MASTER THESIS

THE CHATBOT USABILITY SCALE: AN EVALUATION OF THE DUTCH VERSION OF THE BUS-11

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Abstract

The chatbot market has grown considerably in recent years. One domain in which the demand for chatbots has increased is customer service. Despite this development, there is a lack of standardized methods for evaluating the perceived quality of these systems. The current study evaluated the BUS-11, a questionnaire used to evaluate user satisfaction with chatbots, from both a psychometric and a designometric perspective. This questionnaire is a shorter version of the BUS-15 (Borsci et al., 2021). The five-factor model, originally developed for the BUS-15 by Borsci et al., was evaluated using a confirmatory factor analysis and resulted in an 11-item scale (BUS 11, see: Borsci et al., 2021). In the present study, we aimed to replicate the confirmatory validation of the Dutch version of the BUS-11, the reliability of the questionnaire was evaluated by examining its internal consistency. The BUS-11's concurrent validity was examined by comparing it to the UMUX-Lite and RSME. Finally, the current study explored the effect of previous experiences as declared by participants in using chatbots on user satisfaction as measured by the BUS-11. Results of the confirmatory factor analysis indicated a good fit of the five-factor model for the psychometric perspective, while a potential problem associated with the first item of the scale was identified. From the designometric point of view, due to limited data, it was hard to establish the quality of the factorial model. One of the 11 questionnaire items showed low reliability, a finding which is in line with previous research. This item may be too general. Overall, the BUS-11 was found to have good internal consistency. Furthermore, a Spearman's rank-order test indicated a strong positive correlation of the BUS-11 with both the UMUX-Lite and RSME. No effect of previous experience on user satisfaction as measured by the BUS-11 was found. The findings of the current study suggest that the BUS-11 is a reliable and valid tool for measuring user satisfaction with chatbots at least from the psychometric point of view.

Further research is needed to confirm or reject the five-factor model from the designometric perspective.

Keywords: Chatbots, conversational agents, user satisfaction, BUS-11

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1. The Chatbot Usability Scale: an evaluation of the Dutch version of the BUS-11

A chatbot is a software application designed to simulate human conversation using natural language (Radziwill & Benton, 2017). In the literature, the terms “chatbot” and “conversational agent” are sometimes used interchangeably (Io & Lee, 2017; Vaidyam et al., 2019). For the purpose of this paper, we approach a chatbot as a type of conversational agent that can be used for a variety of goals, such as entertainment or providing customer service. The focus of the current study is on chatbots for customer service. Such a system is intended to help a customer through humanlike conversation, which can occur either through spoken or written language. Chatbots often use Natural Language Understanding (NLU) to understand language and extract the user’s intent. For the dialogue flow, a rule-based approach is generally used. This study will be on rule-based chatbots because these are most common in the customer service area.

1.1 History of chatbots

Although chatbots have gained popularity in recent years, they have already been around for longer. The first chatbot, ELIZA, was developed even before the internet. ELIZA was made in 1966 and simulated the role of a psychotherapist. The chatbot was able to return the user’s sentences in the interrogative form (Adamopoulou & Moussiades, 2020), and was designed specifically for the psychotherapeutic domain. The replies of the bot mainly consisted of rephrasing what the client said and asking standard questions, such as “can you think of a specific example” (Weizenbaum, 1966). The generalizability of this chatbot was therefore limited, considering that many types of conversations require more than rephrasing the user’s statements and asking basic questions.

Further advancement in chatbot technology led to the development of chatbot PARRY by psychiatrist Kenneth Colby in 1971 (Colby et al., 1971). This chatbot was developed to re-enact a patient suffering from schizophrenia. It managed to pass a variation of the Turing Test in which psychiatrists were shown transcriptions of conversations between psychiatrists and real schizophrenic patients, as well as transcriptions of conversations between psychiatrists and PARRY. They were able to make the correct identification in only 48 percent (no better than chance) of the cases (Colby et al., 1971).

With the development of Jabberwacky in 1988, written in CleverScript, chatbots were first able to function using Artificial intelligence (AI). However, Jabberwacky still had limitations. For example, this chatbot could not work with a large number of users (Jwala, 2019). In 1995, ALICE (Artificial Linguistic Internet Computer Entity) was developed. This was the first chatbot, and it made use of pattern-matching. A new language was created specifically for ALICE: Artificial Intelligence Markup Language (AIML). Chatbot SmarterChild was created in 2001 and was the first chatbot able to assist its users with daily tasks (Molnár & Szűts 2018). Information systems such as the news and weather could be accessed by this system, which was a significant contribution to the progress of the human-computer interaction domain.

A recent major shift in chatbot technology occurred in 2016 when the advancements in AI research resulted in a major change in the way users could communicate with companies. More specifically, the integration of chatbots in social media platforms made using such systems easier, resulting in the application of chatbots in fields such as marketing, health care, and entertainment. Other uses of chatbots around this time include industrial solutions and research (Dale, 2016). Finally, Kar & Haldar (2016) stated that "the Internet of Things (IoT) introduced a new era of connected smart objects where the use of chatbots improved communication between them".

1.2 Current day and expected growth

Chatbots have gained popularity in recent years, and it is expected that the demand for chatbots will increase in the coming years. Where the chatbot market size was $6.8 billion in 2021, this market is expected to grow to $18.4 billion by 2026 (Research and markets, 2021). Others expect the market to grow to 10.5 billion by this year (Markets & Markets, 2021), with a 23% Compound Annual Growth Rate (CAGR). Although estimates vary, the conversational agent market will most likely keep growing in the future. Various causes are mentioned for the expected growth of the chatbot market. First, the use of chatbots for purposes such as customer service provides advantages such as saving time and money (Følstad & Brandtzæg, 2017). Second, in a customer relationship management context, chatbots can help users with finding information and decision-making processes (Paikari & van der Hoek, 2018). Lastly, Zamora (2017) emphasizes the importance of human-like behaviour in a chatbot to battle distrust among its users.

To further aid the uptake of chatbots by a larger population, it is valuable to learn about what elements contribute positively to a positive user experience when interacting with chatbots. In other words, it is valuable to learn about user satisfaction when communicating with chatbots. Previous research has led to the development of several tools to measure this concept. In addition, measures have been developed to aid designers in assessing the quality of a chatbot. An overview of important user satisfaction research will be given in the next section

1.3 User satisfaction

User satisfaction is important for the usability, effectiveness, and efficiency of technology (International Organization for Standardization (ISO), 9241-11, 2018). In the ISO 2016/7, the definition of satisfaction was redefined to include cognitive, emotional, and psychomotor responses of the user (Bevan et al., 2016). In Walker et al.'s PARADISE (PARAdigm for Dialogue System Evaluation; 1997), user satisfaction is seen as a combination of maximising task success on the one hand, and the bot's efficiency and quality on the other. The ISO (2018) defines this concept as "the extent to which the user experience that results from actual use meets the user's needs and expectations".

Examples of chatbots that did not live up to their expectation and were discontinued are not uncommon. In a study by Janssen et al. (2020), it was found that 53 of 103 chatbots evaluated during a period of 15 months were discontinued. This reiterates the importance of having useful tools to measure user satisfaction. As Følstad & Brandtzæg (2018) suggest, a lack of attention to users' needs and experiences is a common cause of the failure of a chatbot. This emphasizes the value of a standardized method for testing user satisfaction in chatbots. Standardized questionnaires are efficient in terms of time and finances, making them an attractive tool for companies and researchers (Berkman & Karahoca, 2016), which is why these are used in the present study.

1.4 Measuring user satisfaction

There are different types of questionnaires to measure user satisfaction. One important aspect in which these questionnaires differ is their length. An example of a longer questionnaire to measure user satisfaction is the Questionnaire for User Interface Satisfaction (QUIS, Chin et al., 1988), consisting of 27 Likert-scale items and six open questions. A disadvantage of such questionnaires, however, is that they are not cost- and time-efficient. Shorter questionnaires, on the other hand, are more appropriate if a participant is expected to fill in the survey multiple times during the study, as is the case in the current study. An example of a shorter questionnaire that is frequently used to measure usability is the System Usability Scale (SUS; Brooke, 1996), consisting of 10 items. Participants rate each item on a

5-point Likert scale ranging from strongly disagree to strongly agree. The SUS is quick and easy and has been cited in over 1300 papers (Usability.gov, 2013). Resulting from a need for a shorter questionnaire, the seven-item UMUX was developed by Finstad (2010). The even shorter UMUX-Lite ($\alpha = .86$; Lewis et al., 2015) consists of only two items: “[This system’s] capabilities meet my requirements” And “[This system] is easy to use”.

Although useful short scales such as the UMUX-Lite and SUS are available for assessing the usability of various technologies, many of them are not standardized. In addition, the UMUX-Lite and SUS are not designed for chatbots specifically. These tools are primarily used to evaluate websites, which are often quite static compared to an interactive chatbot. One promising tool developed specifically for evaluating chatbots is the Bot Usability Scale (BUS). The first version of the BUS consisted of 42 items relating to fourteen attributes. An exploratory factor analysis resulted in a version of this scale composed of fifteen items (Borsci et al., 2021) with overall reliability from .76 to .87. Recently, an updated version of this scale, the BUS-11, was developed (Borsci et al., 2021b; Table 1). This shorter scale strongly correlates with the UMUX-Lite and it is composed of five factors. Because of the five-factor structure, the BUS-11 provides more insight into different aspects contributing to user satisfaction, as opposed to questionnaires such as the UMUX-Lite, which only provide a general measurement.

Table 1

The factors (with their abbreviations in brackets) and items of the BUS-11

Factor	Item
	1. The chatbot function was easily detectable (Det)

1 - Perceived accessibility to chatbot functions (ACF)	2. It was easy to find the chatbot (Find)
2 - Perceived quality of chatbot functions (QCF)	3. Communicating with the chatbot was clear (Comm) 4. The chatbot was able to keep track of context (Track) 5. The chatbot's responses were easy to understand (Undr)
3 - Perceived quality of conversation and information provided (QCI)	6. I find that the chatbot understands what I want and helps me achieve my goal (Goal) 7. The chatbot gives me the appropriate amount of information (InfoA) 8. The chatbot only gives me the information I need (InfoB) 9. I feel like the chatbot's responses were accurate (Acc)
4 - Perceived privacy and security (PS)	10. I believe the chatbot informs me of any possible privacy issues (Priv)
5 - Time response (TS)	11. My waiting time for a response from the chatbot was short (Wait)

In a study on the SUS, UMUX, and UMUX- LITE, Borsci et al. (2015) found that prior experience with a system had an effect on user satisfaction with that system. Participants who interacted with a system before were more likely to rate their experience as satisfactory when interacting with that system again than those who interacted with it for the first time.

However, the Borsci et al. study evaluated an online platform, which is different from an interactive system such as a chatbot. In the current study, we will test if there is a positive effect of users' previous experience on their satisfaction with chatbots specifically.

1.5 Age

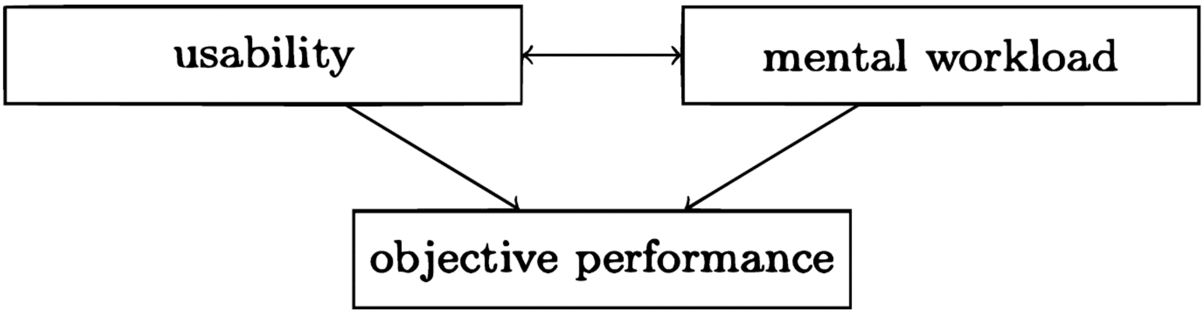
Another variable that may affect user satisfaction is the users' age. According to Moore (2012), millennials (born between 1980 and 1955) are better able to use adaptive technology than baby boomers (born between 1946 and 1964). Therefore, we expect that younger users will generally be more satisfied with chatbots than older users.

1.6 Mental workload

Another factor that may have an influence on user satisfaction is mental workload (often referred to as cognitive workload), a concept frequently researched in the field of Human Factors (Longo, 2018). Longo argues for a model in which mental workload and usability predict objective performance (Figure 1). The subjective workload can be described as an emergent property of the active brain which is tasked with the demands of surviving and prospering in an incompletely specified and under-explained world" (Hancock, 2017, p. 3). Usability, according to Nielsen (1994), relates to satisfaction and can be defined as a method to increase interactive systems' ease of use. Based on Longo's model, it can be hypothesized that a higher level of subjective workload has a negative effect on user satisfaction measured by standardized scales such as the BUS-11.

Figure 1

The relation between usability and mental workload as proposed by Longo (2018)



Schmutz et al. (2009) found that high cognitive load was related to less general satisfaction in the context of e-commerce. Lallemand and Gronier (2012) found a negative correlation between cognitive load and user satisfaction in a study on user experience during waiting time. Although the data on the relationship between mental workload and user satisfaction is limited, there are some indications that these two concepts are negatively correlated. The current study will explore if this relationship exists in the context of chatBots.

A commonly used tool to measure perceived workload is the NASA Task Load Index (NASA-TLX; NASA, 2020). This tool asks participants to rate their mental effort performing a task on six dimensions, with one rating scale per dimension. Alimohammadi et al. (2019) compared three different measures of workload: the Rating Scale of Mental Effort (RSME), the integrated Workload Scale (IWS), and the Overall Workload Scale (OW). All three scales were found to have an internal validity of at least .8. Furthermore, they stated that the RSME is the most reliable scale of the three scales. Because participants will be asked about their perceived mental effort multiple times and in addition to other surveys, a one-item survey is thought to be optimal. Therefore, the RSME will be used to measure mental workload in the current study.

1.7 Psychometrics versus Designometrics

The current study aims to evaluate the BUS-11 from both the psychometric and designometric perspective. Schmettow (2020) describes that “in design research, multi-item validated scales are routinely used for one of two purposes”. One purpose is to answer a research question about the characteristics of participants, the other is to compare different designs on their quality. The psychometric perspective is required for the analysis on the participant level. Applying this to the current study, this perspective gives insight into the influence of age differences and the amount of previous experience a participant has on their user satisfaction with chatbots.

Although the data gives insight into attributes of individuals, a major interest in this study is on how different chatbots compare to each other, and to what extent the BUS-11 is a valuable tool to this end. Thus, we do not only want to be able to say something about participants, but also about chatbots. By letting participants rate items, their individual characteristics can be measured (person by items). An accurate measure of the characteristics of designs such as chatbots, on the other hand, can only be obtained by letting participants rate items for multiple designs. Whereas a large sample size of participants is required for a psychometric scale, a large sample size of designs (e.g., chatbots) is required for a designometric scale.

In the present study, the designometric approach will be taken (in addition to the psychometric approach) to further examine the reliability of the scale from the perspective of designs. A designometric analysis can be performed on a dataset with multiple designs, items, and participants, sometimes referred to as a designometric cuboid. This approach gives insight into the extent to which a questionnaire such as the BUS-11 can accurately distinguish between the performance of different designs, or in this case, different chatbots. A designometric response matrix consisting of three dimensions can be developed from the basis of a psychometric matrix (Schmettow and Borsci, 2020).

1.8 The current study

The present work aims to re-test the factorial organization of the BUS-11 with a different set of chatbots, inspect its reliability, and assess its convergent validity using the UMUX-Lite as an external tool for validation. Based on previous work on the chatBot Usability Scale (e.g., Borsci et al., 2021; Borsci et al., 2021b), it is expected that the BUS-11 will have good psychometric reliability. Furthermore, the current study will explore whether the BUS-11 has good reliability from the designometric perspective.

Based on a study by Borsci et al. (2015), we expect to find an effect of previous experience on user satisfaction with chatbots. Moreover, we aim to test the relationship between cognitive workload during the interaction with chatbots (measured by the RSME) and the satisfaction assessed by the BUS-11, assuming based on literature that workload and satisfaction are inversely correlated (e.g., Schumtz et al., 2009; Lallemand and Gronier, 2012). To achieve these goals, we are going to answer the following research questions:

RQ1: Can the five-factor structure of the BUS-11 as defined by Borsci et al. (under review) be confirmed from the psychometric and designometric point of view?

RQ2: Are the BUS-11 and its factors acceptably reliable (e.g., with a Cronbach's alpha over .7; Cortina, 1993*)?*

RQ3: Do age and previous experience with chatbots declared by participants affect the satisfaction measured by the BUS-11?

RQ4: Is the BUS-11 positively correlated to the UMUX-Lite and negatively correlated to the RSME?

2 Methods

2.1 Participants

The study took place with 53 participants between 18 and 65 years old (*M* = 26, *SD* = 13). All participants needed to be at least 18 years old and needed to have access to a computer and internet connection. Participants were informed that the study was in Dutch. This applied to the study information, questionnaires and chatbots. However, a portion of the participants marked English as their first language. Those who indicated that they were unable to understand a chatbot because of the language were excluded from the dataset.

Participants were recruited through personal connections of the researcher, as well as the Sona system from the University of Twente, which rewards students with points for participating in studies. The ethics committee of the Faculty of Behavioural Management and Social Sciences of the University of Twente approved the study.

2.2 Materials

Participants conducted the study on their computer. A short demographics survey and a brief survey asking about former experience with chatbots were administered. The BUS-11 (Borsci et al., 2021) was used to measure user satisfaction. This survey consists of 11 items to be answered on a 5-point Likert scale, ranging from strongly agree to strongly disagree. The UMUX-Lite was administered as a comparative measure for BUS-11. To measure mental workload, the Rating Scale Mental Effort (RSME; Zijlstra, 1985) was used. Participants were asked to indicate the effort it took to complete a task (Appendix B) using a slide on a scale from 0 to 150. A list of chatbots used in this study can be found in table 2.

Table 2

Chatbots used in the current study

Chatbot used by	Link
Essent	https://www.essent.nl/content/particulier/klantenservice/
DHL	https://mydhl.express.dhl/nl/nl/help-and-support.html#/contact_us
Rabobank	https://www.rabobank.nl/particulieren/contact/
FBTO	https://www.fbto.nl/
Albert Heijn	https://www.ah.nl/klantenservice
ABN Amro	https://www.abnamro.nl/nl/prive/service-en-contact/index.html
Univé	https://services.mijnunivezorg.nl/chatbot
TUI	https://www.tui.nl/contact/
Ikea	https://www.ikea.com/nl/nl/customer-service/services/
Reaal	https://www.reaal.nl/klantenservice/
Centraal Beheer	https://www.centraalbeheer.nl/
Engie	https://www.engie.nl/

2.3 Procedure

Participants performed the study remotely using a Qualtrics survey. They received written instructions, interactive tasks they were to perform with each chatbot and filled in the scales for the assessment. First, a written explanation of the study was provided, and the participant was asked to sign an informed consent form and complete the demographics survey. Then, the participant filled in the demographic questionnaire and the experience questionnaire. Each participant assessed six chatbots randomly selected from a set of twelve chatbots. Randomization was done in such a manner that all chatbots were evenly presented.

For each chatbot, one task was provided to ensure that the participant communicated sufficiently with the chatbot. For example: *In the last month, you have used more energy than usual. You would like to know which possible explanations there are for the increase in energy usage. Ask the chatbot about this (translated).* An overview of all tasks can be found in appendix B. Then, the BUS-11, UMUX-Lite, and RSME were presented in random order. This process was repeated for each of the six chatbots.

2.4 Data analysis

The data was exported from Qualtrics into Excel. The dataset was cleaned so that participants who did not complete the full survey as well as those who declared they did not speak Dutch well were removed. Scores on the 5-point Likert scales (Experience, BUS-11, UMUX-Lite) were converted to a 0-100 points scale following the method of Lewis & Sauro (2020). Scores on the RSME were converted from a 150-point scale to a 0-100 points scale. Then, the data was imported into R Studio for analysis.

A confirmatory factor analysis was performed using the CFA function from the R package 'Lavaan' (Rosseel, 2012). Based on a paper by Hu & Bentler (1999), the following criteria for an acceptable model were used:

- Root Square Error of Approximation (RMSEA) ≤ .06
- Standardized Root Mean Square Residual (SRMR) ≤ .08
- Comparative Fit Index (CFI) ≥ .90
- Tucker-Lewis Index (TLI) ≥ .95

To explore the possible correlation between the BUS-11 and the UMUX-Lite, as well as the BUS-11 and RSME, Spearman's rank-order correlation was used. A correlation coefficient of ≥ .68 is considered a strong correlation, and a correlation coefficient of ≥ .90 is considered a very strong correlation (Taylor, 1990). To test the effects of age and previous experience on user satisfaction, a linear regression analysis was performed.

3 Results

3.1 Data preparation

The dataset was structured in a long format, with one line per participant and chatbot combination. Each of the 53 participants interacted with six randomly selected chatbots, leading to a dataset with 53 * 6 = 318 observations. For the designometric analysis, this dataset was summarized over the average answer of participants per item and per chatbot, leaving 53 observations.

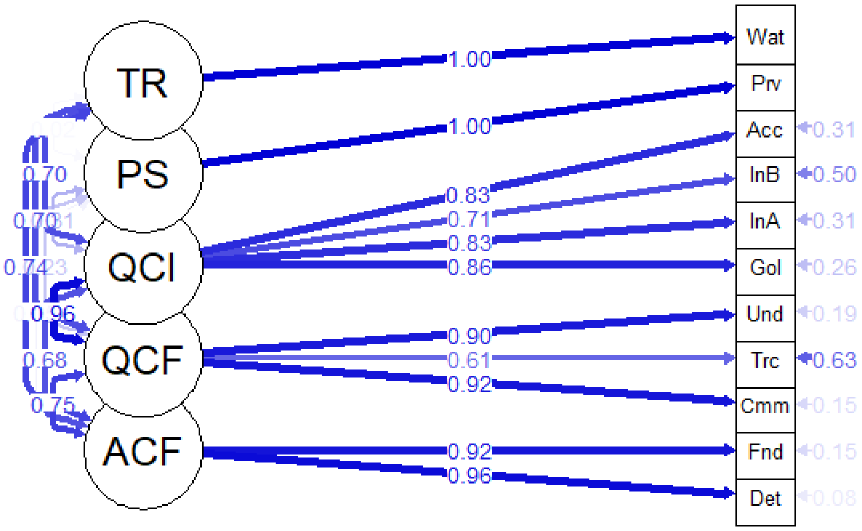
3.2 Confirmatory factor analysis

3.2.1 Psychometric perspective Dutch BUS-11

To test the proposed five-factor model of the BUS-11, a confirmatory factor analysis was performed using the Lavaan package (Rosseel, 2012) in R. First, this was done from the psychometric perspective. The Root Mean Square Error of Approximation of the five-factor model has an indicator of absolute fit above the acceptable level (RMSEA = .09). The Standardized Root Mean Square Residual is acceptable (SRMR = .06). The Comparative Fit Index and Tucker-Lewis Index indicate a good fit (CFI = .96, TLI = .95). A visualization of the factor structure was made using the semPaths function in R (Epskamp, 2019; Figure 2).

Figure 2

Visualization of the factor structure (psychometric perspective, Dutch version of the BUS-11



Note. For an overview of the factors and items, see appendix A.

As can be seen in Figure 2, the latent variables indicate rather strong relations overall. All items explain more than 60% of the variance of each factor. *comm* has the lowest score This item still fits reasonably, but only explains 61% of the variance in QCF. *InfoB* is slightly lower than most other items, yet it is still well above the cut-off of .6. Both *comm* and *InfoB* have acceptable but high levels of variance in answers.

The model shows strong correlations between all factors except PS, which shows correlations with ACF and factor TR of almost zero (Table 3). PS also shows high standard errors compared to the other factors (Table 4).

Table 3

Correlation matrix for the psychometric model (Dutch BUS-11)

Factor	ACF	QCF	QCI	PS
ACF				
QCF	.679			
QCI	.597	.897		
PS	.066	.24	.316	
TR	.719	.641	.636	.025

Table 4

Standard errors for the psychometric model (Dutch BUS-11)

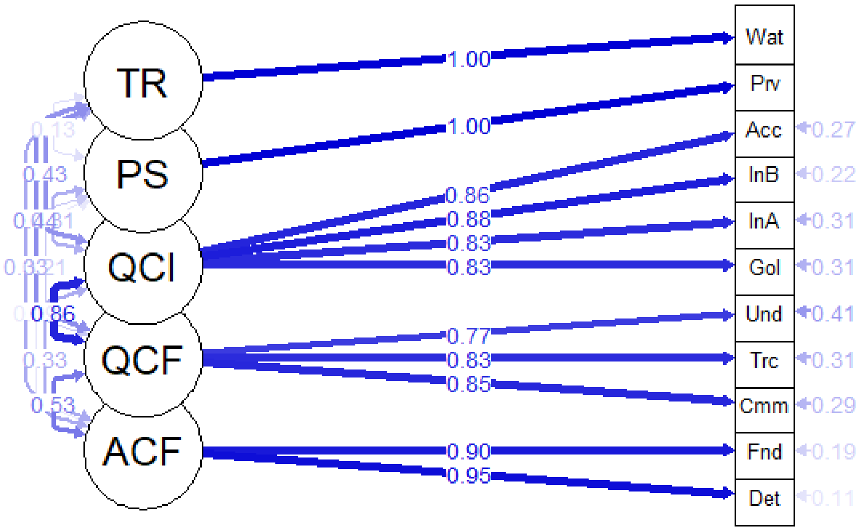
Factor	1	2	3	4
ACF				
QCF	.073			
QCI	.088	.031		
PS	.144	.139	.135	
TR	.069	.079	.081	.140

3.2.2 Psychometric perspective English BUS-11

A confirmatory factor analysis was performed on the data of a study by Braun (2022), in which the English version of the BUS-11 was evaluated among 137 participants and 10 chatbots. For the psychometric analysis, the RSMEA was above the acceptable level (RSMEA = .07). The SRMR was acceptable (SRMR = .03). The CFI and TLI were both sufficiently high (CFI = .98, TLI = .97). A visualization of the factor structure made with the semPaths function (Epskamp, 2019) is shown below (Figure 3)

Figure 3

Visualization of the factor structure (psychometric perspective, English version of the BUS-11)



Note. For an overview of the factors and items, see appendix A.

In this model, all items explain at least 70% of the corresponding factors. None of the items have an exceedingly high variance in answers. PS shows somewhat lower correlations with the other factors, although there is less of a difference compared to the Dutch version (Table 5).

Table 5

Correlation matrix for the psychometric model (English BUS-11)

Factor	ACF	QCF	QCI	PS
ACF				
QCF	.471			
QCI	.301	.772		
PS	.305	.680	.889	
TR	.084	.193	.3	.264

Table 6

Standard errors for the psychometric model (English BUS-11)

Factor	1	2	3	4
ACF				
QCF	.033			
QCI	.038	.016		
PS	.04	.04	.037	
TR	.039	.035	.034	.039

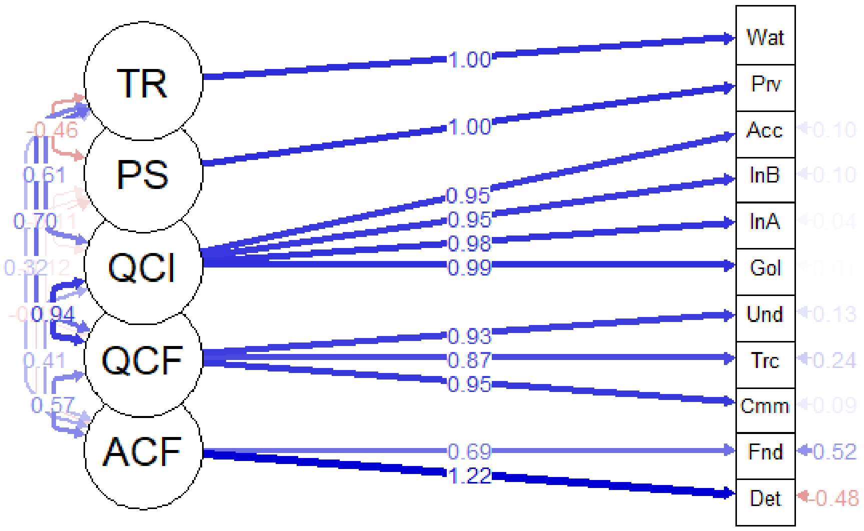
3.2.3 Designometric perspective Dutch BUS-11

A confirmatory analysis was performed for the designometric perspective. Here, the model had a poor indicator of absolute fit (RMSEA = .31). The Standardized Root Mean Square Residual also indicated a poor fit (SRMR = .13 The Comparative Fit Index and Tucker-Lewis Index (CFI = .81, TLI = .71) are somewhat below the threshold of a good fit but are acceptable. A visualization of the factor structure was made using the semPaths figure in R

(Figure 4). *Det* (*The chatbot function was easily detectable.*) was found to have low reliability.

Figure 4

Visualization of the factor structure (designometric perspective, Dutch version of the BUS-11)



Note. For an overview of the factors and items, see appendix A.

In the designometric model, the factor loading of 1.22 and the negative variance of *det* stands out, indicating a problem of variability. The factor loading of *find* is less strong than in the psychometric model but does not appear to be problematic. The factor loadings of factor 2 (Perceived quality of chatbot functions) and factor 3 (Perceived quality of conversation and information provided) are indicative of a strong model.

The fourth factor, PS, has negative correlations with all other factors (Table 7). The negative correlations of PS with TR is quite strong compared to the correlations of PS with the remaining factors. This finding is in contrast to the findings of the psychometric model, which indicated weak but positive correlations of factor 4.

For the Dutch BUS-11, both in the psychometric and designometric model, factor 2 (Perceived quality of chatbot functions) and factor 3 (Perceived quality of conversation and information provided) show the highest correlation (.897 and .921 respectively) and the lowest standard error (.031 and .043 respectively).

Table 7

Correlation matrix for the designometric model (Dutch BUS-11)

Factor	ACF	QCF	QCI	PS
ACF				
QCF	.338			
QCI	.091	.921		
PS	-.215	-.141	-.109	
TR	.105	.671	.58	-.462

Table 8

Standard errors for the designometric model (Dutch BUS-11)

Factor	ACF	QCF	QCI	PS
ACF				
QCF	.182			
QCI	.191	.043		
PS	.206	.292	.286	

TR	.197	.155	.184	.227

3.2.4 Designometric perspective English BUS-11

To compare the model for the Dutch version of the BUS-11 with the model for the English version from the designometric perspective, a confirmatory factor analysis was performed again using the data from Braun (2022). The model did not run with the normal factor structure. Removing ACF made it possible to run the model. The alternative model with four factors and nine items had an RSMEA above the acceptable level (RSMEA = .57). The SRMR was at the acceptable level (SRMR = .06). The CFI and TLI were both too low to be deemed acceptable (CFI = .574, TLI = .332).

Figure 5

Visualization of the factor structure (designometric perspective, English version of the BUS-11)

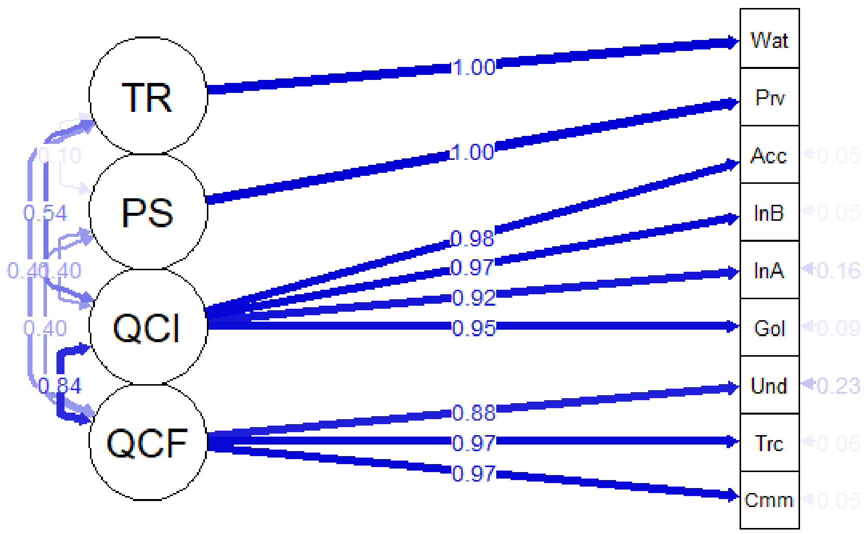


Table 9

Correlation matrix for the designometric model (English BUS-11)

Factor	QCF	QCI	PS
QCF			
QCI	.812		
PS	.436	.412	
TR	.372	.505	.103

Table 10

Standard errors for the designometric model (English BUS-11)

Factor	QCF	QCI	PS
QCF			
QCI	.103		
PS	.270	.268	
TR	.267	.228	.313

3.3 Reliability

A correlation matrix of all 11 items was made to provide a portrayal of the inter-item correlations (Table 11). This shows low correlations of *priv* with most other items.

The internal consistency of the BUS-11 and its factors was evaluated using Cronbach's alpha. The BUS-11 has high internal consistency ($\alpha = .89$). The three factors consisting of multiple items all have high internal consistency (factor 1: $\alpha = .91$, factor 2: $\alpha = .83$, factor 3: $\alpha = .89$). In addition, a split-half reliability analysis was performed by comparing odd- and even-numbered items of the BUS-11, suggesting a predicted reliability of .88.

Table 11

Item correlations of the BUS-11 from the designometric perspective

	1	2	3	4	5	6	7	8	9	10
1										
2	.88									
3	.65	.61								
4	.47	.36	.51							
5	.67	.63	.85	.44						
6	.57	.56	.75	.68	.71					
7	.51	.51	.72	.59	.70	.75				
8	.36	.30	.63	.53	.58	.63	.60			
9	.64	.56	.74	.55	.75	.70	.66	.54		
10	.01	.11	.25	.24	.13	.23	.29	.37	.18	
11	.69	.70	.62	.37	.66	.61	.52	.39	.68	.02

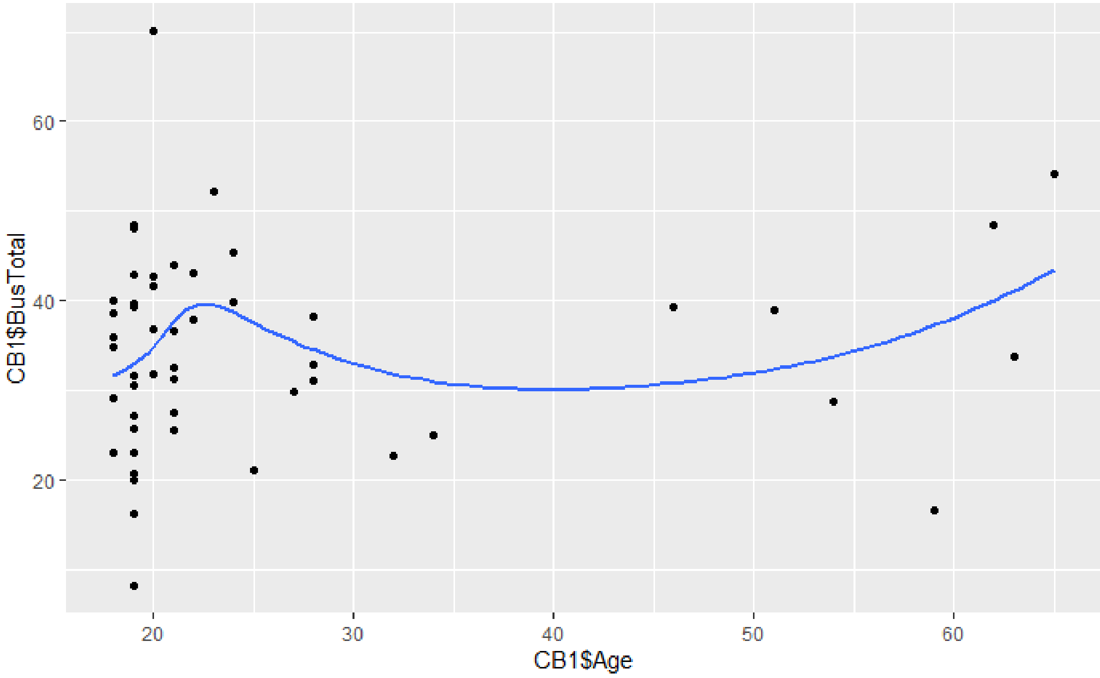
Note. The red-framed cells indicate the correlation coefficients between items of the three factors consisting of multiple items.

3.4 Age and user satisfaction

Age and user satisfaction were examined from the psychometric perspective. A visual inspection (Figure 6) showed a strong tendency towards lower ages. This was confirmed by the descriptive statistics ($M = 26$, $SD = 13$). In previous studies, higher age tended to correspond to lower levels of satisfaction. Based on coefficient estimates, there appears to be a small effect of age on user satisfaction (Table 12). The results indicated a small positive effect of age on QCF and QCI. No effect on PR was found. A small negative of age on ACF and TR was found.

Figure 6

The effect of age on satisfaction



Note. “User Satisfaction” shows the converted scores of the BUS-11 ranging from 0 to 100, with higher scores indicating higher satisfaction. “Age” shows the age of participants in years.

Table 12

Coefficient estimates with 95% credibility limits of age and the factors of the BUS-11

Factor	parameter	fixef	center	lower	upper
BUS-11	Intercept	Intercept	32.75	25.66	39.6
	age	age	.07	-.16	.31
ACF	Intercept	Intercept	27.46	17.65	36.87
	age	age	-.01	-.33	.32
QCF	Intercept	Intercept	31.87	24.44	39.26
	age	age	.03	-.22	.28
QCI	Intercept	Intercept	35.22	28.15	42.16
	age	age	.08	-.16	.33

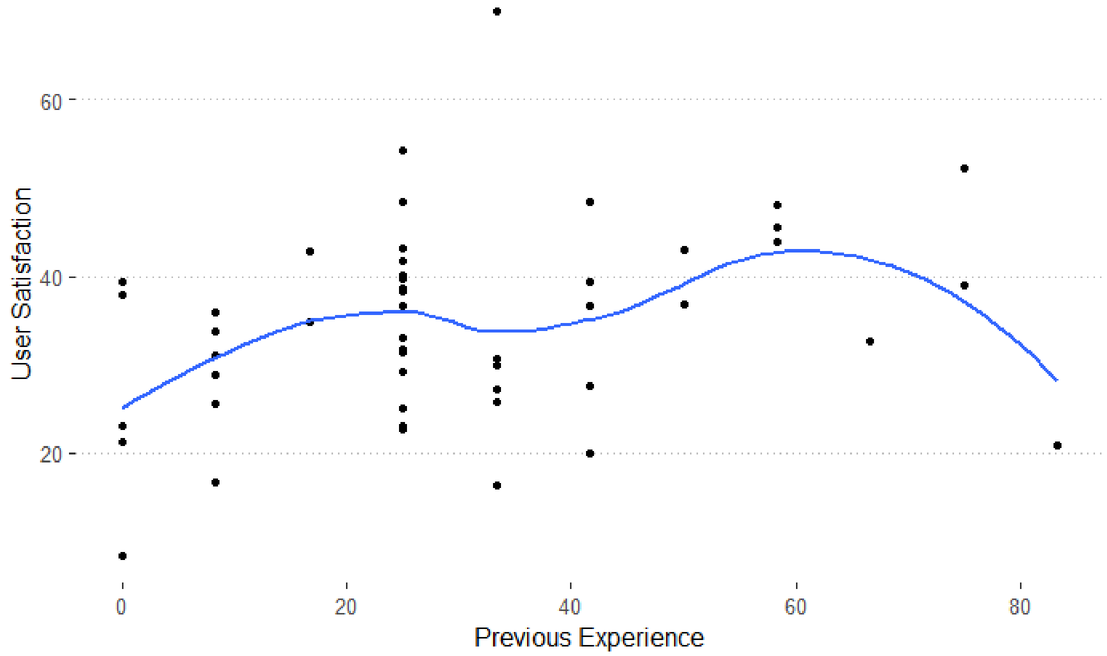
PS	Intercept	Intercept	43.38	32.80	53.98
	age	age	.36	.00	.72
TR	Intercept	Intercept	26.04	15.45	37.51
	age	age	-.02	-.40	.35

3.5 BUS-11 and previous experience

Next, we tested for an effect of previous experience with chatbots on user satisfaction as rated by the BUS-11. A visual inspection was made (Figure 7). A Pearson correlation test indicated that there is no effect of previous experience on user satisfaction (Table 13). Previous experience was shown to have a small positive effect on QCF and QCI. Furthermore, experience had a small negative effect on PS. No effect of previous experience was found on ACF or TR.

Figure 7

The effect of previous experience on satisfaction



Note. “User Satisfaction” shows the converted scores of the BUS-11 ranging from 0 to 100, with higher scores indicating higher satisfaction. “Experience” shows the converted scores of the previous experience survey ranging from 0 to 100, with higher scores indicating more experience.

Table 13

Coefficient estimates with 95% credibility limits of previous experience and the factors of the BUS-11

Factor	parameter	fixef	center	lower	upper
BUS-11	Intercept	Intercept	30.02	24.55	35.29
	experience	experience	.15	.00	.30
ACF	Intercept	Intercept	19.91	12.50	26.96
	experience	experience	.25	.05	.45
QCF	Intercept	Intercept	27.76	21.43	33.78
	experience	experience	.17	-.00	.33
QCI	Intercept	Intercept	33.77	28.01	39.13
	experience	experience	.12	-.03	.28
PS	Intercept	Intercept	55.35	46.78	64.05
	experience	experience	-.08	-.33	.16
TR	Intercept	Intercept	15.85	8.25	23.67
	experience	experience	.32	.11	.54

3.6 BUS-11, UMUX-Lite and RSME

To test the validity of the BUS-11, the correlation between the BUS-11 and the UMUX-Lite was examined using a Spearman correlation test. The same was done to test the correlation of the BUS-11 with subjective mental workload as measured by the RSME (Table 14).

There was a strong positive correlation between the BUS-11 and the UMUX-Lite ($r(53) = .82$). Strong positive correlations were found for two out of the five factors: QCF ($r(53) = .81$) and QCI ($r(53) = .81$). Considering the standards of Taylor (1990), ACF and TR showed a moderate correlation, and PS showed a weak correlation.

A visual inspection indicated a positive correlation between mental workload and user satisfaction (Figure 8). The analysis confirmed that the RSME was moderately positively correlated with the BUS-11 (r(53) = .37) whereas we expected a negative correlation. The scores on the RSME were quite low on average (*M* = 27.62, *SD* = 18.12).

Figure 8

The effect of mental workload on satisfaction

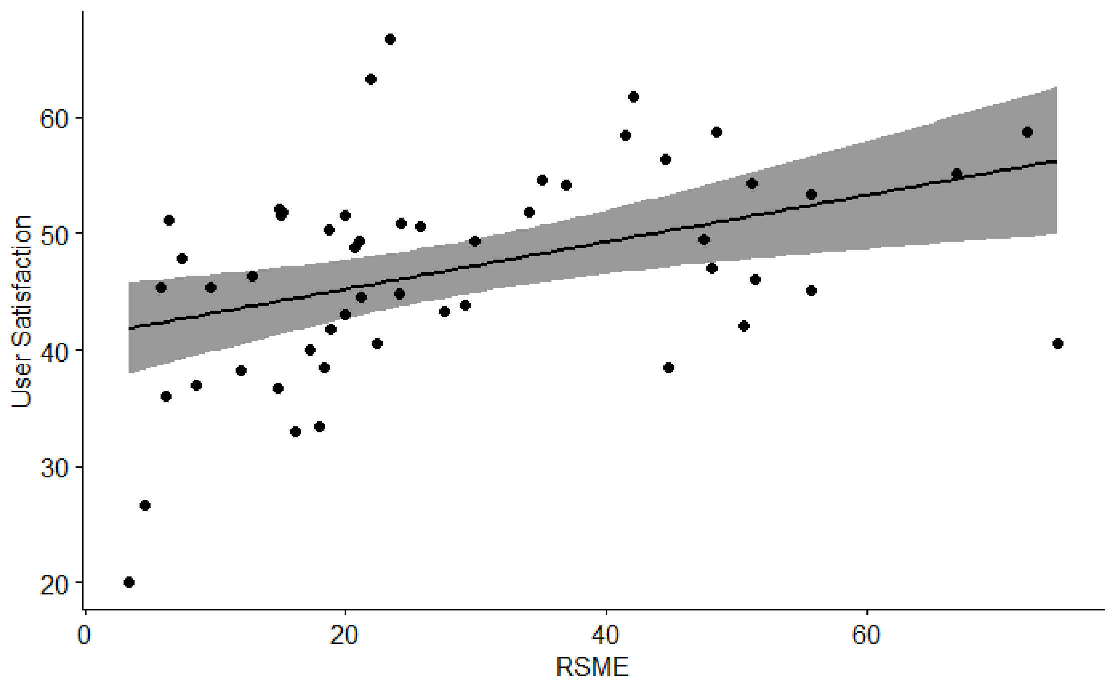


Table 14.

Correlations of the BUS-11 with the UMUX-Lite and RSME

	UMUX-Lite	RSME
BUS-11	**.82**	.37
ACF	.54	.38
QCF	**.81**	.43
QCI	**.81**	.26
PS	.43	.-13

	UMUX-Lite	RSME
TR	.63	.43

Note. Correlation coefficients that are considered strong are in **bold**.

4 Discussion

The current study contributed to a standardized method for measuring user satisfaction with chatbots by evaluating the BUS-11 from both a psychometric perspective, referring to persons, and a designometric perspective, referring to designs (or chatbots). The fact that a large portion of chatbots is discontinued (Janssen et al., 2020), indicates the importance of measuring user satisfaction.

In line with our first research question, "*Can the five-factor structure of the BUS-11 as defined by Borsci et al. (under review) be confirmed from the psychometric and designometric point of view?*", our Confirmatory Factor Analysis suggests that the Dutch version of the scale had good psychometric properties, as did the English version of the BUS-11. Although the RMSEA of the Dutch model was higher than the threshold of .06 proposed by Hu & Bentler (1999), it is below .1 and should be considered marginal (Fabrigar et al., 1999). The overall results of the confirmatory factor analysis indicated a good fit of the 5-factor model from the psychometric perspective, suggesting that overall, the scale can measure how satisfied users are with any chatbot. In the psychometric model, *comm* (The chatbot was able to keep track of context) showed the lowest reliability, explaining 60 percent of the variance of factor 2. This finding is unique to the Dutch BUS-11, as *comm* did explained a larger portion of the variance in factor 2. However, removing this item would likely not negatively impact the strength of the model but doing so would result in losing useful information. The results of the current study thus suggest that *comm* should be retained. *InfoB* showed somewhat lower reliability than the other factors as well, but the same reasoning for retaining *comm* applies. In line with previous studies, the results indicate that the 5-factor structure fits well overall.

The factorial organisation of the scale from a designometric point of view was less strong. The small sample size of 12 chatbots may at least partially explain this. In this sense, it is hard with the current data to accept the assumption that the Dutch version of the BUS-11 measures how satisfying a specific chatbot is for any user. However, the results provide further insight into how the items and factors of the BUS-11 relate based on 12 chatbots. *Det* showed low reliability. The item explained over 100% of factor 2, making this a so-called Heywood case. Possibly, *det* may be too vague or general. The fact that this Heywood case was only found for the Dutch BUS-11 indicates an influence of the translation. Alternatively, settings such as changing the language or switching an avatar on or off are not always available. In such cases, *det* may be misunderstood. A possible solution for this issue is to remove this item if chatbot functionalities are not displayed. In addition, *det* asks how easy it is to detect functionalities which in some cases are not displayed whatsoever, which may confuse participants. If this is the case, *det* should only be used for chatbots that have clear options for functionalities. Alternatively, future studies could clarify this statement with an example, such as: “The chatbot function was easily detectable (e.g., the possibility to modify the settings of the chatbot)”. However, a larger sample size may also lead to different results, as the data for this study was limited.

Furthermore, a negative correlation was found between PS and the other factors of the Dutch model. Privacy and security are generally in a trade-off with usability (e.g. Braz et al., 2007). A possible explanation for the negative correlation between factor 4 and the other factors may be that info about privacy and security is often not reported by chatbots. There was an especially strong negative correlation with factor 5 (Time Response). Such findings reiterate the value of performing a designometric analysis as well as a psychometric analysis. A possible explanation for this finding is that response times comparable to those of a human create a sense of trust, while unnaturally fast responses decrease this feeling, and in turn, decrease the perceived privacy and security.

Furthermore, the current results indicate that *det* is problematic from both perspectives. Future studies could retest the designometric reliability with an adapted version of *det*. In general, more research, preferably with a larger amount of chatbots and participants, is needed to evaluate the BUS-11 from a designometric perspective.

Looking at the relationship between the factors and the overall construct of user satisfaction, factor 4 (Perceived privacy and security) did not appear to be appropriate in the current study. In the psychometric model, factor 4 showed weak positive correlations s with the other factors, and in the designometric model, the correlations were slightly negative. Although the construct of perceived privacy and security may be important for users, it appears that this construct is not closely related to a satisfactory user experience, based on the results of the current study.

Another result from the analysis of the factor correlations is that factor 2 and factor 3 showed a strong correlations with each other. This may be explained by the fact that both these factors concern a form of perceived quality. In the literature, a correlation between scales higher than .85 or .9 is generally seen as a cut-off score for discriminant validity (e.g., Kline, 2011; Henseler et al., 2015). Rönkkö and Cho (2020) argue that more variables should be taken into account, such as the measurement process and the sample. They propose a cut-off classification in which the upper limits of the 95% confidence intervals are considered. A correlation between .9 and 1 as is the case for factors 2 and 3 in the current study is then seen as either a marginal or moderate problem. In line with this approach, these two factors may not be sufficiently different from each other. Future studies could explore a model in which they are merged into one factor.

All in all, the model shows room for improvement from the designometric perspective. When the goal is to use the BUS-11 to compare chatbots (as opposed to participants), one should consider excluding *det*. Furthermore, because *comm* showed negative correlations, this item should be reversed.

The results of the analyses for the second research question, "*Are the BUS 11 and its factors acceptably reliable (e.g., with a Cronbach's alpha over .7* (Cortina, 1993)*)?",* indicate a high Cronbach's Alpha for the overall questionnaire and for all three factors consisting of multiple items (ACF, QCF and QCI). Overall, the results of the reliability analyses indicate that the BUS-11 is a reliable scale.

The third research question was: "*Do age and previous experience with chatbots declared by participants affect the satisfaction measured by the BUS-11?"*.No effect of previous experience on overall user satisfaction was found. A positive effect was also found on QCF and QCI. Previous experience had a small negative effect on PS and no effect on ACF or factor TR. It should be noted that the subjective rating of the sample of the current study indicated they were overall rather familiar with chatbots. For example, to the statement "I am familiar with chatbots," about 76% of the participants answered with either "totally agree" or "agree". On the other hand, about 81% of participants indicated that they rarely use chatbots. Brandtzæg & Følstad (2017) named "novelty" as a motivation for some users to use chatbots. Similarly, McQuail mentioned "satisfying curiosity" as a motivator. Based on this, it could be hypothesized that a proportion of the population used a chatbot one or a few times out of curiosity but ceased to use chatbots once the novelty wore off. Furthermore, in the aforementioned study by Janssen et al. (2020), about half of the evaluated chatbots were out of action within 15 months. The lack of frequent chatbot use may simply be attributed to a lack of current availability.

The effect of age on user satisfaction was small. It should be noted that the proportion of older users was small in the current study. For QCF and QCI, a small positive effect was found, whereas a small negative effect was found for ACF and TR. It appears that older users value the perceived quality of functions, conversation and information slightly more in their assessment of their satisfaction. The opposite is true for accessibility to chatbot functions and time response. PS did not show any relation with age.

Borsci et al. (2015) found that user satisfaction with systems as measured by the SUS and UMUX-Lite was influenced by prior experience. Considering that the UMUX-Lite measures satisfaction similarly to the way the BUS-11 measures this construct, the findings of Borsci et al. and the findings of the current study are not in line with each other. Future studies with user samples that are more diverse in their experience with chatbots may provide further insight into a possible relationship between previous experience and satisfaction with chatbots. In addition, it may be useful to investigate a more standardized method of measuring user satisfaction, considering that different items about this concept in the current study appeared to show contradictory responses.

The final research question was "*Is the BUS-11 correlated to the UMUX-Lite?*". A correlation between these two questionnaires was found. This indicates that the BUS-11 does indeed measure user satisfaction in a comparable manner as the UMUX-Lite does and confirms the findings by Borsci et al. (2021). QCF and QCI were strongly correlated, suggesting that these items measure the same aspect of user satisfaction as the UMUX-Lite. These two factors encompass function and conversation quality, which may contribute to the ease of use of the system measured by the UMUX-Lite (this chatbot is easy to use) and appear fit with users' requirements (this chatbot's capabilities meet my requirements; UMUX-Lite). The other three factors did not show a strong correlation, indicating that these items measure a different aspect of user satisfaction. Based on the results of the current study, it can be argued that the BUS-11 is advantageous over the UMUX-Lite in the sense that it measures user satisfaction on more dimensions. However, due to the low sample size, this notion should be interpreted with caution.

Based on the aforementioned studies by Schmutz et al. (2009) and Lallemand and Gronier (2012), it was expected that a higher workload as measured by the RSME would lead to a lower user satisfaction as measured by the BUS-11. Instead, a moderate positive correlation between these two scales was found. At the moment, the data on the relationship between cognitive workload and user satisfaction is limited, especially in the context of conversational agents. More research is needed to determine if such a relationship exists.

4.1 Limitations and recommendations for future research

Although the current study resulted in some valuable findings, three limitations should be considered. First of all, an unstandardized method for measuring previous experience was used. Based on the current study, it cannot be concluded with certainty that this construct was indeed measured as intended. As a consequence, the relationship between previous experience and user satisfaction as measured through the BUS-11 remains unclear. Future studies should focus on other aspects of experience, such as geekism (Schmettow & Drees, 2014) or computer literacy (e.g., Tobin, 1983; Kegel et al., 2019).

Another limitation is the small sample size for the designometric perspective. This may have resulted in a poor model fit. Thus, the results of the designometric analysis should be interpreted with caution. Only twelve chatbots were evaluated in the current study. The choice for this number of chatbots was made primarily based on consideration of the time spent by participants. Letting participants evaluate all twelve chatbots would likely result in a lack of concentration and motivation towards the latter part of the study. However, a study involving more participants could still let each participant evaluate a similar amount of chatbots but randomly selected out of a larger sample. Additionally, future studies could combine data from existing studies on the BUS-11 in the context of chatbots.

Finally, the language fluency of some of the participants may have hindered results. Although it was made clear to potential participants that the study was only available in Dutch, some participants indicated that their first language was English. Those who commented that the language barrier made it difficult for them to participate, were excluded. However, to maintain a reasonable sample size, participants who indicated that their first language was not Dutch, but did not indicate that this was a problem, were kept in the dataset.

5 Conclusion

The current study contributed to the standardization of the Dutch version of the BUS-11 questionnaire by examining the proposed five-factor structure. The analysis of the reliability and concurrent validity of the BUS-11 indicate that this scale is a valuable method for measuring user satisfaction with chatbots. Furthermore, the results indicate that the five-factor structure can be confirmed from the psychometric perspective. More research is needed to find out if the structure can be confirmed from the designometric perspective as well. Finally, neither previous experience nor age was found to affect user satisfaction in the present study.

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7 Appendices

7.1 Appendix A

The BUS-11 in four languages (Borsci et al., 2021)

Original Version

Factor	Item
1 - Perceived accessibility to chatbot functions (ACF)	1. The chatbot function was easily detectable (Det) 2. It was easy to find the chatbot (Find)
2 - Perceived quality of chatbot functions (QCF)	3. Communicating with the chatbot was clear (Comm) 4. The chatbot was able to keep track of contex (Track) 5. The chatbot's responses were easy to understand (Undr)
3 - Perceived quality of conversation and information provided (QCI)	6. I find that the chatbot understands what I want and helps me achieve my goal (Goal) 7. The chatbot gives me the appropriate amount of information (InfoA) 8. The chatbot only gives me the information I need (InfoB) 9. I feel like the chatbot's responses were accurate (Acc)
4 - Perceived privacy and security (PS)	10. I believe the chatbot informs me of any possible privacy issues (Priv)

5 - Time response (TR)	11. My waiting time for a response from the chatbot was short (Wait)

Dutch

Factor	Item
1 - Perceived accessibility to chatbot functions (ACF)	1. De chatbot functie was makkelijk te ontdekken. 2. Het was makkelijk om de chatbot te vinden.
2 - Perceived quality of chatbot functions (QCF)	3. De communicatie met de chatbot was duidelijk. 4. De chatbot hield de context in het oog. 5. De antwoorden van de chatbot waren gemakkelijk te begrijpen.
3 - Perceived quality of conversation and information provided (QCI)	6. Ik denk dat de chatbot begrijpt wat ik wil en helpt me mijn doel te bereiken. 7. De chatbot gaf me de juiste hoeveelheid informatie. 8. De chatbot gaf me alleen de informatie die ik nodig had. 9. Ik had het gevoel dat de antwoorden van de chatbot klopten.
4 - Perceived privacy and security (PS)	10. Ik denk dat de chatbot me inlicht over mogelijke privacy problemen.
5 - Time response (TR)	11. Ik hoefde kort te wachten op een antwoord van de chatbot.

German

Factor	**Item**
1 - Perceived accessibility to chatbot functions (ACF)	1. Die Chatbot-Funktion war leicht zu erkennen. 2. Es war einfach, den Chatbot zu finden.
2 - Perceived quality of chatbot functions (QCF)	3. Die Kommunikation mit dem Chatbot war eindeutig. 4. Der Chatbot war in der Lage, den Kontext zu verfolgen. 5. Die Antworten des Chatbots waren einfach zu verstehen.
3 - Perceived quality of conversation and information provided (QCI)	6. Ich finde, dass der Chatbot versteht, was ich will und mir hilft, mein Ziel zu erreichen. 7. Der Chatbot gibt mir die angemessene Menge an Informationen. 8. Der Chatbot gibt mir nur die Informationen, die ich brauche. 9. Ich habe das Gefühl, dass die Antworten des Chatbots korrekt waren.
4 - Perceived privacy and security (PS)	10. Ich vertraue darauf, dass der Chatbot mich über mögliche Datenschutzprobleme informiert.
5 - Time response (TR)	11. Meine Wartezeit auf eine Antwort des Chatbots war kurz.

Spanish

Factor	Item
1 - Perceived accessibility to chatbot functions (ACF)	1. Pude reconocer la función del chatbot fácilmente. 2. Fue fácil encontrar/localizar el chatbot.
2 - Perceived quality of chatbot functions (QCF)	3. La comunicación con el chatbot fue clara. 4. El chatbot pudo hacer el seguimiento del contexto de la conversación. 5. Las respuestas del chatbot fueron fáciles de entender.
3 - Perceived quality of conversation and information provided (QCI)	6. Encuentro que el chatbot comprende lo que quiero y me ayuda a lograr mi objetivo. 7. El chatbot me da la cantidad adecuada de información. 8. El chatbot solo me da la información que necesito. 9. Siento que las respuestas del chatbot fueron precisas.
4 - Perceived privacy and security (PS)	10. Creo que el chatbot me informa sobre posibles problemas de privacidad.
5 - Time response (TR)	11. Mi tiempo de espera para recibir una respuesta del chatbot fue breve.

7.2 Appendix B

Tasks

Original (Dutch)

Chatbot	**Task**
Essent	U heeft de afgelopen maand meer energie gebruikt dan normaal. U wilt weten welke mogelijke verklaringen er zijn voor de stijging in van uw energiegebruik. Informeer hiernaar bij de chatbot.
DHL	U wilt een pakketje versturen. Informeer naar de mogelijkheden bij de chatbot.
Rabobank	U hebt een betaalrekening bij Rabobank, maar u wilt nu ook een spaarrekening openen. Informeer hiernaar bij de chatbot.
FBTO	U gaat binnenkort op reis, en wil een reisverzekering afsluiten. Vraag naar de mogelijkheden.
Albert Heijn	U heeft een klacht over uw bestelling. Vraag de chatbot wat u hieraan kunt doen.
ABN Amro	U wilt graag een afspraak maken bij een ABN Amro kantoor. Vraag hiernaar bij de chatbot.

Univé	U heeft recentelijk een nieuw telefoonnummer gekregen. Informeer bij de chatbot hoe u het nieuwe nummer door kunt geven.
TUI	U wilt met de auto naar Schiphol. Vraag welke mogelijkheden er zijn om te parkeren.
Ikea	U wilt weten of u op donderdagavond naar de Ikea kan. Vraag de chatbot naar de openingstijden van een vestiging bij jou in de buurt.
Reaal	U wilt weten wat de kosten voor een financieel adviseur zijn. Vraag hiernaar bij de chatbot.
Centraal Beheer	U wilt een autoverzekering afsluiten bij Centraal Beheer. Vraag de chatbot naar uw premie.
Engie	U bent van plan om een elektrische auto aan te schaffen, en u wilt daarom een (particuliere) laadpaal plaatsen. Vraag de chatbot van Engie naar de mogelijkheden.

Translation

Chatbot	**Task**
Essent	In the last month, you used more energy than usual. You would like to know what possible explanations there are for the increase in your energy usage. Ask the chatbot about this.
DHL	You would like to send a package. Ask the chatbot about the possibilities.
Rabobank	You have a checking account with Rabobank but would like to open a savings account as well. Ask the chatbot about this.
FBTO	You are going to travel soon and would like to make a travel insurance contract. Ask the chatbout about the possibilities.
Albert Heijn	You have a complaint about your order. Ask the chatbot what you can do about this.
ABN Amro	You would like to make an appointment at an ABN Amro office. Ask the chatbot about this.
Univé	You recently got a new cellphone number. Ask the chatbot how you can inform Univé about your new number.

TUI	You want to go to Schiphol by car. Ask about the possibilities for parking.
Ikea	You would like to know if you can go to Ikea on Thursday evening. Ask the chatbot about the opening hours of an Ikea near you.
Reaal	You want to know how much a financial advisor cost. Ask the chatbot about this.
Centraal Beheer	You want to make a car insurance with Centraal Beheer. Ask the chatbot about the costs.
Engie	You are planning to buy an electric car and would like to place a private charging station. Ask the chatbot about the possibilities.

7.3 Appendix C

R Code for the confirmatory factor analysis

Loading packages

```
library(lavaan)

## This is lavaan 0.6-10
## lavaan is FREE software! Please report any bugs.

library(knitr)
library(tidyverse)

## -- Attaching packages --------------------------------------- tidyverse
 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.6     v dplyr   1.0.7
## v tidyr   1.1.4     v stringr 1.4.0
## v readr   2.1.1     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_confl
icts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

library(printr)

## Registered S3 method overwritten by 'printr':
##   method                from
##   knit_print.data.frame rmarkdown

library(lubridate)

##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union

library(polynom)
library(performance)

## Warning: package 'performance' was built under R version 4.1.3

library(rstanarm)

## Loading required package: Rcpp

## This is rstanarm version 2.21.1

## - See https://mc-stan.org/rstanarm/articles/priors for changes to defau
lt priors!

## - Default priors may change, so it's safest to specify priors, even if
equivalent to the defaults.
```

```
## - For execution on a local, multicore CPU with excess RAM we recommend
calling

##   options(mc.cores = parallel::detectCores())

library(brms)

## Loading 'brms' package (version 2.16.3). Useful instructions
## can be found by typing help('brms'). A more detailed introduction
## to the package is available through vignette('brms_overview').

##
## Attaching package: 'brms'

## The following objects are masked from 'package:rstanarm':
##
##     dirichlet, exponential, get_y, lasso, ngrps

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

library(haven)
library(bayr)

## Registered S3 methods overwritten by 'bayr':
##   method             from
##   coef.brmsfit       brms
##   coef.stanreg       rstanarm
##   knit_print.tbl_obs mascutils
##   predict.brmsfit    brms
##   predict.stanreg    rstanarm
##   print.tbl_obs      mascutils

##
## Attaching package: 'bayr'

## The following objects are masked from 'package:brms':
##
##     fixef, ranef

## The following objects are masked from 'package:rstanarm':
##
##     fixef, ranef

library(dplyr)
library(ggpubr)
library(semPlot)
```

#Psychometric perspective data MH Reading dataset

```
MHpsy <- read.delim(file.choose("MHpsy.txt"))
```

Viewing dataset

```
view(MHpsy)
```

Inter item correlation

```
InterCor <- MHpsy[, c("Det", "Find", "Comm", "Track", "Undr", "Goal", "Inf
oA", "InfoB","Acc", "Priv", "Wait")]
item_intercor(InterCor)

## [1] 0.5273424
```

Defining and fitting the model

```
M_MHpsy <- 'ACF =~ Det + Find
          QCF =~ Comm + Track + Undr
          QCI =~ Goal + InfoA + InfoB + Acc
          PS =~ Priv
          TR =~ Wait '
PsyFit_MHpsy <- cfa(M_MHpsy, data=MHpsy, std.lv=TRUE)

MHpsy_f <- read.delim(file.choose("MHpsy_f.txt"))
cor(MHpsy_f, method = "pearson", use = "complete.obs")
```

	ACF	QCF	QCI	PS	TR
ACF	1.0000000	0.6794565	0.5970343	0.0659372	0.7190663
QCF	0.6794565	1.0000000	0.8969313	0.2403225	0.6408211
QCI	0.5970343	0.8969313	1.0000000	0.3164910	0.6362770
PS	0.0659372	0.2403225	0.3164910	1.0000000	0.0249818
TR	0.7190663	0.6408211	0.6362770	0.0249818	1.0000000

Summary

```
summary(PsyFit_MHpsy, fit.measures=TRUE, standardized=TRUE)

## lavaan 0.6-10 ended normally after 60 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        30
##
##                                                   Used       Total
##   Number of observations                            51          53
##
## Model Test User Model:
##
##   Test statistic                                51.141
##   Degrees of freedom                                36
##   P-value (Chi-square)                           0.049
##
## Model Test Baseline Model:
##
##   Test statistic                               476.210
##   Degrees of freedom                                55
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
```

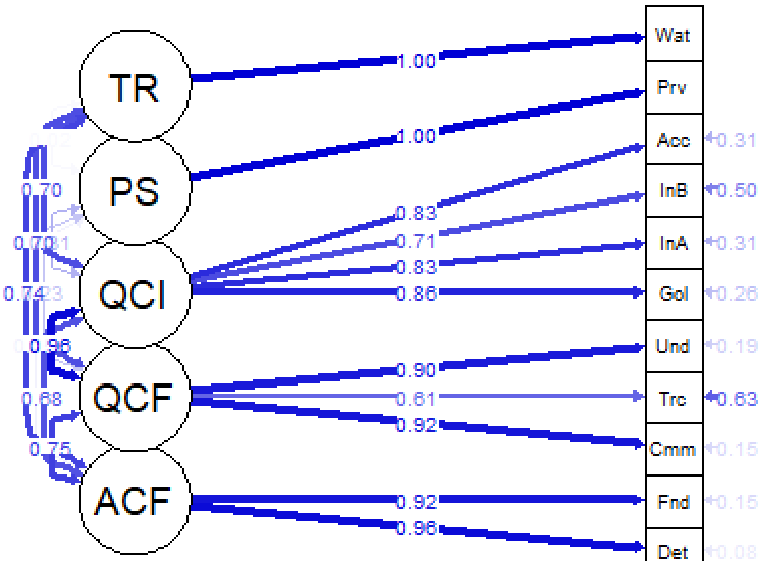
```
##   Comparative Fit Index (CFI)                    0.964
##   Tucker-Lewis Index (TLI)                       0.945
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)              -2084.156
##   Loglikelihood unrestricted model (H1)      -2058.586
##
##   Akaike (AIC)                                4228.313
##   Bayesian (BIC)                              4286.268
##   Sample-size adjusted Bayesian (BIC)         4192.080
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.091
##   90 Percent confidence interval - lower         0.007
##   90 Percent confidence interval - upper         0.144
##   P-value RMSEA <= 0.05                          0.135
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.058
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.al
l
##   ACF =~

##     Det              14.811    1.651    8.971    0.000   14.811    0.95
7
##     Find             14.340    1.700    8.435    0.000   14.340    0.92
3
##   QCF =~

##     Comm             12.653    1.489    8.497    0.000   12.653    0.91
9
##     Track             8.589    1.828    4.699    0.000    8.589    0.60
8
##     Undr             12.633    1.541    8.200    0.000   12.633    0.90
0
##   QCI =~

##     Goal             11.129    1.461    7.618    0.000   11.129    0.86
2
##     InfoA            10.837    1.517    7.143    0.000   10.837    0.82
8
##     InfoB            10.213    1.792    5.699    0.000   10.213    0.70
8
```

```
##     Acc               10.983    1.528    7.188    0.000   10.983    0.83
1
##   PS =~

##     Priv              17.093    1.692   10.100    0.000   17.093    1.00
0
##   TR =~

##     Wait              16.640    1.648   10.100    0.000   16.640    1.00
0
##
## Covariances:
##                     Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.al
l
##   ACF ~~

##     QCF                0.751    0.073   10.260    0.000    0.751    0.75
1
##     QCI                0.682    0.088    7.730    0.000    0.682    0.68
2
##     PS                 0.052    0.144    0.363    0.717    0.052    0.05
2
##     TR                 0.737    0.069   10.742    0.000    0.737    0.73
7
##   QCF ~~

##     QCI                0.963    0.031   30.714    0.000    0.963    0.96
3
##     PS                 0.227    0.139    1.630    0.103    0.227    0.22
7
##     TR                 0.695    0.079    8.758    0.000    0.695    0.69
5
##   QCI ~~

##     PS                 0.307    0.135    2.275    0.023    0.307    0.30
7
##     TR                 0.697    0.081    8.649    0.000    0.697    0.69
7
##   PS ~~

##     TR                 0.025    0.140    0.179    0.858    0.025    0.02
5
##
## Variances:
##                     Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.al
l
##    .Det               20.189   13.167    1.533    0.125   20.189    0.08
4
##    .Find              36.000   13.751    2.618    0.009   36.000    0.14
9
##    .Comm              29.263    9.006    3.249    0.001   29.263    0.15
5
##    .Track            125.701   25.787    4.875    0.000  125.701    0.63
0
```

```
##    .Undr              37.379   10.161    3.678    0.000   37.379    0.19
0
##    .Goal              42.656   10.617    4.018    0.000   42.656    0.25
6
##    .InfoA             53.937   12.561    4.294    0.000   53.937    0.31
5
##    .InfoB            103.944   22.055    4.713    0.000  103.944    0.49
9
##    .Acc               53.955   12.629    4.272    0.000   53.955    0.30
9
##    .Priv               0.000                               0.000    0.00
0
##    .Wait               0.000                               0.000    0.00
0
##     ACF                1.000                               1.000    1.00
0
##     QCF                1.000                               1.000    1.00
0
##     QCI                1.000                               1.000    1.00
0
##     PS                 1.000                               1.000    1.00
0
##     TR                 1.000                               1.000    1.00
0
```

Semplot visualisation

```
semPaths(PsyFit_MHpsy,whatLabels="std",edge.label.cex=1, style = "lisrel",
 residScale=8, layout ="tree3", theme = "colorblind", rotation= 2, what="s
td", nChartNodes = 0, curvePivot= TRUE, sizeMan = 6, sizeLat = 12)

## Warning in qgraph::qgraph(Edgelist, labels = nLab, bidirectional = Bidi
r, : The
## following arguments are not documented and likely not arguments of qgra
ph and
## thus ignored: nChartNodes
```



#Designometric perspective data MH Reading dataset

```
MHdes <- read.delim(file.choose("MHdes.txt"))
```

Viewing dataset

```
view(MHdes)
```

Inter item correlation

```
InterCor <- MHdes[, c("Det", "Find", "Comm", "Track", "Undr", "Goal", "Inf
oA", "InfoB","Acc", "Priv", "Wait")]
item_intercor(InterCor)

## [1] 0.4473854
```

Defining and fitting the model

```
M_MHdes <- 'ACF =~ Det + Find
          QCF =~ Comm + Track + Undr
          QCI =~ Goal + InfoA + InfoB + Acc
          PS =~ Priv
          TR =~ Wait '
desFit_MHdes <- cfa(M_MHdes, data=MHdes, std.lv=TRUE)

## Warning in lav_object_post_check(object): lavaan WARNING: some estimate
d ov
## variances are negative

MHdes_f <- read.delim(file.choose("MHdes_f.txt"))
cor(MHdes_f, method = "pearson", use = "complete.obs")
```

	ACF	QCF	QCI	PS	TR
ACF	1.0000000	0.3383857	0.0905791	-0.2149646	0.1048279
QCF	0.3383857	1.0000000	0.9205148	-0.1408743	0.6709750
QCI	0.0905791	0.9205148	1.0000000	-0.1085965	0.5801866
PS	-0.2149646	-0.1408743	-0.1085965	1.0000000	-0.4618092
TR	0.1048279	0.6709750	0.5801866	-0.4618092	1.0000000

Summary

```
summary(desFit_MHdes, fit.measures=TRUE, standardized=TRUE)

## lavaan 0.6-10 ended normally after 107 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        30
##
##   Number of observations                            12
##
## Model Test User Model:
##
##   Test statistic                                76.923
##   Degrees of freedom                                36
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                               268.922
##   Degrees of freedom                                55
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.809
##   Tucker-Lewis Index (TLI)                       0.708
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -390.598
##   Loglikelihood unrestricted model (H1)       -352.136
##
##   Akaike (AIC)                                 841.196
##   Bayesian (BIC)                               855.743
##   Sample-size adjusted Bayesian (BIC)          765.026
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                          0.308
##   90 Percent confidence interval - lower         0.212
##   90 Percent confidence interval - upper         0.403
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
```

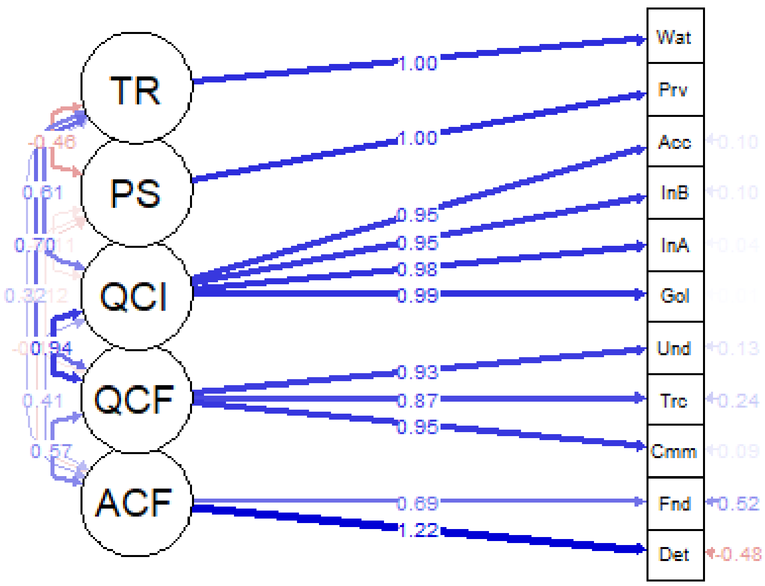
```
##
##   SRMR                                           0.128
##
## Parameter Estimates:
##
##   Standard errors                              Standard
##   Information                                  Expected
##   Information saturated (h1) model           Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.al
l
##   ACF =~

##     Det               6.959    1.155    6.027    0.000    6.959    1.21
7
##     Find              5.202    1.982    2.625    0.009    5.202    0.69
2
##   QCF =~

##     Comm              9.777    2.183    4.479    0.000    9.777    0.95
5
##     Track             7.986    2.081    3.838    0.000    7.986    0.87
2
##     Undr              8.938    2.087    4.282    0.000    8.938    0.93
1
##   QCI =~

##     Goal             13.759    2.847    4.833    0.000   13.759    0.99
3
##     InfoA            12.414    2.634    4.714    0.000   12.414    0.98
1
##     InfoB            11.992    2.699    4.443    0.000   11.992    0.95
0
##     Acc              10.141    2.292    4.424    0.000   10.141    0.94
8
##   PS =~

##     Priv              7.944    1.622    4.899    0.000    7.944    1.00
0
##   TR =~

##     Wait              9.338    1.906    4.899    0.000    9.338    1.00
0
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.al
l
##   ACF ~~

##     QCF               0.574    0.182    3.159    0.002    0.574    0.57
4
##     QCI               0.408    0.191    2.141    0.032    0.408    0.40
8
```

```
##     PS                 -0.193    0.206   -0.937    0.349   -0.193   -0.19
3
##     TR                  0.323    0.197    1.640    0.101    0.323    0.32
3
##   QCF ~~

##     QCI                 0.941    0.043   21.890    0.000    0.941    0.94
1
##     PS                 -0.120    0.292   -0.410    0.682   -0.120   -0.12
0
##     TR                  0.700    0.155    4.529    0.000    0.700    0.70
0
##   QCI ~~

##     PS                 -0.115    0.286   -0.401    0.688   -0.115   -0.11
5
##     TR                  0.607    0.184    3.305    0.001    0.607    0.60
7
##   PS ~~

##     TR                 -0.462    0.227   -2.033    0.042   -0.462   -0.46
2
##
## Variances:
##                      Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.al
l
##    .Det               -15.714   12.736   -1.234    0.217  -15.714   -0.48
0
##    .Find               29.421   13.494    2.180    0.029   29.421    0.52
1
##    .Comm                9.270    4.256    2.178    0.029    9.270    0.08
8
##    .Track              20.120    8.136    2.473    0.013   20.120    0.24
0
##    .Undr               12.270    5.197    2.361    0.018   12.270    0.13
3
##    .Goal                2.515    2.636    0.954    0.340    2.515    0.01
3
##    .InfoA               6.089    3.275    1.859    0.063    6.089    0.03
8
##    .InfoB              15.385    6.808    2.260    0.024   15.385    0.09
7
##    .Acc                11.520    5.077    2.269    0.023   11.520    0.10
1
##    .Priv                0.000                               0.000    0.00
0
##    .Wait                0.000                               0.000    0.00
0
##     ACF                 1.000                               1.000    1.00
0
##     QCF                 1.000                               1.000    1.00
0
##     QCI                 1.000                               1.000    1.00
0
```

```
##      PS                 1.000                                    1.000    1.00
0
##      TR                 1.000                                    1.000    1.00
0
```

Semplot visualisation

```
semPaths(desFit_MHdes,whatLabels="std",edge.label.cex=1, style = "lisrel",
 residScale=8, layout ="tree3", theme = "colorblind", rotation= 2, what="s
td", nChartNodes = 0, curvePivot= TRUE, sizeMan = 6, sizeLat = 12)

## Warning in qgraph::qgraph(Edgelist, labels = nLab, bidirectional = Bidi
r, : The
## following arguments are not documented and likely not arguments of qgra
ph and
## thus ignored: nChartNodes
```



#Psychometric perspective data MB Reading dataset

```
MBpsy <- read.delim(file.choose("MBpsy.txt"))
```

Viewing dataset

```
view(MBpsy)
```

Inter item correlation

```
InterCor <- MBpsy[, c("Det", "Find", "Comm", "Track", "Undr", "Goal", "Inf
oA", "InfoB","Acc", "Priv", "Wait")]
item_intercor(InterCor)

## [1] 0.4350428
```

Testing for normality

P-value > .05, assume normality

Defining and fitting the model

```
M_MBpsy <- 'ACF =~ Det + Find
          QCF =~ Comm + Track + Undr
          QCI =~ Goal + InfoA + InfoB + Acc
          PS =~ Priv
          TR =~ Wait '
psyFit_MBpsy <- cfa(M_MBpsy, data=MBpsy, std.lv=TRUE)

MBpsy_f <- read.delim(file.choose("MBpsy_f.txt"))
cor(MBpsy_f, method = "pearson", use = "complete.obs")
```

	ACF	QCF	QCI	PS	TR
ACF	1.0000000	0.4714890	0.3013233	0.3054504	0.0840678
QCF	0.4714890	1.0000000	0.7723763	0.6804240	0.1929265
QCI	0.3013233	0.7723763	1.0000000	0.8886414	0.2995527
PS	0.3054504	0.6804240	0.8886414	1.0000000	0.2638608
TR	0.0840678	0.1929265	0.2995527	0.2638608	1.0000000

Summary

```
summary(psyFit_MBpsy, fit.measures=TRUE, standardized=TRUE)

## lavaan 0.6-10 ended normally after 32 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        30
##
##                                                   Used       Total
##   Number of observations                           652         653
##
## Model Test User Model:
##
##   Test statistic                               135.562
##   Degrees of freedom                                36
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                              4612.242
##   Degrees of freedom                                55
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.978
##   Tucker-Lewis Index (TLI)                       0.967
```

```
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)             -8130.317
##   Loglikelihood unrestricted model (H1)     -8062.536
##
##   Akaike (AIC)                              16320.634
##   Bayesian (BIC)                            16455.035
##   Sample-size adjusted Bayesian (BIC)       16359.786
##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                         0.065
##   90 Percent confidence interval - lower        0.054
##   90 Percent confidence interval - upper        0.077
##   P-value RMSEA <= 0.05                         0.016
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                          0.028
##
## Parameter Estimates:
##
##   Standard errors                            Standard
##   Information                                Expected
##   Information saturated (h1) model         Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.al
l
##   ACF =~

##     Det               1.052    0.038   27.674    0.000    1.052    0.94
6
##     Find              0.998    0.038   26.032    0.000    0.998    0.90
2
##   QCF =~

##     Comm              0.815    0.032   25.868    0.000    0.815    0.84
6
##     Track             0.835    0.033   25.146    0.000    0.835    0.83
0
##     Undr              0.698    0.031   22.498    0.000    0.698    0.77
0
##   QCI =~

##     Goal              0.864    0.034   25.536    0.000    0.864    0.83
0
##     InfoA             0.905    0.035   25.677    0.000    0.905    0.83
3
##     InfoB             0.948    0.034   28.290    0.000    0.948    0.88
5
##     Acc               0.820    0.031   26.772    0.000    0.820    0.85
5
```

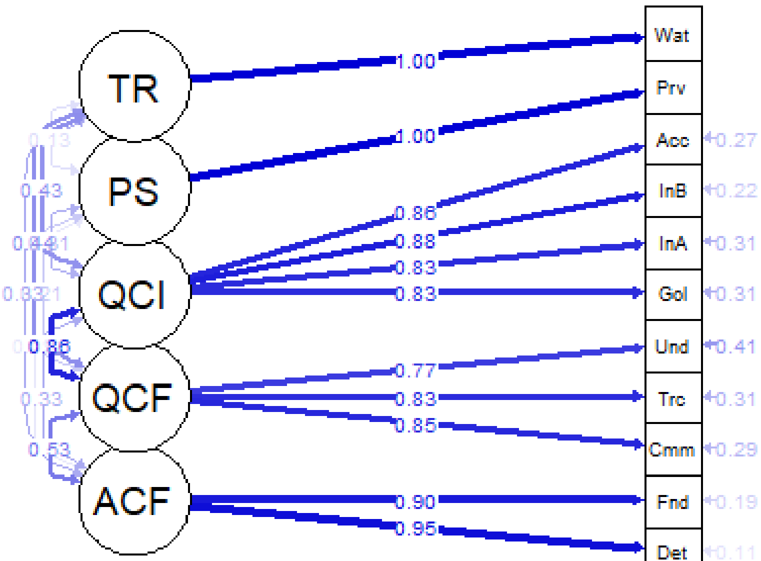
```
##   PS =~
##     Priv              1.122    0.031   36.111    0.000    1.122    1.00
0
##   TR =~
##     Wait              0.950    0.026   36.111    0.000    0.950    1.00
0
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.al
l
##   ACF ~~
##     QCF               0.528    0.033   15.904    0.000    0.528    0.52
8
##     QCI               0.329    0.038    8.579    0.000    0.329    0.32
9
##     PS                0.090    0.040    2.229    0.026    0.090    0.09
0
##     TR                0.333    0.036    9.168    0.000    0.333    0.33
3
##   QCF ~~
##     QCI               0.864    0.016   54.669    0.000    0.864    0.86
4
##     PS                0.210    0.040    5.198    0.000    0.210    0.21
0
##     TR                0.444    0.035   12.841    0.000    0.444    0.44
4
##   QCI ~~
##     PS                0.310    0.037    8.347    0.000    0.310    0.31
0
##     TR                0.428    0.034   12.656    0.000    0.428    0.42
8
##   PS ~~
##     TR                0.127    0.039    3.286    0.001    0.127    0.12
7
##
## Variances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.al
l
##    .Det               0.130    0.043    3.057    0.002    0.130    0.10
5
##    .Find              0.227    0.040    5.716    0.000    0.227    0.18
6
##    .Comm              0.265    0.020   12.920    0.000    0.265    0.28
5
##    .Track             0.315    0.023   13.554    0.000    0.315    0.31
1
##    .Undr              0.336    0.022   15.158    0.000    0.336    0.40
8
```

```
##    .Goal                0.338    0.023    14.896    0.000    0.338    0.31
1
##    .InfoA               0.362    0.024    14.821    0.000    0.362    0.30
6
##    .InfoB               0.249    0.019    12.872    0.000    0.249    0.21
7
##    .Acc                 0.247    0.017    14.148    0.000    0.247    0.26
9
##    .Priv                0.000                                0.000    0.00
0
##    .Wait                0.000                                0.000    0.00
0
##     ACF                 1.000                                1.000    1.00
0
##     QCF                 1.000                                1.000    1.00
0
##     QCI                 1.000                                1.000    1.00
0
##     PS                  1.000                                1.000    1.00
0
##     TR                  1.000                                1.000    1.00
0
```

Semplot visualisation

```
semPaths(psyFit_MBpsy,whatLabels="std",edge.label.cex=1, style = "lisrel",
 residScale=8, layout ="tree3", theme = "colorblind", rotation= 2, what="s
td", nChartNodes = 0, curvePivot= TRUE, sizeMan = 6, sizeLat = 12)
```

```
## Warning in qgraph::qgraph(Edgelist, labels = nLab, bidirectional = Bidi
r, : The
## following arguments are not documented and likely not arguments of qgra
ph and
## thus ignored: nChartNodes
```



#Designometric perspective data MB Reading dataset

```
MBdes <- read.delim(file.choose("MBdes.txt"))
```

Viewing dataset

```
view(MBdes)
```

Inter item correlation

```
InterCor <- MBdes[, c("Det", "Find", "Comm", "Track", "Undr", "Goal", "Inf
oA", "InfoB","Acc", "Priv", "Wait")]
item_intercor(InterCor)

## [1] 0.5958394
```

Defining and fitting the model

M_MBdes <- ‘ACF =~ Det + Find QCF =~ Comm + Track + Undr QCI =~ Goal + InfoA + InfoB + Acc PS =~ Priv TR =~ Wait’ desFit_MBdes <- cfa(M_MBdes, data=MBdes, std.lv=TRUE)

Cannot run model (lavaan ERROR: sample covariance matrix is not positive-definite) –> can run model without factor 1

```
M_MBdes <- 'QCF =~ Comm + Track + Undr
          QCI =~ Goal + InfoA + InfoB + Acc
```

```
          PS =~ Priv
          TR =~ Wait '
desFit_MBdes <- cfa(M_MBdes, data=MBdes, std.lv=TRUE)

MBdes_f <- read.delim(file.choose("MBdes_f.txt"))
cor(MBdes_f, method = "pearson", use = "complete.obs")
```

	ACF	QCF	QCI	PS	TR
ACF	1.0000000	0.6634827	0.3742168	0.4209497	0.5295638
QCF	0.6634827	1.0000000	0.8121531	0.4359762	0.3720310
QCI	0.3742168	0.8121531	1.0000000	0.4123511	0.5052669
PS	0.4209497	0.4359762	0.4123511	1.0000000	0.1030710
TR	0.5295638	0.3720310	0.5052669	0.1030710	1.0000000

Summary

```
summary(desFit_MBdes, fit.measures=TRUE, standardized=TRUE)

## lavaan 0.6-10 ended normally after 52 iterations
##
##   Estimator                                         ML
##   Optimization method                           NLMINB
##   Number of model parameters                        22
##
##   Number of observations                            10
##
## Model Test User Model:
##
##   Test statistic                                98.587
##   Degrees of freedom                                23
##   P-value (Chi-square)                           0.000
##
## Model Test Baseline Model:
##
##   Test statistic                               213.234
##   Degrees of freedom                                36
##   P-value                                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)                    0.574
##   Tucker-Lewis Index (TLI)                       0.332
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)               -243.713
##   Loglikelihood unrestricted model (H1)       -194.419
##
##   Akaike (AIC)                                 531.426
##   Bayesian (BIC)                               538.083
##   Sample-size adjusted Bayesian (BIC)          472.176
##
## Root Mean Square Error of Approximation:
```

```
##
##   RMSEA                                          0.573
##   90 Percent confidence interval - lower         0.460
##   90 Percent confidence interval - upper         0.692
##   P-value RMSEA <= 0.05                          0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                           0.063
##
## Parameter Estimates:
##
##   Standard errors                             Standard
##   Information                                 Expected
##   Information saturated (h1) model          Structured
##
## Latent Variables:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.al
l
##   QCF =~

##     Comm              6.656    1.579    4.214    0.000    6.656    0.97
3
##     Track             6.826    1.636    4.172    0.000    6.826    0.96
8
##     Undr              4.974    1.409    3.529    0.000    4.974    0.87
9
##   QCI =~

##     Goal              6.192    1.516    4.084    0.000    6.192    0.95
5
##     InfoA             7.225    1.907    3.789    0.000    7.225    0.91
6
##     InfoB             7.182    1.690    4.249    0.000    7.182    0.97
5
##     Acc               6.688    1.573    4.251    0.000    6.688    0.97
5
##   PS =~

##     Priv              6.821    1.525    4.472    0.000    6.821    1.00
0
##   TR =~

##     Wait              7.002    1.566    4.472    0.000    7.002    1.00
0
##
## Covariances:
##                    Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.al
l
##   QCF ~~

##     QCI               0.835    0.103    8.086    0.000    0.835    0.83
5
##     PS                0.402    0.270    1.491    0.136    0.402    0.40
```

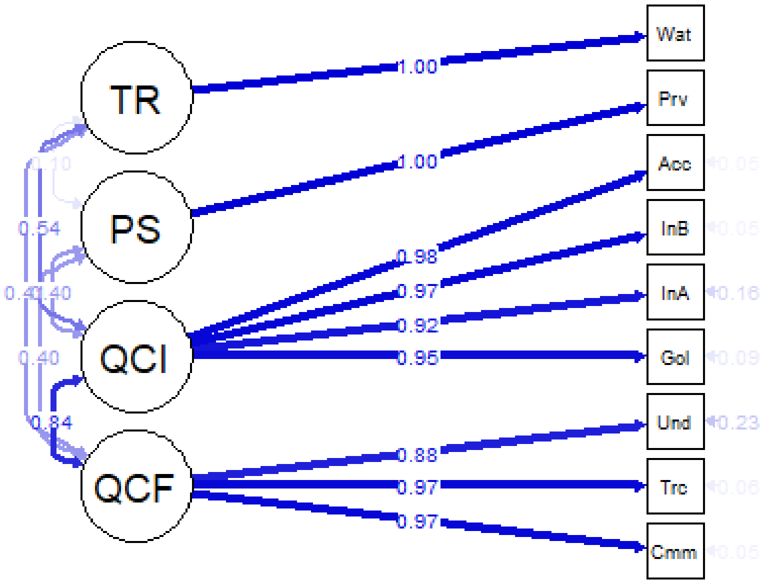
```
2
##      TR                      0.413    0.267    1.547    0.122    0.413    0.41
3
##    QCI ~~

##      PS                      0.403    0.268    1.507    0.132    0.403    0.40
3
##      TR                      0.536    0.228    2.350    0.019    0.536    0.53
6
##    PS ~~

##      TR                      0.103    0.313    0.329    0.742    0.103    0.10
3
##
## Variances:
##                          Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.al
l
##     .Comm                   2.507    2.511    0.998    0.318    2.507    0.05
4
##     .Track                  3.176    2.765    1.149    0.251    3.176    0.06
4
##     .Undr                   7.261    3.581    2.028    0.043    7.261    0.22
7
##     .Goal                   3.718    2.052    1.812    0.070    3.718    0.08
8
##     .InfoA                 10.045    4.954    2.028    0.043   10.045    0.16
1
##     .InfoB                  2.680    1.885    1.422    0.155    2.680    0.04
9
##     .Acc                    2.303    1.628    1.415    0.157    2.303    0.04
9
##     .Priv                   0.000                               0.000    0.00
0
##     .Wait                   0.000                               0.000    0.00
0
##      QCF                    1.000                               1.000    1.00
0
##      QCI                    1.000                               1.000    1.00
0
##      PS                     1.000                               1.000    1.00
0
##      TR                     1.000                               1.000    1.00
0
```

Semplot visualisation

```
semPaths(desFit_MBdes,whatLabels="std",edge.label.cex=1, style = "lisrel",
 residScale=8, layout ="tree3", theme = "colorblind", rotation= 2, what="s
td", nChartNodes = 0, curvePivot= TRUE, sizeMan = 6, sizeLat = 12)
```

```
## Warning in qgraph::qgraph(Edgelist, labels = nLab, bidirectional = Bidi
r, : The
## following arguments are not documented and likely not arguments of qgra
```

```
ph and
## thus ignored: nChartNodes
```



7.4 Appendix D

R Code for the other analyses

Loading packages

```
library(knitr)
library(tidyverse)

## -- Attaching packages --------------------------------------- tidyverse
 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.6     v dplyr   1.0.7
## v tidyr   1.1.4     v stringr 1.4.0
## v readr   2.1.1     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_confl
icts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

library(printr)

## Registered S3 method overwritten by 'printr':
##   method                from
##   knit_print.data.frame rmarkdown

library(corrplot)

## corrplot 0.92 loaded

library(lubridate)

##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##     date, intersect, setdiff, union

library(polynom)
library(rstanarm)

## Loading required package: Rcpp

## This is rstanarm version 2.21.1

## - See https://mc-stan.org/rstanarm/articles/priors for changes to defau
lt priors!

## - Default priors may change, so it's safest to specify priors, even if
equivalent to the defaults.

## - For execution on a local, multicore CPU with excess RAM we recommend
calling
```

```
##   options(mc.cores = parallel::detectCores())

library(brms)

## Loading 'brms' package (version 2.16.3). Useful instructions
## can be found by typing help('brms'). A more detailed introduction
## to the package is available through vignette('brms_overview').

##
## Attaching package: 'brms'

## The following objects are masked from 'package:rstanarm':
##
##     dirichlet, exponential, get_y, lasso, ngrps

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

library(haven)
library(bayr)

## Registered S3 methods overwritten by 'bayr':
##   method             from
##   coef.brmsfit       brms
##   coef.stanreg       rstanarm
##   knit_print.tbl_obs mascutils
##   predict.brmsfit    brms
##   predict.stanreg    rstanarm
##   print.tbl_obs      mascutils

##
## Attaching package: 'bayr'

## The following objects are masked from 'package:brms':
##
##     fixef, ranef

## The following objects are masked from 'package:rstanarm':
##
##     fixef, ranef

library(ltm)

## Loading required package: MASS

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##     select

## Loading required package: msm

## Loading required package: polycor
```

```
library(ggpubr)
library(psych)

##
## Attaching package: 'psych'

## The following object is masked from 'package:ltm':
##
##     factor.scores

## The following object is masked from 'package:polycor':
##
##     polyserial

## The following object is masked from 'package:brms':
##
##     cs

## The following object is masked from 'package:rstanarm':
##
##     logit

## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha

library(tidyr)
library(dplyr)
library(readr)
library(readxl)
library(stringr)
```

Reading dataset

```
CB <- read.delim(file.choose("DataChatbotClean.txt"))
```

Viewing dataset

```
view(CB)
```

Testing BUS-11 for normality

```
shapiro.test(CB$BusTotalAvg)

##
##  Shapiro-Wilk normality test
##
## data:  CB$BusTotalAvg
## W = 0.9812, p-value = 0.5906
```

P-value > .05, assume normality

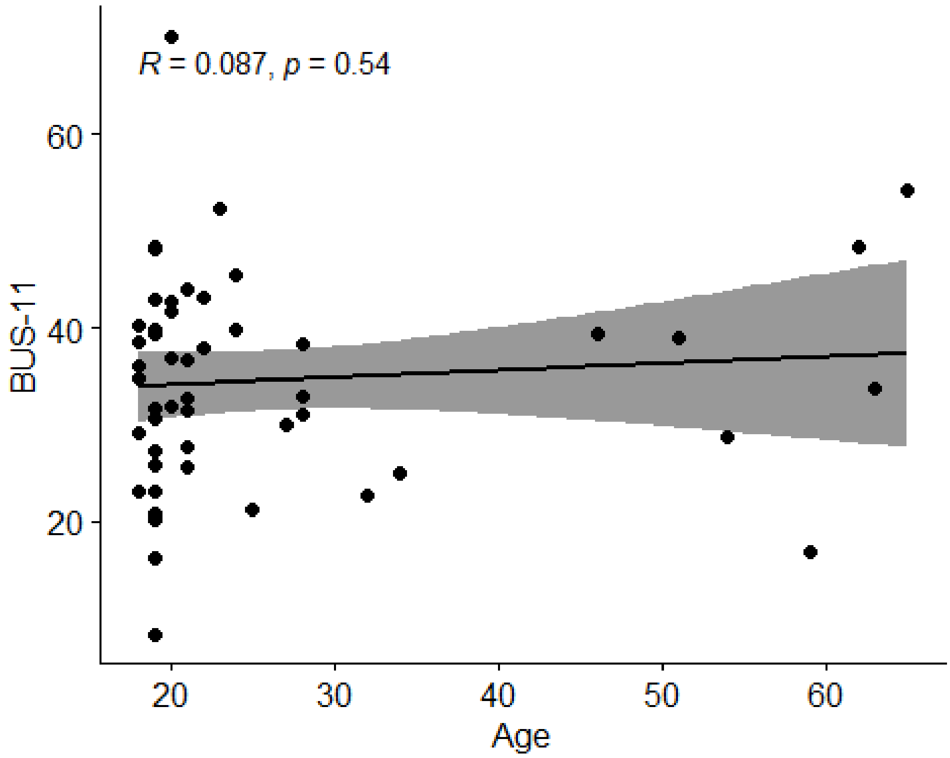
#Age

```
describe(CB$D1)
```

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	53	26	12.9689	21	22.90698	2.9652	18	65	47	1.97588	2.533626	1.781415

Visual inspection

```
ggscatter(CB, x = "D1", y = "BusTotalAvg",
          add = "reg.line", conf.int = TRUE,
          cor.coef = TRUE, cor.method = "pearson",
          xlab = "Age", ylab = "BUS-11")

## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 2 rows containing non-finite values (stat_smooth).

## Warning: Removed 2 rows containing non-finite values (stat_cor).

## Warning: Removed 2 rows containing missing values (geom_point).
```



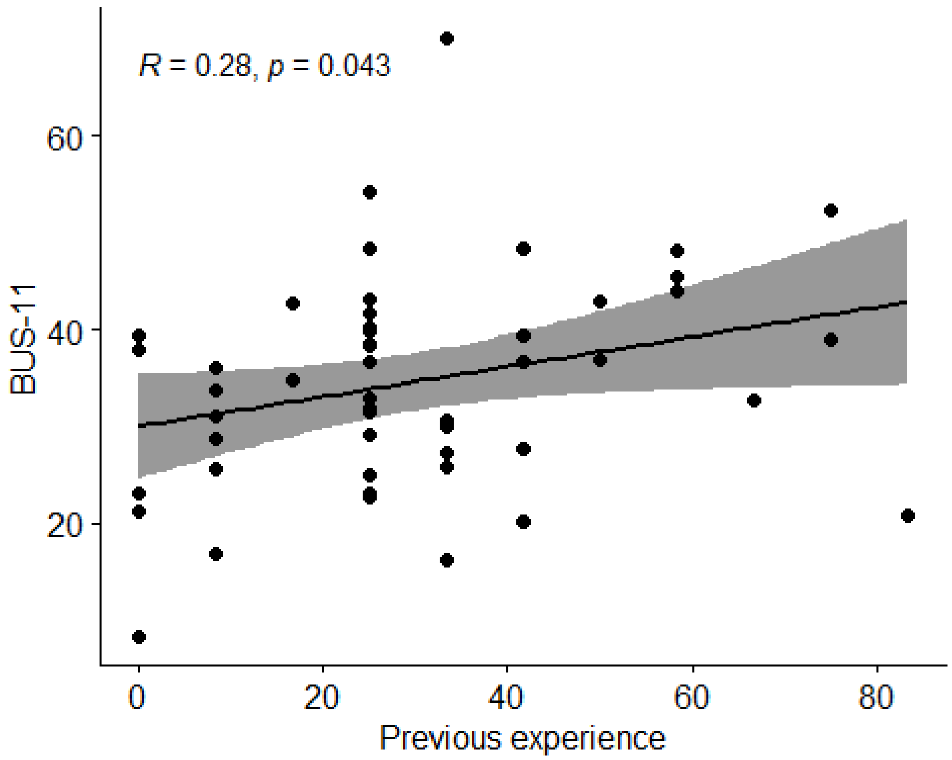
Linear regression

```
lm_age <- lm(BusTotalAvg ~ D1, data = CB)
summary(lm_age)

##
## Call:
## lm(formula = BusTotalAvg ~ D1, data = CB)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
```

```
## -25.708  -7.277   0.879   5.957  35.962
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 32.66655    3.47518    9.40 1.51e-12 ***
## D1           0.07236    0.11862    0.61    0.545
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.04 on 49 degrees of freedom
##   (2 observations deleted due to missingness)
## Multiple R-squared:  0.007537,   Adjusted R-squared:  -0.01272
## F-statistic: 0.3721 on 1 and 49 DF,  p-value: 0.5447
```

#Previous experience Visual inspection

```
ggscatter(CB, x = "Experience", y = "BusTotalAvg",
          add = "reg.line", conf.int = TRUE,
          cor.coef = TRUE, cor.method = "pearson",
          xlab = "Previous experience", ylab = "BUS-11")

## `geom_smooth()` using formula 'y ~ x'

## Warning: Removed 2 rows containing non-finite values (stat_smooth).

## Warning: Removed 2 rows containing non-finite values (stat_cor).

## Warning: Removed 2 rows containing missing values (geom_point).
```



Linear regression

```
lm_experience <- lm(BusTotalAvg ~ Experience, data = CB)
summary(lm_experience)

##
## Call:
## lm(formula = BusTotalAvg ~ Experience, data = CB)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -22.029  -7.243  -0.190   6.169  34.954
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 29.96088    2.67092  11.217 3.88e-15 ***
## Experience   0.15482    0.07458   2.076   0.0432 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 10.63 on 49 degrees of freedom
##   (2 observations deleted due to missingness)
## Multiple R-squared:  0.08084,    Adjusted R-squared:  0.06209
## F-statistic:  4.31 on 1 and 49 DF,  p-value: 0.04316
```

#BUS-11 and UMUX-Lite Testing for normality

```
shapiro.test(CB$UMUXTotalAvg)

##
##  Shapiro-Wilk normality test
##
## data:  CB$UMUXTotalAvg
## W = 0.98882, p-value = 0.9097
```

P-value > .05, assume normality

Correlation BUS-11 and UMUX-Lite

```
Correlation <-cor.test(CB$BusTotalAvg, CB$UMUXTotalAvg,  method = "spearma
n", exact=FALSE)
Correlation

##
##  Spearman's rank correlation rho
##
## data:  CB$BusTotalAvg and CB$UMUXTotalAvg
## S = 4174.9, p-value = 5.358e-13
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##       rho
## 0.8110904
```

Factor correlations UMUX-Lite F1

```
CUF1 <-cor.test(CB$F1,CB$UMUXTotalAvg,  method = "spearman", exact=FALSE)
CUF1
```

```
##
##  Spearman's rank correlation rho
##
## data:  CB$F1 and CB$UMUXTotalAvg
## S = 9755.4, p-value = 2.047e-05
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##       rho
## 0.5585788
```

F2

```
CUF2 <-cor.test(CB$F2,CB$UMUXTotalAvg,  method = "spearman", exact=FALSE)
CUF2
```

```
##
##  Spearman's rank correlation rho
##
## data:  CB$F2 and CB$UMUXTotalAvg
## S = 4574.8, p-value = 4.025e-12
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##      rho
## 0.792994
```

F3

```
CUF3 <-cor.test(CB$F3,CB$UMUXTotalAvg,  method = "spearman", exact=FALSE)
CUF3
```

```
##
##  Spearman's rank correlation rho
##
## data:  CB$F3 and CB$UMUXTotalAvg
## S = 4871.6, p-value = 1.587e-11
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##       rho
## 0.7795658
```

F4

```
CUF4 <-cor.test(CB$F4,CB$UMUXTotalAvg,  method = "spearman", exact=FALSE)
CUF4
```

```
##
##  Spearman's rank correlation rho
##
## data:  CB$F4 and CB$UMUXTotalAvg
## S = 15562, p-value = 0.03506
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##       rho
## 0.2958282
```

F5

```
CUF5 <-cor.test(CB$F5,CB$UMUXTotalAvg,  method = "spearman", exact=FALSE)
CUF5

##
##  Spearman's rank correlation rho
##
## data:  CB$F5 and CB$UMUXTotalAvg
## S = 7496.6, p-value = 1.314e-07
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##       rho
## 0.6607861
```

#BUS-11 and RSME Testing for normality

```
shapiro.test(CB$RSMETotalAvg)

##
##  Shapiro-Wilk normality test
##
## data:  CB$RSMETotalAvg
## W = 0.91534, p-value = 0.001426
```

P-value < .05, cannot assume normality

Correlation BUS-11 and RSME

```
Correlation <-cor.test(CB$BusTotalAvg, CB$RSMETotalAvg,  method = "spearma
n", exact=FALSE)
Correlation

##
##  Spearman's rank correlation rho
##
## data:  CB$BusTotalAvg and CB$RSMETotalAvg
## S = 13714, p-value = 0.006031
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##       rho
## 0.3794406
```

Factor correlations RSME F1

```
CRF1 <-cor.test(CB$F1,CB$RSMETotalAvg,  method = "spearman", exact=FALSE)
CRF1

##
##  Spearman's rank correlation rho
##
## data:  CB$F1 and CB$RSMETotalAvg
## S = 13563, p-value = 0.005111
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##       rho
## 0.3863057
```

F2

```
CRF2 <-cor.test(CB$F2,CB$RSMETotalAvg,  method = "spearman", exact=FALSE)
CRF2

##
##  Spearman's rank correlation rho
##
## data:  CB$F2 and CB$RSMETotalAvg
## S = 12433, p-value = 0.001329
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##       rho
## 0.4374082
```

F3

```
CRF3 <-cor.test(CB$F3,CB$RSMETotalAvg,  method = "spearman", exact=FALSE)
CRF3

##
##  Spearman's rank correlation rho
##
## data:  CB$F3 and CB$RSMETotalAvg
## S = 16233, p-value = 0.05974
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##       rho
## 0.2654637
```

F4

```
CRF4 <-cor.test(CB$F4,CB$RSMETotalAvg,  method = "spearman", exact=FALSE)
CRF4

##
##  Spearman's rank correlation rho
##
## data:  CB$F4 and CB$RSMETotalAvg
## S = 26705, p-value = 0.1423
## alternative hypothesis: true rho is not equal to 0
## sample estimates:
##        rho
## -0.2083502
```

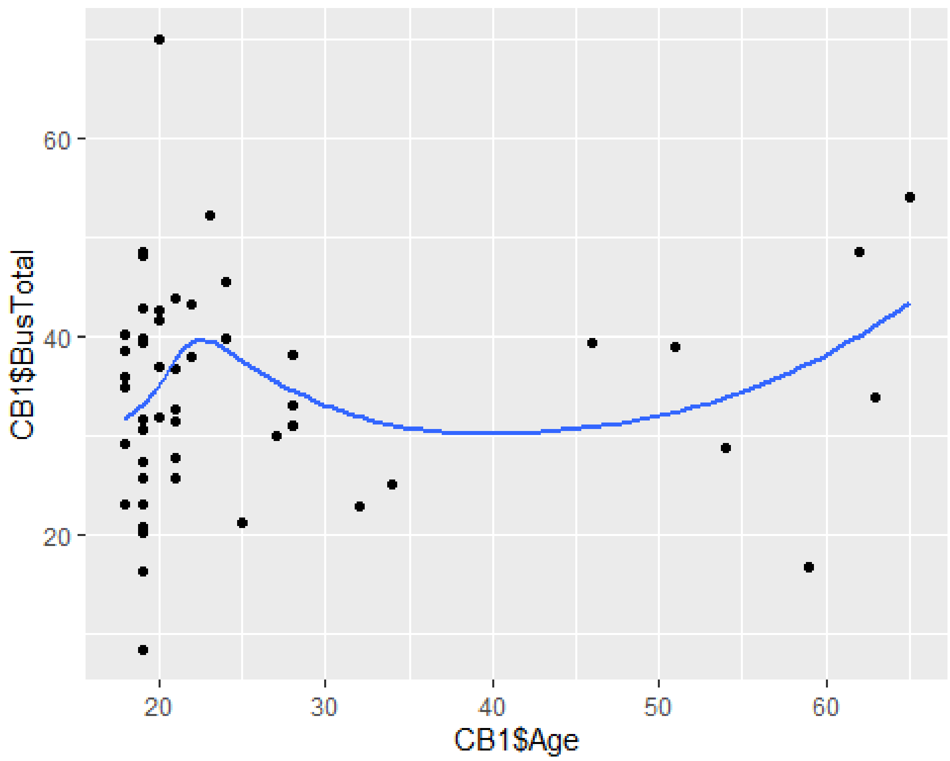
F5

```
CRF5 <-cor.test(CB$F5,CB$RSMETotalAvg,  method = "spearman", exact=FALSE)
CRF5

##
##  Spearman's rank correlation rho
##
## data:  CB$F5 and CB$RSMETotalAvg
## S = 11184, p-value = 0.0002302
## alternative hypothesis: true rho is not equal to 0
```

```
## sample estimates:
##       rho
## 0.4939145
```

New Statistics Age

```
CB1 <- read.delim(file.choose("DataChatbot.txt"))

view(CB1)

attach(CB1)
CB1 %>%
  ggplot(aes(x = CB1$Age, y = CB1$BusTotal)) +
  geom_point() +
  geom_smooth(se = F, fullrange = F)

## Warning: Use of `CB1$Age` is discouraged. Use `Age` instead.

## Warning: Use of `CB1$BusTotal` is discouraged. Use `BusTotal` instead.

## Warning: Use of `CB1$Age` is discouraged. Use `Age` instead.

## Warning: Use of `CB1$BusTotal` is discouraged. Use `BusTotal` instead.

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

## Warning: Removed 2 rows containing non-finite values (stat_smooth).

## Warning: Removed 2 rows containing missing values (geom_point).
```




```
M_age <-
  CB1 %>%
  stan_glm(CB$BusTotal ~ 1 + CB1$Age,
```

```
          data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.071 seconds (Warm-up)
## Chain 1:                0.052 seconds (Sampling)
## Chain 1:                0.123 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.062 seconds (Warm-up)
## Chain 2:                0.061 seconds (Sampling)
## Chain 2:                0.123 seconds (Total)
```

```
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.058 seconds (Warm-up)
## Chain 3:                0.053 seconds (Sampling)
## Chain 3:                0.111 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.057 seconds (Warm-up)
## Chain 4:                0.054 seconds (Sampling)
## Chain 4:                0.111 seconds (Total)
## Chain 4:
```

```
coef(M_age)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	32.6793320	25.7505689	39.1453583
CB1$Age \mid CB1$Age	0.0723048	-0.1580002	0.3054993	

```
M_age1 <-
  CB1 %>%
  stan_glm(CB1$F1 ~ 1 + CB1$Age,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.069 seconds (Warm-up)
## Chain 1:                0.045 seconds (Sampling)
## Chain 1:                0.114 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
```

```
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.06 seconds (Warm-up)
## Chain 2:                0.064 seconds (Sampling)
## Chain 2:                0.124 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.065 seconds (Warm-up)
## Chain 3:                0.049 seconds (Sampling)
## Chain 3:                0.114 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
```

```
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.087 seconds (Warm-up)
## Chain 4:                0.053 seconds (Sampling)
## Chain 4:                0.14 seconds (Total)
## Chain 4:
```

```
coef(M_age1)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	27.5425441	17.7984087	36.8762239
CB1$Age|CB1$Age	-0.0031977	-0.3381434	0.3418797	

```
M_age1 <-
  CB1 %>%
  stan_glm(CB1$F1 ~ 1 + CB1$Age,
           data = .
  )
```

```
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.059 seconds (Warm-up)
## Chain 1:                0.055 seconds (Sampling)
## Chain 1:                0.114 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
```

```
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.071 seconds (Warm-up)
## Chain 2:                0.049 seconds (Sampling)
## Chain 2:                0.12 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.061 seconds (Warm-up)
## Chain 3:                0.052 seconds (Sampling)
## Chain 3:                0.113 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
```

```
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.067 seconds (Warm-up)
## Chain 4:                0.049 seconds (Sampling)
## Chain 4:                0.116 seconds (Total)
## Chain 4:

coef(M_age1)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	27.3626899	17.5989373	37.284368
CB1$Age|CB1$Age	-0.0051065	-0.3439562	0.331597	

```
M_age2 <-
  CB1 %>%
  stan_glm(CB1$F2 ~ 1 + CB1$Age,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
```

```
## Chain 1:
## Chain 1:  Elapsed Time: 0.059 seconds (Warm-up)
## Chain 1:                0.061 seconds (Sampling)
## Chain 1:                0.12 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.055 seconds (Warm-up)
## Chain 2:                0.052 seconds (Sampling)
## Chain 2:                0.107 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.064 seconds (Warm-up)
```

```
## Chain 3:                0.054 seconds (Sampling)
## Chain 3:                0.118 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.06 seconds (Warm-up)
## Chain 4:                0.05 seconds (Sampling)
## Chain 4:                0.11 seconds (Total)
## Chain 4:

coef(M_age2)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	32.1276283	24.2357212	39.6289409
CB1$Age|CB$1Age	0.0256478	-0.2375108	0.2915455	

```
M_age3 <-
  CB1 %>%
  stan_glm(CB1$F3 ~ 1 + CB1$Age,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
```

```
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.075 seconds (Warm-up)
## Chain 1:                0.065 seconds (Sampling)
## Chain 1:                0.14 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.076 seconds (Warm-up)
## Chain 2:                0.063 seconds (Sampling)
## Chain 2:                0.139 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
```

```
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.054 seconds (Warm-up)
## Chain 3:                0.07 seconds (Sampling)
## Chain 3:                0.124 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.074 seconds (Warm-up)
## Chain 4:                0.066 seconds (Sampling)
## Chain 4:                0.14 seconds (Total)
## Chain 4:

coef(M_age3)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	35.1808491	27.9927887	42.8754321
CB1$Age|CB$1Age	0.0800321	-0.1737361	0.3332178	

```
M_age4 <-
  CB1 %>%
  stan_glm(CB1$F4 ~ 1 + CB1$Age,
           data = .
  )
```

```
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.074 seconds (Warm-up)
## Chain 1:                0.044 seconds (Sampling)
## Chain 1:                0.118 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.07 seconds (Warm-up)
## Chain 2:                0.051 seconds (Sampling)
## Chain 2:                0.121 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
```

```
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.075 seconds (Warm-up)
## Chain 3:                0.07 seconds (Sampling)
## Chain 3:                0.145 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.059 seconds (Warm-up)
## Chain 4:                0.053 seconds (Sampling)
## Chain 4:                0.112 seconds (Total)
## Chain 4:
```

```
coef(M_age4)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	43.4285329	32.8799874	54.3987637
CB1$Age|CB$1Age	0.3636455	-0.0012326	0.7233473	

```
M_age5 <-
  CB1 %>%
  stan_glm(CB1$F5 ~ 1 + CB1$Age,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.069 seconds (Warm-up)
## Chain 1:                0.055 seconds (Sampling)
## Chain 1:                0.124 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
```

```
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.063 seconds (Warm-up)
## Chain 2:                0.039 seconds (Sampling)
## Chain 2:                0.102 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.062 seconds (Warm-up)
## Chain 3:                0.051 seconds (Sampling)
## Chain 3:                0.113 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
```

```
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.076 seconds (Warm-up)
## Chain 4:                0.049 seconds (Sampling)
## Chain 4:                0.125 seconds (Total)
## Chain 4:

coef(M_age5)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	26.0355074	14.9571736	36.8771187
CB1$Age|CB$1Age	-0.0217506	-0.3895034	0.3598399	

```
M_exp <-
  CB1 %>%
  stan_glm(CB1$BusTotalAvg ~ 1 + CB1$Exp,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.072 seconds (Warm-up)
## Chain 1:                0.057 seconds (Sampling)
## Chain 1:                0.129 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
```

```
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.082 seconds (Warm-up)
## Chain 2:                0.064 seconds (Sampling)
## Chain 2:                0.146 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.066 seconds (Warm-up)
## Chain 3:                0.051 seconds (Sampling)
## Chain 3:                0.117 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
```

```
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.057 seconds (Warm-up)
## Chain 4:                0.062 seconds (Sampling)
## Chain 4:                0.119 seconds (Total)
## Chain 4:

coef(M_exp)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	29.9790627	24.6083246	35.4181793
CB1$Exp|CB$1Exp	0.1554747	0.0054151	0.2987254	

```
M_exp2 <-
  CB1 %>%
  stan_glm(CB1$F2 ~ 1 + CB1$Exp,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
```

```
## Chain 1:  Elapsed Time: 0.079 seconds (Warm-up)
## Chain 1:                0.052 seconds (Sampling)
## Chain 1:                0.131 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.063 seconds (Warm-up)
## Chain 2:                0.046 seconds (Sampling)
## Chain 2:                0.109 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.065 seconds (Warm-up)
## Chain 3:                0.053 seconds (Sampling)
```

```
## Chain 3:                0.118 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.055 seconds (Warm-up)
## Chain 4:                0.046 seconds (Sampling)
## Chain 4:                0.101 seconds (Total)
## Chain 4:

coef(M_exp2)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	27.8585783	21.9587554	33.4364174
CB1$Exp|CB$1Exp	0.1614583	0.0020332	0.3287414	

```
M_exp3 <-
  CB1 %>%
  stan_glm(CB1$F3 ~ 1 + CB1$Exp,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
```

```
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.07 seconds (Warm-up)
## Chain 1:                0.054 seconds (Sampling)
## Chain 1:                0.124 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.06 seconds (Warm-up)
## Chain 2:                0.047 seconds (Sampling)
## Chain 2:                0.107 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
```

```
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.064 seconds (Warm-up)
## Chain 3:                0.06 seconds (Sampling)
## Chain 3:                0.124 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.061 seconds (Warm-up)
## Chain 4:                0.051 seconds (Sampling)
## Chain 4:                0.112 seconds (Total)
## Chain 4:

coef(M_exp3)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	33.8243148	27.9766169	39.8020205
CB1$Exp|CB$1Exp	0.1179594	-0.0431749	0.2887227	

```
M_exp4 <-
  CB1 %>%
  stan_glm(CB1$F4 ~ 1 + CB1$Exp,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
```

```
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.067 seconds (Warm-up)
## Chain 1:                0.057 seconds (Sampling)
## Chain 1:                0.124 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.067 seconds (Warm-up)
## Chain 2:                0.047 seconds (Sampling)
## Chain 2:                0.114 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
```

```
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.07 seconds (Warm-up)
## Chain 3:                0.061 seconds (Sampling)
## Chain 3:                0.131 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.074 seconds (Warm-up)
## Chain 4:                0.049 seconds (Sampling)
## Chain 4:                0.123 seconds (Total)
## Chain 4:

coef(M_exp4)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper

Intercept	Intercept	55.078966	46.4804043	63.9523246
CB1$Exp|CB$1Exp	-0.077555	-0.3171781	0.1571298	

```
M_exp5 <-
  CB1 %>%
  stan_glm(CB1$F5 ~ 1 + CB1$Exp,
           data = .
  )
```

```
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.074 seconds (Warm-up)
## Chain 1:                0.056 seconds (Sampling)
## Chain 1:                0.13 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
```

```
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.058 seconds (Warm-up)
## Chain 2:                0.049 seconds (Sampling)
## Chain 2:                0.107 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.07 seconds (Warm-up)
## Chain 3:                0.051 seconds (Sampling)
## Chain 3:                0.121 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
```

```
## Chain 4:
## Chain 4:  Elapsed Time: 0.066 seconds (Warm-up)
## Chain 4:                0.051 seconds (Sampling)
## Chain 4:                0.117 seconds (Total)
## Chain 4:

coef(M_exp5)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	15.9097318	7.6714017	23.7491094
CB1$Exp|CB$1Exp	0.3240936	0.1004124	0.5372053	

```
M_UMUX <-
  CB1 %>%
  stan_glm(CB1$F1 ~ 1 + CB1$UMUXTotalAvg,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.067 seconds (Warm-up)
## Chain 1:                0.058 seconds (Sampling)
## Chain 1:                0.125 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
```

```
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.072 seconds (Warm-up)
## Chain 2:                0.05 seconds (Sampling)
## Chain 2:                0.122 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.072 seconds (Warm-up)
## Chain 3:                0.063 seconds (Sampling)
## Chain 3:                0.135 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
```

```
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.054 seconds (Warm-up)
## Chain 4:                0.059 seconds (Sampling)
## Chain 4:                0.113 seconds (Total)
## Chain 4:

coef(M_UMUX)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	7.1698992	-1.6975776	16.4840952
CB1$UMUXTotalAvg|CB$1UMUXTotalAvg	0.6045978	0.3544238	0.8521507	

```
M_UMUX <-
  CB1 %>%
  stan_glm(CB1$F2 ~ 1 + CB1$UMUXTotalAvg,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.063 seconds (Warm-up)
## Chain 1:                0.052 seconds (Sampling)
## Chain 1:                0.115 seconds (Total)
```

```
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.071 seconds (Warm-up)
## Chain 2:                0.071 seconds (Sampling)
## Chain 2:                0.142 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.059 seconds (Warm-up)
## Chain 3:                0.045 seconds (Sampling)
## Chain 3:                0.104 seconds (Total)
## Chain 3:
##
```

```
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.07 seconds (Warm-up)
## Chain 4:                0.056 seconds (Sampling)
## Chain 4:                0.126 seconds (Total)
## Chain 4:

coef(M_UMUX)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	11.0167944	5.2266772	16.5815069
CB1$UMUXTotalAvg$|CB1UMUXTotalAvg	0.6486236	0.4920718	0.8083279	

```
M_UMUX <-
  CB1 %>%
  stan_glm(CB1$F3 ~ 1 + CB1$UMUXTotalAvg,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
```

```
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.069 seconds (Warm-up)
## Chain 1:                0.071 seconds (Sampling)
## Chain 1:                0.14 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.06 seconds (Warm-up)
## Chain 2:                0.066 seconds (Sampling)
## Chain 2:                0.126 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
```

```
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.064 seconds (Warm-up)
## Chain 3:                0.07 seconds (Sampling)
## Chain 3:                0.134 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.062 seconds (Warm-up)
## Chain 4:                0.063 seconds (Sampling)
## Chain 4:                0.125 seconds (Total)
## Chain 4:

coef(M_UMUX)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	16.1713174	10.8037176	21.7788102
CB1$UMUXTotalAvg|CB$1UMUXTotalAvg	0.6352119	0.4808756	0.7782011	

```
M_UMUX <-
  CB1 %>%
  stan_glm(CB1$F4 ~ 1 + CB1$UMUXTotalAvg,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
```

```
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.063 seconds (Warm-up)
## Chain 1:                0.059 seconds (Sampling)
## Chain 1:                0.122 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.059 seconds (Warm-up)
## Chain 2:                0.051 seconds (Sampling)
## Chain 2:                0.11 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
```

```
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.067 seconds (Warm-up)
## Chain 3:                0.059 seconds (Sampling)
## Chain 3:                0.126 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.066 seconds (Warm-up)
## Chain 4:                0.06 seconds (Sampling)
## Chain 4:                0.126 seconds (Total)
## Chain 4:

coef(M_UMUX)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	41.4071743	28.9005304	53.8747527
CB1$UMUXTotalAvg|CB$1UMUXTotalAvg	0.3419685	0.0032539	0.6863977	

```
M_UMUX <-
  CB1 %>%
  stan_glm(CB1$F5 ~ 1 + CB1$UMUXTotalAvg,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.066 seconds (Warm-up)
## Chain 1:                0.058 seconds (Sampling)
## Chain 1:                0.124 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
```

```
## Chain 2:  Elapsed Time: 0.059 seconds (Warm-up)
## Chain 2:                0.06 seconds (Sampling)
## Chain 2:                0.119 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.058 seconds (Warm-up)
## Chain 3:                0.058 seconds (Sampling)
## Chain 3:                0.116 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.058 seconds (Warm-up)
## Chain 4:                0.058 seconds (Sampling)
```

```
## Chain 4:                0.116 seconds (Total)
## Chain 4:

coef(M_UMUX)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	-0.2495549	-9.4366024	9.396835
CB1$UMUXTotalAvg\|CB1$UMUXTotalAvg	0.7697089	0.5145791	1.029503	

```
view(CB1)

M_RSME <-
  CB1 %>%
  stan_glm(CB1$BusTotal ~ 1 + CB1$RSMETotalAvg,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.065 seconds (Warm-up)
## Chain 1:                0.055 seconds (Sampling)
## Chain 1:                0.12 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
```

```
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2: 
## Chain 2:  Elapsed Time: 0.06 seconds (Warm-up)
## Chain 2:                0.072 seconds (Sampling)
## Chain 2:                0.132 seconds (Total)
## Chain 2: 
## 
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3: 
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3: 
## Chain 3: 
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3: 
## Chain 3:  Elapsed Time: 0.07 seconds (Warm-up)
## Chain 3:                0.051 seconds (Sampling)
## Chain 3:                0.121 seconds (Total)
## Chain 3: 
## 
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4: 
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4: 
## Chain 4: 
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
```

```
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.069 seconds (Warm-up)
## Chain 4:                0.069 seconds (Sampling)
## Chain 4:                0.138 seconds (Total)
## Chain 4:

coef(M_RSME)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	29.3845506	23.8186557	34.931340
CB1$RSMETotalAvg \vert CB$1RSMETotalAvg	0.1816276	0.0087246	0.341818	

```
M_RSME <-
  CB1 %>%
  stan_glm(CB1$F1 ~ 1 + CB1$RSMETotalAvg,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.062 seconds (Warm-up)
## Chain 1:                0.06 seconds (Sampling)
## Chain 1:                0.122 seconds (Total)
## Chain 1:
```

```
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.059 seconds (Warm-up)
## Chain 2:                0.05 seconds (Sampling)
## Chain 2:                0.109 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.066 seconds (Warm-up)
## Chain 3:                0.054 seconds (Sampling)
## Chain 3:                0.12 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
```

```
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.063 seconds (Warm-up)
## Chain 4:                0.05 seconds (Sampling)
## Chain 4:                0.113 seconds (Total)
## Chain 4:

coef(M_RSME)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	18.0179593	10.7211433	25.4807109
CB1$RSMETotalAvg|CB$1RSMETotalAvg	0.3235235	0.1038507	0.5434223	

```
M_RSME <-
  CB1 %>%
  stan_glm(CB1$F2 ~ 1 + CB1$RSMETotalAvg,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
```

```
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.061 seconds (Warm-up)
## Chain 1:                0.052 seconds (Sampling)
## Chain 1:                0.113 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.056 seconds (Warm-up)
## Chain 2:                0.055 seconds (Sampling)
## Chain 2:                0.111 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
```

```
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.067 seconds (Warm-up)
## Chain 3:                0.054 seconds (Sampling)
## Chain 3:                0.121 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.068 seconds (Warm-up)
## Chain 4:                0.049 seconds (Sampling)
## Chain 4:                0.117 seconds (Total)
## Chain 4:

coef(M_RSME)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	26.0273777	20.0237030	31.9204349
CB1$RSMETotalAvg|CB$1RSMETotalAvg	0.2299411	0.0605426	0.4061207	

```
M_RSME <-
  CB1 %>%
  stan_glm(CB1$F3 ~ 1 + CB1$RSMETotalAvg,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
```

```
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.064 seconds (Warm-up)
## Chain 1:                0.055 seconds (Sampling)
## Chain 1:                0.119 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.06 seconds (Warm-up)
## Chain 2:                0.06 seconds (Sampling)
## Chain 2:                0.12 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
```

```
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.058 seconds (Warm-up)
## Chain 3:                0.059 seconds (Sampling)
## Chain 3:                0.117 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.069 seconds (Warm-up)
## Chain 4:                0.054 seconds (Sampling)
## Chain 4:                0.123 seconds (Total)
## Chain 4:

coef(M_RSME)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	33.9213079	27.8244434	39.8345040
CB1$RSMETotalAvg|CB$1RSMETotalAvg	0.1225209	-0.0602178	0.2967104	

```
M_RSME <-
  CB1 %>%
```

```
  stan_glm(CB1$F4 ~ 1 + CB1$RSMETotalAvg,
           data = .
  )
```

```
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.072 seconds (Warm-up)
## Chain 1:                0.062 seconds (Sampling)
## Chain 1:                0.134 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.062 seconds (Warm-up)
## Chain 2:                0.052 seconds (Sampling)
```

```
## Chain 2:                0.114 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.07 seconds (Warm-up)
## Chain 3:                0.059 seconds (Sampling)
## Chain 3:                0.129 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.059 seconds (Warm-up)
## Chain 4:                0.049 seconds (Sampling)
## Chain 4:                0.108 seconds (Total)
## Chain 4:
```

```
coef(M_RSME)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	61.1347798	52.3856482	69.3886103
CB1$RSMETotalAvg|CB$1RSMETotalAvg	-0.2850945	-0.5428103	-0.0244991	

```
M_RSME <-
  CB1 %>%
  stan_glm(CB1$F5 ~ 1 + CB1$RSMETotalAvg,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.072 seconds (Warm-up)
## Chain 1:                0.055 seconds (Sampling)
## Chain 1:                0.127 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
```

```
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.059 seconds (Warm-up)
## Chain 2:                0.054 seconds (Sampling)
## Chain 2:                0.113 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.062 seconds (Warm-up)
## Chain 3:                0.053 seconds (Sampling)
## Chain 3:                0.115 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
```

```
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.057 seconds (Warm-up)
## Chain 4:                0.048 seconds (Sampling)
## Chain 4:                0.105 seconds (Total)
## Chain 4:

coef(M_RSME)
```

Coefficient estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	12.6800578	4.842002	20.6468783
CB1$RSMETotalAvg|CB$1RSMETotalAvg	0.4455139	0.214850	0.6810278	

```
M_Exp <-
  CB1 %>%
  stan_glm(CB$BusTotal ~ 1 + CB1$Exp,
           data = .
  )

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.065 seconds (Warm-up)
## Chain 1:                0.055 seconds (Sampling)
## Chain 1:                0.12 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
```

```
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.065 seconds (Warm-up)
## Chain 2:                0.058 seconds (Sampling)
## Chain 2:                0.123 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.06 seconds (Warm-up)
## Chain 3:                0.053 seconds (Sampling)
## Chain 3:                0.113 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
```

```
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.055 seconds (Warm-up)
## Chain 4:                0.048 seconds (Sampling)
## Chain 4:                0.103 seconds (Total)
## Chain 4:

clu(M_Exp)
```

Parameter estimates with 95% credibility limits

parameter	fixef	center	lower	upper
Intercept	Intercept	30.0217756	24.8722490	35.3657939
CB1$Exp|CB$1Exp	0.1532088	0.0076253	0.3011725	
sigma_resid	NA	10.7033462	8.9261857	13.3401779

With every year of age, users get 0.07 seconds slower

```
CB1 <-
  CB1 %>%
  mutate(Age_shft = CB1$Age - 18, Age_cntr = CB1$Age - mean(CB1$Age)
  )

M_age_shft <-
  stan_glm(CB1$BusTotal ~ 1 + CB1$Age_shft, data = CB1)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
```

```
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.06 seconds (Warm-up)
## Chain 1:                0.061 seconds (Sampling)
## Chain 1:                0.121 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.067 seconds (Warm-up)
## Chain 2:                0.051 seconds (Sampling)
## Chain 2:                0.118 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
```

```
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.056 seconds (Warm-up)
## Chain 3:                0.054 seconds (Sampling)
## Chain 3:                0.11 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.048 seconds (Warm-up)
## Chain 4:                0.065 seconds (Sampling)
## Chain 4:                0.113 seconds (Total)
## Chain 4:

M_age_cntr <-
  stan_glm(CB1$BusTotal ~ 1 + CB1$Age_cntr, data = CB1)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
```

```
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.05 seconds (Warm-up)
## Chain 1:                0.055 seconds (Sampling)
## Chain 1:                0.105 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.061 seconds (Warm-up)
## Chain 2:                0.051 seconds (Sampling)
## Chain 2:                0.112 seconds (Total)
## Chain 2:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
```

```
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.053 seconds (Warm-up)
## Chain 3:                0.053 seconds (Sampling)
## Chain 3:                0.106 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.062 seconds (Warm-up)
## Chain 4:                0.054 seconds (Sampling)
## Chain 4:                0.116 seconds (Total)
## Chain 4:
```

```
P_age <-
  bind_rows(
    posterior(M_age),
    posterior(M_age_shft),
    posterior(M_age_cntr)
  )
coef(P_age)
```

Coefficient estimates with 95% credibility limits

model	parameter	fixef	center	lower	upper
M_age	Intercept	Intercept	32.6793320	25.7505689	39.1453583
M_age	CB1$Age|CB$1Age	0.0723048	-0.1580002	0.3054993	
M_age_cntr	Intercept	Intercept	34.4906451	31.4653364	37.4487349
M_age_cntr	CB1$Age_cntr|CB$1Age_cntr	0.0708467	-0.1696452	0.3103154	
M_age_shft	Intercept	Intercept	33.9509461	30.3704178	37.6062122

M_age_shft CB1$Age_shft|CB$1Age_shft 0.0731514 -0.1724563 0.3039718

Split half reliability of the BUS-11 ###ext.vars <- data.frame(CB1$Q1, CB$1Q2,

CB1$Q3, CB$1Q4, CB1$Q5, CB$1Q6, CB1$Q7, CB$1Q8, CB1$Q9, CB$1Q10, CB1$Q11)

head(ext.vars) item_split_half(ext.vars)###

Correlations of items ### res <- cor(ext.vars, use = "complete.obs") round(res, 2)###

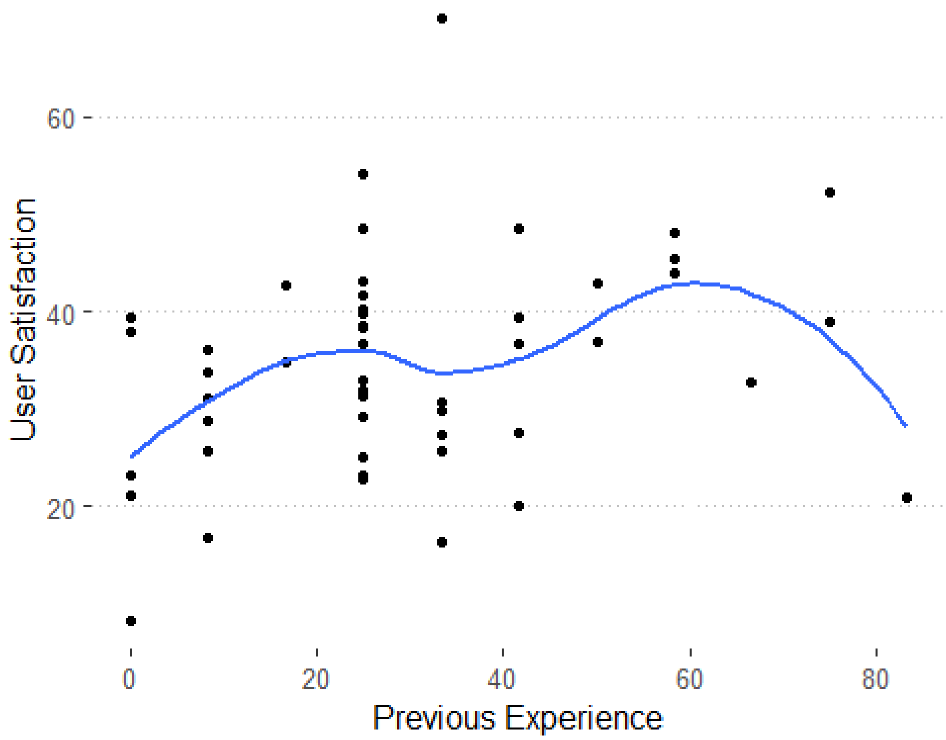
corrplot(res, type = "upper", tl.col = "black", tl.srt = 45) ### Experience

```
theme_set(theme_pubclean())

attach(CB1)

## The following objects are masked from CB1 (pos = 3):
##
##     Age, BUS.11_ABN_1, BUS.11_ABN_10, BUS.11_ABN_11, BUS.11_ABN_2,
##     BUS.11_ABN_3, BUS.11_ABN_4, BUS.11_ABN_5, BUS.11_ABN_6,
##     BUS.11_ABN_7, BUS.11_ABN_8, BUS.11_ABN_9, BUS.11_AH_1,
##     BUS.11_AH_10, BUS.11_AH_11, BUS.11_AH_2, BUS.11_AH_3, BUS.11_AH_4,
##     BUS.11_AH_5, BUS.11_AH_6, BUS.11_AH_7, BUS.11_AH_8, BUS.11_AH_9,
##     BUS.11_CB_1, BUS.11_CB_10, BUS.11_CB_11, BUS.11_CB_2, BUS.11_CB_3,
##     BUS.11_CB_4, BUS.11_CB_5, BUS.11_CB_6, BUS.11_CB_7, BUS.11_CB_8,
##     BUS.11_CB_9, BUS.11_DHL_1, BUS.11_DHL_10, BUS.11_DHL_11,
##     BUS.11_DHL_2, BUS.11_DHL_3, BUS.11_DHL_4, BUS.11_DHL_5,
##     BUS.11_DHL_6, BUS.11_DHL_7, BUS.11_DHL_8, BUS.11_DHL_9,
##     BUS.11_Engie_1, BUS.11_Engie_10, BUS.11_Engie_11, BUS.11_Engie_2,
##     BUS.11_Engie_3, BUS.11_Engie_4, BUS.11_Engie_5, BUS.11_Engie_6,
##     BUS.11_Engie_7, BUS.11_Engie_8, BUS.11_Engie_9, BUS.11_Essent_1,
##     BUS.11_Essent_10, BUS.11_Essent_11, BUS.11_Essent_2,
##     BUS.11_Essent_3, BUS.11_Essent_4, BUS.11_Essent_5, BUS.11_Essent_6,
##     BUS.11_Essent_7, BUS.11_Essent_8, BUS.11_Essent_9, BUS.11_FBTO_1,
##     BUS.11_FBTO_10, BUS.11_FBTO_11, BUS.11_FBTO_2, BUS.11_FBTO_3,
##     BUS.11_FBTO_4, BUS.11_FBTO_5, BUS.11_FBTO_6, BUS.11_FBTO_7,
##     BUS.11_FBTO_8, BUS.11_FBTO_9, BUS.11_Ikea_1, BUS.11_Ikea_10,
##     BUS.11_Ikea_11, BUS.11_Ikea_2, BUS.11_Ikea_3, BUS.11_Ikea_4,
##     BUS.11_Ikea_5, BUS.11_Ikea_6, BUS.11_Ikea_7, BUS.11_Ikea_8,
##     BUS.11_Ikea_9, BUS.11_Rabo_1, BUS.11_Rabo_10, BUS.11_Rabo_11,
##     BUS.11_Rabo_2, BUS.11_Rabo_3, BUS.11_Rabo_4, BUS.11_Rabo_5,
##     BUS.11_Rabo_6, BUS.11_Rabo_7, BUS.11_Rabo_8, BUS.11_Rabo_9,
##     BUS.11_Reaal_1, BUS.11_Reaal_10, BUS.11_Reaal_11, BUS.11_Reaal_2,
##     BUS.11_Reaal_3, BUS.11_Reaal_4, BUS.11_Reaal_5, BUS.11_Reaal_6,
##     BUS.11_Reaal_7, BUS.11_Reaal_8, BUS.11_Reaal_9, BUS.11_TUI_1,
##     BUS.11_TUI_10, BUS.11_TUI_11, BUS.11_TUI_2, BUS.11_TUI_3,
##     BUS.11_TUI_4, BUS.11_TUI_5, BUS.11_TUI_6, BUS.11_TUI_7,
##     BUS.11_TUI_8, BUS.11_TUI_9, BUS.11_Univé_1, BUS.11_Univé_10,
##     BUS.11_Univé_11, BUS.11_Univé_2, BUS.11_Univé_3, BUS.11_Univé_4,
##     BUS.11_Univé_5, BUS.11_Univé_6, BUS.11_Univé_7, BUS.11_Univé_8,
##     BUS.11_Univé_9, BusABNAvg, BusAHAvg, BusCBAvg, BusDHLAvg,
##     BusEngieAvg, BusEssentAvg, BusFBTOAvg, BusIkeaAvg, BusRaboAvg,
##     BusReaalAvg, BusTotalAvg, BusTUIAvg, BusUniAvg, D2, D3, D3_3_TEXT,
```

```
##     E1_1, E1_2, E1_3, E2_1, Experience, F1, F2, F3, F4, F5, Finished,
##     Informed_consent, Part, Progress, Q1, Q10, Q11, Q2, Q3, Q4, Q5, Q6,
##     Q7, Q8, Q9, RSME_ABN_1, RSME_AH_1, RSME_CB_1, RSME_DHL_1,
##     RSME_Engie_1, RSME_Essent_1, RSME_FBTO_1, RSME_Ikea_1, RSME_Rabo_1,
##     RSME_Reaal_1, RSME_TUI_1, RSME_Univé_1, RSMETotalAvg, Succes_Reaal,
##     Succes_Reaal_2_TEXT, Success_ABN, Success_ABN_2_TEXT, Success_AH,
##     Success_AH_2_TEXT, Success_CB, Success_CB_2_TEXT, Success_DHL,
##     Success_DHL_2_TEXT, Success_Engie, Success_Engie_2_TEXT,
##     Success_Essent, Success_Essent_2_TEXT, Success_FBTO,
##     Success_FBTO_2_TEXT, Success_Ikea, Success_Ikea_2_TEXT,
##     Success_Rabo, Success_Rabo_2_TEXT, Success_TUI, Success_TUI_2_TEXT,
##     Success_Univé, Success_Univé_2_TEXT, UMUX.Lite_ABN_1,
##     UMUX.Lite_ABN_2, UMUX.Lite_AH_1, UMUX.Lite_AH_2, UMUX.Lite_CB_1,
##     UMUX.Lite_CB_2, UMUX.Lite_DHL_1, UMUX.Lite_DHL_2,
##     UMUX.Lite_Engie_1, UMUX.Lite_Engie_2, UMUX.Lite_Essent_1,
##     UMUX.Lite_Essent_2, UMUX.Lite_FBTO_1, UMUX.Lite_FBTO_2,
##     UMUX.Lite_Ikea_1, UMUX.Lite_Ikea_2, UMUX.Lite_Rabo_1,
##     UMUX.Lite_Rabo_2, UMUX.Lite_Reaal_1, UMUX.Lite_Reaal_2,
##     UMUX.Lite_TUI_1, UMUX.Lite_TUI_2, UMUX.Lite_Univé_1,
##     UMUX.Lite_Univé_2, UMUXABNAvg, UMUXAHAvg, UMUXCBAvg, UMUXDHLAvg,
##     UMUXEngieAvg, UMUXEssentAvg, UMUXFBTOAvg, UMUXIkeaAvg, UMUXRaboAvg,
##     UMUXReaalAvg, UMUXTotalAvg, UMUXTUIAvg, UMUXUniAvg, UserLanguage
```

```
CB1 %>%
  ggplot(aes(x = CB1$Exp, y = CB1$BusTotal)) +
  geom_point() +
  geom_smooth(se = F, fullrange = F) +
  labs(x="Previous Experience",
       y="User Satisfaction")
```

```
## Warning: Use of `CB1$Exp` is discouraged. Use `Exp` instead.

## Warning: Use of `CB1$BusTotal` is discouraged. Use `BusTotal` instead.

## Warning: Use of `CB1$Exp` is discouraged. Use `Exp` instead.

## Warning: Use of `CB1$BusTotal` is discouraged. Use `BusTotal` instead.

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

## Warning: Removed 2 rows containing non-finite values (stat_smooth).

## Warning: Removed 2 rows containing missing values (geom_point).
```




```
cor(CB$Exp, CB$BusTotal, use = "complete.obs")

## [1] 0.2843304

model <- lm(CB$BusTotal ~ CB$Exp, data = CB1)
model

##
## Call:
## lm(formula = CB$BusTotal ~ CB$Exp, data = CB1)
##
## Coefficients:
## (Intercept)       CB$Exp
##     29.9609       0.1548

CorExp <- cor.test(CB1$Exp, CB1$BusTotal,
                    method = "pearson")
CorExp

##
##  Pearson's product-moment correlation
##
## data:  CB1$Exp and CB1$BusTotal
## t = 2.076, df = 49, p-value = 0.04316
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.009490408 0.519228977
## sample estimates:
##       cor
## 0.2843304

CB2 <- read.delim(file.choose("DataChatbotClean2.txt"))
```

```
M_cor <- stan_glm(CB2$BusTotal ~ CB2$Exp, data = CB1)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.128 seconds (Warm-up)
## Chain 1:                0.107 seconds (Sampling)
## Chain 1:                0.235 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2:
## Chain 2:  Elapsed Time: 0.07 seconds (Warm-up)
## Chain 2:                0.075 seconds (Sampling)
## Chain 2:                0.145 seconds (Total)
## Chain 2:
```

```
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3:
## Chain 3:  Elapsed Time: 0.073 seconds (Warm-up)
## Chain 3:                0.054 seconds (Sampling)
## Chain 3:                0.127 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4:
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4:
## Chain 4:  Elapsed Time: 0.063 seconds (Warm-up)
## Chain 4:                0.07 seconds (Sampling)
## Chain 4:                0.133 seconds (Total)
## Chain 4:
```

```
beta_1 <- coef(M_cor)$center[2]
r <- beta_1 * sd(CB2$Exp) / sd(CB2$BusTotal)
cat("the correlation is: ", r)

## the correlation is:  0.2593111

M_cor <- stan_glm(CB2$BusTotal ~ CB2$D1, data = CB1)

##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 1: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 1: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 1: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 1: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 1: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 1: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 1: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 1:
## Chain 1:  Elapsed Time: 0.074 seconds (Warm-up)
## Chain 1:                0.056 seconds (Sampling)
## Chain 1:                0.13 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 2: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 2: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 2: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 2: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 2: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]  (Sampling)
```

```
## Chain 2: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 2: 
## Chain 2:  Elapsed Time: 0.088 seconds (Warm-up)
## Chain 2:                0.062 seconds (Sampling)
## Chain 2:                0.15 seconds (Total)
## Chain 2: 
## 
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 3).
## Chain 3: 
## Chain 3: Gradient evaluation took 0 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3: 
## Chain 3: 
## Chain 3: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 3: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 3: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 3: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 3: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 3: 
## Chain 3:  Elapsed Time: 0.07 seconds (Warm-up)
## Chain 3:                0.057 seconds (Sampling)
## Chain 3:                0.127 seconds (Total)
## Chain 3: 
## 
## SAMPLING FOR MODEL 'continuous' NOW (CHAIN 4).
## Chain 4: 
## Chain 4: Gradient evaluation took 0 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would
take 0 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4: 
## Chain 4: 
## Chain 4: Iteration:    1 / 2000 [  0%]  (Warmup)
## Chain 4: Iteration:  200 / 2000 [ 10%]  (Warmup)
## Chain 4: Iteration:  400 / 2000 [ 20%]  (Warmup)
## Chain 4: Iteration:  600 / 2000 [ 30%]  (Warmup)
## Chain 4: Iteration:  800 / 2000 [ 40%]  (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]  (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]  (Sampling)
## Chain 4: Iteration: 1200 / 2000 [ 60%]  (Sampling)
## Chain 4: Iteration: 1400 / 2000 [ 70%]  (Sampling)
## Chain 4: Iteration: 1600 / 2000 [ 80%]  (Sampling)
## Chain 4: Iteration: 1800 / 2000 [ 90%]  (Sampling)
## Chain 4: Iteration: 2000 / 2000 [100%]  (Sampling)
## Chain 4: 
```

```
## Chain 4:  Elapsed Time: 0.07 seconds (Warm-up)
## Chain 4:                0.057 seconds (Sampling)
## Chain 4:                0.127 seconds (Total)
## Chain 4:
```

```
beta_1 <- coef(M_cor)$center[2]
r <- beta_1 * sd(CB2$D1) / sd(CB2$BusTotal)
cat("the correlation is: ", r)
```

```
## the correlation is:  0.01062974
```