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Modeling Driver Take-over Reaction Time and Emergency Response Time Using an Integrated Cognitive Architecture

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ABSTRACT

Objective. Drivers' take-over reaction time in partially automated vehicles is a fundamental component of automated vehicle design requirements, and take-over reaction time is affected by many factors such as distraction and drivers' secondary tasks. In this study, we built cognitive-architecture models to simulate drivers' take-over reaction time in different secondary task conditions. **Method.** Models were built using the Queueing Network-Adaptive Control of Thought Rational (QN-ACTR) cognitive architecture. Drivers' task-specific skills and knowledge were programmed as production rules. A driving simulator program was connected to the models to produce prediction of reaction time. Model results were compared to human results in both single-task and multi-task conditions. The models were built without adjusting any parameter to fit the human data. **Results.** The models could produce simulation results of take-over reaction time similar to the human results in take-over conditions with visual or auditory concurrent tasks, as well as emergency response time in a manual driving condition. Overall, R square was 0.96, root mean square error (RMSE) was 0.5 s, and mean absolute percentage error (MAPE) was 9%. **Conclusion.** The models could produce simulation results of reaction time similar to the human results from different task conditions. The production rules are plausible representations of drivers' strategies and skills. The models provide a useful tool for the evaluation of take-over alert design and the prediction of driver performance. **(224 words)**

Keywords: Driving safety, Take-over, Reaction time, QN-ACTR, Concurrent tasks.

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INTRODUCTION

Autonomous vehicles with increasing levels of automation will allow drivers to delegate longitudinal and lateral control to the vehicle and also allow drivers' eyes off the road to engage in activities unrelated to driving (*1*). A medium level of automation is called Level 3 automation (SAE 3), where a driver is allowed to engage in non-driving related tasks but is still needed as a fallback level in case of system limits or failures (*1*). At this level of automation, drivers must resume manual driving in conditions not yet supported by automation. Transition between automation and manual driving can be initiated by the driver, while in some cases automation can also take the initiative and request the driver to take over control (*2*). Such requests are called take-over requests (TOR). Since self-driving cars are still not perfectly reliable, manual control is still needed as the fallback plan (*3*). From the cognitive perspective, drivers' cognitive resources are limited (*4*), and task switching takes time. Knowledge about human performance in TOR scenarios is essential to the design of fallback procedures dealing with automation limitations and failure.

During the take-over process, the time budget refers to the time duration available for drivers to perceive the scenario, regain situation awareness, make decision, and execute responses (*5*). The take-over process has been extensively analyzed in terms of reaction times. In particular, intervention time refers to the duration from the TOR warning to the moment when a driver's first effectiveness steering or brake/throttle action is observed (*6–10*). Intervention time is an important index to measure driver performance in TOR tasks, and faster intervention time is considered better and safer.

In autonomous vehicles, drivers are likely to be involved in non-driving tasks such as conversation or surfing the Internet (*11, 12*). It has been found that non-driving tasks (both visual and auditory) affect driver performance of take-over in automated driving (*5,6,14*). Driver's Engagement in non-driving related tasks before TOR can impair driver's performance in TOR situations. Different non-driving tasks may have different levels of impact. It is important to investigate the influence of different non-driving related tasks on driver reaction time in TOR situations.

LITERATURE REVIEW

Several previous studies have reported drivers' take-over performance measured in driving simulators under the presence of non-driving related task, including mental, visual, motor, and other combined tasks (*6, 8, 14–16*). A frequently used visual-motor task is SuRT, which stands for Surrogate reference task (*17*). It is a user-paced task, where subjects have to find and select a slightly larger circle among smaller circles on a visual display. It is intended to generate visual-motor workload and represent visual tasks such as mobile phone interaction (*6, 8, 15, 16*). Another frequently used task is auditory n-back tasks (*14*). An auditory n-back task continuously plays a series of numbers or letters and asks participants to judge whether the currently played item is the same as another item played n steps before; in other cases, participants can also be asked to directly report the item played n steps before (*18*). Auditory n-back tasks are intended to generate auditory workload and represent auditory tasks such as conversation and phone calling (*19*). While SuRT and n-back are the frequently used ones, other non-driving tasks reported in the literature include 20-Questions (*20*), simulated phone conversation (*21*), and mobile phone interaction (*22*). Both visual and auditory tasks could lead to distraction and loss of situation awareness and therefore impair TOR reaction time performance (*14*).

Although previous studies have shown the effects of non-driving tasks on TOR reaction time, there is still a lack of computational models that can simulate and predict such effects and distraction. In the current study, we aim to build computational models for this purpose using

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cognitive architecture methods that have shown successful results in modeling driving behavior and multitasking performance.

A cognitive architecture is both a computerized simulation program and a unified theory of cognition. It combines cognitive theories of human capability and limitation to explain the effects of different cognitive factors on human performance and workload. It can be used as an engineering tool to predict and simulate human performance in different human-machine interaction tasks. Examples of cognitive architectures are Adaptive Control of Thought-Rational (ACT-R) (*23*) and Queuing Network (QN) cognitive architectures (*24, 25*). In particular, Queuing Network-Adaptive Control of Thought Rational (QN-ACTR) is a recent cognitive architecture which integrates QN and ACT-R architectures, combining not only the advantages of modeling multi-task performance in Queuing Network methods but also the advantages of modeling complex cognitive activities in ACT-R (*24*). Since QN-ACTR is a production rule system, production rules (i.e., condition-action pairs) are used by models in QN-ACTR to represent operators' task-specific knowledge and skills, while the limitation and capacity of human mental processing are built in the cognitive architecture as algorithms and parameters. Previous modeling work has provided the foundation for the models in the current study. Salvucci (*26, 27*) proposed and examined a driving model . This model included basic methods to simulate lane keeping, lane changing, and car following. Subsequently, this modeling method has been used in a series of studies to model driving experience and collision avoidance braking (*28*), the development of vehicle lateral control skills (*29*), driving with a memory rehearsal task (*30*), and driving with a speech comprehension task (*28*). However, driving and TOR scenarios have not been modeled in previous studies. A visual task (e.g., SuRT) and an auditory task (e.g., auditory n-back) could both affect TOR reaction time, but the visual task may have a larger effect because it shares more common resources with the driving task that is mainly visual, according to multiple resource theory (*4*). We expect that this difference can be simulated in computational models.

In the current study, we built models using the QN-ACTR cognitive architecture to simulate driver's emergency response time in both SAE 0 (i.e., manual driving) and SAE 3 conditions (i.e., take-over reaction time). QN-ACTR was selected because previous studies have established a working model of driving behavior, multitask scheduling mechanisms, and a simulation platform that connects QN-ACTR with a driving simulator (*31*). The non-driving related tasks included both SuRT and auditory 2-back tasks, to be compared with a manual driving baseline condition. To validate the models, we compared model intervention time with human reaction time obtained in the same tasks. The human data were taken from previous empirical studies (*32, 17, 19, 5, 14, 6*). In the method section, we describe the human empirical studies and the modeling details. The comparison between human results and model results is presented in the result section.

METHODOLOGY

To simulate and predict driver's emergency response time, we first built single-task models for the non-driving tasks and driving tasks. We defined drivers' task-specific knowledge and skills using a series of production rules, following previous models established in the research field. Then, single-task models were combined following multitask scheduling mechanisms established in previous studies. Simulation was performed to collected model results, which were then compared with corresponding human results available from previous studies, including both non-driving single-tasks and TOR tasks (*32, 17, 19, 5, 14, 6*). All parameters in the cognitive architecture were using their default values without adjusting any parameter to fit the human data.

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Human data

The human data were from six empirical experiments that have been reported previously (*32, 17, 19, 5, 14, 6*). Participant information from previous empirical studies is shown in Table 1. Experiment 1 (*32*) was an auditory 2-back single-task test. Experiment 2 (*17*) was a SuRT single-task test. Experiment 3 (*19*) was a DRT single-task test. DRT refers to detection response task, and this DRT task component (i.e., a visual simple reaction task) was used to visually present a warning signal to the driver, showing the emergency and requesting the driver's attention. Experiment 4 (*5, 6*) was an SAE 0 (i.e., manual driving) test in which participants performed a 2-back task while driving and needed to respond to an emergency on an expressway in a simulator. The emergency was signaled to the driver by an alert (i.e., DRT component). Experiment 5 (*5, 14, 6*) was an SAE 3 (called SAE 3a in this study) take-over test in which participants performed a 2-back task while take-over on an expressway in a simulator. Experiment 6 (*5, 14, 6*) was another SAE 3 (called SAE 3b in this study) take-over test in which participants performed a SuRT task while take-over on an expressway in a simulator. In this paper, we use SAE 3a to refer to the condition of automated driving while doing a concurrent auditory 2-back task (eyes on the road), and SAE 3b to refer to the condition of automated driving while doing a concurrent visual SuRT task (eyes off the road).

(PLACE TABLE 1 ABOUT HERE)

In Experiment 1, the auditory 2-back items were presented as recorded auditory stimuli and participants responded verbally. The items consisted of single digits (0-9), presented one at a time, in random order, at an interval of 2.25 seconds between the start of each item presentation (*32*). During this task, participants were required to repeat out loud the number that was presented two numbers ago (2-back).

In Experiment 2, the participants were asked to perform a typical SuRT task (*17*) shown on a tablet display attached to the central console of a car. The participants used a keypad to select the location of the target and confirm the answer.

In Experiment 3, the DRT task was a visual simple reaction task. Signals (LED light signal) were randomly presented every 4~5 s (signal onset to onset) and remained on for 1 s or until participants' responses. Participants were asked to respond as quickly and accurately as possible to these signals via intervention, which refers to a first steering or brake/throttle action is observed with the effectiveness of control actions in terms of preventing rule conflicts or accidents, and the reasonable thresholds of control actions are 2 degrees steering wheel angle and 10 percent braking pedal position (*19, 5, 14, 6*).

In Experiment 4, 5 and 6, participants drove in driving simulators at 120 km/h on a three-lane highway (straight road), when an obstacle consisting of two stationary vehicles with flashing warning lights appeared at their ego-lane at 233 m ahead, representing a time budget of 7 s. The obstacle appeared suddenly to ensure that the time budget was the same for all conditions. Participants could prevent a collision by braking and/or performing a lane change. Experiment 4 tested manual driving while performing an auditory 2-back task before the obstacle appeared. A collision warning alert was given with the same time budget, making this manual condition comparable to the automated driving conditions in terms of reaction time calculation. Experiment 5 tested automated driving and TOR while performing an auditory 2-back task before the TOR warning. And Experiment 6 tested automated driving and TOR while performing a SuRT task. The position of the SuRT task was on a screen below the mid console and therefore requested visual attention away from the road.

Modeling and simulation

N-back model

The n-back model was built for the 2-back single task. The production rules were defined following previous models with similar sound monitoring and speech comprehension (memorization) task components (*33–35*).

The production rules and their descriptions are shown in Table 2. Each production rule represents a stage in the task procedure. The definition of these production rules follows the modeling principles used in previous cognitive models. The goal stage initiated from *1* at the beginning of each trial. All parameters were using their default values.

(PLACE TABLE 2 ABOUT HERE)

SuRT model

The SuRT model was built for the SuRT single task. The production rules were defined following previous models with similar visual search and reading task components (*36*). It is assumed that participants followed ordered serial visual search rather than random search, and therefore they can avoid attending to the same target more than once. This assumption is reasonable as people are familiar with reading in a certain order. At the implementation level, the model could remember the visual locations that had been scanned, so it would not re-visit them in future visual search (*45*).

The production rules and descriptions for them were shown in Table 3. Each production rule represented a step in the task procedure. The definition of these production rules followed the modeling principles used in previous cognitive models. And the goal step initiated from *1* at the beginning of each trial. All parameters were using their default values.

(PLACE TABLE 3 ABOUT HERE)

DRT model

The DRT model was built for the DRT task, representing task switching from non-driving related tasks to vehicle control after the warning signal was perceived. The production rules were defined following previous models with similar visual search components. The production rules and their descriptions are shown in Table 4. Each production rule represents a stage in the task procedure. All parameters were using their default values.

(PLACE TABLE 4 ABOUT HERE)

Driving model (control and monitoring)

To simulate driving performance, a model used in previous work was adopted (*26*, *29*, *37*). Sixteen production rules are defined to complete each control cycle. The descriptions of the production rules are represented in Table 5. All parameters were using their default values.

(PLACE TABLE 5 ABOUT HERE)

Lane change model

To simulate lane change performance, a model used in previous work was adopted (*26*, *29*, *37*). This model assumes that drivers decide lane changing or lane keeping according to the perceived information of other lanes. Four visual zones to extract such information are defined as *left, right, left-mirror* and *right-mirror* around the driver's vehicle. The information from the other lane

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represents the lane changing direction and is used as input to a control function, which determines the adjustment of steering wheel angle (*38*). Fifty production rules are defined. The descriptions of example production rules are shown in Table 6. The rules' flowchart is shown in Figure 1. The goal stage initiated from *0* at the beginning of each task cycle. All parameters were using their default values.

(PLACE TABLE 6 ABOUT HERE)

(PLACE FIGURE 1 ABOUT HERE)

Multi-task model of take-over

The multi-task models for the simulation of automated vehicle control take-over were built by combining single-task models introduced previously. The general methods and principles of combining single-task models that to form a multi-task model have been been shown in previous work of the QN-ACTR literature (*39*, *24*, *37*). Goal representations from multiple tasks can be stored in the goal buffer at the same time, so production rules from different tasks can be matched and selected. However, only one production rule can be executed for each processing cycle of the procedural module, which is a basic assumption used in the cognitive architecture. The multi-task scheduling mechanism in QN-ACTR considers both the need to maintain the continuation of each single task and the need to share limited mental resources across multiple concurrent tasks. In order to share resources across multiple tasks, a natural queuing mechanism gives priority to the task with the longest waiting time. However, to maintain necessary continuation within each task, a filtering discipline has been built to confine procedural module processing resources within the same task for the duration needed.

When a production rule needs follow-up processing, it will not release the procedural resources to other task components. A production rule requires follow-up if it has any action containing declarative retrieval request, imaginal creation request, aural encoding request, aural-location request, visual encoding request, and visual-location request. Abiding by the filtering discipline, one production rule (*hear-sound*) from the 2-back model, three production rules (*find-unattended-circle,*and *attend-circle, encode-circle*) from the SuRT model, one production rule (*attend-visual-warning*) from the DRT model, seven production rules (*create-imaginal-buffer-chunk-for-monitor-zone, drive-control-attend-near, drive-control-process-near-attend-far, drive-monitor-zone-left, drive-monitor-zone-right, drive-monitor-zone-left-mirror,* and *drive-monitor-zone-right-mirror*) from the driving model, and eight production rules (*try-lc-recall-left, try-lc-recall-left-mirror, try-lc-recall-right, try-lc-recall-right-mirror, try-lc-look-left, try-lc-look-left-mirror, try-lc-look-right,* and *try-lc-look-right-mirror*) from the lane change model require follow-up processing. These production rules were marked in Table 2, 3, 4, 5 and 6. Major parameters and their default values are shown in Table 7.

(PLACE TABLE 7 ABOUT HERE)

Simulation

The tests for the models were programmed to be the same as corresponding tests in the human experiments (*32*, *17*, *19*). To simulate vehicle control take-over, the mental models built in QN-ACTR were connected with a driving simulation program TORCS

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(http://torcs.sourceforge.net) via User Datagram Protocol (UDP), showing the same expressway scenario as in human experiment (*5, 14, 6*). Regarding the model simulation, the current model focuses on representing average human performance without any goal to fit human variance. More runs of simulation will reduce the variance of model results until it is small enough for the average results to be considered certain within an acceptable range (*40*). In each experimental condition, the model simulation was repeated for 500 trials for single-task (Experiment 1, 2 and 3), 10 trials for multi-task (Experiment 4, 5 and 6), in order to reach a criterion that the width of 95% confidence interval of response time was within 200 ms (*13*). Average response time from each experimental condition was calculated and compared with corresponding human results.

RESULTS

Regarding the human results, response time was summarized below for each human experiment. In the human experiment 1, 2 and 3, mean reaction time was 1.041 s for 2-back (SD = 0.032 s), 4.585 s for SuRT, and 0.472 s for DRT respectively. In human experiment 4, 5, and 6, mean response time was 4.45 s for SAE 0 (SD = 5.5 s), 4.85 s for SAE 3a (SD = 5.0 s), and 5.86 s for SAE 3b (SD = 6.8 s) respectively.

Regarding the model results, for the single task, predicted reaction time was 1.017 s for 2-back, 5.086 s for SuRT, and 0.495 s for DRT respectively. For the multi-task, predicted intervention time was 3.860 s for SAE 0, 4.260 s for SAE 3a, and 5.302 s for SAE 3b respectively. For comparison, the human and model results were plotted in Figure 2.

(PLACE FIGURE 2 ABOUT HERE)

Regarding statistical tests for model fitness, it is possible to conduct regression analysis and examine R square, in addition to root mean squared error (RMSE) and mean absolute percentage error (MAPE). R square can reflect how the model's prediction captures the changes of the patterns of human data in different conditions, whereas RMSE and MAPE reflect the absolute difference between the model's prediction and human data (*41*).

RMSE is a frequently used measure of the difference between values predicted by a model and the values observed from human studies. The formula of RMSE is:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{human,i} - X_{model,i})^2}{n}} \tag{1}$$

where $X_{human,i}$ is the human value, $X_{model,i}$ is the model value in condition i, and n is the sample size.

MAPE is a measure of prediction accuracy of a forecasting method in statistics. It is defined by the formula:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{X_{human,i} - X_{model,i}}{X_{human,i}}\right|\% \tag{2}$$

Regarding overall model fitness from all the six task conditions, $R^2 = 0.96$ (the regression was significant, $F(1, 4) = 99.94$, $p = 0.001$). RMSE was 0.5 s, and MAPE was 9%.

DISCUSSION

An integrated cognitive architecture is not only a unified theory of cognition but also an engineering tool for the simulation of human performance. Based on an integrated cognitive architecture, a model is a synthesized account for task environment, human constraints and human knowledge. In this study, models were built based on QN-ACTR to predict the driver's emergency response time in SAE 0 and SAE 3 tests for different types of non-driving tasks. The models for both non-driving and driving task components closely followed previous models in the literature. The driving and lane change model components were directly adopted from previous work (*26, 29, 37*). All parameters were using their own default values in the cognitive architecture, and we did not adjust any parameter to fit the human data. The model simulation results were similar to the human results measured by RMSE and MAPE. It also demonstrated a benefit of the cognitive architecture approach. Models established in completed work can be applied in future modeling work that requires simulating human performance in similar tasks.

The multi-task model was built by combining the single-task models following the multi-task scheduling mechanisms that have previously been established in QN-ACTR. The benefit of these mechanisms is that once single-task models are built, they can be naturally combined to form more complex models for the simulation of multi-tasking performance without the need to build specific production rules or strategies for the coordination between multiple concurrent goals. The current results further demonstrated that QN-ACTR's multi-task scheduling mechanisms are valid and effective.

Cognitive-architecture-based models are cognitive simulation models that can consider multiple factors, such as road condition, traffic condition, driver attention, and driver fatigue. These factors can be programmed in an integrated simulation platform, and models can interact with different driving conditions under different assumptions about the driver's mental capacity. This is an advantage of the QN-ACTR models in the simulation of driver's emergency response time.

A limitation for the current models is that only one strategy was used. Different drivers may have different strategies; even the same driver may choose different strategies in different trials. Part of the strategy difference could be represented in different production rules. In addition, the parameters in the architecture could also represent strategies, for example, more aggressive steering versus less aggressive steering. While the current model focuses on simulating average results observed from the empirical study, future studies can explore the use of different parameter sets or different production rules to represent different groups of drivers. The models in the current study are intended to represent average adult drivers without any cognitive impairment driving in sunny weather conditions. Future studies could consider using different parameter sets in the steering wheel and throttle-brake control equations (*43*) to represent drivers with different vehicle control capabilities or control behaviors in different weather conditions. In addition, we plan to explore the modeling of aggressive vs conservative driving styles (*42*) in risky situations such as near collision on highway (*28,44*). Some drivers preferred to switch from the automated mode to manual driving earlier than others who preferred to stay in the automated mode for longer time until a traffic conflict is imminent (*44*). Different strategies may be modeled as different sets of production rules, and preferences may be modeled as different weights between the rules. It is important to remember that the current models are intended for prediction at the population level rather than for predicting any specific individual performance. Future work is needed to consider individual difference and model the variance of reaction time.

CONCLUSIONS

QN-ACTR models were created to predict driver's emergency response time in both SAE 0 and SAE 3 tests. The drivers' task-specific knowledge and skills were programmed as production rules. The models were built based on existing modeling methods without adjusting any parameter to fit the human data. The models' prediction was similar to the human data, and it could capture

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the different reaction time in different task conditions. The results demonstrated the models' predictive power. It also suggested that the production rules were plausible representations of drivers' skills and strategies. The models can be applied as a useful tool for the prediction of driver performance as well as evaluation of automated vehicle control take-over alert timing. The models from the current study can provide support to future work that simulates driving and lane change performance in other tasks and traffic environments.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: Chao Deng, Shi Cao, Chaozhong Wu; data collection: Chaozhong Wu, Nengchao Lyu; analysis and interpretation of results: Chao Deng, Shi Cao, Chaozhong Wu; draft manuscript preparation: Chao Deng, Shi Cao. All authors reviewed the results and approved the final version of the manuscript.

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TABLE 1 Participant information from previous empirical studies

Exp.	Automation & Task	Automation level	Participant Age (Mean±SD, years)	Participant Gender (N=Number,F=Female,M=Male)	Study
1	2-back	*n.a.*	26.5	N=20, F=14, M=6	(*32*)
2	SuRT	*n.a.*	34.7±13.3	N=23, F=10, M=13	(*17, 47*)
3	DRT	*n.a.*	23.0	N=17, F=5, M=12	(*19*)
4	Manual & 2-back & DRT	SAE 0	33.5±9.0	N=48, F=10, M=38	(*5, 14, 6*)
5	Automated & 2-back & DRT	SAE 3a (eyes on the road)			
6	Automated & SuRT & DRT	SAE 3b (eyes off the road)			

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TABLE 2 Procedures and production rules for 2-back single task

Production rules	Task procedure (description of the source code)
*hear-sound**	IF the goal stage is *1*, an aural-location has been found, and the aural module is currently free, THEN move auditory attention to the aural-location to encode its information, change the goal stage to *2*,
encode-first-digit	IF the goal stage is *2*, the goal buffer's digit1 attribute is empty, aural module has encoded a digit sound, THEN store the content of the digit sound in the goal buffer's digit1 attribute, and change the goal stage to *1*.
encode-second-digit	IF the goal state is *2*, the goal buffer has stored digit1 attribute but not digit2 attribute, aural module has encoded a digit sound, THEN store the content of the digit sound in the goal buffer's digit2 attribute, and change the goal stage to *1*.
speak	IF the goal state is *2*, the goal buffer has stored two digit sound in digit1 and digit2 attributes, aural module has encoded a digit sound, and the vocal module is currently free, THEN speak the digit sound in digit1 attribute, and update digit1 with the content in digit2 attribute, and store the content of the new digit sound in the goal buffer's digit2 attribute, and change the goal stage to *1*.

*: production rules that require follow-up processing (explained in the multi-task model section).

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TABLE 3 Procedures and production rules for SuRT single task

Production rules	Task procedure (description of the source code)
*find-unattended-circle**	IF the goal stage is *1*, THEN find an unattended visual-location in the visual field that is close to the left, and change the goal stage to *2*.
*attend-circle**	IF the goal stage is *2*, a visual-location has been found, and the visual module is currently free, THEN move visual attention to the visual-location to encode its information, change the goal stage to *3*, and store the coordinate of the visual-location in the goal buffer.
*encode-circle**	IF the goal stage is *3*, visual module has encoded a circle, and imaginal module is free, THEN create a mental representation of the circle in the imaginal buffer, and change the goal stage to *4*.
respond-left-first	IF the goal stage is *4*, the circle mental representation is the same as the target circle, the manual module is free, and the coordinate of the circle is within the near left column, THEN press the key representing the leftward answer (e.g., key left), and change the goal stage to *6*.
respond-left-repetition	IF the goal stage is *4*, the circle mental representation is the same as the target circle, the manual module is free, and the coordinate of the circle is within the far left column, THEN press the key representing the leftward answer (e.g., key left), and change the goal stage to *5*.
respond-left-second	IF the goal stage is *5*, the manual module is free, and the coordinate of the circle is within the far left column, THEN press the key representing the leftward answer (e.g., key left), and change the goal stage to *6*.
respond-right-first	IF the goal stage is *4*, the circle mental representation is the same as the target circle, the manual module is free, and the coordinate of the circle is within the near right column, THEN press the key representing the rightward answer (e.g., key right), and change the goal stage to *6*.
respond-right-repetition	IF the goal stage is *4*, the circle mental representation is the same as the target circle, the manual module is free, and the coordinate of the circle is within the far right column, THEN press the key representing the rightward answer (e.g., key right), and change the goal stage to *5*.
respond-right-second	IF the goal stage is *5*, the manual module is free, and the coordinate of the circle is within the far right column, THEN press the key representing the rightward answer (e.g., key right), and change the goal stage to *6*.
respond-confirm	IF the goal stage is *6*, the manual module is free, THEN press the key representing the confirm answer (e.g., key down), and the trial is done.
read-again	IF the goal stage is *4*, and the circle mental representation is not the same as the target circle, THEN, change the goal stage back to *1*.

*: production rules that require follow-up processing (explained in the multi-task model section).

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TABLE 4 Procedures and production rules for DRT task component

Production rules	Task procedure (description of the source code)
*attend-visual-warning**	IF a visual-location in the warning signal area has been found, and the visual module is currently free, THEN move visual attention to the visual-location to encode its information, change the goal stage to *attend*.
switch-tasks-a	IF visual module has encoded a TOR warning signal, and the imaginal module is currently free, THEN change the goal states of driving control and lane change task components from inactive to active, change this switch task goal into inactive.
switch-tasks-b	IF visual module has encoded a TOR warning signal, and the imaginal module is not currently free (used by other task components such as SuRT), THEN clear the imaginal module, and change the goal states of driving control and lane change task components from inactive to active, change this switch task goal into inactive.

*: production rules that require follow-up processing (explained in the multi-task model section).

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TABLE 5 Procedures and production rules for the driving task (control and monitoring)

Production rules	Task procedure (description of the source code)
*create-imaginal-buffer-chunk-for-monitor-zone**	At the beginning of simulation, create the imaginal buffer chunk for monitoring sub-task.
*drive-control-attend-near**	At the start of each steering control cycle, look for visual-location of *near-point*.
*drive-control-process-near-attend-far**	IF a *near-point* is focused in visual-location buffer, THEN update *near-point* information in the goal buffer, and look for visual-location of *far-point*.
drive-control-process-far	IF a *far-point* is focused in visual-location buffer, THEN update *far-point* information in the goal buffer, and send motor commands to steer the wheel and control the pedals.
*drive-monitor-zone-left/right/left-mirror/right-mirror (4 rules)**	IF randomly decide to moitor left lane/right lane/left mirror/right mirror, THEN look for the visual-location of left lane/right lane/left mirror/right mirror.
monitor-zone-process-car-left/right/left-mirror/right-mirror (4 rules)	IF a visual-location of left lane/right lane/left mirror/right mirror is found, and there is an object/car close to self in the zone, and the visual module is currently free, THEN move visual attention to the visual-location, store the distance of the object/car and the current time as a chunk representing the appearance of the object in the memory, and the monitoring sub-task is done.
monitor-zone-process-none-left/right/left-mirror/right-mirror (4 rules)	IF there is no object/car in the safe distance in the zone, THEN the monitoring sub-task is done.

*: production rules that require follow-up processing (explained in the multi-task model section).

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TABLE 6 Example of procedures and production rules for the lane change task when no car is close to self in left mirror

Production rules	**Task procedure (description of the source code)**
*try-lc-recall-left-mirror**	IF trying to change to the left lane, retrieval model is free, THEN retrieve from memory for any chunk storing the appearance of objects in the left-mirror zone.
try-lc-recall-left-mirror-car-far-enough	IF a chunk is recalled with the object's distance equal or larger than the safe distance parameter (see Table 7), THEN continue to the next step in the flow (see Figure 1).
try-lc-recall-left-mirror-none	IF a chunk is recalled representing no object was seen in the left mirror zone, THEN continue to the next step in the flow (see Figure 1).
try-lc-recall-left-mirror-failure	IF no such chunk can be recalled (i.e., the model never looked at the left mirror zone or cannot remember it), THEN continue to the next step in the flow (see Figure 1).
*try-lc-look-left-mirror**	IF decide to look at left mirror zone, THEN set the left mirror zone as the target zone in the imaginal buffer, and look for a visual-location in the left mirror.
try-lc-look-left-mirror-far-enough	IF the visual-location contains an object with a distance equal or larger than the safe distance parameter (see Table 7), visual module is free, THEN move visual attention to the visual-location, store the distance of the object/car and the current time as a chunk representing the appearance of the object in the memory, and continue to the next step in the flow (see Figure 1).

*: production rules that require follow-up processing (explained in the multi-task model section).

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TABLE 7 Major parameters and their default values

Parameter Name	Default Value	Description
:dat (production rule default action time)	0.05	The parameter specifies the default time that it takes to fire a production in seconds. That is the amount of time that passes between the production's selection and fired events. The default value is 0.05 s and generally that value is not changed.
:imaginal-delay	0.2	The parameter controls how long it takes a request or modification request to the imaginal buffer to complete. It can be set to a non-negative time (in seconds) and defaults to 0.2 s.
:le (retrieval time latency exponent)	1	The latency exponent value, *f*, in the equation for retrieval times. It can be set to any non-negative value and defaults to 1.0.
:lf (retrieval time latency factor)	1	The latency factor value, *F*, in the equation for retrieval times. It can be set to any non-negative value and defaults to 1.0.
:visual-attention-latency	0.085	The parameter specifies how long a visual attention shift will take in seconds. The default value is 0.085 s.
:tone-detect-delay	0.05	The parameter controls the content delay time given to tone sounds created with the new-tone-sound command measured in seconds. It can be set to any non-negative number and the default is 0.05 s (*46*).
lc-safe-distance	40 m	Lane change safe distance (*28*). The model will not change lane if another car is closer than this distance in the target lane.

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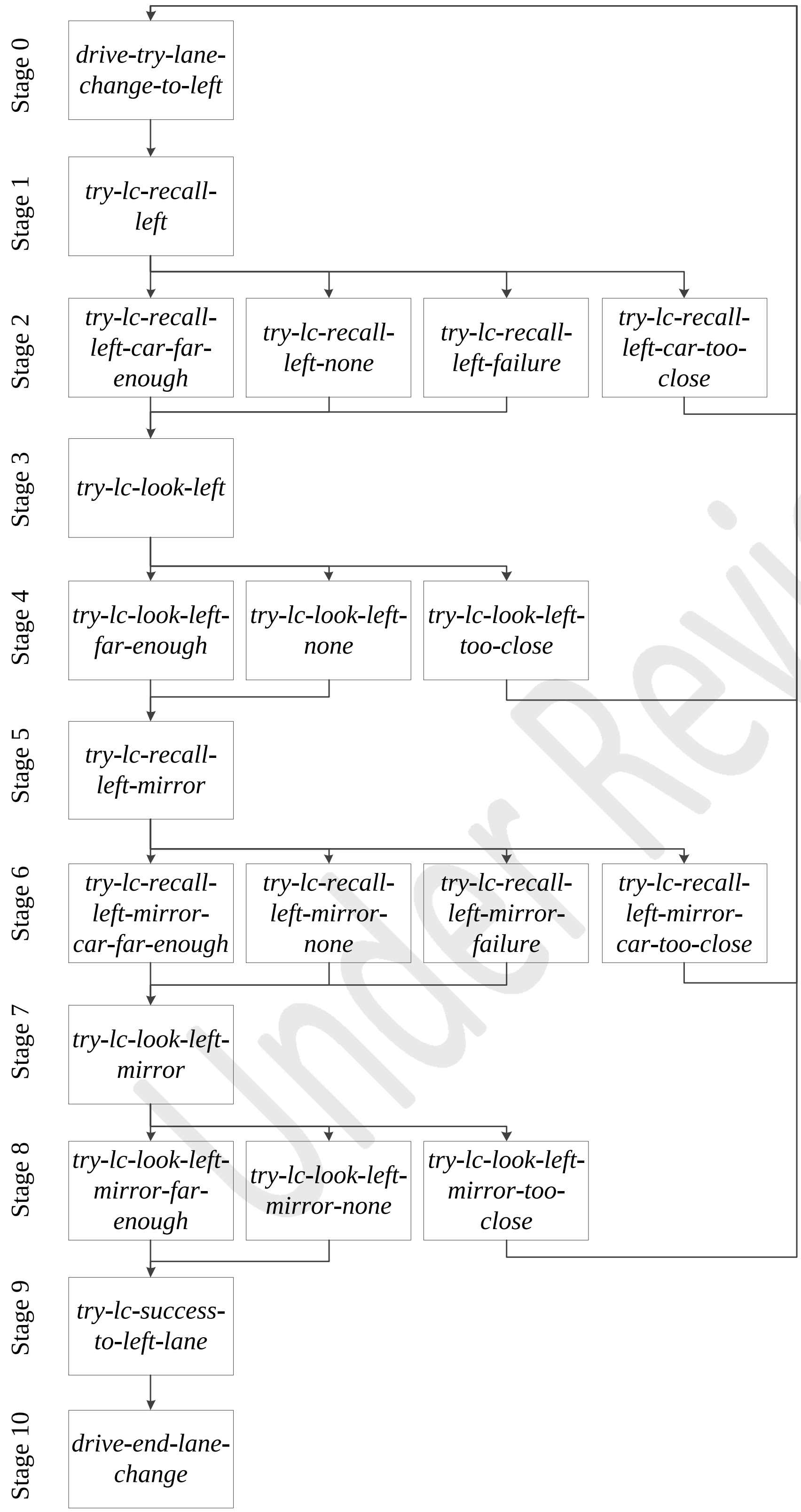

FIGURE 1 Flowchart of the model for the lane change task (e.g., object is not close to self in left mirror).

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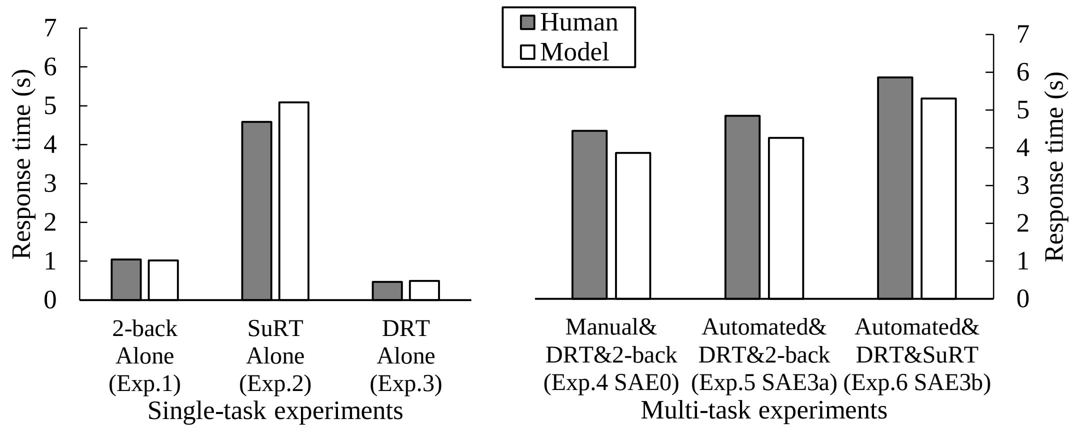

FIGURE 2 Response time from different conditions for both human and model.

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Figure 1 Click here to access/download;Figure;FIGURE 1.tif

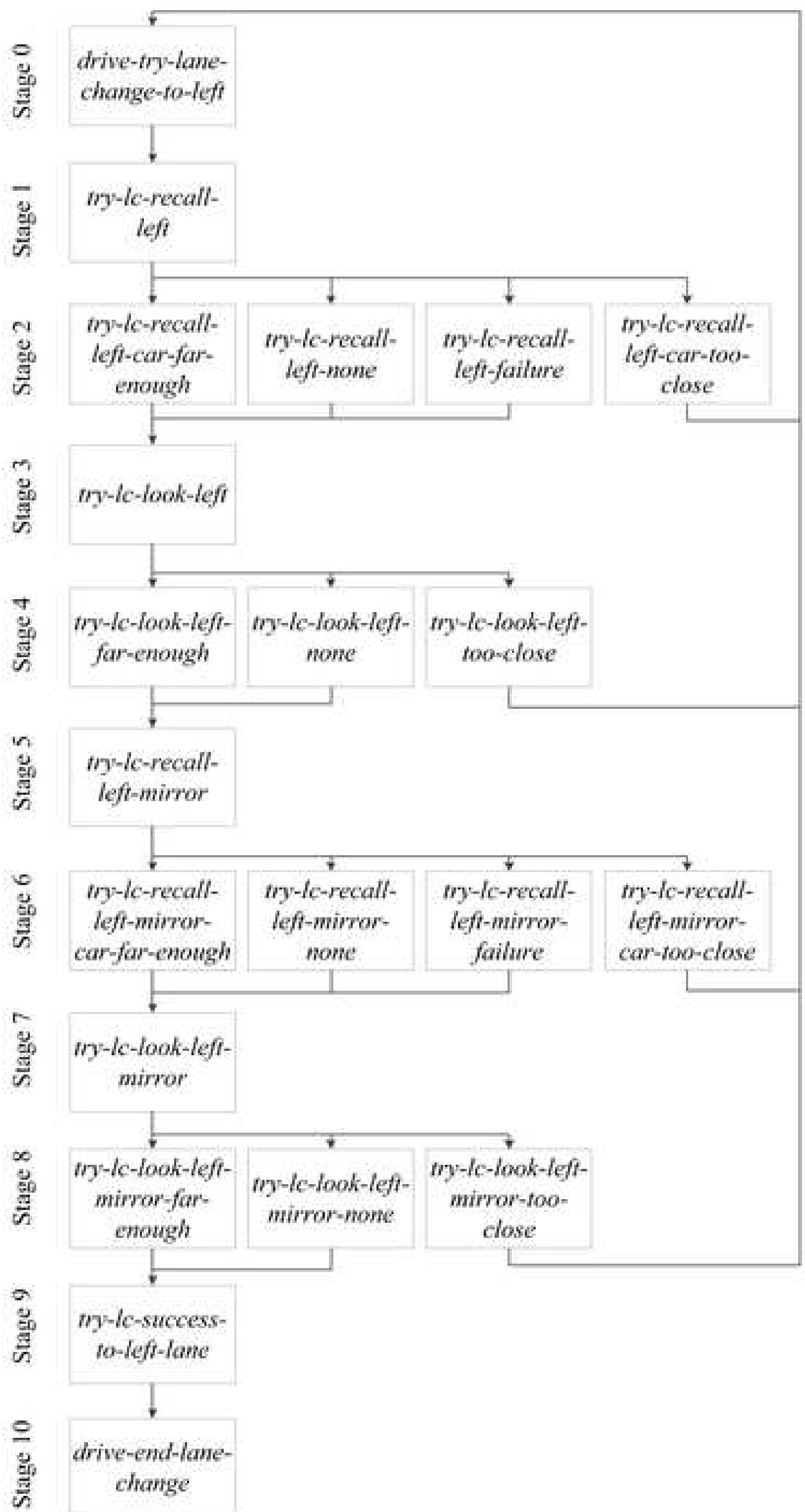

Figure 2

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