number of study results the model can consider for its simulation, as can be seen in Figure 14. This limitation can be overcome in the future however, by extending the model's database with results from additional studies. Here, the model would greatly benefit if information concerning the intermediate stages (i.e., stages 2, 3, and 4) would be reported more frequently in the literature in general. Another possibility to counteract the limited data available for the intermediate stages could be to add results from other fields that may share certain traits with the transition of control. For example, response times to different alert modalities outside of semi-automated driving (e.g., [16,22]) could be added to the model's database in order to see how they compare to the initial response to the alert (i.e., stage 2 or stage 3) in semi-automated driving.

The model focusses on the effects different factors have on transition times during the take-over process. However, the quality of driving can be reduced for an extended period of time after control was taken back by the driver [60]. For example, cognitively demanding tasks have been found to impact driving performance in general [88,92]. Such tasks could put a constraint on the driver even after manually suspending the task. The model should thus not be considered as a complete account of possible effects on take-over performance stemming from different external and internal influences. Instead, it should be used as one tool out of many in order to better understand the complex take-over process from automated to manual driving in level 3 automated vehicles.

The model optionally allows the user to calculate the stage onset times in relation to its preceding stage, rather than to the alert onset. This functionality was implemented with the expectation that drivers go through each stage of the transition of control consecutively (see section 'Shape of the Distribution'). Testing showed however, that this is not necessarily the case for all stages, considering that the onset time for stage 4 (suspension of the NDRT) occasionally preceded that of stage 3 (orientation). More work is needed to refine the expected shape of the distribution between different stages. This functionality of the model should thus be used with caution by future users.

Finally, in the estimation of the underlying distributions for the stages, the assumption was made that stage onset times show similar patterns than reaction times in general [82]. A log-normal distribution was thus used to approximate that pattern (see section 'Shape of the

Distribution'). With increasing alert onset times, the true underlying distributions might however evoke more complex shapes, since drivers may base their decision to transition from the NDRT to the driving task on a multitude of internal and external factors. Given the limited data available for longer alert onset times, the model's simulation of longer alert onset times was difficult to study in more detail for this thesis, making it difficult to adjust the underlying distributions accordingly. The model would benefit if more data would be available from research studying transitions of control with longer alert onset times.

6 CONCLUSION

The transition of control model presented in this thesis gave valuable insight on the influence different factors such as alert onset time, alert modality, and the non-driving related task have on the transition of control process in semi-automated driving. Not only does the model help to study the overall take-over time, but it also sheds light on intermediate stages of that process, and accounts for transitions with longer take-over times. Future users can easily extend the database of the model, thereby further increasing the variety of simulations the model can perform and the influencing factors that can be studied with it. This makes it a valuable tool for future researchers and engineers to improve our understanding of the transition of control process in semi-automated driving. Readers of this thesis are encouraged to test the model themselves in order to investigate the multitude of simulations the model can perform.

Supplementary Materials

The model and the excel-table comprising the database are available on request to the author of this thesis (l.praetorius@student.rug.nl) or to the supervisors Dr. Chris Janssen (c.p.janssen@uu.nl) and Dr. Jelmer Borst (j.p.borst@rug.nl).

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Appendix A - Studies Included in the Database

NR	Authors (Year)	Title	Ref.
1	Befelein, Boschet, Neukum (2018)	Influence of non-driving-related tasks' motivational aspects and interruption effort on driver take-over performance in conditionally automated driving	[7]
2	Berghöfer, Purucker, Naujoka, Wiedemann, Marberger (2018)	Prediction of Take-over Time Demand in Conditionally Automated Driving. Results of a real world Driving Study	[8]
3	Braunagel, Rosenstiel, Kasneci (2017)	Ready for Take-over? A New Driver Assistance System for an Automated Classification of Driver Take-Over Readiness	[12]
4	Bueno, Dogan, Hadj Selem, Monacelli, boverie, Guillaume (2016)	How different mental workload levels affect the take-over control after automated driving	[13]
5	Çapalar, Olaverri-Monreal (2017)	Hypovigilance in limited self-driving automation: Peripheral visual stimulus for a balanced level of automation and cognitive workload	[14]
6	Clark, Feng (2017)	Age differences in the takeover of vehicle control and engagement in non-driving-related activities in simulated driving with conditional automation	[17]
7	Cohen-Lazry, Borowsky, Oron-Gilad (2017)	The effects of continuous driving-related feedback on drivers' response to automation failures	[18]
8	Cohen-Lazry, Katzman, Borowsky, Oron-Gilad (2018)	Ipsilateral Versus Contralateral Tactile Alerts for Take-Over Requests in Highly Automated Driving	[19]
9	Feldhütter, Gold, Schneider, Bengler (2016)	How the duration of automated driving influences takeover performance and gaze behavior	[21]
10	Gold, Berisha, Bengler (2015)	Utilization of drivetime - performing non-driving related tasks while driving highly automated	[23]
11	Gold, Körber, Lechner, Bengler (2016)	Taking over control from highly automated vehicles in complex traffic situations: the role of traffic density	[25]
12	Gold, Lorenz, Damböck, Bengler (2013)	partially automated driving as a fallback level of high automation	[26]
13	Hergeth, Lorenz, Krems (2017)	prior familiarization with takeover requests affects drivers' takeover performance and automation trust	[29]
14	Jarosch, Kuhnt, Paradies, Bengler (2017)	It's out of our hands now! Effects of non-driving related tasks during highly automated driving on drivers' fatigue	[38]
15	Josten, Zlocki, Eckstein (2016)	Untersuchung der Bewältigungsleistung des Fahrens von kurzfristig auftretenden Wiederübernahmesituationen nach teilautomatisiertem, freihändigen Fahren	[39]
16	Kerschbaum, Lorenz, Bengler (2015)	A transforming steering wheel for highly automated cars	[40]
17	Kerschbaum, Omozik Wagner, Levin, Hemsdörfer, Bengler (2017)	How does a symmetrical steering wheel transformation influence the take-over process?	[41]
18	Kim, Yang, (2017)	Takeover requests in simulated partially autonomous vehicles considering human factors	[43]
19	Lapoehn, Dziennus, Utesch, Kelsch, Schieben, Dotzauer, Hesse, Köster (2016)	interaction design for nomadic devices in highly automated vehicles	[46]
20	Lau, Harbluk, Burns, El-Hage (2018)	The Influence of interface design on driver behavior in automated driving	[48]
21	Li, Blythe, Guo, Namdeo (2018)	Investigation of older driver's takeover performance in highly automated vehicles in adverse weather conditions	[50]
22	Louw, Merat, Jamson (2015)	Engaging with highly automated driving: to be or not to be in the loop?	[53]
23	Lu, Zhang, Feldhütter, Happee, Martens, De Winter (2018)	Beyond mere take-over requests: the effects of monitoring requests on driver attention, take-over	[54]

		performance, and acceptance	
24	Manawadu, Hayashi, Ema, Kawano, Kamezaki, Sugano (2018)	Tactical-level input with multimodal feedback for unscheduled takeover situations in human-centered automated vehicles	[55]
25	Melcher, Rauh, Diederichs, Widlroither, Bauer (2015)	Take-over requests for automated driving	[57]
26	Miller, Sun Johns, Ive, Sirkin, Aich, Ju (2015)	Distraction becomes engagement in automated driving	[62]
27	Morgan, Alford, Williams, Parkhurst, Pipe (2017)	Manual takeover and handover of a simulated fully autonomous vehicle within urban and extra urban settings	[66]
28	Mueller, Ogrizek, Bier, Abendroth (2018)	Design concept for a visual, vibrotactile and acoustic take-over request in a conditional automated vehicle during non-driving-related tasks	[67]
29	Naujoks, Höfling, Purucker, Zeeb (2018)	From partial and high automation to manual driving: Relationship between non-driving related tasks, drowsiness and take-over performance	[68]
30	Olaverri-Monreal, Kumar, Diaz-Alvarez (2018)	Automated Driving: interactive automation control system to enhance situational awareness in conditional automation	[69]
31	Payre, Cestac, Dang, Vienne, Delhomme (2017)	Impact of training and in-vehicle task performance on manual control recovery in an automated car	[72]
32	Petermeijer, Cieler, de Winter (2017)	Comparing spatially static and dynamic vibrotactile take-over requests in the driver seat	[73]
33	Petermeijer, Bazilinskyy, Bengler, de Winter (2017)	Take-over again: Investigating multimodal and directional TORs to get the driver back into the loop	[74]
34	Petermeijer, Doubek, de Winter (2017)	Driver response time to auditory, visual, and tactile take-over requests: A simulator study with 101 participants	[75]
35	Politis, Brewster, Pollick (2015)	Language-Based Multimodal displays for the handover of control in autonomous cars	[77]
36	Politis, Langdon, Adebayo, Bradley, Clarkson, Skrypchuk, Mouzakitis, Eriksson, Brown, Revell, Stanton (2018)	An evaluation of inclusive dialogue-based interfaces for the takeover of control in autonomous cars	[78]
37	Radlmayr, Fischer, Bengler (2019)	The influence of non-driving related tasks on driver availability in the context of conditionally automated driving	[80]
38	Radlmayr, Gold, Lorenz, Farid, Bengler (2014)	How traffic situations and non-driving related tasks affect the take-over quality in highly automated driving	[81]
39	Roche, Brandenburg (2018)	Should the urgency of auditory-tactile takeover requests match the criticality of takeover situations?	[83]
40	Sadeghian Borojeni, Boll, Heuten, Bülthoff, Chuang (2018)	Feel the movement: real motion influences responses to take-over requests in highly automated vehicles	[85]
41	Sadeghian Borojeni, Weber, Heuten, Boll (2018)	From reading to driving - priming mobile users for take-over situations in highly automated driving	[86]
42	Schartmüller, Riener, Wintersberger (2018)	Steer-by-Wifi: lateral vehicle control for takeovers with nomadic devices	[89]
43	Schartmüller, Riener, Wintersberger, Frison (2018)	Workaholistic: on balancing typing and handover-performance in automated driving	[90]
44	Sportillo, Paljic, Ojeda (2018)	Get ready for automated driving using virtual reality	[91]
45	Telpaz, Rhindress, Zelman, Tsimhoni (2015)	Haptic seat for automated driving: preparing the driver to take control effectively	[93]
46	van den Beukel, van der Voort, Edger (2016)	Supporting the changing driver's task: Exploration of interface designs for supervision and intervention in automated driving	[9]

47	van der Meulen, Kun, Janssen (2016)	Switching back to manual driving: how does it compare to simply driving away after parking?	[61]
48	Vlakveld, van Nes, de Bruin, Vissers, van der Kroft (2018)	Situation awareness increases when drivers have more time to take over the wheel in a level 3 automated car: a simulator study	[95]
49	Vogelpohl, Kuehn, Hummel, Gehlert, Vollrath (2018)	Transitioning to manual driving requires additional time after automation deactivation	[96]
50	Walch, Lange, Baumann, Weber (2015)	Autonomous Driving: investigating the feasibility of car-driver handover assistance	[98]
51	Wan, Wu (2018)	The effects of vibration patterns of take-over request and non-driving tasks on taking-over control of automated vehicles	[99]
52	Wandtner, Schömig, Schmidt (2018b)	secondary task engagement and disengagement in the context of highly automated driving	[102]
53	Wandtner, Schmidt, Schömig, Kunde (2018)	non-driving related tasks in highly automated driving - effects of task modalities and cognitive workload on take-over performance	[100]
54	Wandtner, Schömig, Schmidt (2018a)	effects of non-driving related task modalities on takeover performance in highly automated driving	[101]
55	Wehlack, Baur, Radlmayr, Bill, Muhr, Bengler (2017)	Highly automated driving: how to get the driver drowsy and how does drowsiness influence various take-over aspects?	[104]
56	Wintersberger, Riener, Schartmüller, Frison, Weigl (2018)	let me finish before I take over: towards attention aware device integration in highly automated vehicles	[107]
57	Yang, Gerlicher, Bengler (2018)	How does relaxing posture influence take-over performance in an automated vehicle?	[110]
58	Yang, Götze, Laqua, Dominioni, Kawabe, Bengler (2017)	A method to improve driver's situation awareness in automated driving	[111]
59	Yang, Karakaya, Dominioni, Kawabe, Bengler (2018)	An HMI Concept to improve driver's visual behavior and situation awareness in automated vehicle	[112]
60	Yoon, Kim, Ji (2019)	The effects of takeover request modalities on highly automated car control transitions	[113]
61	Zeeb, Buchner, Schrauf (2015)	What determines the take-over time? An integrated model approach of driver take-over after automated driving	[116]
62	Zeeb, Buchner, Schrauf (2016)	Is take-over time all that matters? The impact of visual-cognitive load on driver take-over quality after conditionally automated driving	[117]
63	Zeeb, Härtel, Buchner, Schrauf (2017)	Why is steering not the same as braking? The impact of non-driving related tasks on lateral and longitudinal driver interventions during conditionally automated driving	[118]
64	Zhang, Wilschut, Willemse, Martens (2018)	Transitions to manual control from highly automated driving in non-critical truck platooning scenarios	[119]
65	Lotz, Russwinkel, Wohlfarth (2019)	Response times and gaze behavior of truck drivers in time critical conditional automated driving take-overs	[52]
66	Yoon, Ji (2019)	Non-driving-related tasks, workload, and takeover performance in highly automated driving contexts	[114]
67	van der Heiden, Iqbal, Janssen (2017)	Priming drivers before handover in semi-autonomous cars	[28]

Appendix B - Standard Deviation for Distribution Between Two Means

Let A be a distribution with mean μ_A, standard deviation σ_A and weight *p*, and *B* a distribution with mean μ_B, standard deviation σ_B and weight *q*.

$$A{\sim}N(\mu_A, \sigma_A)\ ;\ B{\sim}N(\mu_B, \sigma_B)\ ;$$

Here, $0 \le p \le 1$ and $q = 1 - p$.
The average value of the mixture of *AB* is:

$$\mu_{AB} = (p \times \mu_A) + (q \times \mu_B)$$

In general, the probability density function (PDF) of the mixture between PDFs can be expressed as:

$$f(x) = \sum_i p_i f_i(x)$$

With weight *p* and PDF *f* of distribution *x*.

The first moment of the mixture can be also expressed as:

$$\mu_{AB} = \mathbb{E}_f[x] = \sum_i p_i \mu_i$$

The second moment can be expressed as:

$$\sigma_{AB}^2 = \mathbb{E}[x^2] - (\mathbb{E}[x])^2 = \sum_i p_i {\mu_i}^{(2)} - \left(\sum_i p_i {\mu_i}^{(1)}\right)^2$$

The variance can be expressed as:

$$Var(f) = \sum_i p_i {\sigma_i}^2 + \sum_i p_i (\mu_i^{(1)})^2 - \left(\sum_i p_i {\mu_i}^{(1)}\right)^2$$

The variance of f_{AB} can be written as:

$$\sigma_{AB}^2 = p\sigma_A^2 + q\sigma_B^2 + p\mu_A^2 + q\mu_B^2 - \mu_{AB}^2$$

We assume that the *p = q = ½,* because *A* and *B* come from the same population. Therefore, μ_{AB} is:

$$\mu_{AB} = \frac{\mu_A + \mu_B}{2}$$

Hence, the variance of the mixture f_{AB} is:

$$\sigma_{AB}^2 = \frac{(\sigma_A^2 + \mu_A^2) + (\sigma_B^2 + \mu_B^2)}{2} - \left(\frac{\mu_A + \mu_B}{2}\right)^2$$

From there follows that the standard deviation between *A* and *B* is thus:

$$\sigma_{AB} = \sqrt{\frac{(\sigma_A^2 + \mu_A^2) + (\sigma_B^2 + \mu_B^2)}{2} - \left(\frac{\mu_A + \mu_B}{2}\right)^2}$$

Appendix C - Distribution from Test 1 per Stage