The Effects of Performing a Secondary Task on the Preparation of Lane Change Manoeuvres.

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UNIVERSITY OF TWENTE.

The Effects of Performing a Secondary Task on the Preparation of Lane Change Manoeuvres.

Abstract

In the last decade in-vehicle systems have developed to an important and integral part in the car industry. These systems are supposed to help the driver in crucial situations and deliver information to the driver, who then can react accordingly and keep him or herself and the surrounding safe. But to keep driving safe, the systems have to give reliable information and the systems should not distract the driver. A rather disastrous situation may occur when information systems provide wrong information in a situation when the driver is distracted. Therefore, we investigated the effects of valid and invalid advanced information for the performance of lane change manoeuvres in a simulated driving environment. The manoeuvers were either performed in a control condition without secondary task or in two blocks of dual task condition. Distraction was realized by a secondary task, which had to be performed during the primary driving task. The main findings of the study are that as in previous studies participants without any advanced information had longer reaction times than with advanced information and that the performance of the participants in the distracted situation improved over time due to less errors and an increase in the performance of the secondary task. In contrast to our expectations reaction time and error analyses did not provide hints that preparation was affected by dual task load. Also, in contrast to our expectations invalid advanced information did not differ from neutral information. The findings may suggest, that distraction has no effect on valid and invalid advanced information. However, alternative explanations may be possible and are addressed in the discussion of the results.

Preface

In the following you will read "The effects of performing a secondary task, whilst on response preparation manoeuvres in a Lane Change Task", the basis of which is a study on human-machine interaction that was conducted among 21 participants. It was written to fulfil the graduation requirements of the Human Factors and Psychological Engineering Program at the University of Twente.

The project was undertaken at the Leibniz Research Centre for Working Environment and Human Factors. My research question was formulated together with my supervisor, Gerhard Rinkenauer. The research was difficult and exhausting and my thesis is the report of this long process, which in the end did not lead to the results I hoped for, but gave me great insight in scientific research. Fortunately, both Dr. Rinkenauer and my supervisor from the University of Twente, Prof. Dr. Ing. Willem Verwey, were always available and willing to answer my questions.

I would like to thank my supervisors for their guidance and support during this process. Further I wish to thank all of the respondents for taking part in my experiment.

To my other colleagues at the Leibniz Research Centre for Working Environment and Human Factors: I would like to thank you for your cooperation as well. It was always helpful to discuss ideas about my research with you. I also benefitted from debating issues with my friends and family. If I ever lost interest, you kept me motivated. My parents deserve a particular note of thanks: your thoughtful advice and kind words have, as always, served me well.

Enschede, September 2, 2017

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Introduction

Driving is a multitasking challenge. Nowadays, a driver should not only collect data from outside to keep the car on the road but also to coordinate several tasks simultaneously inside the car which for example are acquired from support systems like intelligent driver support systems (IDSS). IDSS can be separated into in-vehicle information systems (IVIS) and advanced driver assistance systems (ADAS). The in-vehicle information systems include, for example navigation displays, a radio display and further types of application like entertainment and communication systems. ADAS include safety features to prevent accidents by using technologies such as cruise control, automatic braking or control the blind spot. The goal of the both systems is to prepare the driver for upcoming actions by using information beforehand. Although these systems deliver information to the driver with the aim to support him or her, the driver can be overwhelmed and distracted by the increased amount of information provided. The safety issue of in-vehicle technology is one of the major concerns for car companies (Burns, Trbovich, McCurdie, & Harbluk, 2005). The question arises, what impact advanced information systems in vehicles have on the driver's attention, viz. to what extent she or he is distracted by this additional information.

Research has shown that drivers are able to cope with the demands of multitasking in traffic situations, by compensating additional cognitive load and adapting their driving behaviour accordingly (Baumann & Lange, 2016). For example, some drivers compensate the cognitive demands by slowing down velocity or increasing the distance to the vehicle ahead of them (Burns et al., 2005; Harbluk, Mitroi, & Burns, 2009). Recent studies have shown that participants performed worse in path control while performing a secondary task than without a secondary task due to the effects of distraction on driving performance (Burns et al., 2005; Engström, Markkula, 2007). Consequently, the distraction can lead to critical traffic situations, which in a worst-case scenario may result in an accident. These findings are attributed to driver distraction and a lot of studies confirm the negative effects of distraction on driving performance in the laboratory (e.g. Hancock, Lesch & Simons, 2003; Horberry, Anderson, Regan, Triggs & Brown, 2006; Kass, Cole & Stanny, 2007; Patten, Kircher, Oestlund & Nilsson, 2004). Here, the key is to identify the risk potential of distracting effects and to minimize the safety reductions produced by the in-vehicle systems. IDSS like for example Advanced Driver Assistant Systems (ADAS) can prepare the driver for upcoming events but in the case of invalid information lead to higher distraction. Sensory cues include visual, auditory, haptic, olfactory and environmental cues and prepare the driver to react accordingly forthcoming situations. For example, if a curve appears in the far distance the driver can anticipate that she or he needs to take action and steer into the curve. Besides of such environmental cues, traffic signs and the above-mentioned in-vehicle information systems act as cues.

The purpose of the current study is to investigate the effect of a secondary task on response preparation in a course-keeping task by combining conditions of valid and invalid advance information (Hofmann et al., 2010; Hofmann & Rinkenauer, 2013) with an additional distracting task (cf. Mattes, 2008). The theoretical goal of the study is to better understand how preparation and distraction affect information processing. In general it is expected that valid information facilitate information processing, whereas invalid information and distraction has adverse effect on information processing. Such a better understanding may lead to better designs of ADAS, e.g. how to avoid the worst case, viz. the presentation of invalid or uncertain information in distracting situations

Driving relevant studies from basic research

From a psychological perspective, the question has been addressed how motor action can be prepared to anticipate upcoming events. Rosenbaum (1980) developed an experimental paradigm, the movement pre-cueing technique, to examine motor preparation. The aim of the movement pre-cueing technique is to elucidate information processes related to action preparation.

Three responses were possible. First, Rosenbaum varied the arm (left or right), then the direction (towards or away of the frontal plane) and finally the extent (short vs. long distance). In this experiment participants reacted as fast as possible to an imperative stimulus presented shortly before. The participants received full, partial or no prior information about the upcoming movement by a pre-cue. The results showed that prior information leads to faster and more accurate responses to the imperative stimulus (Rosenbaum, 1980). The decrease in reaction time is called the pre-cueing effect. It is assumed that previous information allows specifying certain response parameters before response signal onset. The more parameters can be specified in advance – depending on previous information – the larger is the pre-cuing effect. Figure 1 demonstrates this idea in more detail. After the pre-cue appears, the information can be used to specify the appropriate values of motor parameters beforehand. After the detection of the response signal the remaining values, which are not pre-cued, need to be specified. After that the response can be initiated and executed. The reaction time is defined as the time from response signal onset until response onset.

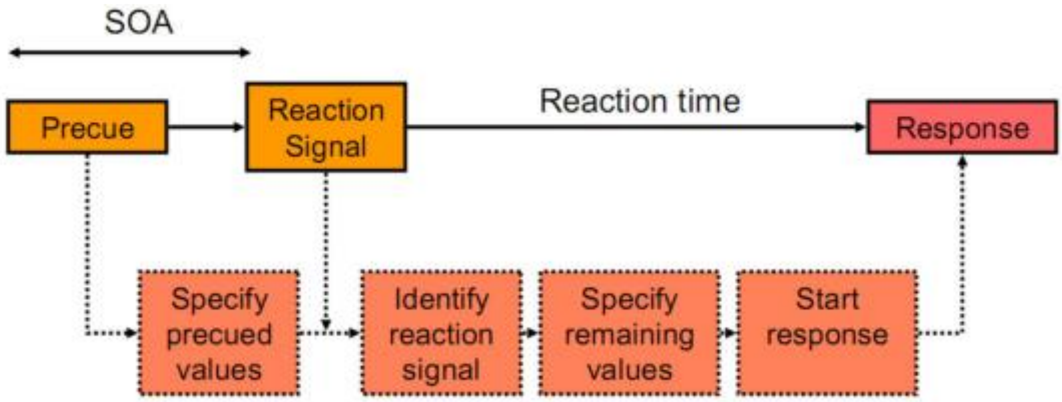

Figure 1. Information processing chain divided into different stages of processing (Rosenbaum, 1980).

Hofmann, Rinkenauer and Gude (2010) extended the experimental paradigm of Rosenbaum to traffic manoeuvres. These authors investigated the movement preparation in a simulated lane change task. They tested if complex steering movements like lane-changing benefit from response preparation. In contrast to Rosenbaum, who only used valid or neutral trials, Hofmann and Rinkenauer (2013) added invalid pre-cues to the valid and neutral cues to examine how participants react to unexpected events. The results revealed that reaction times decreased when valid information was provided beforehand. Additionally, the results showed that information about direction of the lane change had a bigger effect than the number of lane changes. Further, Hoffman and Rinkenauer (2013) found a validity effect for reaction time, viz. conditions with invalid advance information caused longer RTs than conditions without any prior information. Moreover, they analysed the kinematics of the steering wheel movement in both studies and the results suggested that steering movement profits from preparatory effects. Participants with fully information beforehand were faster and more accurate when they were changing the lane. They state that the decrease in reaction time is connected to the reduction of specific stages in the human information processing chain. Analogous to the experiment of Rosenbaum (1980) the lane change task provided either no previous information or advance information about the direction or the number of lanes, which had to be crossed, or both (full information).

As mentioned above, the pre-cueing technique is used to assess preparatory processes and revealed that valid information reduces the reaction time, whereas invalid cues increase the reaction time due to reprogramming of the movement. The aim of introducing a secondary task is to assess to what extent (valid and invalid) preparation is affected by additional load.

As aforesaid, driving performance in general is negatively affected by dual task situations. In contrast, previous valid information facilitates driving. The practical relevance of the study is to examine in how far invalid information of in-vehicle assistance systems affect the performance of the driver. It is expected that invalid information lead to increased reaction time due to the fact that drivers have to adjust their movement actions.

A common method to investigate driver distraction is the Lane Change Task, which can be used to measure the influence of secondary tasks on driving performance. Mattes (2003) developed a method, which can be used as an indicator of driving distraction. In his simulator study the road consisted of three lanes and the task was to react appropriately to road signs that indicated a lane change. That task also can be used to examine visual, cognitive and motor distraction depending on the secondary task used in the simulation. Advantages of the Lane Change Test are that this method is easy to implement, has low cost and is standardized.

As mentioned earlier, in-vehicle systems can be the cause of distraction. As a result, the ADAM project (Mattes, 2003) designed and tested several surrogate tasks to examine their impact on driving performance. The surrogate task consisted of a search task which aimed to simulate a visual information system (e.g. navigation system). These surrogate tasks consist of different levels of cognitive and visual tasks. The secondary task in the present experiment is the Surrogate Reference Task (SuRT), which is retrieved from the ADAM project. The idea behind the SuRT is to simulate the interaction with an in-vehicle information system, for example programming a navigation system or searching for a radio station in which drivers search and identify relevant information. The SuRT allows to manipulate the search difficulty and the effect of the distraction can be measured by comparing driving performance with and without several levels of dual task load.

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Method

Sample

Twenty-one participants took part in the study and the average age was 24 years (age range 18-29). After introducing the participants to the task and informing them about the experiment, the participants filled out the consent form and had to do a vision test which assessed the eyesight of each participant. All participants were right-handed and had normal vision. Furthermore, all the participants had valid driving licenses. The experiment took about 2 hours and the drivers were paid for their participation (10 Euro/h). The mean driving experience was around 5.9 years and the covered driving distance was 8376 km per year.

Apparatus

The participants were seated in front of the steering wheel and the distance to the screen was approximately 1.70 m with a visual angle of 45.90 x 35.20. The Screen had a resolution of 1920 x 1080 pixel. A gaming steering wheel (Logitech Type G920 Driving Force) was used to execute the simulated driving task. The SuRT was performed on a Lenovo ThinkPad SL510 Laptop and had a resolution of 1366 x 768.

Stimuli and feedback information

The signs on the screen were red and green lines or arrows: red to indicate pre-cue information, green to indicate the imperative stimuli (Figure 2). The signs were projected on the windscreen, Head-Up Display (HUD, Figure 4). The red signs were used as pre-cues and were presented before the imperative stimulus appeared in the HUD. The pre-cues could be valid, invalid and neutral in relation to the imperative stimulus and prepare the driver in which direction the car had to change. In the case of neutral pre-cues, the driver had no prior information to which lane he or she had to change. The task for the participants was to keep the line and to change the lane as fast and accurately as possible when the imperative stimulus appeared. The Surrogate Reference Task was displayed on a laptop, which was located next to the driver as a central console and had a resolution of 1366 x 768 pixel. The right arm of the participant was positioned on the table next to the laptop simulating an armrest in a car.

Figure 2. Red arrows and line indicate pre-cues and green arrows indicate imperative stimulus.

Figure 3. Lane Change Task.

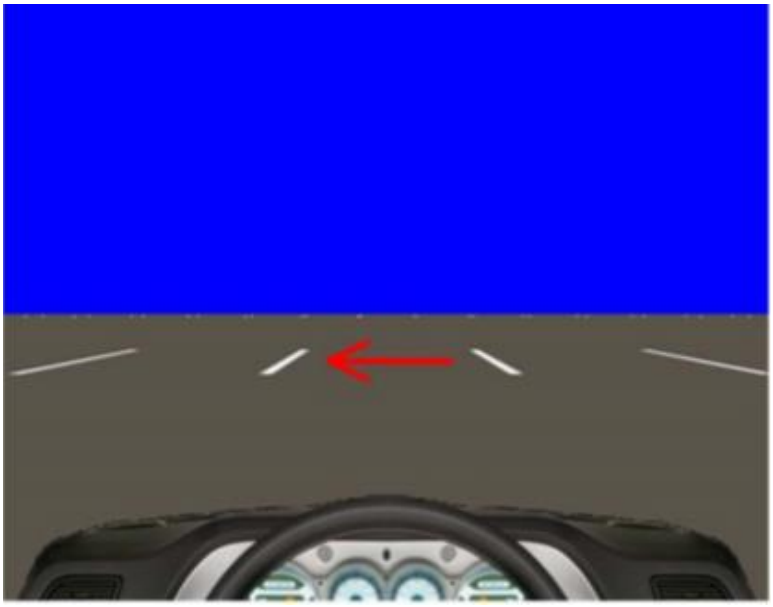

Figure 4. Participants' view on the virtual driving environment.

Tasks

Primary Task. The lane change task (LCT) used in this study resembles the ideas of the setup, developed by Mattes in 2003. The difference between Mattes' setup and the setup used in this research was that the LCT in this test was designed to assess preparation effects and not distraction. The driving speed was constantly kept at 60 km/h comparable to the research of Mattes (2003) to avoid compensation of dual task load by reducing driving velocity.

Secondary Task. The participants performed a visual search task, which had to be performed throughout each trial. In the first block the secondary task was excluded to measure the baseline for the primary task. The SuRT included white circles on a black screen and the imperative stimulus varied in size compared to the distractor circles (Figure 4). The stimulus and the distractors are white circles on a black screen and the target stimulus, distinguished itself by being bigger than the other white circles. The participants were to indicate at which side of the screen the target stimulus was located by pressing left or right and confirming their choice by pressing the up arrow. This procedure is being repeated throughout the trial and the position of the target stimulus and the distractors randomly vary from screen to screen. The trial was over once the participant had chosen a side and a new trial appeared immediately on the screen. It was the choice of the participant how many trials he did.

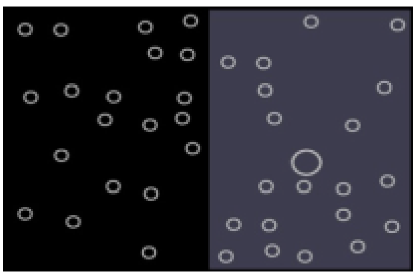

Figure 5. Surrogate Reference Task.

Procedure

Participants were informed about the experiment and were seated in front of the steering wheel. Then participants were instructed to change lanes as quickly and accurately as possible and perform as many trials as possible in the secondary task. After instructing the participants about the task, they began with a training block of 80 trials. After training the participants performed three blocks of Lane Change Task to establish a baseline. Subsequently, the participants were instructed to perform both tasks, but instructed to drive as safe as possible and complete the secondary task as accurately as possible. The participants had to perform 15 blocks consisting of 80 trial each. The 80 trials were distributed into 40 neutral trials, 30 valid and 10 invalid trials. The trial took 2 hours.

Experimental design

The design of the experiment was a 3 (advance information) x 2 (distraction) within-subject design. Advance information consisted of the pre-cue “neutral”, “valid” and “invalid”. Distraction included the levels “with secondary task” and “without secondary task” (single vs. dual task). The dependent variables were the reaction time and error rates of the driver during the LCT. Reaction time was defined as onset of imperative stimulus until the response threshold. Response threshold was defined as 10% of maximum steering wheel angle velocity (cf. Hofmann & Rinkenauer, 2013).

Results

Data Preparation

7.2% of the trials had to be excluded due to mistakes in the experiment and problems in the understanding of the task. Mistakes were characterized by not responding to the cues (error: 3.5%) and reacting before the cue appeared (anticipation error: 3.7%).

Reaction time analysis

In our analysis, we aggregated the 15 blocks into three blocks. Block one consisted of the trials with the single task condition, block two and three were composed of the first and second five blocks and represented the dual task condition. The reason for using two blocks of dual task condition was to assess learning effects. This approach allows to compare the single task condition with the dual task condition. We used the program R and conducted an analysis of variance (ANOVA) to examine the relation between single and dual task condition and to examine the effect of advance information. Resulting *F*-values, *p*-values, and generalized eta squared (η_G^2) are reported (e.g. Bakeman, 2005).

The ANOVA showed for both conditions between the single task condition and dual task condition statistically significant results. There was a main effect of response preparation (F(2,40)=13.99, p<.05, $\eta_G^2 = .037$) and a main effect of Block (F(2, 40)=4.32, p<.05, $\eta_{\square}^2 = .030$) but no significant interaction between the two factors (F(2,80)=1.1, p>.3). The means (see Fig. 6) indicate that reaction time decreases when previous valid information is given. Separate ANOVAs revealed that there are significant effects of response preparation between the neutral level and valid information (F(1,40)=18.01, p<.01, $\eta_{\square}^2 = .036$) and invalid and valid prior information (F(1,40)=18.9, p<.01, $\eta_{\square}^2 = .042$). Because of multiple comparisons alpha level Bonferroni correction was used to adjust the alpha level. Nonetheless, in contrast to our expectation there was no effect between neutral and invalid advanced information (F(1,40)=.98, p>.3).

Further, increase of RT between block one and two showed a trend (F(1,20)=3.8, p=.06, $\eta_{\square}^2 = .04$) and was significant between block one and three (F(1,20)=5.02, p<.05, $\eta_{\square}^2 = .04$). Though, there was no significant difference of RT between block two and three

(F(1,20)=2.3, p>.1). This result indicates that the load of the dual task had an effect on RT but there was no learning effect between block 2 and 3 in average during the dual task condition. Separate analyses did not show any interaction effects between the two factors p's > 0.2, which indicate that response preparation, was not modulated by distraction (dual task load).

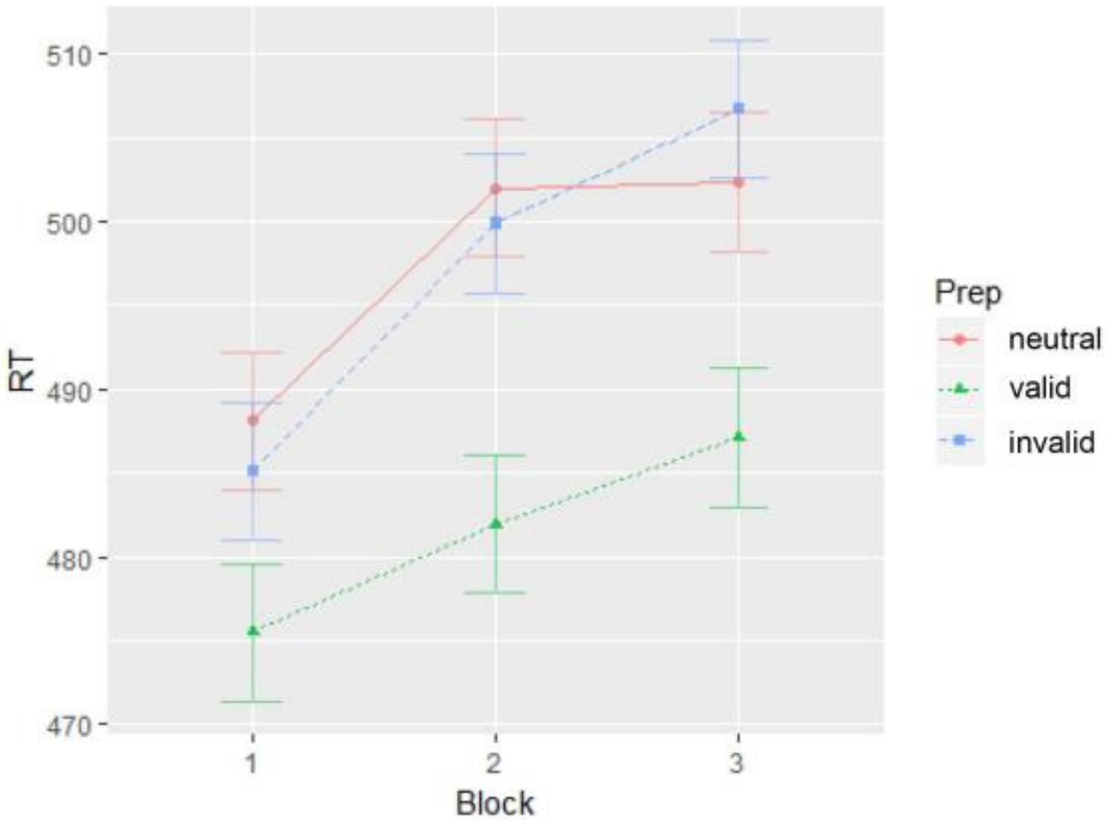

Figure 6. Reaction time as a function of block and response preparation.

Error rates analysis

An analogous ANOVA was performed for the error rate. The ANOVA analysis revealed significant main effects on the independent variables advance information (F(2, 40)= 5.91, p<.05, $\eta_p^2 = .025$) and block (F(2,40)= 4.4, p<.05, $\eta_p^2 = .09$). There was no interaction between the two factors (F(4,80)= .86, p>.3). Participants performed most errors in the second block, where participants were firstconfronted with the dual - task condition. In the first block the average error rate was 0.017, in the second 0.043 and last block the average error rate was 0.024, which indicates a learning effect from block 2 to 3, in which participants were in the dual task condition. Additional ANOVAs (Bonferroni corrected) revealed that the error rate significantly increased between Block 1 an 2 ($F(1,20)=5.02$, $p<.025$) and decreased between block 2 and 3 ($F(1,20)=10.46$, $p<.001$, $\eta^2 = .06$) . In contrast to the RT analyses, the latter decrease indicates a learning effect. Thus, learning in the dual task condition obviously did not take place by reducing the RT but by reducing the error rate. Additionally, separate analyses did not reveal a significant interaction between the two factors, p's > .16. Analogously to the RT analyses the missing interaction suggests that response preparation was not affected by distraction (dual task load).

Another aspect indicating a learning effect is that participants not only made fewer errors but also completed more tasks in the SuRT in the dual task condition. The SuRT task was analysed with a paired t-test and revealed a significant difference between the two dual task conditions ($t = -2.653$, $p<0.05$). The confidence interval strengthens the significance of the results (-2.24, -18.73). Participants in the last dual task condition completed 10 more trials than in the first dual task condition.

If we take a closer look at the independent variable advance information the results show that participants made most mistakes in the neutral trials (mean error rate:0.035) and the fewest mistakes in the invalid trials (mean error rate:0.021). The mean error rate in the valid trials was 0.028.

As illustrated in figure 7 we can see that error rates are lowest in block 1 and reach the peak in the second block as the participants are involved in the dual task condition. But in block three we have a decrease of error rates. The plot shows that the lowest error rate in block three belongs to the invalid cues, whereas highest error rates are neutral. The error rates of valid trials are close to the error rates of invalid trials but the gap between these two has a tremendous difference in the third block.

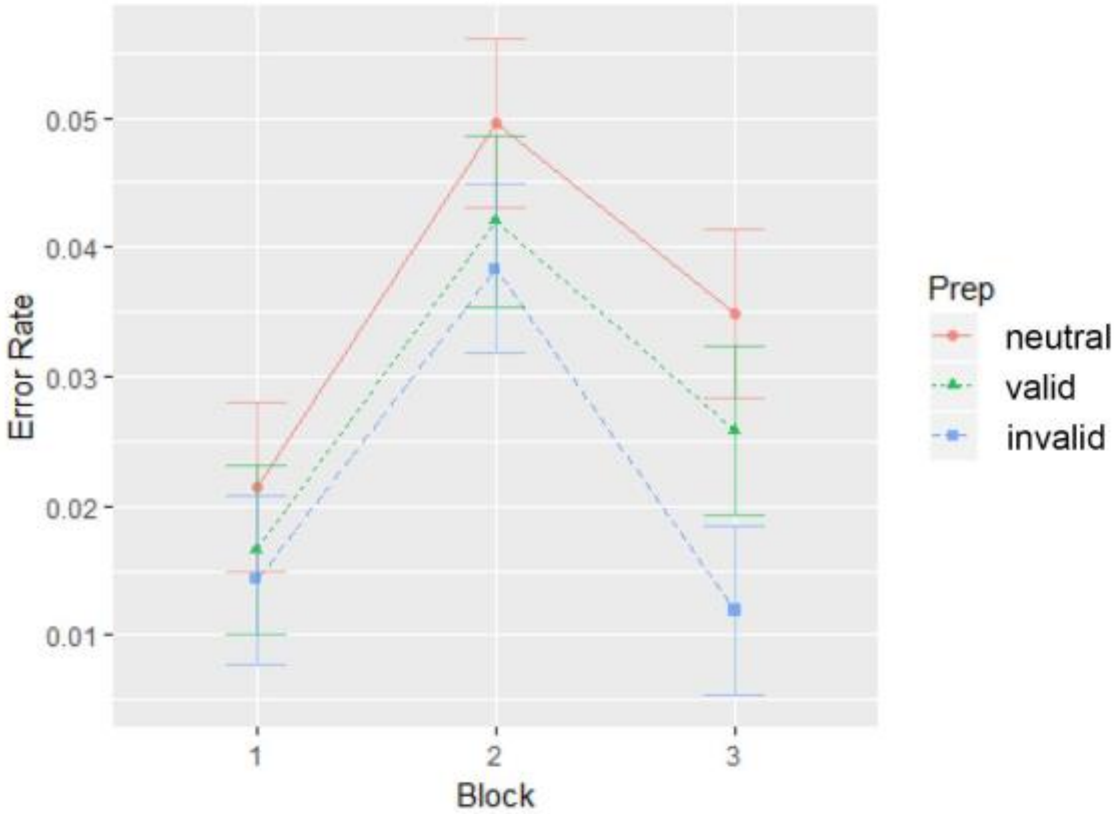

Figure 7. Error rate as a function of block and response preparation.

Discussion

The aim of this study was to assess whether distraction manipulated by dual task load affects valid and invalid response preparation during lane change manoeuvres. To our knowledge this approach is new and was not evaluated in such a detailed experimental approach yet.

It was predicted that distraction would lead to increased reaction time on initiating a lane change manoeuvre and that valid, invalid and neutral pre-cues would have a validity effect on reaction time, viz. invalid information should increase RT. Unfortunately, the findings of this study did not agree with our expectations. However, a training effect was found which may suggest that participants developed strategies to cope with the task. Findings were that as in previous studies participants without any advance information had longer reaction times than with prior information and that the performance of the participants improved over time due to less errors and an increase in the performance of the second task. In contrast to our expectations RT and error analyses did not provide hints that preparation was affected by dual task load, viz. distraction. However, also in contrast to our expectations invalid information beforehand did not differ from neutral information. Thus, the validity effect of Hofmann & Rinkenauer (2013) could not be replicated and this may limit the interpretability of the data.

Reaction time and error rate

In comparison to trials with invalid and neutral cues, the valid cues caused a significantly shorter reaction time to lane change stimuli. Even in the dual task condition the participants reacted quickest as the pre-cue was valid, although the average reaction time increased. These findings indicate that the participants were capable of using the previous information. However, the benefits of pre-cues were smaller than expected concerning response preparation and the error rate was extremely low. It was assumed that valid trials in comparison to invalid trials have a greater impact on reaction time and drivers confronted with invalid information have a higher probability of more erroneous lane changes. There are several aspects, which may explain the unexpected findings. First, participants had no time pressure to execute. They could compensate and adjust their steering behaviour and also might be cautious because they learned that invalid trials are in the driving simulation. Secondly, a learning effect occurred, meaning that the performance of the participants improved. This can be seen in the error rate analysis, in which participants made less errors in the last block compared to the second block and in the number of tasks completed in the Surrogate Reference Task.

It was expected that RT increases as invalid information is presented, but surprisingly, the RT analysis revealed that invalid information did not show an adverse effect on RT. Further the results show that participants did less errors when confronted with invalid information than with valid and neutral information. The other important aspect of the study is that the dual task condition leads to increased reaction time but the learning effect took only place in the control of errors. One preliminary explanation of such a pattern of behaviour may be that participants developed strategies in adjusting their speed-accuracy trade-off which could not be controlled by the experimental setting.

Although the difference in reaction time was statistically significant, the effect size is not big and the difference in reaction time between neutral and invalid trials is only 4.9 ms, which in fact makes not much difference on the road. As already mentioned the participants were aware of the fact that the pre-cue could be invalid and they may have adjusted their behaviour to this situation, which was possible in the experimental setting of our study. In a natural setting and real-world condition, in-vehicle systems are expected to always work safely and right. Nevertheless, in the unlikely case of an incorrect response preparation caused by the in-vehicle system, the driver might have a much longer reaction time to re-program his response, because he would not expect the in-vehicle system to produce wrong information. Such an effect of misinformation may even be more adverse under dual or multi-task conditions. Hence, it is still a challenge to find experimental and save simulation setups to assess driver behaviour in situations of miss information and dual or multi task conditions. Still, such information is of real importance for the developers of in-vehicle systems.

Limitations

The generalizability of the findings in this experiment is limited because the external validity is reduced due to specific aspects in following part.

As the study was a driving simulation in an experimental setting the generalizability into the real world has to be kept in mind (Kemeny and Panerai, 2003). The driving speed was constant during the whole experiment and the road consisted of lanes side by side and did not include any real-world aspects. This sparse environment (no landscape or sky simulated) has the advantage that confounding variables can be controlled.

Another aspect, which needs to be considered, is that mainly young people participated in the experiment and the generalizability for other age groups is restricted. Rinkenauer and Hofmann (2011) showed that there are age differences in the steering wheel movement. Further Lesch et al. (2011) revealed that older drivers have bigger problems in understanding warning signs.

Conclusion

The study investigated psychological paradigms like the pre-cueing technique and dual task paradigms. In contrast to earlier studies we could not replicate the validity effect. A preliminary interpretation of the results may be that participants were able to adjust their performance to the task that they in general responded slower to keep a certain accuracy level. Such a behaviour was possible because of the repeated presentation of the different tasks and the laboratory situation. It was not possible with the current experimental setup to decide to what extent distraction may affect preparation. Or how preparation may compensate the adverse effects of distraction. The research question itself is still of great importance because as future in-vehicle systems become more complex and adapt more tasks of the human driver it is important to know the limits of human information processing. Therefore, future experimental setups will extent the current experimental setup in such way that participants will not be informed about invalid information conditions and that more complex dual task situations will be used.

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Appendix A

General information

Allgemeine Informationen

Versuchsleiter:	______________________		
VP-Nr.:	______________________		
Datum:	______________________		
Beginn (Uhrzeit):	______________________		
Ende (Uhrzeit):	______________________		
Alter:	______________________		
Geschlecht:	☐ männlich	☐ weiblich	
Händigkeit:	☐ rechts	☐ links	☐ beidhändig
Besitz des Führerscheins			
In Jahren:			
Tätigkeit:	____		
Falls Student:			
Studienfach:	____		

Einverständniserklärung

Lane Change Task

Die Details der Studie wurden mir erklärt, und alle meine Fragen zu meiner Zufriedenheit beantwortet. Ich bin sicher, dass ich betreffend meiner Teilnahme an der Studie alles verstanden habe. Die einführenden Erklärungen des Informationsblattes habe ich gelesen. Ich weiß, dass ich meine Teilnahme an der Studie jederzeit ohne die Angabe von Gründen, und ohne dass mir dadurch Nachteile entstehen, widerrufen kann.

Ich, ____

Name Vorname geb.

erkläre hiermit mein Einverständnis, an der oben genannten Studie freiwillig teilzunehmen.

Alle meine personenbezogenen Daten werden vertraulich behandelt. Die Weitergabe meiner Daten für statistische Auswertungen erfolgt in jedem Fall anonymisiert und ausschließlich zu wissenschaftlichen Zwecken. Hiermit bin ich einverstanden.

______________________ ________________________________

Ort, Datum Unterschrift

Ich bin an weiteren Untersuchungen interessiert. Meine Daten (Email, Tel.-Nummer) dürfen **innerhalb** des IfADos auch an andere Projektgruppen weitergegeben werden.

☐ Ja ☐ Nein

E-Mail: ____

Telefonnummer: ________________________________

Dortmund, ____________________________________

Datum, Unterschrift

Appendix B
LCT Distraction Analysis

Analysis

Prep: 0 = without cue, 1 = with direction cue, 2 = with lane cue, 3 = with both cues, 4 = with opposite direction cue

LC_direct: 1 = left, 2 = right

Targetpos: 0 = center, 1 = left, 2 = right

The descripition of SigAlpha, SigBeta, SigA und ForceSDDev in the evaluation:

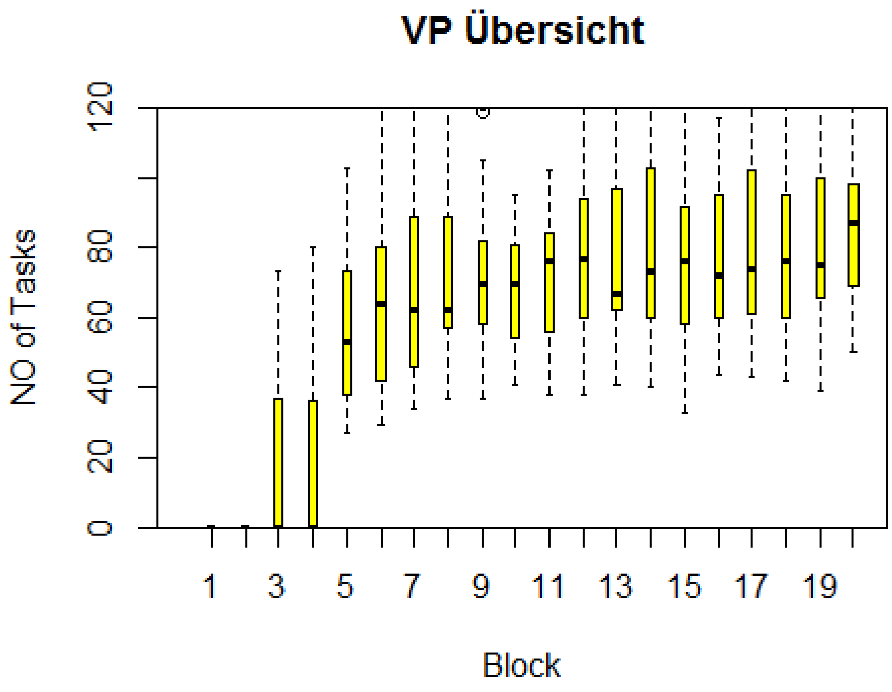
Alpha, Beta und A are the parameter of the Sigmoid-curve with the following equation:

S(x)=SigA/(1+exp(-SigBeta(x-SigAlpha)))

Dev is the sum of the absolute difference between the actual position on the road and the adjusted curve from the reaction time until the end of the trial

```
library(ez)
library(gplots)

##
## Attaching package: 'gplots'

## The following object is masked from 'package:stats':
##
##     lowess

rm(list = ls())

remove_outliers <- function(x, na.rm = TRUE, ...) {
  qnt <- quantile(x, probs=c(.25, .75), na.rm = na.rm, ...)
  H <- 3 * IQR(x, na.rm = na.rm) # ursprünglich H <- 1.5 * IQR(x, na.rm = na.rm)
  y <- x
  y[x < (qnt[1] - H)] <- NA
  y[x > (qnt[2] + H)] <- NA
  y
}


replace_outliers <- function(x, na.rm = TRUE, ...) {
  M <- median(x, na.rm = na.rm)   #Alternative: median
  qnt <- quantile(x, probs=c(.25, .75), na.rm = na.rm, ...)
  H <- 2 * IQR(x, na.rm = na.rm) # ursprünglich H <- 1.5 * IQR(x, na.rm = na.rm)
  y <- x
  y[x < (qnt[1] - H)] <- M
  y[x > (qnt[2] + H)] <- M
  y
}



setwd("D:/00_aktuelle_Arbeit/00_Master_Twente/Stuart Chapman/Experiment/Analysen")
source("summarySE.R")









#Secondary Task


#single task, Block 1-2: VPs : 1,10,11,14,15,19
#single task, Block 1-4: VPs : 2,3,4,5,6,7,9,13,17,18,20,22,24,25,26
```

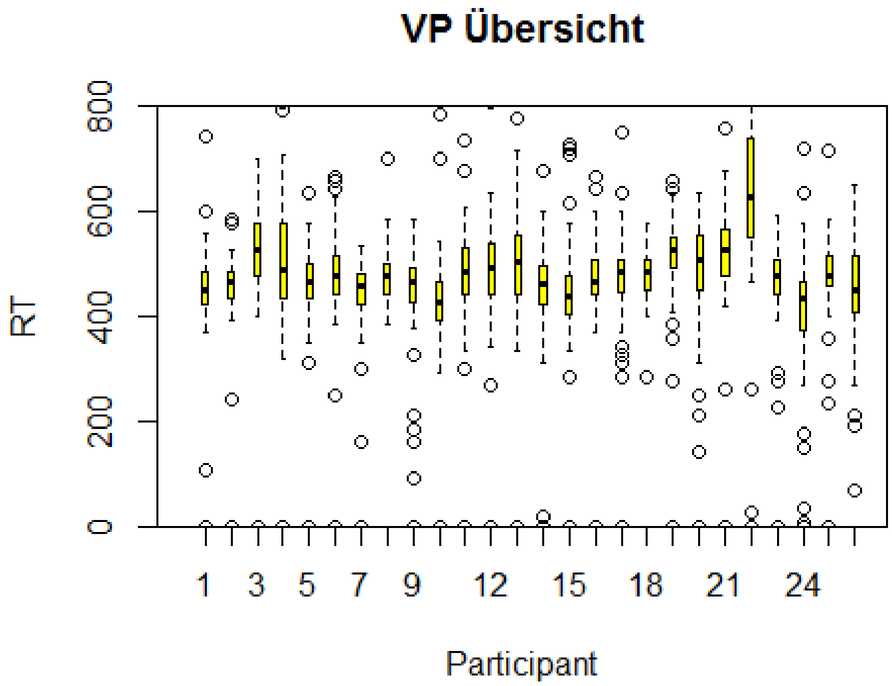
```
table (in_dat_sec_$Subject)
##
##  1  2  3  4  5  6  7  9 10 11 13 14 15 17 18 19 20 22 24 25 26
## 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20 20
boxplot(Vis_Task_Count ~ Block, data = in_dat_sec_,
      boxwex = 0.25, at = 1:20 - 0.2,
      subset = in_dat_sec_$Subject %in% c(1,2,3,4,5,6,7,9,10,11,13,14,15,17,18,19,20,22,24,25,26),
#c(2,3,4,5,6,7,9,13,17,18,20,22,24,25,26)
      col = "yellow",
      main = "VP Übersicht",
      xlab = "Block",
      ylab = "NO of Tasks",
      xlim = c(0, 20), ylim = c(0, 120), yaxs = "i")
```



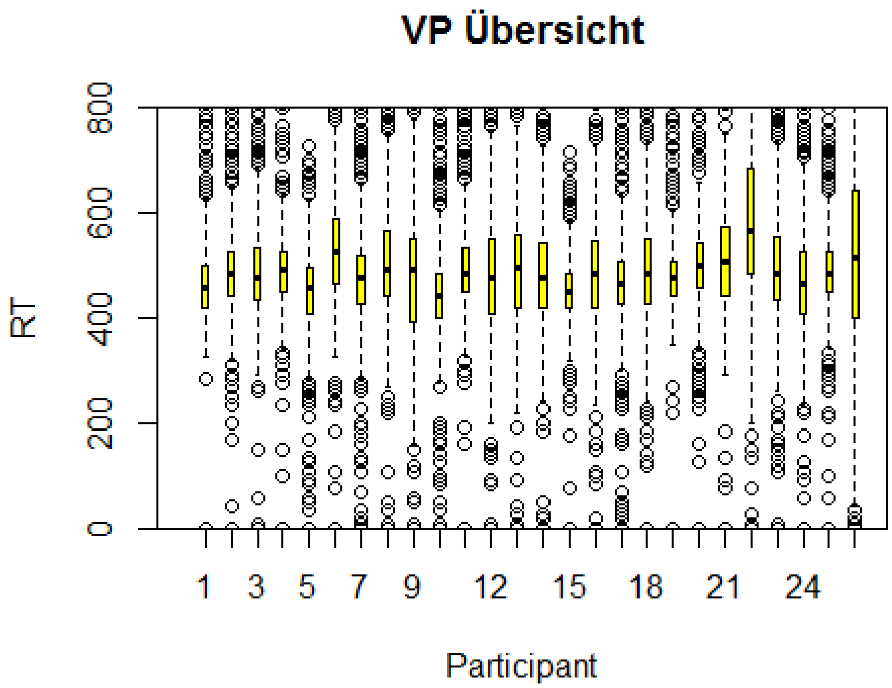

```
#count NAs for groups
#aggregate(RT ~ Participant, data=in_dat_, function(x) {sum(is.na(x))}, na.action = NULL)
#sum(is.na(in_dat_$RT))

length(in_dat_$Participant)/800
## [1] 26
N_VPs <- 26

#remove NAs (missing data)
#in_dat_ <- na.omit(in_dat_orig)

colnames(in_dat_)
##  [1] "Participant"      "Block"            "Trial"
##  [4] "Prep"             "No_of_Lanes"      "LC_direct"
##  [7] "Targetpos"        "Secondary_Task"   "N"
## [10] "RT"               "Errors"           "Anticip"
## [13] "TTP1"             "TTO1"             "TTP2"
## [16] "TTO2"             "T1"               "T2"
## [19] "T3"               "T4"               "T5"
## [22] "A1"               "A2"               "SigBase"
## [25] "SigAlpha"         "SigBeta"          "SigA"
## [28] "SigDev"           "WS_Wheel_Mean"    "WS_Wheel_Var"
## [31] "RS_Wheel_Mean"    "RS_Wheel_Var"     "WS_WheelDiff_Mean"
## [34] "WS_WheelDiff_Var" "RS_WheelDiff_Mean" "RS_WheelDiff_Var"
## [37] "WS_Lane_Mean"     "WS_Lane_Var"      "RS_Lane_Mean"
## [40] "RS_Lane_Var"
table(in_dat_$Participant)
```

```
##
##   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17  18
## 800 800 800 800 800 800 800 800 800 800 800 800 800 800 800 800 800 800
##  19  20  21  22  23  24  25  26
## 800 800 800 800 800 800 800 800
boxplot(in_dat_$RT)
```

```
mean(in_dat_$RT[in_dat_$Secondary_Task == 0], na.rm = TRUE)
## [1] 470.6702
mean(in_dat_$RT[in_dat_$Secondary_Task == 1], na.rm = TRUE)
## [1] 471.5745
table(in_dat_$Prep)
##
##     0     3     4
## 10400  7800  2600
mean(in_dat_$RT[in_dat_$Prep == 0], na.rm = TRUE)
## [1] 476.7763
mean(in_dat_$RT[in_dat_$Prep == 3], na.rm = TRUE)
## [1] 462.2312
mean(in_dat_$RT[in_dat_$Prep == 4], na.rm = TRUE)
## [1] 478.0735
mean(in_dat_$RT[in_dat_$Block %in% c(1,2,3,4)], na.rm = TRUE)
## [1] 476.0938
mean(in_dat_$Errors[in_dat_$Block %in% c(1,2,3,4)], na.rm = TRUE)
## [1] 0.01826923
table(in_dat_$Block)
##
##    1    2    3    4    5    6    7    8    9   10   11   12   13   14   15
## 1040 1040 1040 1040 1040 1040 1040 1040 1040 1040 1040 1040 1040 1040 1040
##   16   17   18   19   20
## 1040 1040 1040 1040 1040

print(table(in_dat_$Participant))
##
##   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17  18
## 800 800 800 800 800 800 800 800 800 800 800 800 800 800 800 800 800 800
##  19  20  21  22  23  24  25  26
## 800 800 800 800 800 800 800 800
boxplot(RT ~ Participant, data = in_dat_,
        boxwex = 0.25, at = 1:N_VPs - 0.2,
        subset = Secondary_Task == "0",
        col = "yellow",
        main = "VP Übersicht",
        xlab = "Participant",
        ylab = "RT",
        xlim = c(0, N_VPs), ylim = c(0, 800), yaxs = "i")
```



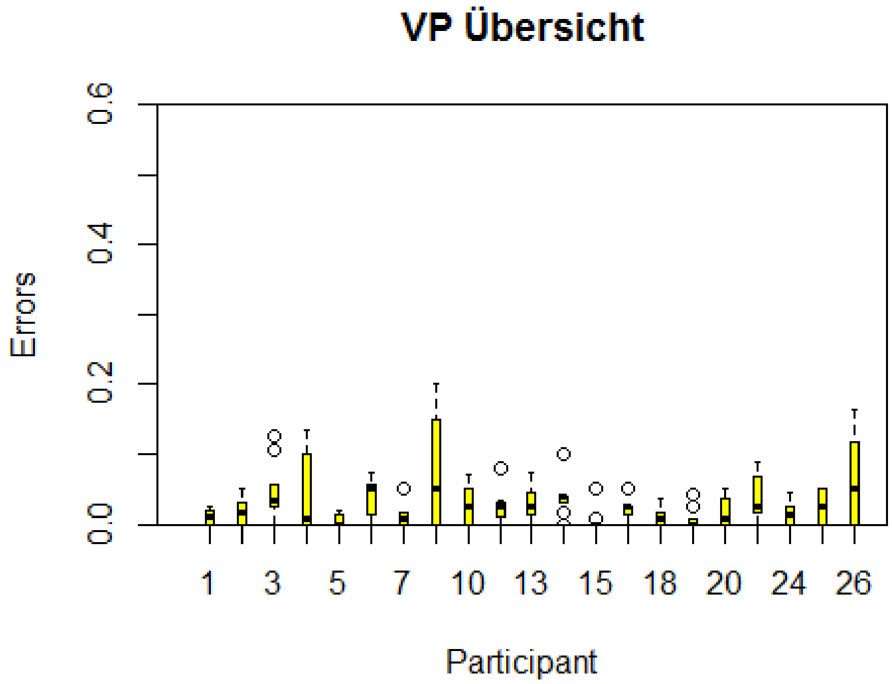

```
boxplot(RT ~ Participant, data = in_dat_,
    boxwex = 0.25, at = 1:N_VPs - 0.2,
    subset = Secondary_Task == "1",
    col = "yellow",
    main = "VP Übersicht",
    xlab = "Participant",
    ylab = "RT",
    xlim = c(0, N_VPs), ylim = c(0, 800), yaxs = "i")
```



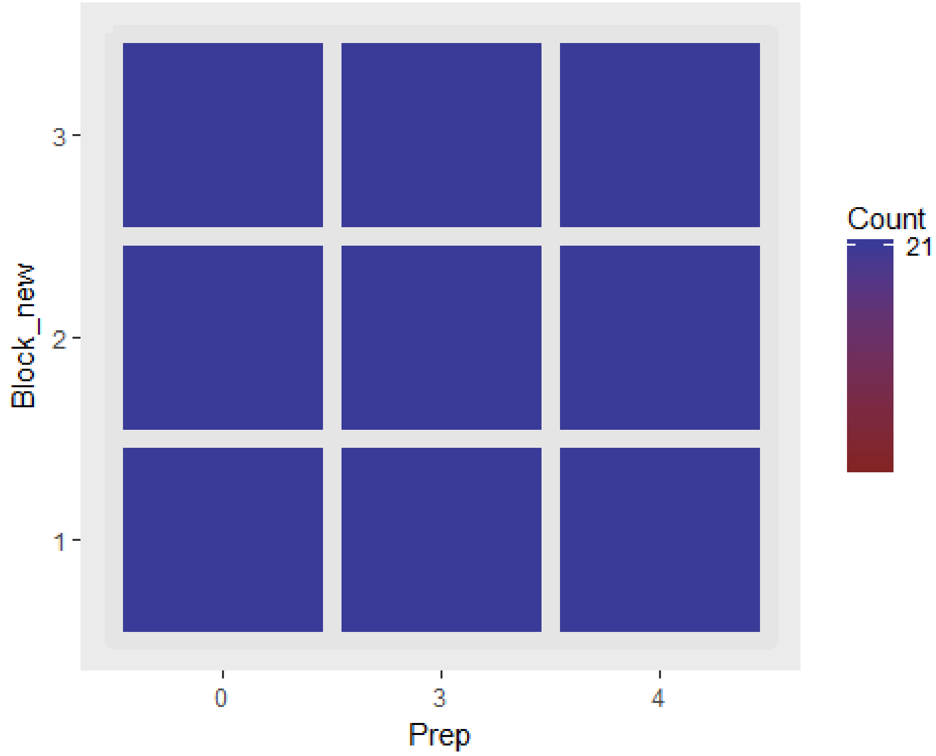

```
#in_dat_ <- in_dat_[!(in_dat_$RT == 0), ]

#Versuchspresonenauswahl without anticipation and full advanced information
```

```
in_dat_red <- in_dat_[in_dat_$Participant %in% c(1,2,3,4,5,6,7,9,10,11,13,14,15,17,18,19,20,22,24,25,26), ]


#combining the blocks
in_dat_red$Block_new <- c(0)
in_dat_red[in_dat_red$Block %in% c(1,2) & in_dat_red$Participant %in% c(1,10,11,14,15,19), ]$Block_new <- 1
in_dat_red[in_dat_red$Block %in% c(1,2,3,4) & in_dat_red$Participant %in% c(2,3,4,5,6,7,9,13,17,18,20,22,24,25,26), ]$Block_new <- 1
in_dat_red[in_dat_red$Block %in% c(3, 4, 5, 6, 7, 8, 9,10,11,12) & in_dat_red$Participant %in% c(1,10,11,14,15,19), ]$Block_new <- 2
in_dat_red[in_dat_red$Block %in% c( 5, 6, 7, 8, 9,10,11,12) & in_dat_red$Participant %in% c(2,3,4,5,6,7,9,13,17,18,20,22,24,25,26),
]$Block_new <- 2
#in_dat_red[in_dat_red$Block %in% c( 5, 6, 7, 8, 9,10,11,12), ]$Block_new <- 2
in_dat_red[in_dat_red$Block %in% c(13,14,15,16,17,18,19,20), ]$Block_new <- 3

table(in_dat_red$Block_new)
##
##    1    2    3
## 2880 7200 6720
N_VPs <- length (c(1,2,3,4,5,6,7,9,10,11,13,14,15,17,18,19,20,22,24,25,26))

table(in_dat_red$Participant)
##
##   1   2   3   4   5   6   7   9  10  11  13  14  15  17  18  19  20  22
## 800 800 800 800 800 800 800 800 800 800 800 800 800 800 800 800 800 800
##  24  25  26
## 800 800 800
colnames (in_dat_red)
##  [1] "Participant"      "Block"            "Trial"
##  [4] "Prep"             "No_of_Lanes"      "LC_direct"
##  [7] "Targetpos"        "Secondary_Task"   "N"
## [10] "RT"               "Errors"           "Anticip"
## [13] "TTP1"             "TTO1"             "TTP2"
## [16] "TTO2"             "T1"               "T2"
## [19] "T3"               "T4"               "T5"
## [22] "A1"               "A2"               "SigBase"
## [25] "SigAlpha"         "SigBeta"          "SigA"
## [28] "SigDev"           "WS_Wheel_Mean"    "WS_Wheel_Var"
## [31] "RS_Wheel_Mean"    "RS_Wheel_Var"     "WS_WheelDiff_Mean"
## [34] "WS_WheelDiff_Var"  "RS_WheelDiff_Mean" "RS_WheelDiff_Var"
## [37] "WS_Lane_Mean"     "WS_Lane_Var"      "RS_Lane_Mean"
## [40] "RS_Lane_Var"      "Block_new"
#Fehleranalyse
in_dat <- with(in_dat_red, #in_dat_red
        aggregate(list(RT=RT,  Errors=Errors,
                TTP1=TTP1,   TTO1=TTO1,  TTP2=TTP2,  TTO2=TTO2,  T1=T1,  T2=T2,
                T3=T3,   T4=T4,  T5=T5,  A1=A1,  A2=A2,  SigAlpha=SigAlpha,
                SigBeta=SigBeta,  SigA=SigA,  SigDev=SigDev),
              list(Prep = Prep, Block_new = Block_new, Participant = Participant),
                 mean), na.action = na.omit)


# adjust structure
in_dat$Participant <- as.factor(in_dat$Participant)
in_dat$Block_new <- as.factor(in_dat$Block_new)
in_dat$Prep <- as.factor(in_dat$Prep)
#in_dat$Secondary_Task <- as.factor(in_dat$Secondary_Task)

mean(in_dat$Errors)
## [1] 0.02831129
mean(in_dat$RT) # aufgrund der Fehleranalyse
## [1] 474.453
#test
aggregate(RT ~ Participant, data=in_dat, function(x) {sum(is.na(x))}, na.action = NULL)
##    Participant RT
## 1            1  0
## 2            2  0
## 3            3  0
## 4            4  0
## 5            5  0
## 6            6  0
## 7            7  0
## 8            9  0
## 9           10  0
## 10          11  0
## 11          13  0
```

```
## 12        14  0
## 13        15  0
## 14        17  0
## 15        18  0
## 16        19  0
## 17        20  0
## 18        22  0
## 19        24  0
## 20        25  0
## 21        26  0
length(in_dat$RT[in_dat$RT == 1])
## [1] 0
table(in_dat$Participant)
##
##  1  2  3  4  5  6  7  9 10 11 13 14 15 17 18 19 20 22 24 25 26
##  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9  9
boxplot(Errors ~ Participant, data = in_dat,
       boxwex = 0.25, at = 1:N_VPs - 0.2,
       #subset = Secondary_Task == "1",
       col = "yellow",
       main = "VP Übersicht",
       xlab = "Participant",
       ylab = "Errors",
       xlim = c(0, N_VPs), ylim = c(0, 0.6), yaxs = "i")
```




```
#check the design
test_design = ezDesign(
  data = in_dat
  , x = Prep
  , y = Block_new
  #, row =
  #, col = block
)

plot(test_design)
```

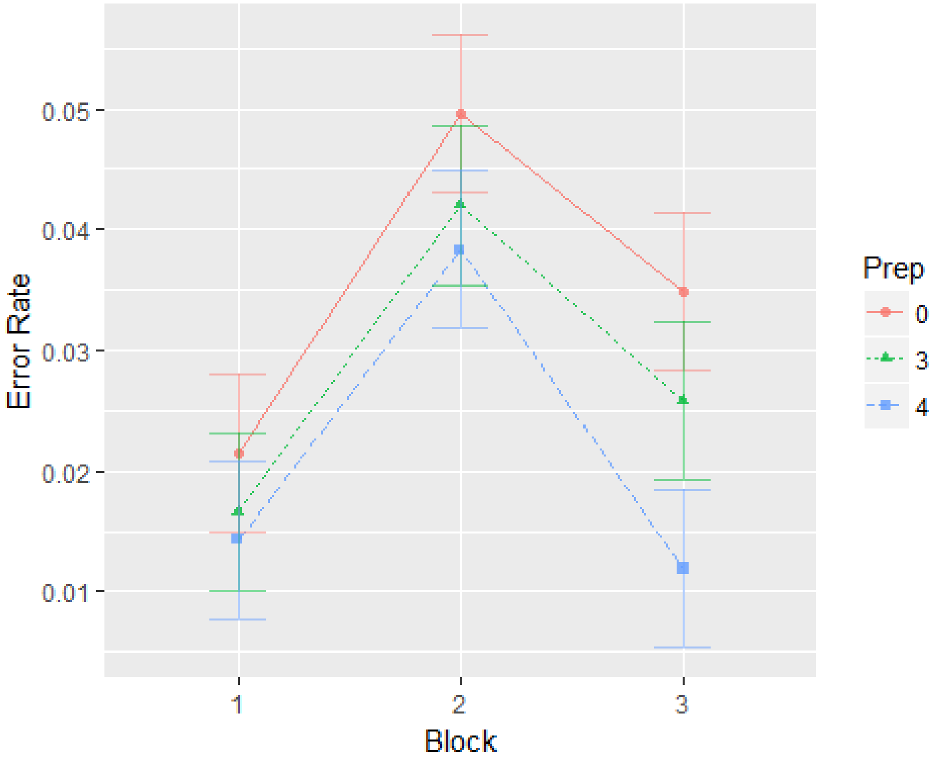



```
#ANOVAs für 'Errors' voll
print('ANOVAS Errors, voll')
## [1] "ANOVAS Errors, voll"
print('================')
## [1] "================"
test_anova_Errors_full = ezANOVA(
  in_dat
  , dv = Errors
  , wid = Participant
  , within = .(Prep, Block_new)
  #, between = Age
  #    , detailed = TRUE
)

print(test_anova_Errors_full)
## $ANOVA
##           Effect DFn DFd         F           p p<.05         ges
## 2           Prep   2  40 5.9073896 0.005651019     * 0.025424165
## 3      Block_new   2  40 4.3966276 0.018793341     * 0.089992781
## 4 Prep:Block_new   4  80 0.8589457 0.492361826       0.006768581
##
## $`Mauchly's Test for Sphericity`
##           Effect         W           p p<.05
## 2           Prep 0.6621977 0.019924281     *
## 3      Block_new 0.5190148 0.001968826     *
## 4 Prep:Block_new 0.6887622 0.652485635
##
## $`Sphericity Corrections`
##           Effect       GGe     p[GG] p[GG]<.05       HFe      p[HF]
## 2           Prep 0.7474946 0.01184531         * 0.7942382 0.01032250
## 3      Block_new 0.6752262 0.03501212         * 0.7067061 0.03295883
## 4 Prep:Block_new 0.8630447 0.47963738           1.0650308 0.49236183
##   p[HF]<.05
## 2         *
## 3         *
## 4
means_anova_Errors_full = ezStats(
  in_dat
  , dv = Errors
  , wid = Participant
  , within = .(Prep,Block_new)
  #, between = Age
```

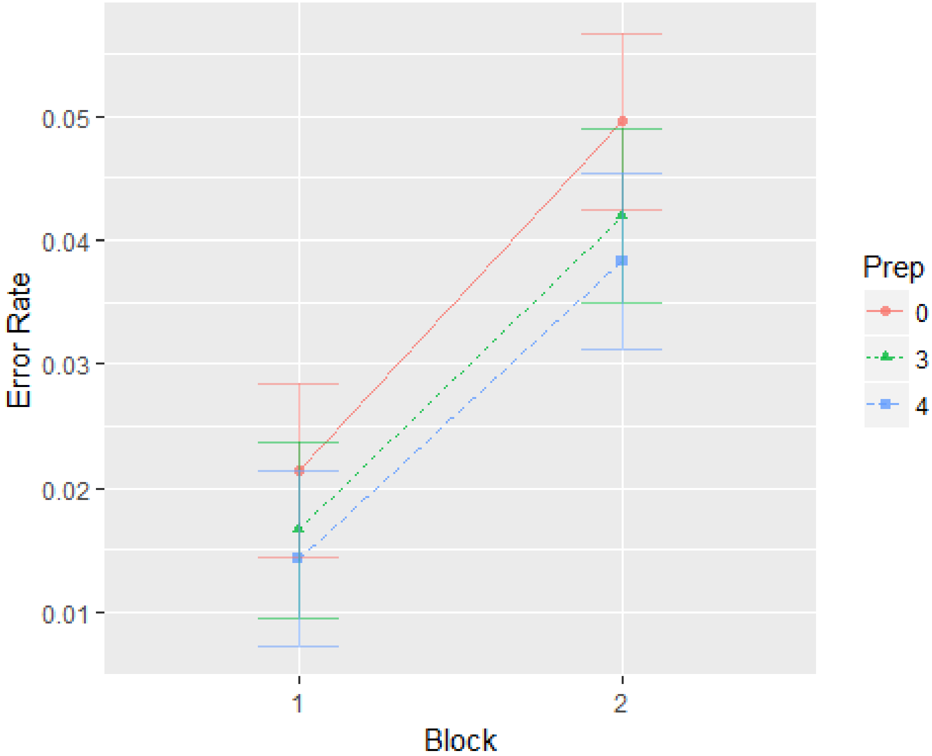
```
)

print(means_anova_Errors_full)
##   Prep Block_new  N       Mean         SD      FLSD
## 1    0         1 21 0.02142857 0.02908577 0.0130901
## 2    0         2 21 0.04958333 0.04544628 0.0130901
## 3    0         3 21 0.03482143 0.04264550 0.0130901
## 4    3         1 21 0.01666667 0.02981424 0.0130901
## 5    3         2 21 0.04198413 0.04670123 0.0130901
## 6    3         3 21 0.02579365 0.02155496 0.0130901
## 7    4         1 21 0.01428571 0.03218252 0.0130901
## 8    4         2 21 0.03833333 0.04243623 0.0130901
## 9    4         3 21 0.01190476 0.01874008 0.0130901
# Means averaged across Prep
means_anova_Errors = ezStats(
  in_dat
  , dv = Errors
  , wid = Participant
  , within = .(Block_new)
  #, between = Age
)

print(means_anova_Errors)
##   Block_new  N       Mean         SD       FLSD
## 1         1 21 0.01746032 0.02696581 0.01827654
## 2         2 21 0.04330026 0.04026051 0.01827654
## 3         3 21 0.02417328 0.02294466 0.01827654
print(mean(means_anova_Errors$Mean))
## [1] 0.02831129
# Means averaged across Block
means_anova_Errors = ezStats(
  in_dat
  , dv = Errors
  , wid = Participant
  , within = .(Prep)
  #, between = Age
)
print(means_anova_Errors)
##   Prep  N       Mean         SD        FLSD
## 1    0 21 0.03527778 0.02831750 0.008098229
## 2    3 21 0.02814815 0.02013253 0.008098229
## 3    4 21 0.02150794 0.01694685 0.008098229
print(mean(means_anova_Errors$Mean))
## [1] 0.02831129
#ANOVAs für 'Errors' partial
print('ANOVAS Errors, partial, Block 1 vs. 2')
## [1] "ANOVAS Errors, partial, Block 1 vs. 2"
print('=================')
## [1] "================="
test_anova_Errors = ezANOVA(
  in_dat [in_dat$Block_new %in% c(1,2), ]
  , dv = Errors
  , wid = Participant
  , within = .(Prep, Block_new)
  #, between = Age
  #    , detailed = TRUE
)

print(test_anova_Errors)
## $ANOVA
##           Effect DFn DFd          F          p p<.05          ges
## 2           Prep   2  40 2.46966178 0.09742473       0.0103599703
## 3      Block_new   1  20 5.02363136 0.03650741     * 0.1065545854
## 4 Prep:Block_new   2  40 0.09050142 0.91365954       0.0005262716
##
## $`Mauchly's Test for Sphericity`
##           Effect         W         p p<.05
## 2           Prep 0.7930438 0.1104900
## 4 Prep:Block_new 0.9488746 0.6074126
##
## $`Sphericity Corrections`
##           Effect       GGe     p[GG] p[GG]<.05       HFe     p[HF]
## 2           Prep 0.8285305 0.1086569           0.8940301 0.1042516
## 4 Prep:Block_new 0.9513613 0.9053960           1.0486985 0.9136595
```

```
##   p[HF]<.05
## 2
## 4
#ANOVAs für 'Errors' partial
print('ANOVAS Errors, partial Block 2 vs. 3')
## [1] "ANOVAS Errors, partial Block 2 vs. 3"
print('=================')
## [1] "================="
test_anova_Errors = ezANOVA(
  in_dat [in_dat$Block_new %in% c(2,3), ]
  , dv = Errors
  , wid = Participant
  , within = .(Prep, Block_new)
  #, between = Age
  #    , detailed = TRUE
)

print(test_anova_Errors)
## $ANOVA
##           Effect DFn DFd          F           p p<.05         ges
## 2           Prep   2  40  4.7503794 0.014091677     * 0.034101017
## 3      Block_new   1  20 10.4622213 0.004155093     * 0.062239123
## 4 Prep:Block_new   2  40  0.8959974 0.416234225       0.004873799
##
## $`Mauchly's Test for Sphericity`
##           Effect         W           p p<.05
## 2           Prep 0.6069918 0.008714383     *
## 4 Prep:Block_new 0.9099739 0.408107740
##
## $`Sphericity Corrections`
##           Effect       GGe      p[GG] p[GG]<.05       HFe     p[HF]
## 2           Prep 0.7178709 0.02587939         * 0.7581928 0.0237187
## 4 Prep:Block_new 0.9174092 0.40905567           1.0055277 0.4162342
##   p[HF]<.05
## 2         *
## 4
#ANOVAs für 'Errors' partial
print('ANOVAS Errors, partial Block 1 vs. 3')
## [1] "ANOVAS Errors, partial Block 1 vs. 3"
print('=================')
## [1] "================="
test_anova_Errors = ezANOVA(
  in_dat [in_dat$Block_new %in% c(1,3), ]
  , dv = Errors
  , wid = Participant
  , within = .(Prep, Block_new)
  #, between = Age
  #    , detailed = TRUE
)

print(test_anova_Errors)
## $ANOVA
##           Effect DFn DFd         F           p p<.05        ges
## 2           Prep   2  40 5.3208484 0.008933772     * 0.04212952
## 3      Block_new   1  20 0.5818746 0.454482191       0.01296120
## 4 Prep:Block_new   2  40 1.8625120 0.168499524       0.01276775
##
## $`Mauchly's Test for Sphericity`
##           Effect         W         p p<.05
## 2           Prep 0.8784222 0.2918645
## 4 Prep:Block_new 0.9575723 0.6624146
##
## $`Sphericity Corrections`
##           Effect       GGe      p[GG] p[GG]<.05       HFe       p[HF]
## 2           Prep 0.8916011 0.01175367         * 0.9729274 0.009566155
## 4 Prep:Block_new 0.9592991 0.17038414           1.0588384 0.168499524
##   p[HF]<.05
## 2         *
## 4
#Plot for Block 1,2,3
plot_anova_err_ID = ezPlot(
  data = in_dat
  , dv = Errors
  , wid = Participant
```

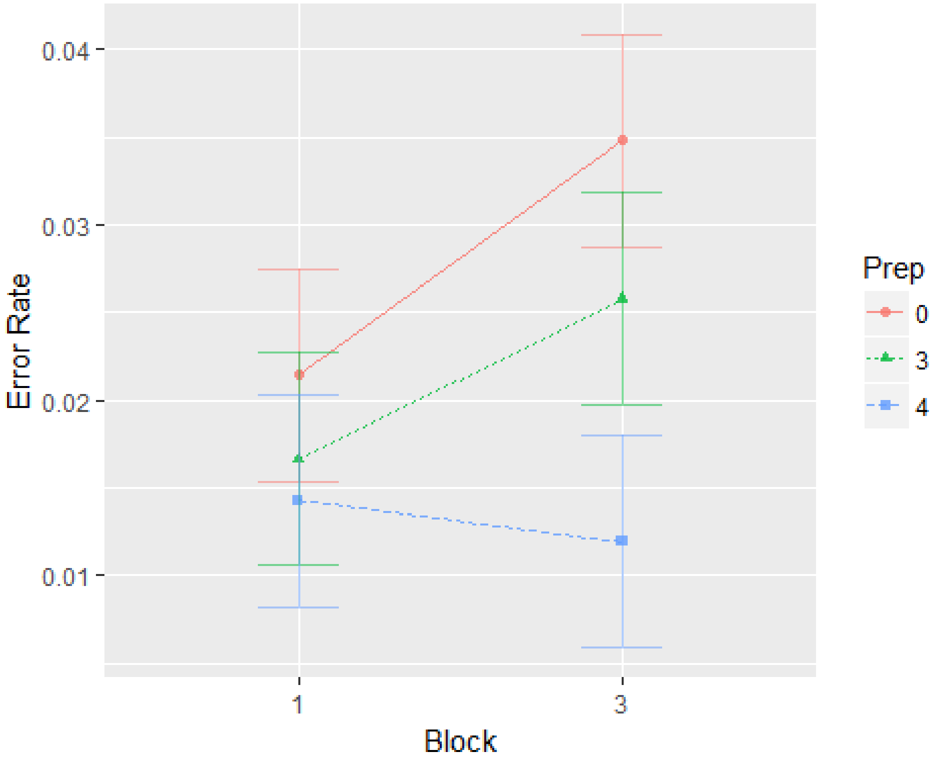
```
  , within = .(Prep, Block_new)
  , x = .(Block_new)
  #, col = .(Secondary_Task)
  , split = .(Prep)
  , x_lab = 'Block'
  , y_lab = 'Error Rate'
  #  , split_lab = 'Age'
  #, between = Age
)
plot(plot_anova_err_ID)
```



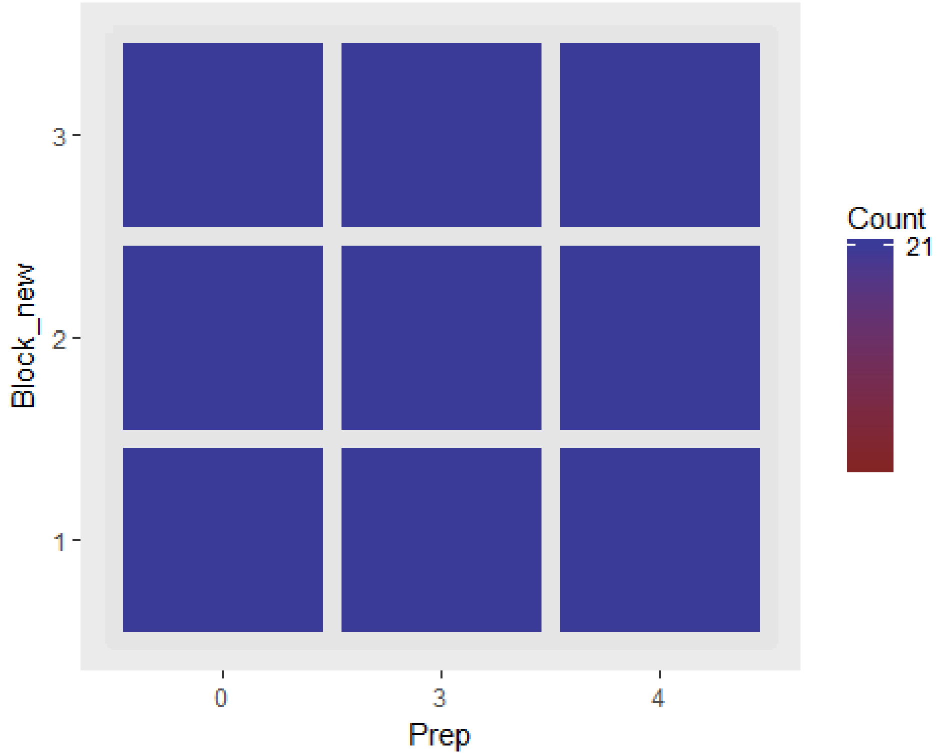

```
# Plot for Block 1 vs. 2
plot_anova_err_ID = ezPlot(
  data = in_dat [in_dat$Block_new %in% c(1,2), ]
  , dv = Errors
  , wid = Participant
  , within = .(Prep, Block_new)
  , x = .(Block_new)
  #, col = .(Secondary_Task)
  , split = .(Prep)
  , x_lab = 'Block'
  , y_lab = 'Error Rate'
  #  , split_lab = 'Age'
  #, between = Age
)
plot(plot_anova_err_ID)
```




```
# Plot for Block 1 vs. 3
plot_anova_err_ID = ezPlot(
  data = in_dat [in_dat$Block_new %in% c(1,3), ]
  , dv = Errors
  , wid = Participant
  , within = .(Prep, Block_new)
  , x = .(Block_new)
  #, col = .(Secondary_Task)
  , split = .(Prep)
  , x_lab = 'Block'
  , y_lab = 'Error Rate'
  #  , split_lab = 'Age'
  #, between = Age
)
plot(plot_anova_err_ID)
```




```
#RT-Analyse
in_dat <- with(in_dat_red[in_dat_red$RT > 100 & in_dat_red$RT < 1500 & in_dat_red$Errors == 0, ],  # !!!!!
           aggregate(list(RT=RT,  Errors=Errors,
                     TTP1=TTP1,    TTO1=TTO1,  TTP2=TTP2,  TTO2=TTO2, A1=A1,   A2=A2,  SigAlpha=SigAlpha,
                     SigBeta=SigBeta,  SigA=SigA,  SigDev=SigDev, SigBase=SigBase),
                list(Prep = Prep, Block_new = Block_new, Participant = Participant), median),  na.rm = TRUE)


# adjust structure
in_dat$Participant <- as.factor(in_dat$Participant)
in_dat$Block_new <- as.factor(in_dat$Block_new)
in_dat$Prep <- as.factor(in_dat$Prep)
#in_dat$Secondary_Task <- as.factor(in_dat$Secondary_Task)


#check design
test_design = ezDesign(
  data = in_dat
  , x = Prep
  , y = Block_new
  #, row = Participant
  #, col = Participant
)

plot(test_design)
```

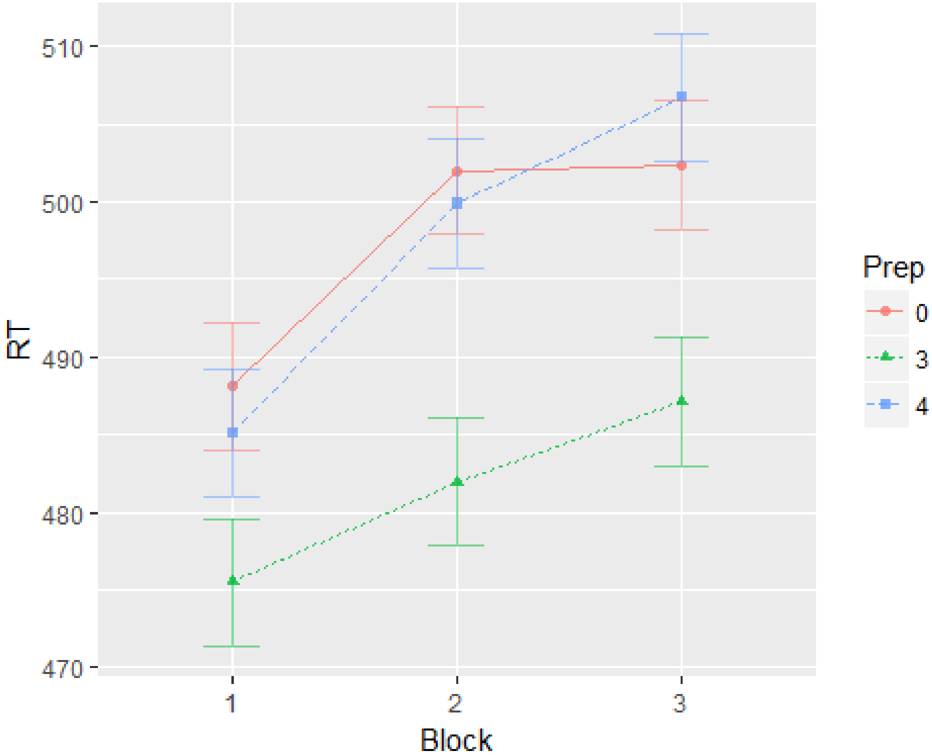



```
#ANOVAs für 'RT' voll
print('ANOVAS RT, voll')
## [1] "ANOVAS RT, voll"
print('================')
## [1] "================"
test_anova_RT_full = ezANOVA(
    in_dat #[in_dat$Block %in% c(1,2), ]
  , dv = RT
  , wid = Participant
  , within = .(Prep, Block_new) #Secondary_Task
  #, between = Age
#    , detailed = TRUE
)

print(test_anova_RT_full)
## $ANOVA
##          Effect DFn DFd         F            p p<.05         ges
## 2          Prep   2  40 13.993681 2.469654e-05     * 0.037044625
## 3     Block_new   2  40  4.328425 1.987559e-02     * 0.030046724
## 4 Prep:Block_new   4  80  1.136906 3.451929e-01       0.003000157
##
## $`Mauchly's Test for Sphericity`
##          Effect         W            p p<.05
## 2          Prep 0.9222517 4.635216e-01
## 3     Block_new 0.3503401 4.706013e-05     *
## 4 Prep:Block_new 0.5453688 2.664460e-01
##
## $`Sphericity Corrections`
##          Effect       GGe        p[GG] p[GG]<.05       HFe        p[HF]
## 2          Prep 0.9278604 4.348846e-05         * 1.0187822 2.469654e-05
## 3     Block_new 0.6061855 4.150274e-02         * 0.6243415 4.011889e-02
## 4 Prep:Block_new 0.7851220 3.422784e-01           0.9482815 3.447412e-01
##   p[HF]<.05
## 2         *
## 3         *
## 4
#=========separate ANOVAs ==============

print('ANOVAS RT, partial Prep 0 vs. 3')
## [1] "ANOVAS RT, partial Prep 0 vs. 3"
print('================')
## [1] "================"
```

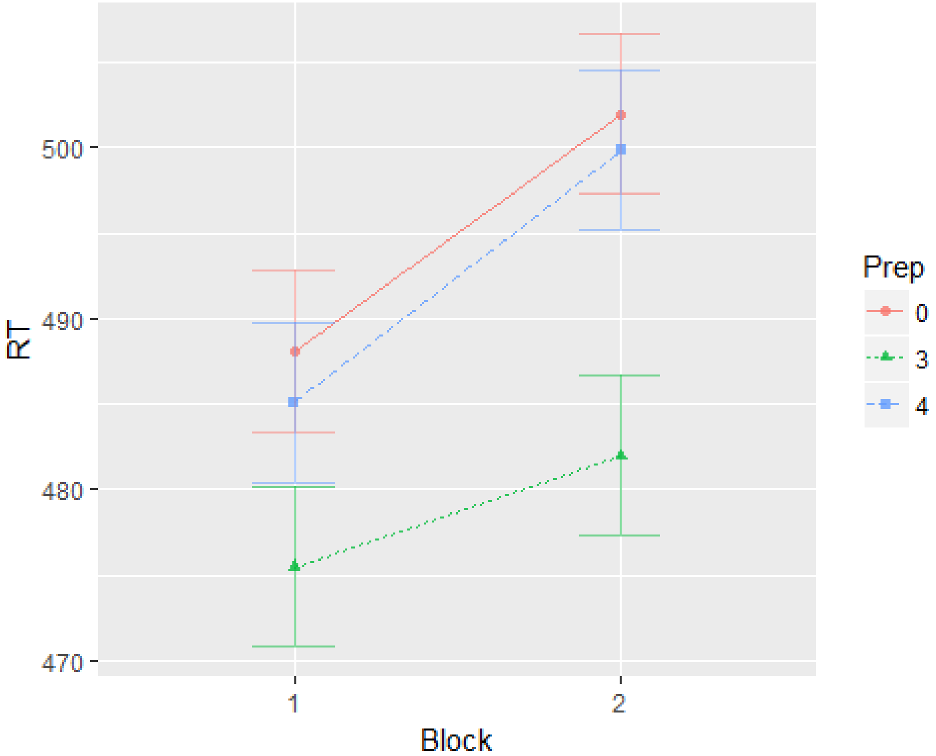
```
test_anova_RT = ezANOVA(
  in_dat [in_dat$Prep %in% c(0,3), ]
  , dv = RT
  , wid = Participant
  , within = .(Prep, Block_new) #Secondary_Task
  #, between = Age
  #    , detailed = TRUE
)

print(test_anova_RT)
## $ANOVA
##           Effect DFn DFd          F            p p<.05         ges
## 2           Prep   1  20 18.0632158 0.0003920251     * 0.040468766
## 3      Block_new   2  40  2.9663197 0.0629175501       0.020055168
## 4 Prep:Block_new   2  40  0.9595988 0.3916883093       0.001566397
##
## $`Mauchly's Test for Sphericity`
##           Effect         W           p p<.05
## 3      Block_new 0.5025842 0.001450387     *
## 4 Prep:Block_new 0.7305570 0.050665691
##
## $`Sphericity Corrections`
##           Effect       GGe     p[GG] p[GG]<.05       HFe      p[HF]
## 3      Block_new 0.6678172 0.0862939           0.6978089 0.08390762
## 4 Prep:Block_new 0.7877471 0.3747232           0.8435878 0.37972088
##   p[HF]<.05
## 3
## 4
print('ANOVAS RT, partial Prep 0 vs. 4')
## [1] "ANOVAS RT, partial Prep 0 vs. 4"
print('=================')
## [1] "================="
test_anova_RT = ezANOVA(
  in_dat [in_dat$Prep %in% c(0,4), ]
  , dv = RT
  , wid = Participant
  , within = .(Prep, Block_new) #Secondary_Task
  #, between = Age
  #    , detailed = TRUE
)

print(test_anova_RT)
## $ANOVA
##           Effect DFn DFd           F          p p<.05          ges
## 2           Prep   1  20 0.007914998 0.92999358       1.180259e-05
## 3      Block_new   2  40 4.232240785 0.02151436     * 3.953606e-02
## 4 Prep:Block_new   2  40 0.980822247 0.38383964       1.853196e-03
##
## $`Mauchly's Test for Sphericity`
##           Effect         W            p p<.05
## 3      Block_new 0.3235202 2.208328e-05     *
## 4 Prep:Block_new 0.8579184 2.332045e-01
##
## $`Sphericity Corrections`
##           Effect       GGe      p[GG] p[GG]<.05       HFe      p[HF]
## 3      Block_new 0.5964880 0.04455058         * 0.6128693 0.04325654
## 4 Prep:Block_new 0.8755942 0.37513000           0.9528006 0.38071846
##   p[HF]<.05
## 3         *
## 4
print('ANOVAS RT, partial Prep 3 vs. 4')
## [1] "ANOVAS RT, partial Prep 3 vs. 4"
print('=================')
## [1] "================="
test_anova_RT = ezANOVA(
  in_dat [in_dat$Prep %in% c(3,4), ]
  , dv = RT
  , wid = Participant
  , within = .(Prep, Block_new) #Secondary_Task
  #, between = Age
  #    , detailed = TRUE
)

print(test_anova_RT)
```

```
## $ANOVA
##          Effect DFn DFd         F            p p<.05         ges
## 2          Prep   1  20 18.883611 0.0003136712     * 0.042728605
## 3     Block_new   2  40  5.006274 0.0114714965     * 0.032996037
## 4 Prep:Block_new   2  40  1.391695 0.2604328454       0.003419145
##
## $`Mauchly's Test for Sphericity`
##          Effect         W            p p<.05
## 3     Block_new 0.3897371 0.0001295183     *
## 4 Prep:Block_new 0.7775998 0.0916607586
##
## $`Sphericity Corrections`
##          Effect       GGe    p[GG] p[GG]<.05       HFe      p[HF]
## 3     Block_new 0.6210166 0.027745         * 0.6419325 0.02642022
## 4 Prep:Block_new 0.8180627 0.260425           0.8810405 0.26066850
##   p[HF]<.05
## 3         *
## 4
#==========================================

print('ANOVAS RT, partial Block 1 vs. 2')
## [1] "ANOVAS RT, partial Block 1 vs. 2"
print('=================')
## [1] "================="
test_anova_RT = ezANOVA(
    in_dat [in_dat$Block_new %in% c(1,2), ]
  , dv = RT
  , wid = Participant
  , within = .(Prep, Block_new) #Secondary_Task
  #, between = Age
#    , detailed = TRUE
)

print(test_anova_RT)
## $ANOVA
##          Effect DFn DFd          F            p p<.05         ges
## 2          Prep   2  40 10.8445198 0.0001725995     * 0.034683673
## 3     Block_new   1  20  3.7807279 0.0660462175       0.023410306
## 4 Prep:Block_new   2  40  0.9609521 0.3911828332       0.002412073
##
## $`Mauchly's Test for Sphericity`
##          Effect         W         p p<.05
## 2          Prep 0.8634172 0.2477973
## 4 Prep:Block_new 0.9584807 0.6684085
##
## $`Sphericity Corrections`
##          Effect       GGe        p[GG] p[GG]<.05       HFe        p[HF]
## 2          Prep 0.8798303 0.0003568442         * 0.9581201 0.0002222336
## 4 Prep:Block_new 0.9601358 0.3883896606           1.0599082 0.3911828332
##   p[HF]<.05
## 2         *
## 4
print('ANOVAS RT, partial Block 2 vs. 3')
## [1] "ANOVAS RT, partial Block 2 vs. 3"
print('=================')
## [1] "================="
test_anova_RT = ezANOVA(
  in_dat [in_dat$Block_new %in% c(2,3), ]
  , dv = RT
  , wid = Participant
  , within = .(Prep, Block_new) #Secondary_Task
  #, between = Age
  #    , detailed = TRUE
)

print(test_anova_RT)
## $ANOVA
##          Effect DFn DFd         F            p p<.05         ges
## 2          Prep   2  40 11.942327 8.575689e-05     * 0.049648534
## 3     Block_new   1  20  2.302826 1.447877e-01       0.002952259
## 4 Prep:Block_new   2  40  1.203458 3.107893e-01       0.001345004
##
## $`Mauchly's Test for Sphericity`
##          Effect         W         p p<.05
```

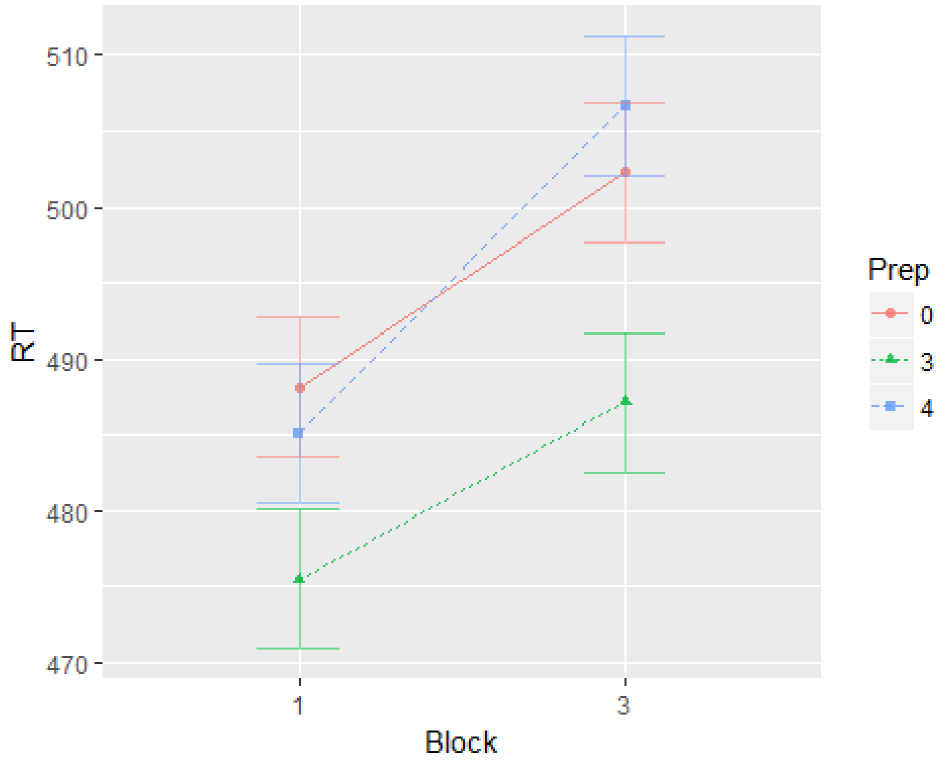
```
## 2           Prep 0.9284249 0.4938490
## 4 Prep:Block_new 0.9388722 0.5492393
##
## $`Sphericity Corrections`
##           Effect       GGe        p[GG] p[GG]<.05      HFe        p[HF]
## 2           Prep 0.9332057 0.0001340123         * 1.025573 8.575689e-05
## 4 Prep:Block_new 0.9423936 0.3093993856           1.037264 3.107893e-01
##   p[HF]<.05
## 2         *
## 4
print('ANOVAS RT, partial Block 1 vs. 3')
## [1] "ANOVAS RT, partial Block 1 vs. 3"
print('================')
## [1] "================"
test_anova_RT = ezANOVA(
    in_dat [in_dat$Block_new %in% c(1,3), ]
  , dv = RT
  , wid = Participant
  , within = .(Prep, Block_new) #Secondary_Task
  #, between = Age
#    , detailed = TRUE
)

print(test_anova_RT)
## $ANOVA
##           Effect DFn DFd         F           p p<.05         ges
## 2           Prep   2  40 11.594849 0.000106727     * 0.029247657
## 3      Block_new   1  20  5.024099 0.036499589     * 0.039913262
## 4 Prep:Block_new   2  40  1.290453 0.286353159       0.002949598
##
## $`Mauchly's Test for Sphericity`
##           Effect         W         p p<.05
## 2           Prep 0.9835457 0.8541773
## 4 Prep:Block_new 0.9611393 0.6862306
##
## $`Sphericity Corrections`
##           Effect       GGe        p[GG] p[GG]<.05      HFe       p[HF]
## 2           Prep 0.9838120 0.0001185215         * 1.090264 0.000106727
## 4 Prep:Block_new 0.9625929 0.2859880525           1.063051 0.286353159
##   p[HF]<.05
## 2         *
## 4
plot_anova_err_ID = ezPlot(
  data = in_dat  #[in_dat$Block %in% c(1,3), ]
  , dv = RT
  , wid = Participant
  , within = .(Prep, Block_new) #Secondary_Task
  , x = .(Block_new)
  #, col = .()
  , split = .(Prep)
  , x_lab = 'Block'
  , y_lab = 'RT'
  #  , split_lab = 'Age'
  #, between = Age
)

plot(plot_anova_err_ID)
```




```
plot_anova_err_ID = ezPlot(
  data = in_dat  [in_dat$Block_new %in% c(1,2), ]
  , dv = RT
  , wid = Participant
  , within = .(Prep, Block_new) #Secondary_Task
  , x = .(Block_new)
  #, col = .()
  , split = .(Prep)
  , x_lab = 'Block'
  , y_lab = 'RT'
  #  , split_lab = 'Age'
  #, between = Age
)

plot(plot_anova_err_ID)
```




```
plot_anova_err_ID = ezPlot(
  data = in_dat  [in_dat$Block_new %in% c(1,3), ]
  , dv = RT
  , wid = Participant
  , within = .(Prep, Block_new) #Secondary_Task
  , x = .(Block_new)
  #, col = .()
  , split = .(Prep)
  , x_lab = 'Block'
  , y_lab = 'RT'
  #  , split_lab = 'Age'
  #, between = Age
)

plot(plot_anova_err_ID)
```




```
#====================================================
#ANOVAs für secondary task

in_dat_sec_ <- read.csv2("D:/00_aktuelle_Arbeit/00_Master_Twente/Stuart Chapman/Experiment/Analysen/LCT_Stuart_VisTask_2017-01-11.csv", sep = ";",dec = ".", header = TRUE)

# summarySEwithin(data = in_dat_sec_[in_dat_sec_$Block %in% c(1,2,3,4), ], # & in_dat_sec_$Subject %in% c(2,3,4,5,6,7,9,13,17,18,20,22,24,25,26), ],
#               measurevar = "Vis_Task_Count",
#               withinvars = c("Subject"),
#               idvar = "Block")



#combining the blocks
in_dat_sec_$Block_new <- c(0)
in_dat_sec_[in_dat_sec_$Block %in% c(1,2) & in_dat_sec_$Subject %in% c(1,10,11,14,15,19), ]$Block_new <- 1
in_dat_sec_[in_dat_sec_$Block %in% c(1,2,3,4) & in_dat_sec_$Subject %in% c(2,3,4,5,6,7,9,13,17,18,20,22,24,25,26), ]$Block_new <- 1
in_dat_sec_[in_dat_sec_$Block %in% c(3, 4, 5, 6, 7, 8, 9,10,11,12) & in_dat_sec_$Subject %in% c(1,10,11,14,15,19), ]$Block_new <- 2
in_dat_sec_[in_dat_sec_$Block %in% c(5, 6, 7, 8, 9,10,11,12) & in_dat_sec_$Subject %in% c(2,3,4,5,6,7,9,13,17,18,20,22,24,25,26), ]$Block_new <- 2
in_dat_sec_[in_dat_sec_$Block %in% c(13,14,15,16,17,18,19,20), ]$Block_new <- 3

table(in_dat_sec_$Vis_Task_Count[in_dat_sec_$Block_new == 2])
##
##  27  29  32  33  34  35  36  37  38  39  41  42  43  44  45  46  47  48
##   1   1   1   1   1   2   2   6   3   2   4   2   2   2   1   2   3   5
##  50  51  52  53  54  55  56  57  58  59  60  61  62  63  64  65  66  68
##   3   4   3   5   1   2   5   6   4   1   2   2   4   1   3   5   2   3
##  69  70  71  73  74  75  76  77  78  80  81  82  83  84  85  86  87  89
##   2   4   1   4   2   4   2   3   8   2   4   1   2   1   1   1   1   5
##  90  92  94  95  97  98 100 101 102 103 105 108 110 119 121 124 127 128
##   1   1   1   1   1   1   2   1   2   2   1   1   1   2   1   1   1   1
## 133 136 139 141 144 151 172 174 180
##   2   1   1   2   2   2   1   1   1
in_dat_sec <- with(in_dat_sec_,
         aggregate(list(Vis_Task_Count=Vis_Task_Count),
               list(Block_new = Block_new, Subject = Subject),
               mean),  na.rm = TRUE)

t.test(in_dat_sec$Vis_Task_Count[in_dat_sec$Block_new == 2],in_dat_sec$Vis_Task_Count[in_dat_sec$Block_new == 3],paired=TRUE)
```

```
##
##  Paired t-test
##
## data:  in_dat_sec$Vis_Task_Count[in_dat_sec$Block_new == 2] and in_dat_sec$Vis_Task_Count[in_dat_sec$Block_new == 3]
## t = -2.6534, df = 20, p-value = 0.01525
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -18.733387  -2.242804
## sample estimates:
## mean of the differences
##              -10.4881
mean(in_dat_sec$Vis_Task_Count[in_dat_sec$Block_new == 2])
## [1] 71.30357
mean(in_dat_sec$Vis_Task_Count[in_dat_sec$Block_new == 3])
## [1] 81.79167
summarySEwithin(data = in_dat_sec_[in_dat_sec_$Block_new %in% c(1,2,3), ],
                measurevar = "Vis_Task_Count",
                withinvars = c("Block_new"),
                idvar = "Subject")
## Automatically converting the following non-factors to factors: Block_new
## Loading required package: plyr
##   Block_new   N Vis_Task_Count Vis_Task_Count_norm       sd       se
## 1         1  72        0.00000            1.599405 25.65139 3.023045
## 2         2 180       71.89444           71.254683 20.48787 1.527076
## 3         3 168       81.79167           81.791667 18.21577 1.405377
##         ci
## 1 6.027781
## 2 3.013386
## 3 2.774595
boxplot(Vis_Task_Count ~ Block_new, data = in_dat_sec,
        boxwex = 0.25, at = 1:2 - 0.2,
        subset = Block_new %in% c(2,3),
        col = "yellow",
        main = "Secondary Task",
        xlab = "Block",
        ylab = "No of Tasks",
        xlim = c(0, 2), ylim = c(0, 160), yaxs = "i")
```