Mandarin Chinese translation of the Artificial-Social-Agent questionnaire instrument for evaluating human-agent interaction

Underlying Analyses

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Contents

1 Note

The original 10 December 2022 file contained an error with regard to comparison of Human-ASA Interaction between different cultural backgrounds. For each second construct/dimension, the means were swapped between Chinese and English data in the output tables, and consequently, the plus and minus signs for the delta and CI values were also wrong. That has been corrected in this document.

2 Introduction

This document presents statistical analyses of correlation and variation between English and Chinese ASA questionnaires for item level, construct/dimension level, and short versions of the ASA questionnaire, as well as a comparison of human-ASA interaction between different cultural backgrounds, i.e., mixed international English-speaking group and bilingual group with Chinese mother tongue as reported in the paper:

Mandarin Chinese translation of Artificial-Social-Agent questionnaire instrument for evaluating human-agent interaction

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We use the following packages:

```r
library(foreign) # Open various data files
library(nlme)    # Run multilevel linear models
library(car)     # Package linear regression
# devtools::install_github("rasmusab/bayesian_first_aid")
library(BayesianFirstAid)  # Run Bayesian t-test
# devtools::install_github("rmcelreath/rethinking")
library(rethinking) # Run ulam
library(haven) # Use read_sav fuction
library(dplyr) # Use select function
library(knitr) # Get markdown file
library(tinytex) # Use TeX environment
library(rticles) # Use CTeX documents template
library(pander) # For pandering tables
panderOptions("table.alignment.default","left")
```

Note: Knitting this document requires installing Stan and JAGS on your computer. Stan can be downloaded from https://mc-stan.org/ and JAGS from https://mcmc-jags.sourcef orge.io/. It also requires installing rticles to use Mandarin Chinese template by creating R markdown file from template 'CTeX documents'. Moreover, it requires xelatex as latex_engine and header.tex.

3 Data files

The input data used in the analysis were transformed from seven raw data files 'ASA_1.sav', 'ASA_1.1.sav', 'ASA_1.2.sav', 'ASA_2.sav', 'ASA_2.1.sav', 'ASA_2.2.sav' and 'result_all.csv'. As a result, three data files were used as input data for the analysis reported in this paper, i.e., data01.sav, data02.sav and data_culture.sav. The detailed transformation from raw data to these input data files was explained in the markdown file 'Transformation from raw data to the input data files'.

3.1 File data01.sav

We divided the 90 ASA items and participants into two groups to control fatigue effects. In the first group, human-ASA interaction evaluation data of the first 44 items (Construct 1-8: the first 12 constructs/dimensions) were collected from 121 bilingual participants with Chinese mother tongue who are native Chinese and fluent English speakers. Bilingual participants rated human-ASA interaction on 44 English items and corresponding Chinese translations plus 15 attention control questions. All participants' evaluation data were included as they failed no more than 2 out of the 15 attention control questions. We removed irrelevant data, e.g., attention control questions, just retaining scores of English items and corresponding Chinese translations, also with 'AgentID' and 'agentName'. We also converted the data from the range [1,7] into the range [-3,3], and reversed scores of reverse-scoring questionnaire items and Chinese translations. The steps above were conducted and explained in the markdown file 'Transformation from raw data to the input data files', resulting in a single data file 'data01.sav'. Up to this step, rating scores of 44 English items and corresponding Chinese translations were ready for further analysis.

```r
data01 <- read.spss("data01.sav", use.value.labels=TRUE, to.data.frame=TRUE)
print_table_fields(data01, "data01.sav") # Print all column names in the file
```

Table 1: Fields and label from SPSS file data01.sav

variable	label
HLA1	[Field-agentName]'s appearance is human
HLA2	[Field-agentName] has the appearance of a human
HLA3	[Field-agentName] has a human-like outside
HLA4	[Field-agentName]'s appearance makes me think of a human
HLB1	A human would behave like [Field-agentName]
HLB2	[Field-agentName]'s manners is consistent with that of people
HLB3	[Field-agentName] behavior makes me think of human behavior
HLB4	[Field-agentName] behaves like a real person
HLB5	[Field-agentName] has a human-like manner
NA1	[Field-agentName] appears like something that could exist in nature
NA2	[Field-agentName] has a natural physique
NA3	[Field-agentName]'s resemblance has an organic origin

variable	label
NA4	[Field-agentName] seems natural from the outward appearance
NA5	How [Field-agentName] is represented is realistic
NB1	[Field-agentName] is alive
NB2	[Field-agentName] acts naturally
NB3	[Field-agentName] reacts like a living organism
AAS1	[Field-agentName] 's appearance is appropriate
AAS2	[Field-agentName]'s physique is suitable for its role
AAS3	[Field-agentName]' appearance was suitable
AU1	[Field-agentName] is easy to use
AU2	Learning to work with [Field-agentName] is easy
AU3	Learning how to communicate with [Field-agentName] is quick
PF1	[Field-agentName] does its task well
PF2	[Field-agentName] does not hinder the user
PF3	The user is capable of succeeding with [Field-agentName]
AL1	[Field-agentName]'s appearance is pleasing
AL2	I like [Field-agentName]
R_AL3	I dislike [Field-agentName]
AL4	[Field-agentName] is cooperative
AL5	I want to hang out with [Field-agentName]
AS1	[Field-agentName] can easily mix socially
AS2	It is easy to mingle with [Field-agentName]
AS3	[Field-agentName] interacts socially with the user
APP1	[Field-agentName] has a distinctive character
R_APP2	[Field-agentName] is characterless
APP3	[Field-agentName] is an individual
UAA1	The user will use [Field-agentName] again in future
UAA2	The user can see themselves using [Field-agentName] in the future
R_UAA3	The user oppose further interaction with [Field-agentName]
R_AE1	[Field-agentName] is boring
AE2	It is interesting to interact with [Field-agentName]
AE3	The user enjoys interacting with [Field-agentName]
R_AE4	[Field-agentName] is unpleasant to deal with
HLA1_CH	[Field-agentName] 的外观和人类一样
HLA2_CH	[Field-agentName] 具有人类的外观
HLA3_CH	[Field-agentName] 具有和人类相似的外观
HLA4_CH	[Field-agentName] 的外观让我联想到人类
HLB1_CH	人类会做出和 [Field-agentName] 一样的行为
HLB2_CH	[Field-agentName] 的举止与人一致

variable	label
HLB3_CH	[Field-agentName] 的行为让我联想到人类
HLB4_CH	[Field-agentName] 的行为像一个真人
HLB5_CH	[Field-agentName] 具有类人的举止
NA1_CH	[Field-agentName] 看着像自然界中可能存在的物体
NA2_CH	[Field-agentName] 具有自然的体形
NA3_CH	[Field-agentName] 的外观具有自然的起源
NA4_CH	[Field-agentName] 从外观来看是自然的
NA5_CH	[Field-agentName] 的外观具有现实意义
NB1_CH	[Field-agentName] 是活着的
NB2_CH	[Field-agentName] 行动自然
NB3_CH	[Field-agentName] 可以像生物一样做出反应
AAS1_CH	[Field-agentName] 的外观是合适的
AAS2_CH	[Field-agentName] 的体格适合其角色
AAS3_CH	[Field-agentName] 的外观适宜
AU1_CH	[Field-agentName] 易于使用
AU2_CH	学习使用 [Field-agentName] 很容易
AU3_CH	学会和 [Field-agentName] 交流是快捷的
PF1_CH	[Field-agentName] 很好地完成了它的任务
PF2_CH	[Field-agentName] 不妨碍用户
PF3_CH	用户能够成功使用 [Field-agentName]
AL1_CH	[Field-agentName] 的外观令人满意
AL2_CH	我喜欢 [Field-agentName]
R_AL3_CH	我不喜欢 [Field-agentName]
AL4_CH	[Field-agentName] 的表现很配合
AL5_CH	我愿意与 [Field-agentName] 玩耍
AS1_CH	[Field-agentName] 可以很容易参与社交
AS2_CH	很容易与 [Field-agentName] 打成一片
AS3_CH	[Field-agentName] 与用户进行社交互动
APP1_CH	[Field-agentName] 具有独特的性格
R_APP2_CH	[Field-agentName] 是没有个性的
APP3_CH	[Field-agentName] 是一个个体
UAA1_CH	用户将在未来再次使用 [Field-agentName]
UAA2_CH	用户可以看到自己将来会使用 [Field-agentName]
R_UAA3_CH	用户反对与 [Field-agentName] 进一步互动
R_AE1_CH	[Field-agentName] 是令人厌倦的
AE2_CH	和 [Field-agentName] 互动是有趣的
AE3_CH	用户喜欢和 [Field-agentName] 互动
R_AE4_CH	[Field-agentName] 不好相处

variable	label
agentName	iCAT, DEEPBLUE, AMY, FURBY, POPPIE, SIRI, HAL 9000, SIM SENSEI, CHAPPIE, AIBO, SARAH, NAO, MARCUS, DOG
AgentID	1=iCAT, 2=DEEPBLUE, 3=AMY, 4=FURBY, 5=POPPIE, 6=SIRI, 7=HAL 9000, 8=SIM SENSEI, 9=CHAPPIE, 10=AIBO, 11=SARAH, 12=NAO, 13=MARCUS, 14=DOG

```
data01 <- data.frame(read_sav("data01.sav"))
d1 <- select(data01, HLA1:R_AE4_CH) # Select 44 item scores and Chinese translation scores
```

3.2 File data02.sav

In the second group, evaluation scores of the remaining 46 English items and corresponding Chinese translations were collected from another 121 bilingual participants and transformed following the same procedure as explained in the section 'File data01.sav'. We obtained the input data file 'data02.sav' from the markdown file 'Transformation from raw data to the input data files'.

```
data02 <- read.spss("data02.sav", use.value.labels=TRUE, to.data.frame=TRUE)
print_table_fields(data02, "data02.sav")
```

Table 2: Fields and label from SPSS file data02.sav

variable	label
UE1	The user was concentrated during the interaction with [Field-agentName]
UE2	The interaction captured the user's attention
UE3	The user was alert during the interaction with [Field-agentName]
UT1	[Field-agentName] always gives good advice
UT2	[Field-agentName] acts truthfully
UT3	The user can rely on [Field-agentName]
UAL1	[Field-agentName] and the user have a strategic alliance
UAL2	Collaborating with [Field-agentName] is like a joint venture
UAL3	[Field-agentName] joins the user for mutual benefit
UAL4	[Field-agentName] can collaborate in a productive way
UAL5	[Field-agentName] and the user are in sync with each other
UAL6	[Field-agentName] understands the user
AA1	[Field-agentName] remains focused on the user throughout the interaction
AA2	[Field-agentName] is attentive
AA3	The user receives [Field-agentName]'s full attention throughout the interaction

variable	label
R_AC1	[Field-agentName]'s behavior does not make sense
R_AC2	[Field-agentName]'s behavior is irrational
R_AC3	[Field-agentName] is inconsistent
R_AC4	[Field-agentName] appears confused
AI1	[Field-agentName] acts intentionally
AI2	[Field-agentName] knows what it is doing
R_AI3	[Field-agentName] has no clue of what it is doing
AI4	[Field-agentName] can make its own decision
AT1	The user sees the interaction with [Field-agentName] as something positive
AT2	The user views the interaction as something favorable
R_AT3	The user thinks negatively of the interaction with [Field-agentName]
SP1	[Field-agentName] has a social presence
SP2	[Field-agentName] is a social entity
SP3	The user has the same social presence as [Field-agentName]
IIS1	The user's friends would recommend them to use [Field-agentName]
IIS2	Others would encourage the user to use [Field-agentName]
IIS3	[Field-agentName] makes the user look good
IIS4	People would look favorably at the user because of their interaction with [Field-agentName]
AEI1	[Field-agentName] is emotional
AEI2	[Field-agentName] experiences emotions
R_AEI3	[Field-agentName] is emotionless
AEI4	[Field-agentName] can express its feelings
R_AEI5	[Field-agentName] cannot experience emotions
UEP1	[Field-agentName]'s attitudes influences how the user feels]
UEP2	The user is influenced by [Field-agentName]'s moods
UEP3	The emotions the user feels during the interaction are caused by [Field-agentName]
UEP4	The user's Interaction with [Field-agentName] gives them an emotional sensation
UAI1	The user's emotions influence the mood of the interaction
UAI2	[Field-agentName] reciprocates the user's actions
UAI3	[Field-agentName]'s and the user's behaviors are in direct response to each other's behavior
UAI4	[Field-agentName]'s and the user's emotions change to what they do to each other
UE1_CH	用户在与 [Field-agentName] 互动中是注意力集中的
UE2_CH	交互吸引了用户的注意力

variable	label
UE3_CH	用户在与 [Field-agentName] 交互期间保持警觉
UT1_CH	[Field-agentName] 总是提供好的建议
UT2_CH	[Field-agentName] 如实行事
UT3_CH	[Field-agentName] 是可靠的
UAL1_CH	用户与 [Field-agentName] 有战略联盟
UAL2_CH	与 [Field-agentName] 合作就像合资
UAL3_CH	[Field-agentName] 加入用户互惠互利
UAL4_CH	用户与 [Field-agentName] 可以高效协作
UAL5_CH	[Field-agentName] 和用户相互同步
UAL6_CH	[Field-agentName] 理解用户
AA1_CH	[Field-agentName] 在整个交互过程中始终关注用户
AA2_CH	[Field-agentName] 是专注的
AA3_CH	在互动中用户获得了 [Field-agentName] 的全部关注
R_AC1_CH	[Field-agentName] 的行为讲不通
R_AC2_CH	[Field-agentName] 的行为是不合逻辑的
R_AC3_CH	[Field-agentName] 的行为不连贯
R_AC4_CH	[Field-agentName] 的行为显得很混乱
AI1_CH	[Field-agentName] 的行动是有意图的
AI2_CH	[Field-agentName] 知道它在做什么
R_AI3_CH	[Field-agentName] 不知道它在做什么
AI4_CH	[Field-agentName] 可以自己做决定
AT1_CH	用户认为与 [Field-agentName] 的交互是积极的
AT2_CH	用户认为交互是有利的
R_AT3_CH	用户对与 [Field-agentName] 的交互持负面看法
SP1_CH	[Field-agentName] 具有社会临场感
SP2_CH	[Field-agentName] 是一个社会实体
SP3_CH	用户具有与 [Field-agentName] 相同的社会临场感
IIS1_CH	用户的朋友会推荐他们使用 [Field-agentName]
IIS2_CH	其他人会鼓励用户使用 [Field-agentName]
IIS3_CH	[Field-agentName] 使用户看起来很好
IIS4_CH	与 [Field-agentName] 的交互让人们对该用户有好印象
AEI1_CH	[Field-agentName] 是情绪化的
AEI2_CH	[Field-agentName] 可以体验情绪
R_AEI3_CH	[Field-agentName] 是没有情绪的
AEI4_CH	[Field-agentName] 可以表达它的情感
R_AEI5_CH	[Field-agentName] 无法体验情绪
UEP1_CH	[Field-agentName] 的态度影响用户的感受
UEP2_CH	用户受 [Field-agentName] 的情绪影响

variable	label
UEP3_CH	用户在交互过程中感受到的情绪是由 [Field-agentName] 引起的
UEP4_CH	用户与 [Field-agentName] 的互动给他们一种情感上的感觉
UAI1_CH	用户的情绪会影响交互的氛围
UAI2_CH	[Field-agentName] 会回应用户的行为
UAI3_CH	[Field-agentName] 和用户的行为是对彼此行为的直接反应
UAI4_CH	[Field-agentName] 和用户的情绪根据他们对彼此的行为而改变
agentName	iCAT, DEEPBLUE, AMY, FURBY, POPPIE, SIRI, HAL 9000, SIM SENSEI, CHAPPIE, AIBO, SARAH, NAO, MARCUS, DOG
AgentID	1=iCAT, 2=DEEPBLUE, 3=AMY, 4=FURBY, 5=POPPIE, 6=SIRI, 7=HAL 9000, 8=SIM SENSEI, 9=CHAPPIE, 10=AIBO, 11=SARAH, 12=NAO, 13=MARCUS, 14=DOG

```
data02 <- data.frame(read_sav("data02.sav"))
d2 <- select(data02, UE1:UAI4_CH) # Select 46 item scores and Chinese translation scores
```

3.3 File data_culture.sav

Based on human-ASA interaction evaluation scores of 532 mixed international English-speaking participants in our previous study (accessible at https://osf.io/hxpsg) and 242 bilingual participants in this study (data01.sav and data02.sav), data_culture.sav was integrated (see 'Transformation from raw data to the input data files'). It consists of human-ASA evaluation on 24 English constructs and related dimensions for 14 ASAs by the participants from two cultural backgrounds. The analysis is helpful for exploring the differences in English questionnaire scores between these two cultural backgrounds. For clarity, irrelevant data, i.e., attention control question scores were removed from the file. All scores have been converted into the range [-3,3], and scores have been reversed for the items and translations that need reversion. Moreover, the description of all columns in the 'data_culture.sav' can be found in Table 3.

```
data_culture <- read.spss("data_culture.sav", use.value.labels=TRUE, to.data.frame=TRUE)
print_table_fields(data_culture, "data_culture.sav")
```

Table 3: Fields and label from SPSS file data_culture.sav

variable	label
agentName	iCAT, DEEPBLUE, AMY, FURBY, POPPIE, SIRI, HAL 9000, SIM SENSEI, CHAPPIE, AIBO, SARAH, NAO, MARCUS, DOG
AgentID	1=iCAT, 2=DEEPBLUE, 3=AMY, 4=FURBY, 5=POPPIE, 6=SIRI, 7=HAL 9000, 8=SIM SENSEI, 9=CHAPPIE, 10=AIBO, 11=SARAH, 12=NAO, 13=MARCUS, 14=DOG
Rating	Rating scores of 24 constructs/dimensions by 242 bilingual participants and 532 mixed international English-speaking participants
Culture	0=bilingual cultural background, 1=mixed international English-speaking cultural backgroup
ConstructID	1=HLA, 2=HLB, 3=NA, 4=NB, 5=AAS, 6=AU, 7=PF, 8=AL. 9=AS, 10=APP, 11=UAA, 12=AE, 13=UE, 14=UT, 15=UAL, 16=AA, 17=AC, 18=AI, 19=AT, 20=SP, 21=IIS, 22=AEI, 23=UEP, 24=UAI

```
data_culture <- data.frame(read_sav("data_culture.sav"))
```

4 Analyses results reported in Section Results

4.1 Correlation between English and Chinese ASA Questionnaire

We combined the scores of 44 items and 46 items as well as their corresponding translations in data frames ‘d1’ and ‘d2’. Then we calculated ICC values for the 90 items. The multilevel model that we fit on the data set is a random intercept model. This model includes a fixed intercept (~1) and participant as a random intercept, indicated by random = ~1|id. Here, ‘id’ indicates the participant code for 121 bilingual participants whose scores were used to calculate ICC values.

4.1.1 ICC values for 90 items

We combined the scores of 44 items and 46 items as well as their corresponding translations in data frames 'd1' and 'd2'. Then we calculated ICC values for the 90 items. The multilevel model that we fit on the data set is a random intercept model. This model includes a fixed intercept (~1) and participant as a random intercept, indicated by random = ~1|id. Here, 'id' indicates the participant code for 121 bilingual participants whose scores were used to calculate ICC values. We calculated ICC as: $\rho_I = \frac{\tau^2}{\tau^2+\sigma^2}$ whereby τ^2 is the variance between participants, and σ^2 is the variance within the score of individual (Finch, Bolin, and Kelley 2019). For the ICC calculation we defined the *getICC* function.

```
getICC <-function(model)
# Function for ICC value calculation using multilevel linear model
{
  vc.model <- VarCorr(model)
  # Estimated variances and correlations between the random-effects terms
  sigma_var <-as.numeric(vc.model[2,1])
  # Variance within the groups
  tau_var <- as.numeric(vc.model[1,1])
  # Variance between the groups
  icc <- tau_var/(tau_var + sigma_var)
  # Calculate ICC value
  return(icc)
}
```

Data frames 'd1' and 'd2' both have 121 data points, which we combined in single data frame.

```
d_total <- cbind(select(d1,HLA1:R_AE4), select(d2,UE1:UAI4),
                 select(d1,HLA1_CH:R_AE4_CH), select(d2,UE1_CH:UAI4_CH))
# Combine evaluation scores of 44 items and 46 items
```

Next, we defined a function to run a multilevel model and obtain the associated ICC value for that model. As input, this function accepts the scores in both languages and the participant ID number. Before the model can be fitted this input data is transformed into a long format. The function returns ICC in value.

```
getLME <-function(s_1,s_2)
# Function for a linear mixed-effects model
{
  id<-rownames(s_2)
  # Row names that represent the ID number of each participant
  Score_Chinese<- data.frame(id, s_1, language= 1)
```

```
  # Transform Chinese scores from wide format to long format and label as 1
  Score_English<- data.frame(id, s_2, language= 2)
  # Transform English scores from wide format to long format and label as 2
  Score_total <- rbind(Score_Chinese, Score_English)
  # Combine Chinese and English scores in the long format
  m0 <- lme(score ~ 1, data = Score_total, random = ~1|id, method = "ML")
  # Linear mixed-effects model with a fixed intercept and
  # a random intercept of participant's ID number
  return(getICC(m0))
}
```

With the *getLME* function defined, the next step is to use this function to calculate the ICC value for each of the 90 ASA questionnaire items, and in addition, calculate the grand mean of these 90 ICC values. When going to the list of ASAQ items, we use the fact that in the data frame the first 90 columns present the results of the English ASAQ version and the last 90 columns present the results of the Chinese ASAQ version.

```
l_ICC <- data.frame(ItemID = double(), Item = character(), icc = double())
# Initialize output of ICC values of 90 items
n <- ncol(d_total)
# Numbers of columns in d_total
Chinese_column_offset <- ncol(d_total) /2
# Offset, the first column with scores of the Chinese version of ASAQ item

for (i in 1:90)
# Go step by step to 90 items of the ASA questionnaire, whereby i is the ASA questionnaire item nu
{
  score_Chinese <- data.frame(score=d_total[,i + Chinese_column_offset])
  # Select scores of Chinese version of ASAQ item i

  score_English <- data.frame(score=d_total[,i])
  # Select scores of English version of ASAQ items i

  l_ICC <- rbind(l_ICC, data.frame (i, icc = getLME(score_Chinese, score_English)))
  # Calculated ICC and add it to the list of ICC values,
  # with ID number of the ASA questionnaire item
}
l_ICC$Item = colnames(select(d_total,HLA1:UAI4)) # Add name code for each item
pander(l_ICC, caption = "ICC values for 90 items")
```

Table 4: ICC values for 90 items

i	icc	Item
1	0.8431	HLA1
2	0.8983	HLA2
3	0.8983	HLA3
4	0.7955	HLA4
5	0.6746	HLB1
6	0.532	HLB2
7	0.7866	HLB3
8	0.7705	HLB4
9	0.759	HLB5
10	0.6353	NA1
11	0.7622	NA2
12	0.7003	NA3
13	0.7443	NA4
14	0.547	NA5
15	0.8283	NB1
16	0.7354	NB2
17	0.6436	NB3
18	0.7867	AAS1
19	0.6014	AAS2
20	0.5717	AAS3
21	0.7246	AU1
22	0.6083	AU2
23	0.712	AU3
24	0.6994	PF1
25	0.4936	PF2
26	0.3662	PF3
27	0.7347	AL1
28	0.9165	AL2
29	0.8461	R_AL3
30	0.5472	AL4
31	0.666	AL5
32	0.701	AS1
33	0.6198	AS2
34	0.6557	AS3
35	0.7133	APP1
36	0.614	R_APP2

i	icc	Item
37	0.694	APP3
38	0.6934	UAA1
39	0.5807	UAA2
40	0.1873	R_UAA3
41	0.4327	R_AE1
42	0.6258	AE2
43	0.6297	AE3
44	0.5861	R_AE4
45	0.5989	UE1
46	0.5425	UE2
47	0.4036	UE3
48	0.5258	UT1
49	0.4216	UT2
50	0.5664	UT3
51	0.5522	UAL1
52	0.3784	UAL2
53	0.543	UAL3
54	0.495	UAL4
55	0.578	UAL5
56	0.5398	UAL6
57	0.5395	AA1
58	0.4139	AA2
59	0.6662	AA3
60	0.6477	R_AC1
61	0.5697	R_AC2
62	0.274	R_AC3
63	0.3903	R_AC4
64	0.4654	AI1
65	0.7185	AI2
66	0.6783	R_AI3
67	0.6878	AI4
68	0.5589	AT1
69	0.5176	AT2
70	0.5908	R_AT3
71	0.621	SP1
72	0.5668	SP2
73	0.439	SP3
74	0.6937	IIS1

i	icc	Item
75	0.6794	IIS2
76	0.5384	IIS3
77	0.6133	IIS4
78	0.6821	AEI1
79	0.6971	AEI2
80	0.7329	R_AEI3
81	0.7031	AEI4
82	0.7407	R_AEI5
83	0.6793	UEP1
84	0.5017	UEP2
85	0.5815	UEP3
86	0.5344	UEP4
87	0.6137	UAI1
88	0.289	UAI2
89	0.4207	UAI3
90	0.5811	UAI4

```
Variable <- c("Grand_mean","SD","Minimum","Maximum")
# Define the names of the statistics
Value <- c(round(mean(l_ICC$icc),digits=4),round(sd(l_ICC$icc),digits=4),
           round(min(l_ICC$icc),digits=4),round(max(l_ICC$icc),digits=4))
# Calculate the grand mean, standard deviation, minimum and maximum values of ICC values of 90 ite
description <- cbind(Variable, Value) # Descriptive statistics of ICC values of 90 items

# Print results
pander(description, caption = "Descriptive statistics of ICC values of 90 items")
```

Table 5: Descriptive statistics of ICC values of 90 items

Variable	Value
Grand_mean	0.6148
SD	0.139
Minimum	0.1873
Maximum	0.9165

For the assessment of the correlation between the English and Chinese ASA Questionnaire, we followed Cicchetti's classification of ICC categories (Cicchetti 1994). Then we get the categories of ICC classifications and number of ICC values in classification category.

```
Classification <- c("Excellent","Good","Fair","Poor")
ICC_Range <- c("0.75-1.00","0.60-0.74","0.40-0.59","0-0.39")
# Categories of ICC classifications by Cicchetti (1994)
n_item <- length(l_ICC$icc) # Number of ICC values
round_ICC <- round(l_ICC$icc, digits=2) # Round ICC values
Number <- c(length(l_ICC[which(round_ICC>=0.75&round_ICC<=1),]$icc),
            length(l_ICC[which(round_ICC>=0.60&round_ICC<=0.74),]$icc),
            length(l_ICC[which(round_ICC>=0.40&round_ICC<=0.59),]$icc),
            length(l_ICC[which(round_ICC>=0.00&round_ICC<=0.39),]$icc))
# Calculate number of ICC values in classification category
Percentage <- c(round(Number[1]/n_item,digits=4)*100, round(Number[2]/n_item,digits=4)*100,
                round(Number[3]/n_item,digits=4)*100, round(Number[4]/n_item,digits=4)*100)
# Calculate percentage of ICC values in classification category
ICC_category <- cbind(Classification,ICC_Range,Number,Percentage)

# Print results
pander(ICC_category, caption = "Categories of ICC classifications and
       number of ICC values in classification category for 90 items")
```

Table 6: Categories of ICC classifications and number of ICC values in classification category for 90 items

Classification	ICC_Range	Number	Percentage
Excellent	0.75-1.00	12	13.33
Good	0.60-0.74	39	43.33
Fair	0.40-0.59	33	36.67
Poor	0-0.39	6	6.67

4.1.2 ICC values for 24 constructs and related dimensions

We combined the scores of Construct1-8 (data01.sav) and Construct 9-19 (data02.sav), as the input data for the correlation analysis for 24 constructs/dimensions. Then we called the function $getLME$ to calculate ICC values for each construct/dimension.

```
i <- which(names(d_total)%in%c("HLA1","HLB1","NA1","NB1","AAS1","AU1","PF1","AL1",
          "AS1","APP1","UAA1","R_AE1","UE1","UT1","UAL1","AA1","R_AC1","AI1","AT1",
          "SP1","IIS1","AEI1","UEP1","UAI1"))
```

```r
# 'i' is a vector with the column number of the first English
# version of item of the construct/dimension

k1 <- c(ncol(select(d_total, HLA1:HLA4)),ncol(select(d_total, HLB1:HLB5)),
        ncol(select(d_total, NA1:NA5)),ncol(select(d_total, NB1:NB3)),
        ncol(select(d_total, AAS1:AAS3)),ncol(select(d_total, AU1:AU3)),
        ncol(select(d_total, PF1:PF3)),ncol(select(d_total, AL1:AL5)),
        ncol(select(d_total, AS1:AS3)),ncol(select(d_total, APP1:APP3)),
        ncol(select(d_total, UAA1:R_UAA3)),ncol(select(d_total, R_AE1:R_AE4)))
# 'k1' is a vector with the number of questionnaire items of each
# construct/dimension for Construct 1-8
# Note that we assume here that construct/dimension items are
# adjacent columns in the data frame

k2 <- c(ncol(select(d_total, UE1:UE3)),ncol(select(d_total, UT1:UT3)),
        ncol(select(d_total, UAL1:UAL6)),ncol(select(d_total, AA1:AA3)),
        ncol(select(d_total, R_AC1:R_AC4)),ncol(select(d_total, AI1:AI4)),
        ncol(select(d_total, AT1:R_AT3)),ncol(select(d_total, SP1:SP3)),
        ncol(select(d_total, IIS1:IIS4)),ncol(select(d_total, AEI1:R_AEI5)),
        ncol(select(d_total, UEP1:UEP4)),ncol(select(d_total, UAI1:UAI4)))
# 'k2' is a vector with the number of questionnaire items of each
# construct/dimension for Construct 9-19

k = c(k1,k2)
# Combine k1 and k2 into a single vector with the number of questionnaire
# items of each construct/dimension of the entire ASAQ
h <- cbind.data.frame(i,k)
# Combine i and k into a data frame, whereby i indicates the column number
# of the first English item of a construct and k the total number of adjacent
# questionnaire items associated with the construct

l_ICC <- data.frame(ConstructID=double(), Construct=character(), icc=double())
# Initialize output of ICC values of 24 constructs/dimensions

for( p in 1:24 )
# Go step by step to 24 constructs/dimensions of the ASA questionnaire
{
  i <- h[p,1]
  # Column number of the first ASAQ item in English of the construct/dimension
```

```
  j <- i+ Chinese_column_offset
  # The column number of the first ASAQ item in the
  # Chinese version of the construct/dimension
  k <- h[p,2]
  # The number of ASAQ items associate to the construct/dimension
  s_Chinese <- data.frame(d_total[,j:(j+k-1)])
  # Select the scores of all the ASAQ items in Chinese
  # associated with the construct/dimension
  s_English <- data.frame(d_total[,i:(i+k-1)])
  # Select the score of all the ASAQ items in English associated
  # with the construct/dimension
  average_s_Chinese <- data.frame(rowMeans(s_Chinese))
  # Calculate the mean score of ASAQ items in Chinese associated
  # with the construct/dimension per participant
  average_s_English <- data.frame(rowMeans(s_English))
  # Doing the same but now for English version of the items
  colnames(average_s_Chinese) <- c("score") # Rename Chinese mean column
  colnames(average_s_English) <- c("score") # Rename English mean column
  l_ICC <- rbind(l_ICC, data.frame (p, icc = getLME(average_s_Chinese, average_s_English)))
  # Call function 'getLME' for ICC value calculation
}
l_ICC$Construct = c('HLA','HLB','NA','NB','AAS','AU','PF','AL','AS','APP',
'UAA','AE','UE','UT','UAL','AA','AC','AI','AT','SP','IIS','AEI','UEP','UAI')
# Add construct/dimension name code
pander(l_ICC, caption = "ICC values for 24 constructs/dimensions")
```

Table 7: ICC values for 24 constructs/dimensions

p	icc	Construct
1	0.9514	HLA
2	0.9067	HLB
3	0.8829	NA
4	0.8407	NB
5	0.8286	AAS
6	0.8105	AU
7	0.7271	PF
8	0.9146	AL
9	0.7953	AS
10	0.8071	APP

p	icc	Construct
11	0.6107	UAA
12	0.8174	AE
13	0.6525	UE
14	0.6665	UT
15	0.7781	UAL
16	0.7295	AA
17	0.715	AC
18	0.7921	AI
19	0.7227	AT
20	0.721	SP
21	0.774	IIS
22	0.8909	AEI
23	0.8202	UEP
24	0.7344	UAI

```
Variable <- c("Grand_mean","SD","Minimum","Maximum")
# Define the names of the statistics
Value <- c(round(mean(l_ICC$icc),digits=4),round(sd(l_ICC$icc),digits=4),
           round(min(l_ICC$icc),digits=4),round(max(l_ICC$icc),digits=4))
# Calculate the grand mean, standard deviation, minimum and
# maximum values of ICC values of 24 constructs/dimensions
description <- cbind(Variable, Value)
# Descriptive statistics of ICC values of 24 constructs/dimensions

# Print results
pander(description, caption = "Descriptive statistics of ICC values
of 24 constructs/dimensions")
```

Table 8: Descriptive statistics of ICC values of 24 constructs/dimensions

Variable	Value
Grand_mean	0.7871
SD	0.0866
Minimum	0.6107
Maximum	0.9514

```r
Classification <- c("Excellent","Good","Fair","Poor")
ICC_Range <- c("0.75-1.00","0.60-0.74","0.40-0.59","0-0.39")
# Categories of ICC classifications by Cicchetti (1994)
n_item <- length(l_ICC$icc) # Number of ICC values
round_ICC <- round(l_ICC$icc, digits=2) # Round ICC values
Number <- c(length(l_ICC[which(round_ICC>=0.75&round_ICC<=1),]$icc),
            length(l_ICC[which(round_ICC>=0.60&round_ICC<=0.74),]$icc),
            length(l_ICC[which(round_ICC>=0.40&round_ICC<=0.59),]$icc),
            length(l_ICC[which(round_ICC>=0.00&round_ICC<=0.39),]$icc))
# Calculate number of ICC values in classification category
Percentage <- c(round(Number[1]/n_item,digits=4)*100, round(Number[2]/n_item,digits=4)*100,
                round(Number[3]/n_item,digits=4)*100, round(Number[4]/n_item,digits=4)*100)
# Calculate percentage of ICC values in classification category
ICC_category <- cbind(Classification,ICC_Range,Number,Percentage)

# Print results
pander(ICC_category, caption = "Categories of ICC classifications and number
       of ICC values in classification category for 24 constructs/dimensions")
```

Table 9: Categories of ICC classifications and number of ICC values in classification category for 24 constructs/dimensions

Classification	ICC_Range	Number	Percentage
Excellent	0.75-1.00	15	62.5
Good	0.60-0.74	9	37.5
Fair	0.40-0.59	0	0
Poor	0-0.39	0	0

4.1.3 ICC values between English and Chinese scores for the short version of ASA questionnaire

The last ICC calculation is for the ASAQ items of the short version of the ASAQ. The procedure is similar to ICC calculation of the 90 items, only this time, we select only the relevant 24 items first.

```r
s_Chinese <- select(d_total,HLA2_CH,HLB5_CH,NA4_CH,NB3_CH,AAS1_CH,AU1_CH,PF1_CH,
      AL2_CH,AS1_CH,APP1_CH,UAA1_CH,R_AE1_CH,UE2_CH,UT3_CH,UAL1_CH,
      AA2_CH,R_AC1_CH,R_AI3_CH,AT1_CH,SP2_CH,IIS2_CH,R_AEI3_CH,UEP3_CH,UAI4_CH)
# Select Chinese versions of the 24 representative ASAQ items
s_English <- select(d_total,HLA2,HLB5,NA4,NB3,AAS1,AU1,PF1,AL2,AS1,APP1,UAA1,
```

```r
      R_AE1,UE2,UT3,UAL1,AA2,R_AC1,R_AI3,AT1,SP2,IIS2,R_AEI3,UEP3,UAI4)
# Select English versions of the 24 representative ASAQ items
ss <- cbind(s_Chinese,s_English)
# Combine Chinese and English scores

n <- ncol(ss) # Numbers of all columns in ss
English_column_offset <- n /2

l_ICC <- data.frame(ID=double(), Item=character(), icc=double())
# Initialize output of ICC values of 24 representative items
for (i in 1:24)
# Go step by step to 24 representative items of the ASA questionnaire
{
  score_Chinese <- data.frame(score=ss[,i])
  # Select Chinese scores of the ASAQ item
  score_English <- data.frame(score=ss[,i+ English_column_offset])
  # Select English scores of the ASAQ item
  l_ICC <- rbind(l_ICC, data.frame (i, icc = getLME(score_Chinese, score_English)))
  # Call function 'getLME' for ICC value calculation
}
l_ICC$Item <- colnames(s_English) # Add item name code
pander(l_ICC, caption = "ICC values for 24 representative items")
```

Table 10: ICC values for 24 representative items

i	icc	Item
1	0.8983	HLA2
2	0.759	HLB5
3	0.7443	NA4
4	0.6436	NB3
5	0.7867	AAS1
6	0.7246	AU1
7	0.6994	PF1
8	0.9165	AL2
9	0.701	AS1
10	0.7133	APP1
11	0.6934	UAA1
12	0.4327	R_AE1
13	0.5425	UE2

i	icc	Item
14	0.5664	UT3
15	0.5522	UAL1
16	0.4139	AA2
17	0.6477	R_AC1
18	0.6783	R_AI3
19	0.5589	AT1
20	0.5668	SP2
21	0.6794	IIS2
22	0.7329	R_AEI3
23	0.5815	UEP3
24	0.5811	UAI4

```r
Variable <- c("Grand_mean","SD","Minimum","Maximum")
# Define the names of the statistics
Value <- c(round(mean(l_ICC$icc),digits=4),round(sd(l_ICC$icc),digits=4),
           round(min(l_ICC$icc),digits=4),round(max(l_ICC$icc),digits=4))
# Calculate the grand mean, standard deviation, minimum
# and maximum values of ICC values of 24 representative items
description <- cbind(Variable, Value)
# Descriptive statistics of ICC values of 24 representative items

# Print results
pander(description, caption = "Descriptive statistics of ICC values
of 24 representative items")
```

Table 11: Descriptive statistics of ICC values of 24 representative items

Variable	Value
Grand_mean	0.6589
SD	0.1235
Minimum	0.4139
Maximum	0.9165

```r
Classification <- c("Excellent","Good","Fair","Poor")
ICC_Range <- c("0.75-1.00","0.60-0.74","0.40-0.59","0-0.39")
# Categories of ICC classifications by Cicchetti (1994)
```

```r
n_item <- length(l_ICC$icc) # Number of ICC values
round_ICC <- round(l_ICC$icc, digits=2) # Round ICC values
Number <- c(length(l_ICC[which(round_ICC>=0.75&round_ICC<=1),]$icc),
            length(l_ICC[which(round_ICC>=0.60&round_ICC<=0.74),]$icc),
            length(l_ICC[which(round_ICC>=0.40&round_ICC<=0.59),]$icc),
            length(l_ICC[which(round_ICC>=0.00&round_ICC<=0.39),]$icc))
# Calculate number of ICC values in classification category
Percentage <- c(round(Number[1]/n_item,digits=4)*100, round(Number[2]/n_item,digits=4)*100,
                round(Number[3]/n_item,digits=4)*100, round(Number[4]/n_item,digits=4)*100)
# Calculate percentage of ICC values in classification category
ICC_category <- cbind(Classification,ICC_Range,Number,Percentage)

# Print results
pander(ICC_category, caption = "Categories of ICC classifications and number
       of ICC values in classification category for 24 representative items")
```

Table 12: Categories of ICC classifications and number of ICC values in classification category for 24 representative items

Classification	ICC_Range	Number	Percentage
Excellent	0.75-1.00	4	16.67
Good	0.60-0.74	11	45.83
Fair	0.40-0.59	9	37.5
Poor	0-0.39	0	0

4.2 Variation Between English and Chinese ASA Questionnaire

The results were reported in the subsection of Variation Between English and Chinese ASA Questionnaire. The mean score differences between the English and Chinese questionnaires are estimates for absolute accuracy in score equivalence between the two languages. 95% credible interval of mean paired difference was calculated by Bayesian paired t-test, for item level, construct and dimension level, and the short version of the ASA questionnaire. We used the combined input data of data01.sav and data02.sav.

4.2.1 Mean score differences for 90 items

We used the Bayesian pairwise t-test to estimate the difference in ASAQ items score between the English and the Chinese version. First we define function establish sample means and standard deviation, next relevant information is extracted from output date produced by Bayesian t-test.

```r
getBAYES <-function(ID, ss_1, ss_2, B_output)
# Function to obtain mean, and sd values of ss_1 (Chinese)
# and ss_2 (English), and relevant information from
# Bayesian t-test output stored in B_output,
# this is take from the 1 line for Bayes output
# which relates to the estimation of the means and mean difference
# ID is the identification number added in the return data
# frame row to identify an item or construct
{ l <- data.frame(ID,
                  mean_Chinese = mean(ss_1), # Mean of Chinese translation
                  sd_Chinese = sd(ss_1), # Standard deviation of Chinese translation
                  mean_English = mean(ss_2), # Mean of English item
                  sd_English = sd(ss_2), # Standard deviation of English item
                  mean_diff = as.numeric(B_output[["stats"]][1,1]), # Mean of mu difference
                  sd_diff = as.numeric(B_output[["stats"]][1,2]), # Standard deviation
                  HDIlo = as.numeric(B_output[["stats"]][1,5]), # HDIlo
                  HDIup = as.numeric(B_output[["stats"]][1,6]), # HDIup
                  ess_bulk = as.numeric(B_output[["stats"]][1,16]),# ess_bulk
                  Rhat = as.numeric(B_output[["stats"]][1,15]), # Rhat
                  P_posterior = max(B_output[["stats"]][1,8],   # %<comp
                                    B_output[["stats"]][1,7]),  # %>comp
                  zero_excl = ifelse((as.numeric(B_output[["stats"]][1,5])>0)   # HDIlo
                                     | (as.numeric(B_output[["stats"]][1,6])<0),# HDIup
                                     '*','')
#add “*” marker if the low bound of HDI is large than zero,
# or the upper bound is smaller than zero
  )
return(l)  # Line 1 in the bayes.t.test output of mu_diff
}
```

With the function *getBAYES* defined, we now go examine for ASAQ item the difference between Chinese and English scores.

```r
item_list <- data.frame(Item=character(),ID=double(),mean_Chinese=double(),
                        sd_Chinese=double(),mean_English=double(),sd_English=double(),
                        mean_diff=double(),sd_diff=double(),HDIlo=double(),
                        HDIup=double(),zero_excl=character())
# Initialize output of Items with credible bias indication

set.seed(1) # Make sure that estimations of Bayesian analyses remain the same
```

```r
n <- ncol(d_total)
# Numbers of all columns in d_total, i.e. English and Chinese scores combined
Chinese_column_offset <- n /2
# Offset for the column position of the first Chinese ASAQ items

for (i in 1:90)
# Go step by step to 90 ASA questionnaire items
{
  score_Chinese <- d_total[,i+ Chinese_column_offset] # Chinese scores
  score_English <- d_total[,i] # English item scores
  fit <- bayes.t.test(score_Chinese, score_English, paired = TRUE)
  # conduct a Bayesian paired t-test on the Chinese and English score of ASAQ item

  item_list <- rbind(item_list, getBAYES(i, score_Chinese, score_English, fit))
  # store results from Bayesian analysis in a list to print later
}

# Print results
item_list$Item = colnames(select(d_total,HLA1:UAI4))
# Add item name code
pander(select(item_list,ID,mean_Chinese,sd_Chinese,mean_English,sd_English,Item),
       caption = "Items with credible bias indication (Part 1)")
```

Table 13: Items with credible bias indication (Part 1)

ID	mean_Chinese	sd_Chinese	mean_English	sd_English	Item
1	-1.025	2.023	-0.843	2.145	HLA1
2	-0.7521	2.207	-0.7355	2.152	HLA2
3	-0.7273	2.156	-0.6942	2.089	HLA3
4	-0.4132	2.088	-0.5289	2.086	HLA4
5	0.07438	1.79	-0.3388	1.904	HLB1
6	-0.3058	1.774	0.1818	1.727	HLB2
7	-0.01653	2.021	0.01653	1.91	HLB3
8	-0.4545	1.862	-0.1322	1.789	HLB4
9	0.1818	1.889	0.3306	1.846	HLB5
10	-0.7355	2.048	-0.5207	2.013	NA1
11	-0.1983	2.015	-0.3223	1.972	NA2
12	-0.4628	1.95	-0.2893	1.899	NA3
13	-0.314	1.945	-0.3554	1.901	NA4

ID	mean_Chinese	sd_Chinese	mean_English	sd_English	Item
14	0.281	1.766	0.3802	1.582	NA5
15	-0.8264	2.171	-0.876	2.124	NB1
16	0.01653	1.807	0.08264	1.759	NB2
17	0.6116	1.823	0.2231	1.895	NB3
18	0.9421	1.604	1.008	1.48	AAS1
19	0.7521	1.545	1.008	1.497	AAS2
20	0.6777	1.757	0.9256	1.577	AAS3
21	1.149	1.289	1.008	1.345	AU1
22	1.008	1.307	0.9669	1.449	AU2
23	1.05	1.29	1.149	1.364	AU3
24	1.339	1.382	1.124	1.547	PF1
25	1.124	1.394	1	1.372	PF2
26	1.554	1.04	1.083	1.358	PF3
27	0.4959	1.664	0.3554	1.668	AL1
28	0.4628	1.798	0.5537	1.746	AL2
29	0.8512	1.838	1.017	1.793	R_AL3
30	1.322	1.343	1.339	1.229	AL4
31	0.4463	1.708	-0.1983	1.926	AL5
32	0.3471	1.601	0.1983	1.563	AS1
33	0.405	1.498	0.6529	1.407	AS2
34	0.8099	1.599	0.9421	1.392	AS3
35	0.2231	1.605	0.4132	1.504	APP1
36	0.2231	1.646	0.1405	1.665	R_APP2
37	0.3967	1.828	0.06612	1.847	APP3
38	0.9917	1.268	1.107	1.283	UAA1
39	0.9008	1.313	0.9421	1.439	UAA2
40	1.107	1.606	1.132	1.668	R_UAA3
41	1.157	1.39	0.4628	1.643	R_AE1
42	0.8017	1.503	0.9339	1.448	AE2
43	0.8926	1.401	1.041	1.502	AE3
44	1.231	1.296	1.347	1.407	R_AE4
45	1.818	1.111	1.719	1.26	UE1
46	1.57	1.251	1.727	1.133	UE2
47	0.8926	1.702	1.322	1.523	UE3
48	-0.08264	1.492	-0.2479	1.479	UT1
49	1.017	1.225	0.8595	1.293	UT2
50	0.6116	1.387	0.438	1.532	UT3
51	-0.02479	1.666	0.2727	1.571	UAL1

ID	mean_Chinese	sd_Chinese	mean_English	sd_English	Item
52	-0.06612	1.553	0.4298	1.334	UAL2
53	0.5372	1.291	0.314	1.517	UAL3
54	0.9174	1.275	1.017	1.39	UAL4
55	0.9835	1.218	0.8678	1.323	UAL5
56	0.8099	1.468	0.9339	1.459	UAL6
57	1.438	1.328	1.678	1.156	AA1
58	1.364	1.36	1.306	1.161	AA2
59	1.603	1.393	1.537	1.342	AA3
60	1.579	1.395	1.405	1.492	R_AC1
61	1.57	1.365	1.479	1.489	R_AC2
62	1.017	1.516	1.306	1.29	R_AC3
63	1.479	1.438	1.372	1.634	R_AC4
64	0.4876	1.679	0.6529	1.436	AI1
65	0.7025	1.6	0.843	1.597	AI2
66	1.14	1.635	1.05	1.731	R_AI3
67	0.09917	1.748	0.2479	1.753	AI4
68	0.9669	1.494	1.107	1.431	AT1
69	1.107	1.442	1.058	1.337	AT2
70	1.149	1.579	1.273	1.628	R_AT3
71	0.1488	1.631	0.3058	1.647	SP1
72	-0.5455	1.612	-0.1322	1.522	SP2
73	0.2562	1.552	-0.5124	1.761	SP3
74	0.3884	1.54	0.438	1.554	IIS1
75	0.5124	1.403	0.5455	1.565	IIS2
76	0.3388	1.452	0.3802	1.556	IIS3
77	0.686	1.354	0.4215	1.448	IIS4
78	-0.843	1.683	-0.686	1.732	AEI1
79	-0.314	1.821	-0.5207	1.844	AEI2
80	-0.3306	2.031	-0.3884	1.859	R_AEI3
81	0.06612	1.759	-0.01653	1.817	AEI4
82	-0.3884	1.929	-0.5124	1.853	R_AEI5
83	1.314	1.304	1.083	1.525	UEP1
84	0.8182	1.576	0.4463	1.756	UEP2
85	0.9339	1.559	1.041	1.588	UEP3
86	0.6364	1.789	0.6777	1.561	UEP4
87	1.14	1.404	1.099	1.551	UAI1
88	1.818	1.19	1.091	1.396	UAI2
89	1.397	1.114	1.306	1.359	UAI3

ID	mean_Chinese	sd_Chinese	mean_English	sd_English	Item
90	0.7355	1.672	0.7025	1.406	UAI4

```r
pander(select(item_list,ID,mean_diff,sd_diff,HDIlo,HDIup,Item),
       caption = "Items with credible bias indication (Part 2)")
```

Table 14: Items with credible bias indication (Part 2)

ID	mean_diff	sd_diff	HDIlo	HDIup	Item
1	-7.188e-07	9.937e-05	-0.0001955	0.0001924	HLA1
2	3.67e-07	8.218e-05	-0.0001653	0.0001573	HLA2
3	4.401e-09	7.967e-05	-0.0001553	0.0001567	HLA3
4	-1.271e-06	0.0001988	-0.0003689	0.0003796	HLA4
5	0.2539	0.1141	0.04005	0.4834	HLB1
6	-0.4202	0.1528	-0.7245	-0.1284	HLB2
7	-0.03565	0.1018	-0.2396	0.1617	HLB3
8	-0.1784	0.1216	-0.405	0.03016	HLB4
9	-0.1249	0.1077	-0.3373	0.08507	HLB5
10	-0.08581	0.114	-0.3175	0.1327	NA1
11	0.1671	0.1066	-0.0386	0.3785	NA2
12	-0.1369	0.1383	-0.4033	0.1394	NA3
13	0.001093	0.01531	-0.03078	0.03403	NA4
14	-0.09682	0.1394	-0.3723	0.1779	NA5
15	1.471e-07	0.0001033	-0.0002013	0.000203	NB1
16	-0.02706	0.05939	-0.165	0.08089	NB2
17	0.2013	0.1126	-0.01095	0.4202	NB3
18	-2.532e-07	9.214e-05	-0.0001849	0.0001756	AAS1
19	-6.584e-05	0.001138	-0.002095	0.001959	AAS2
20	-0.1443	0.1024	-0.3431	0.05828	AAS3
21	-9.323e-07	9.369e-05	-0.0001824	0.0001849	AU1
22	0.004655	0.03196	-0.06187	0.07011	AU2
23	-2.613e-07	0.000159	-0.0002939	0.0002895	AU3
24	0.09081	0.08185	-0.04065	0.2515	PF1
25	0.09248	0.09531	-0.09291	0.2809	PF2
26	0.392	0.1087	0.1759	0.6051	PF3
27	0.08177	0.09641	-0.1071	0.2742	AL1
28	-5.536e-07	6.323e-05	-0.0001254	0.0001222	AL2
29	-6.155e-07	8.904e-05	-0.0001726	0.0001764	R_AL3

ID	mean_diff	sd_diff	HDIlo	HDIup	Item
30	0.04041	0.0851	-0.1252	0.2127	AL4
31	0.6105	0.1267	0.3575	0.8529	AL5
32	0.1047	0.1067	-0.1002	0.3193	AS1
33	-0.1921	0.1122	-0.4164	0.02279	AS2
34	-0.07396	0.1093	-0.2939	0.1336	AS3
35	-0.1894	0.1051	-0.399	0.01535	APP1
36	0.01919	0.1099	-0.1971	0.2369	R_APP2
37	0.01018	0.02504	-0.02594	0.05835	APP3
38	-2.276e-07	9.552e-05	-0.0001874	0.0001885	UAA1
39	-0.03225	0.05357	-0.1625	0.04307	UAA2
40	-0.0468	0.1342	-0.3125	0.2156	R_UAA3
41	0.6811	0.1312	0.4244	0.9397	R_AE1
42	-0.1496	0.09065	-0.3277	0.01357	AE2
43	-0.09706	0.1023	-0.3022	0.1009	AE3
44	-0.1166	0.1017	-0.3205	0.08084	R_AE4
45	-1.596e-08	9.835e-05	-0.0001918	0.0001934	UE1
46	-0.01851	0.04458	-0.1306	0.03728	UE2
47	-0.08769	0.07973	-0.2596	0.0448	UE3
48	-5.078e-07	0.0001796	-0.000339	0.0003163	UT1
49	0.125	0.1063	-0.07878	0.3345	UT2
50	0.1132	0.09759	-0.0741	0.3065	UT3
51	-0.01024	0.08947	-0.1951	0.1632	UAL1
52	-0.3377	0.1539	-0.6339	-0.04552	UAL2
53	0.1959	0.1172	-0.03197	0.4269	UAL3
54	-0.1006	0.12	-0.3314	0.1405	UAL4
55	0.1348	0.1018	-0.06713	0.3303	UAL5
56	-0.1814	0.1111	-0.3967	0.03888	UAL6
57	-0.007201	0.02541	-0.05543	0.03126	AA1
58	0.08272	0.1166	-0.1501	0.3092	AA2
59	-3.442e-07	0.0001106	-0.0002178	0.000218	AA3
60	0.09318	0.08796	-0.07185	0.2712	R_AC1
61	-0.04882	0.06895	-0.1988	0.07674	R_AC2
62	-0.2658	0.1524	-0.5665	0.03382	R_AC3
63	-0.04125	0.08572	-0.2109	0.1343	R_AC4
64	-0.06886	0.1319	-0.3364	0.18	AI1
65	6.113e-07	0.0001805	-0.000349	0.0003413	AI2
66	1.404e-05	0.001557	-0.002447	0.002436	R_AI3
67	-0.04672	0.06395	-0.1957	0.05222	AI4

ID	mean_diff	sd_diff	HDIlo	HDIup	Item
68	-0.1579	0.1102	-0.3763	0.05469	AT1
69	0.0956	0.1053	-0.1099	0.3027	AT2
70	-2.401e-07	0.0001691	-0.0003336	0.0003231	R_AT3
71	-0.04868	0.1129	-0.2819	0.1625	SP1
72	-0.3319	0.1194	-0.5713	-0.09939	SP2
73	0.7703	0.1476	0.4755	1.056	SP3
74	-6.38e-07	0.0001086	-0.0002109	0.0002127	IIS1
75	4.663e-07	0.0001121	-0.0002202	0.0002209	IIS2
76	-0.03015	0.1067	-0.2433	0.1783	IIS3
77	0.1769	0.09481	-0.002427	0.3622	IIS4
78	-0.06355	0.07865	-0.2394	0.06533	AEI1
79	0.1074	0.1212	-0.1289	0.3456	AEI2
80	0.01417	0.08331	-0.1525	0.1801	R_AEI3
81	-0.003044	0.05801	-0.1262	0.1198	AEI4
82	1.265e-06	0.0002116	-0.000411	0.0003941	R_AEI5
83	0.2038	0.1036	0.005842	0.4133	UEP1
84	0.3114	0.1557	0.009181	0.6192	UEP2
85	-0.001132	0.006757	-0.00804	0.00589	UEP3
86	0.09677	0.1406	-0.1778	0.3749	UEP4
87	0.0713	0.1008	-0.1241	0.2696	UAI1
88	0.6992	0.1307	0.4426	0.9548	UAI2
89	0.07676	0.1208	-0.1573	0.3141	UAI3
90	0.0706	0.1035	-0.1314	0.2796	UAI4

```r
pander(select(item_list,ID,ess_bulk,Rhat,P_posterior,zero_excl,Item),
       caption = "Items with credible bias indication (Part 3)")
```

Table 15: Items with credible bias indication (Part 3)

ID	ess_bulk	Rhat	P_posterior	zero_excl	Item
1	22554	1.001	0.504		HLA1
2	20787	1	0.5032		HLA2
3	20563	1	0.5013		HLA3
4	14866	1.007	0.5026		HLA4
5	7564	1.001	0.9904	*	HLB1
6	10415	1	0.9974	*	HLB2
7	17483	1.001	0.6412		HLB3

ID	ess_bulk	Rhat	P_posterior	zero_excl	Item
8	877	1.025	0.943		HLB4
9	17814	1	0.8785		HLB5
10	11185	1	0.7775		NA1
11	17861	1	0.9435		NA2
12	14317	1	0.8394		NA3
13	11214	1.001	0.5219		NA4
14	17334	1	0.7614		NA5
15	19320	1	0.5009		NB1
16	3708	1.002	0.6726		NB2
17	5300	1.001	0.9768		NB3
18	20535	1.001	0.5011		AAS1
19	1874	1.004	0.5088		AAS2
20	15135	1.001	0.9249		AAS3
21	21193	1	0.5024		AU1
22	8353	1.004	0.5553		AU2
23	17655	1.001	0.5023		AU3
24	1078	1.003	0.8794		PF1
25	14426	1	0.8351		PF2
26	17078	1	0.9998	*	PF3
27	10368	1	0.806		AL1
28	22418	1	0.5042		AL2
29	21466	1	0.5046		R_AL3
30	17783	1	0.6875		AL4
31	14908	1.001	1	*	AL5
32	14407	1.001	0.8399		AS1
33	10780	1	0.9598		AS2
34	12626	1	0.7501		AS3
35	18597	1	0.9628		APP1
36	16781	1.001	0.5651		R_APP2
37	3034	1.006	0.6683		APP3
38	22670	1	0.5006		UAA1
39	828	1.006	0.7457		UAA2
40	18697	1.001	0.6387		R_UAA3
41	18190	1	1	*	R_AE1
42	4885	1	0.9637		AE2
43	16590	1	0.8297		AE3
44	17324	1	0.8773		R_AE4
45	18563	1	0.5001		UE1

ID	ess_bulk	Rhat	P_posterior	zero_excl	Item
46	316	1.244	0.6527		UE2
47	3039	1.003	0.9042		UE3
48	14212	1.038	0.5003		UT1
49	16083	1	0.8831		UT2
50	10879	1	0.8824		UT3
51	11675	1	0.5288		UAL1
52	3181	1.001	0.9933	*	UAL2
53	16403	1	0.9546		UAL3
54	18254	1	0.7981		UAL4
55	17877	1	0.9068		UAL5
56	16776	1	0.9489		UAL6
57	2300	1.096	0.6021		AA1
58	19628	1	0.7617		AA2
59	22227	1	0.5021		AA3
60	12702	1	0.8579		R_AC1
61	8211	1	0.7728		R_AC2
62	17197	1	0.9586		R_AC3
63	17227	1	0.6975		R_AC4
64	11837	1	0.6939		AI1
65	14989	1.008	0.5004		AI2
66	1543	1.04	0.5009		R_AI3
67	2286	1.001	0.7877		AI4
68	17451	1	0.9263		AT1
69	18483	1	0.8168		AT2
70	19240	1	0.501		R_AT3
71	11015	1	0.6628		SP1
72	7766	1	0.9986	*	SP2
73	19180	1	1	*	SP3
74	19673	1	0.5038		IIS1
75	22010	1.001	0.5019		IIS2
76	17411	1	0.6086		IIS3
77	4958	1.001	0.976		IIS4
78	2827	1.001	0.8041		AEI1
79	8076	1.002	0.8116		AEI2
80	16598	1	0.5679		R_AEI3
81	12723	1.001	0.5233		AEI4
82	15910	1.003	0.5046		R_AEI5
83	15779	1	0.9755	*	UEP1

ID	ess_bulk	Rhat	P_posterior	zero_excl	Item
84	11677	0.9999	0.9782	*	UEP2
85	976	1.303	0.5323		UEP3
86	12116	1	0.7577		UEP4
87	18249	1	0.7604		UAI1
88	16332	1	1	*	UAI2
89	18216	1	0.7364		UAI3
90	18613	1	0.7566		UAI4

```r
# Calculate Grand mean information across the statistics obtained from 90 items
Variable <- c("mean_Chinese","sd_Chinese","mean_English","sd_English",
              "mean_diff","sd_diff","minimum_diff","maximum_diff",
              "n_zero_excl","percent_zero_excl")
# Define the names of the statistics

Grand_mean <- c(mean(item_list$mean_Chinese),mean(item_list$sd_Chinese),
                mean(item_list$mean_English),mean(item_list$sd_English),
                mean(abs(item_list$mean_diff)),mean(item_list$sd_diff),
                min(item_list$mean_diff),max(item_list$mean_diff),
                sum(item_list$zero_excl=="*"),round(sum(item_list$zero_excl=="*")
                /length(item_list$ID),digits=4)*100)
# Calculate the grand means of mean_Chinese, sd_Chinese, mean_English, sd_English,
# sd_diff, grand mean of the absolute value of mean differences, number of items
# with credible bias indication, and percentage of these items

# Print results
GrandMean <- cbind(Variable, Grand_mean)
pander(GrandMean, caption = "Grand mean of 90 items")
```

Table 16: Grand mean of 90 items

Variable	Grand_mean
mean_Chinese	0.567217630853994
sd_Chinese	1.58707052276564
mean_English	0.555922865013774
sd_English	1.59449315576764
mean_diff	0.113213305038185
sd_diff	0.0772717227688591

Variable	Grand_mean
minimum_diff	-0.420182682686443
maximum_diff	0.770314335594873
n_zero_excl	11
percent_zero_excl	12.22

4.2.2 Mean score differences for 24 constructs and related dimensions

Next, step is to repeat the Bayesian *t*-test analysis but this time on a construct level. 95% credible interval of mean pairwise difference by Bayesian paired *t*-test was calculated for 24 constructs and related dimensions. It would reveal the variation between 24 English ASA constructs/dimensions and corresponding Chinese translations. Before the *t*-test can be performed, we first have to calculate the construct score for each participant by taking the average score of the related ASAQ score. We have to do this both for the English and the Chinese version of the ASAQ.

```
con_list<-data.frame(Construct=character(),ID=double(),mean_Chinese=double(),
                     sd_Chinese=double(),mean_English=double(),sd_English=double(),
                     mean_diff=double(),sd_diff=double(),mean_diff=double(),
                     HDIlo=double(),HDIup=double(),zero_excl=character())
# Initialize output of Constructs/dimensions with credible bias indication

n <- ncol(d_total)
# Numbers of all columns in d_total, i.e. English and Chinese scores combined
Chinese_column_offset <- n /2
# Offset for the column position of the first Chinese ASAQ items

for(p in 1:24)
# Go step by step to 24 constructs/dimensions
{
  i = h[p,1]
  # The column with the first English ASAQ item of the construct/dimension
  j = i+ Chinese_column_offset
  # The column with the first Chinese ASAQ item of the construct/dimension
  k = h[p,2] # The number of columns/items of the construct/dimension
  s_Chinese <- data.frame(d_total[,j:(j+k-1)]) # Select Chinese scores
  s_English <- data.frame(d_total[,i:(i+k-1)]) # Select English scores
  average_s_Chinese <- data.frame(rowMeans(s_Chinese))
  # Chinese score means for each construct/dimension per participant
  average_s_English <- data.frame(rowMeans(s_English))
```

```r
  # English score means for each construct/dimension per participant
  colnames(average_s_Chinese) <- c("score")
  # Rename Chinese mean column
  colnames(average_s_English) <- c("score")
  # Rename English mean column
  score <- data.frame(cbind(average_s_Chinese,average_s_English))
  # Combine averaged scores of Chinese and English constructs/dimensions
  score_Chinese <- score[,1]
  # Select averaged scores of each Chinese construct/dimension,
  # make sure data format is suitable for Bayesian paired t-test
  score_English <- score[,2]
  # Select averaged scores of each English construct/dimension,
  # make sure data format is suitable for Bayesian paired t-test
  fit <- bayes.t.test(score_Chinese,score_English, paired = TRUE)
  # Conduct Bayesian t-test
  con_list <- rbind(con_list,getBAYES(p,score_Chinese,score_English,fit))
  # Call function 'getBAYES' to obtain relevant information
  # from Bayesian t-test output and add result to output list
}

# Print results
con_list$Construct=c('HLA','HLB','NA','NB','AAS','AU','PF','AL','AS','APP',
'UAA','AE','UE','UT','UAL','AA','AC','AI','AT','SP','IIS','AEI','UEP','UAI')
# Add construct/dimension name code
pander(select(con_list,ID,mean_Chinese,sd_Chinese,mean_English,sd_English,Construct),
       caption = "Constructs/dimensions with credible bias indication (Part 1)")
```

Table 17: Constructs/dimensions with credible bias indication (Part 1)

ID	mean_Chinese	sd_Chinese	mean_English	sd_English	Construct
1	-0.7293	1.983	-0.7004	2.021	HLA
2	-0.1041	1.615	0.01157	1.613	HLB
3	-0.286	1.674	-0.2215	1.546	NA
4	-0.06612	1.607	-0.1901	1.648	NB
5	0.7906	1.423	0.9807	1.349	AAS
6	1.069	1.178	1.041	1.238	AU
7	1.339	0.9991	1.069	1.14	PF
8	0.7157	1.369	0.6132	1.35	AL

ID	mean_Chinese	sd_Chinese	mean_English	sd_English	Construct
9	0.5207	1.366	0.5978	1.238	AS
10	0.281	1.398	0.2066	1.378	APP
11	1	1.062	1.061	1.074	UAA
12	1.021	1.063	0.9463	1.175	AE
13	1.427	0.9381	1.59	1.037	UE
14	0.5152	1.077	0.3499	1.12	UT
15	0.5262	0.9806	0.6391	0.983	UAL
16	1.468	1.129	1.507	1.022	AA
17	1.411	1.243	1.39	1.152	AC
18	0.6074	1.227	0.6983	1.205	AI
19	1.074	1.23	1.146	1.263	AT
20	-0.04683	1.243	-0.1129	1.259	SP
21	0.4814	1.197	0.4463	1.236	IIS
22	-0.362	1.602	-0.4248	1.636	AEI
23	0.9256	1.237	0.812	1.308	UEP
24	1.273	0.9984	1.05	1.133	UAI

```
pander(select(con_list,ID,mean_diff,sd_diff,HDIlo,HDIup,Construct),
       caption = "Constructs/dimensions with credible bias indication (Part 2)")
```

Table 18: Constructs/dimensions with credible bias indication (Part 2)

ID	mean_diff	sd_diff	HDIlo	HDIup	Construct
1	-0.005436	0.05393	-0.1105	0.1008	HLA
2	-0.104	0.06399	-0.234	0.01759	HLB
3	-0.04549	0.07177	-0.1871	0.0935	NA
4	0.1192	0.07419	-0.0248	0.2675	NB
5	-0.1629	0.06631	-0.2958	-0.0361	AAS
6	0.009714	0.05363	-0.09523	0.1166	AU
7	0.2429	0.05422	0.1304	0.3454	PF
8	0.08116	0.05003	-0.01799	0.1772	AL
9	-0.08111	0.07757	-0.2337	0.07075	AS
10	0.07656	0.07749	-0.07596	0.2262	APP
11	-0.04735	0.08356	-0.2126	0.1165	UAA
12	0.06353	0.06009	-0.0552	0.179	AE
13	-0.1555	0.07149	-0.2973	-0.0182	UE

ID	mean_diff	sd_diff	HDIlo	HDIup	Construct
14	0.1855	0.07181	0.04631	0.328	UT
15	-0.1101	0.05783	-0.2239	0.004367	UAL
16	0.07303	0.05962	-0.04502	0.1888	AA
17	0.01912	0.08228	-0.1457	0.1771	AC
18	-0.09261	0.0669	-0.2223	0.03868	AI
19	-0.05003	0.07581	-0.1983	0.09672	AT
20	0.08395	0.08558	-0.08647	0.2466	SP
21	0.02713	0.06243	-0.09636	0.1478	IIS
22	0.07648	0.06434	-0.05177	0.1999	AEI
23	0.1352	0.05996	0.01759	0.2517	UEP
24	0.2373	0.06289	0.1125	0.3587	UAI

```r
pander(select(con_list,ID,ess_bulk,Rhat,P_posterior,zero_excl,Construct),
       caption = "Constructs/dimensions with credible bias indication (Part 3)")
```

Table 19: Constructs/dimensions with credible bias indication (Part 3)

ID	ess_bulk	Rhat	P_posterior	zero_excl	Construct
1	13167	1.001	0.5323		HLA
2	17129	1	0.9479		HLB
3	17268	1	0.7361		NA
4	17549	1	0.9483		NB
5	15670	1	0.9926	*	AAS
6	17726	0.9999	0.5699		AU
7	19330	1	1	*	PF
8	15898	1.001	0.951		AL
9	17588	1	0.8525		AS
10	19443	0.9999	0.8406		APP
11	18699	1	0.7148		UAA
12	18525	1	0.8541		AE
13	17557	1	0.9863	*	UE
14	17617	1	0.9948	*	UT
15	18274	0.9999	0.9712		UAL
16	13870	1	0.8907		AA
17	19537	1	0.5895		AC
18	19619	1	0.9164		AI

ID	ess_bulk	Rhat	P_posterior	zero_excl	Construct
19	16869	1	0.7436		AT
20	17838	1	0.8352		SP
21	17809	1	0.6721		IIS
22	18451	1	0.882		AEI
23	17515	1	0.9878	*	UEP
24	18399	1	0.9998	*	UAI

```
# Determine grand (abs) means
Variable <- c("mean_Chinese","sd_Chinese","mean_English","sd_English",
              "mean_diff","sd_diff","minimum_diff","maximum_diff",
              "n_zero_excl","percent_zero_excl")
Grand_mean <- c(mean(con_list$mean_Chinese),mean(con_list$sd_Chinese),
                mean(con_list$mean_English),mean(con_list$sd_English),
                mean(abs(con_list$mean_diff)),mean(con_list$sd_diff),
                min(con_list$mean_diff),max(con_list$mean_diff),
                sum(con_list$zero_excl=="*"),round(sum(con_list$zero_excl=="*")
                /length(con_list$ID),digits=4)*100)
GrandMean <- cbind(Variable, Grand_mean)
# Calculate grand mean of mean_Chinese, sd_Chinese, mean_English, sd_English,
# sd_diff, grand mean of the absolute value of mean differences, number of
# constructs/dimensions with credible bias indication, and percentage of these
# constructs/dimensions
pander(GrandMean, caption = "Grand mean of 24 constructs/dimensions")
```

Table 20: Grand mean of 24 constructs/dimensions

Variable	Grand_mean
mean_Chinese	0.618807392102847
sd_Chinese	1.28492749417871
mean_English	0.604390495867769
sd_English	1.2968861102169
mean_diff	0.0952251753189493
sd_diff	0.0669878839695093
minimum_diff	-0.162861501604663
maximum_diff	0.242889677485211
n_zero_excl	6
percent_zero_excl	25

4.2.3 Mean score differences between English and Chinese short version of ASA questionnaire

As with ICC, we also conduct again difference analysis for representative ASAQ items in short version of ASAQ.

```
rep_list<-data.frame(Item=character(),ID=double(),mean_Chinese=double(),
                     sd_Chinese=double(),mean_English=double(),sd_English=double(),
                     mean_diff=double(),sd_diff=double(),HDIlo=double(),
                     HDIup=double(),zero_excl=character())
# Initialize output of Representative items with credible bias indication

n <- ncol(ss) # Numbers of all columns in ss
English_column_offset <- n /2

for (i in 1:24)
# Go step by step to 24 representative items of the ASA questionnaire
{
  score_Chinese <- as.numeric(ss[,i]) # Select Chinese scores
  score_English <- as.numeric(ss[,i+ English_column_offset]) # Select English scores
  fit<- bayes.t.test(score_Chinese, score_English, paired = TRUE)
  rep_list <- rbind(rep_list, getBAYES(i, score_Chinese, score_English, fit))
}

# Print results
rep_list$Item <- c('HLA2','HLB5','NA4','NB3','AAS1','AU1','PF1','AL2',
                  'AS1','APP1','UAA1','R_AE1','UE2','UT3','UAL1','AA2',
                  'R_AC1','R_AI3','AT1','SP2','IIS2','R_AEI3','UEP3','UAI4')
# Add item name code
pander(select(rep_list,ID,mean_Chinese,sd_Chinese,mean_English,sd_English,Item),
       caption = "Representative items with credible bias indication (Part 1)")
```

Table 21: Representative items with credible bias indication (Part 1)

ID	mean_Chinese	sd_Chinese	mean_English	sd_English	Item
1	-0.7521	2.207	-0.7355	2.152	HLA2
2	0.1818	1.889	0.3306	1.846	HLB5
3	-0.314	1.945	-0.3554	1.901	NA4

ID	mean_Chinese	sd_Chinese	mean_English	sd_English	Item
4	0.6116	1.823	0.2231	1.895	NB3
5	0.9421	1.604	1.008	1.48	AAS1
6	1.149	1.289	1.008	1.345	AU1
7	1.339	1.382	1.124	1.547	PF1
8	0.4628	1.798	0.5537	1.746	AL2
9	0.3471	1.601	0.1983	1.563	AS1
10	0.2231	1.605	0.4132	1.504	APP1
11	0.9917	1.268	1.107	1.283	UAA1
12	1.157	1.39	0.4628	1.643	R_AE1
13	1.57	1.251	1.727	1.133	UE2
14	0.6116	1.387	0.438	1.532	UT3
15	-0.02479	1.666	0.2727	1.571	UAL1
16	1.364	1.36	1.306	1.161	AA2
17	1.579	1.395	1.405	1.492	R_AC1
18	1.14	1.635	1.05	1.731	R_AI3
19	0.9669	1.494	1.107	1.431	AT1
20	-0.5455	1.612	-0.1322	1.522	SP2
21	0.5124	1.403	0.5455	1.565	IIS2
22	-0.3306	2.031	-0.3884	1.859	R_AEI3
23	0.9339	1.559	1.041	1.588	UEP3
24	0.7355	1.672	0.7025	1.406	UAI4

```r
pander(select(rep_list,ID,mean_diff,sd_diff,HDIlo,HDIup,Item),
       caption = "Representative items with credible bias indication (Part 2)")
```

Table 22: Representative items with credible bias indication (Part 2)

ID	mean_diff	sd_diff	HDIlo	HDIup	Item
1	-1.333e-06	8.067e-05	-0.0001592	0.0001561	HLA2
2	-0.125	0.1071	-0.336	0.08432	HLB5
3	0.001278	0.01736	-0.03425	0.03748	NA4
4	0.2018	0.1106	-0.004103	0.419	NB3
5	-1.492e-06	9.2e-05	-0.0001806	0.0001791	AAS1
6	3.308e-07	9.433e-05	-0.0001897	0.0001808	AU1
7	0.09154	0.08085	-0.03165	0.2561	PF1
8	-2.498e-07	6.282e-05	-0.0001241	0.0001221	AL2

ID	mean_diff	sd_diff	HDIlo	HDIup	Item
9	0.1043	0.1055	-0.09469	0.3203	AS1
10	-0.1902	0.1048	-0.3937	0.01876	APP1
11	-3.723e-07	9.671e-05	-0.0001847	0.0001965	UAA1
12	0.6802	0.1308	0.4277	0.9385	R_AE1
13	-0.01213	0.03636	-0.09696	0.03702	UE2
14	0.1114	0.09715	-0.06646	0.3124	UT3
15	-0.009434	0.08932	-0.1961	0.1604	UAL1
16	0.08243	0.1179	-0.1425	0.3218	AA2
17	0.09383	0.08875	-0.07474	0.2712	R_AC1
18	-2.844e-05	0.001495	-0.002333	0.002382	R_AI3
19	-0.1589	0.1086	-0.3774	0.04651	AT1
20	-0.3302	0.1203	-0.5659	-0.09343	SP2
21	-1.386e-06	0.0001131	-0.0002286	0.0002184	IIS2
22	0.01443	0.0823	-0.1461	0.1809	R_AEI3
23	-0.0001736	0.002868	-0.004169	0.004159	UEP3
24	0.06997	0.1052	-0.1349	0.2765	UAI4

```
pander(select(rep_list,ID,ess_bulk,Rhat,P_posterior,zero_excl,Item),
       caption = "Representative items with credible bias indication (Part 3)")
```

Table 23: Representative items with credible bias indication (Part 3)

ID	ess_bulk	Rhat	P_posterior	zero_excl	Item
1	21034	0.9999	0.5071		HLA2
2	17621	0.9999	0.88		HLB5
3	7737	1.007	0.5245		NA4
4	5137	1	0.9793		NB3
5	22129	1.001	0.506		AAS1
6	24465	1	0.5009		AU1
7	878	1.008	0.8843		PF1
8	28906	1	0.5009		AL2
9	16494	1	0.8421		AS1
10	17671	1.001	0.9662		APP1
11	24490	1	0.503		UAA1
12	17394	1	1	*	R_AE1
13	511	1.051	0.625		UE2

ID	ess_bulk	Rhat	P_posterior	zero_excl	Item
14	11409	1	0.8799		UT3
15	12000	1	0.5234		UAL1
16	17839	1	0.7579		AA2
17	13751	1	0.8583		R_AC1
18	3799	1.055	0.5067		R_AI3
19	18036	1.001	0.9284		AT1
20	8891	1	0.9982	*	SP2
21	24163	1	0.5027		IIS2
22	17100	1.001	0.5622		R_AEI3
23	802	1.028	0.5091		UEP3
24	17756	1	0.7445		UAI4

```r
# Calculate grand (abs) mean results
Variable <- c("mean_Chinese","sd_Chinese","mean_English","sd_English",
              "mean_diff","sd_diff","minimum_diff","maximum_diff",
              "n_zero_excl","percent_zero_excl")
Grand_mean <- c(mean(rep_list$mean_Chinese),mean(rep_list$sd_Chinese),
                mean(rep_list$mean_English),mean(rep_list$sd_English),
                mean(abs(rep_list$mean_diff)),mean(rep_list$sd_diff),
                min(rep_list$mean_diff),max(rep_list$mean_diff),
                sum(rep_list$zero_excl=="*"),round(sum(rep_list$zero_excl=="*")
                /length(rep_list$ID),digits=4)*100)
GrandMean <- cbind(Variable, Grand_mean)
# Calculate grand mean of mean_Chinese, sd_Chinese, mean_English, sd_English
# sd_diff, grand mean of the absolute value of mean differences, number of
# representative items with credible bias indication, and percentage of these items
pander(GrandMean, caption = "Grand mean of 24 representative items")
```

Table 24: Grand mean of 24 representative items

Variable	Grand_mean
mean_Chinese	0.618801652892562
sd_Chinese	1.59430948942655
mean_English	0.600550964187328
sd_English	1.5790269156525
mean_diff	0.0948916083507092
sd_diff	0.0628215402716066

Variable	Grand_mean
minimum_diff	-0.330201922224588
maximum_diff	0.680225911230241
n_zero_excl	2
percent_zero_excl	8.33

4.3 Comparison of Human-ASA Interaction between Different Cultural Backgrounds

The results were reported in the subsection of Comparison of Human-ASA Interaction between Different Cultural Backgrounds. The analysis was based on human-ASA interaction evaluation of 532 mix international English-speaking participants in our previous study and 242 bilingual participants with Chinese mother tongue in this study, using the data file 'data_culture.sav'. We compared human-ASA interaction between these two cultural background populations mentioned above. Two-level linear regression model was implemented to explore construct and dimension score differences between two sample groups, with agent as random intercept to control for dependency of agent assignment. For the Bayesian analysis we used the rethinking package developed by Richard McElreath[1].

```
cul_list <- data.frame(ConstructID=double(),mean_Chi=double(),sd_Chi=double(),
                       mean_Eng=double(),sd_Eng=double(),mean_diff=double(),
                       sd_diff=double(),lo2_5=double(),
                       hi97_5=double(),ess_bulk=double(),rhat=double(),
                       P_posterior=double(),zero_excl=character())
#Initialize output list of Construct/dimension differences between two cultural groups

data_culture$Culture <- (data_culture$Culture * -1) +1
# Change culture code for Chinese and English scores
# In the 10 December 2022 version this line was mistakenly placed within the for-loop
# below.

for(j in 1:24)
# Go step by step to 24 constructs/dimensions of the ASA questionnaire
{
  d_c<-subset(data_culture, ConstructID==j, select=c(AgentID, Culture, Rating))
  # select scores data for ASAQ construct j

  # Define the model we fit on the data. This is a multilevel model,
```

[1] https://www.rdocumentation.org/packages/rethinking/versions/2.13

```r
# with agent as random intercept to control for
# dependency of agent assignment, and culture as fixed effect
set.seed(1) # For reproducibility

m <- ulam(
  alist(
    #Likelihood
    Rating ~ dnorm(mu, sigma),

    #Linear model
    mu <- a + a_Agent[AgentID] + c_cult*Culture,

    #Adaptive prior
    a_Agent[AgentID] ~ dnorm(0, sigma_agent),

    #Hyper prior
    sigma_agent ~ dcauchy(0, 1),

    #Fixed priors
    a ~ dnorm(0, 2),
    c_cult ~ dnorm(0, 1),
    sigma ~ dcauchy(0, 1)
  ), data = d_c, iter = 50000, chains = 4, cores = 4, log_lik = TRUE,
  control=list(adapt_delta=.99)
)


# Calculate posterior probability
post_samples <- extract.samples(m, 1e5)
# Extract 100000 samples from the posterior distribution
c_cult <- as.numeric(post_samples$c_cult)
H0_post <- subset(c_cult, c_cult>0)
# Select samples with positive posterior values (positive bias)

H0_post_p <- length(H0_post)/length(c_cult)
# Calculate probability of a positive bias
H1_post_p <- 1 - H0_post_p
# Probability of a negative bias
```

```
  d_c_Chi <- subset(d_c, Culture == 1)
  # Subset of only Chinese mother tongue sample

  d_c_Eng <- subset(d_c, Culture == 0)
  # Subset of only Mixed international sample

  o <- precis(m,  depth=2, prob=.95)
  l <- data.frame(ConstructID = j,
                  mean_Chi = mean(d_c_Chi$Rating),
                  sd_Chi = sd(d_c_Chi$Rating),
                  mean_Eng = mean(d_c_Eng$Rating),
                  sd_Eng = sd(d_c_Eng$Rating),
                  mean_diff = as.numeric(o$mean[17]),
                  sd_diff = as.numeric(o$sd[17]),
                  lo2_5 = as.numeric(o$`2.5%`[17]),
                  hi97_5 = as.numeric(o$`97.5%`[17]),
                  ess_bulk = as.numeric(o$ess_bulk[17]),
                  rhat = as.numeric(o$rhat[17]),
                  P_posterior = max(H0_post_p,H1_post_p),
                  zero_excl = ifelse((as.numeric(o$`2.5%`[17])>0)
                                   | (as.numeric(o$`97.5%`[17])<0),
                                   '*','')
                  )
  # Line 17 in the precis output, are the results related to c_cul coefficient
  cul_list <- rbind(cul_list, l)
  # Store results in a list to print later on
}
```

The last step is the print the results of the model analysis.

```
# Print results
cul_list$Construct=c('HLA','HLB','NA','NB','AAS','AU','PF','AL','AS','APP',
'UAA','AE','UE','UT','UAL','AA','AC','AI','AT','SP','IIS','AEI','UEP','UAI')
# Add construct/dimension name code
pander(select(cul_list,ConstructID,mean_Chi,sd_Chi,mean_Eng,sd_Eng,Construct),
       caption="Construct/dimension differences between two cultural groups (Part 1)")
```

Table 25: Construct/dimension differences between two cultural groups (Part 1)

ConstructID	mean_Chi	sd_Chi	mean_Eng	sd_Eng	Construct
1	-0.7004	2.021	-0.7533	2.013	HLA
2	0.01157	1.613	0.04398	1.602	HLB
3	-0.2215	1.546	-0.2429	1.487	NA
4	-0.1901	1.648	-0.2932	1.555	NB
5	0.9807	1.349	1.346	1.221	AAS
6	1.041	1.238	1.234	1.192	AU
7	1.069	1.14	1.306	1.121	PF
8	0.6132	1.35	0.7699	1.4	AL
9	0.5978	1.238	0.3164	1.488	AS
10	0.2066	1.378	0.1986	1.489	APP
11	1.061	1.074	1.311	1.183	UAA
12	0.9463	1.175	1.252	1.225	AE
13	1.59	1.037	1.812	1.009	UE
14	0.3499	1.12	0.4311	1.211	UT
15	0.6391	0.983	0.5125	1.146	UAL
16	1.507	1.022	1.654	1.156	AA
17	1.39	1.152	1.549	1.067	AC
18	0.6983	1.205	0.6852	1.349	AI
19	1.146	1.263	1.431	1.335	AT
20	-0.1129	1.259	-0.1629	1.508	SP
21	0.4463	1.236	0.648	1.145	IIS
22	-0.4248	1.636	-0.6684	1.705	AEI
23	0.812	1.308	0.6245	1.285	UEP
24	1.05	1.133	0.7946	1.202	UAI

```r
pander(select(cul_list,ConstructID,mean_diff,sd_diff,lo2_5,hi97_5,Construct),
       caption="Construct/dimension differences between two cultural groups (Part 2)")
```

Table 26: Construct/dimension differences between two cultural groups (Part 2)

ConstructID	mean_diff	sd_diff	lo2_5	hi97_5	Construct
1	-0.03025	0.1287	-0.2827	0.2232	HLA
2	-0.08146	0.1368	-0.3495	0.1861	HLB

ConstructID	mean_diff	sd_diff	lo2_5	hi97_5	Construct
3	-0.04438	0.1202	-0.2795	0.1937	NA
4	0.03386	0.128	-0.216	0.2844	NB
5	-0.3726	0.1154	-0.5985	-0.1461	AAS
6	-0.168	0.1103	-0.3831	0.04906	AU
7	-0.239	0.1083	-0.4518	-0.02776	PF
8	-0.1842	0.122	-0.4233	0.05667	AL
9	0.2606	0.1294	0.007298	0.5153	AS
10	-0.0138	0.1257	-0.2602	0.2324	APP
11	-0.2605	0.1088	-0.4732	-0.04718	UAA
12	-0.3152	0.1093	-0.5282	-0.1011	AE
13	-0.2259	0.09799	-0.4178	-0.03346	UE
14	-0.0539	0.1109	-0.2731	0.1629	UT
15	0.1205	0.1065	-0.08755	0.3295	UAL
16	-0.154	0.1116	-0.3732	0.06377	AA
17	-0.1293	0.1033	-0.3328	0.07362	AC
18	0.02089	0.1177	-0.2094	0.2512	AI
19	-0.2508	0.1115	-0.4698	-0.03226	AT
20	0.008498	0.1376	-0.2602	0.2783	SP
21	-0.1876	0.1082	-0.3988	0.02421	IIS
22	0.165	0.1398	-0.1093	0.4394	AEI
23	0.1272	0.1127	-0.09293	0.3488	UEP
24	0.2204	0.111	0.003133	0.4369	UAI

```r
pander(select(cul_list,ConstructID,ess_bulk,rhat,P_posterior,zero_excl,Construct),
       caption="Construct/dimension differences between two cultural groups (Part 3)")
```

Table 27: Construct/dimension differences between two cultural groups (Part 3)

ConstructID	ess_bulk	rhat	P_posterior	zero_excl	Construct
1	47895	1	0.5918		HLA
2	66728	1	0.7237		HLB
3	57506	1	0.6448		NA
4	59813	1	0.6043		NB
5	86365	1	0.9993	*	AAS
6	84436	1	0.9351		AU
7	127247	1	0.9865	*	PF

ConstructID	ess_bulk	rhat	P_posterior	zero_excl	Construct
8	68945	1	0.9343		AL
9	79251	1	0.9781	*	AS
10	55089	1	0.5426		APP
11	73548	1	0.9918	*	UAA
12	84882	1	0.9978	*	AE
13	89774	1	0.9894	*	UE
14	101009	1	0.6868		UT
15	107538	1	0.871		UAL
16	112744	1	0.9158		AA
17	117413	1	0.8965		AC
18	98260	1	0.5705		AI
19	57105	1	0.9877	*	AT
20	98071	1	0.524		SP
21	112187	1	0.9588		IIS
22	55475	1	0.8808		AEI
23	77372	1	0.871		UEP
24	116607	1	0.9766	*	UAI

```r
# Print grand means
Variable <- c("mean_Chi","sd_Chi","mean_Eng","sd_Eng","mean_diff","sd_diff",
              "minimum_diff","maximum_diff","n_zero_excl","percent_zero_excl")
Grand_mean <- c(mean(cul_list$mean_Chi),mean(cul_list$sd_Chi),
                mean(cul_list$mean_Eng),mean(cul_list$sd_Eng),
                mean(abs(cul_list$mean_diff)),mean(cul_list$sd_diff),
                min(cul_list$mean_diff),max(cul_list$mean_diff),
                sum(cul_list$zero_excl=="*"),round(sum(cul_list$zero_excl=="*")
                /length(cul_list$ConstructID),digits=4)*100)
GrandMean <- cbind(Variable, Grand_mean)
# Calculate grand mean of mean_Chi, sd_Chi, mean_Eng, sd_Eng
# sd_diff, grand mean of the absolute value of mean differences, number of
# constructs/dimensions with credible bias indication,
# and percentage of these constructs/dimensions
pander(GrandMean, caption = "Grand mean of 24 constructs/dimensions between two cultural groups")
```

Table 28: Grand mean of 24 constructs/dimensions between two cultural groups

Variable	Grand_mean
mean_Chi	0.604390495867769
sd_Chi	1.2968861102169
mean_Eng	0.658302005012531
sd_Eng	1.33723154741264
mean_diff	0.152835495097145
sd_diff	0.117152346512682
minimum_diff	-0.372642827858267
maximum_diff	0.260619537687262
n_zero_excl	8
percent_zero_excl	33.33

References

Cicchetti, Domenic V. 1994. "Guidelines, Criteria, and Rules of Thumb for Evaluating Normed and Standardized Assessment Instruments in Psychology." *Psychological Assessment* 6 (4): 284. https://doi.org/10.1037/1040-3590.6.4.284.

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