Appendix methods for identifying CPL needs in four countries

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Contents

Software Information **3**

Data TALIS 2018 ISCED-2 and sample descriptives **4**

descriptive statistics selected teachers **6**

Sample Australia . . . 6

Sample England . . . 6

Sample Japan . . . 6

Sample the Netherlands . . . 7

Australia . . . 9

England . . . 9

Japan . . . 9

Netherlands . . . 10

Descriptives for teachers' continous professional leanring needs . . . 10

Correlations for teachers' continous professional leanring needs . . . 13

An application of three Latent measurement models: Overview and model fit criteria **14**

The Generalized Partial Credit Model (GPCM) . . . 14

GPCM: Model fit 2018 . . . 15

GPCM: Model fit 2013 . . . 15

GPCM: Interpretation output . . . 15

The Generalized Graded Unfolding Model (GGUM) . . . 18

GGUM: Model fit 2018 . . . 19

GGUM: Model fit 2013 . . . 19

GGUM: Interpretation output . . . 19

Circumplex Model . . . 19

Circumplex Model: Model fit . . . 24

Circumplex model: Results **26**

Visual respresentation of area locations in 2013 and 2018 . . . 26

Circumplex model: Assessment of Differential Item Functioning as an indicator of trends in teachers' perceptions . . . 33

Circumplex model: Teacher positions . . . 35

Linear metrics: Differences in teachers' level of need . . . 40

Software Information

The following packages were loaded and mostly used for analysis. In addition several Latex packages not listed below were loaded. These were: *titlesec*, *floatrow*, *subfig*, *tikz*, *positioning*, *arrows.meta*, *arrows*, and *pdflscape*.

```
##packages for circular statistics
if(!require("circular")) install.packages("circular"); library("circular")
if(!require("DescTools")) install.packages("DescTools"); library("DescTools")
if(!require("bpnreg")) install.packages("bpnreg"); library("bpnreg")

# package for multilevel correlations
if(!require("correlation")) install.packages("correlation"); library("correlation")

# pacakages for linear IRT and unfolding scaling
if(!require("ltm")) install.packages("ltm"); library("ltm")
if(!require("mirt")) install.packages("mirt"); library("mirt")
if(!require("eRm")) install.packages("eRm"); library("eRm")
#if(!require("GGUM")) install.packages("GGUM"); library("GGUM")

## packages for datamanagement
if(!require("plyr")) install.packages("plyr"); library("plyr")
if(!require("dplyr")) install.packages("dplyr"); library("dplyr")
if(!require("data.table")) install.packages("data.table"); library("data.table")
if(!require("rstatix")) install.packages("rstatix"); library("rstatix")

# packages for data visualization
if(!require("kableExtra")) install.packages("kableExtra"); library("kableExtra")
if(!require("pryr")) install.packages("pryr"); library("pryr")
if(!require("tidyverse")) install.packages("tidyverse"); library("tidyverse")
if(!require("ggplot2")) install.packages("ggplot2"); library("ggplot2")
if(!require("WrightMap")) install.packages("WrightMap"); library("WrightMap")

## packages for reading in data
if(!require("foreign")) install.packages("foreign"); library("foreign")

## packages for data imputation
if(!require("mice")) install.packages("mice"); library("mice")
if(!require("mitools")) install.packages("mitools"); library("mitools")
if(!require("miceadds")) install.packages("miceadds"); library("miceadds")
```

Information about the R and Rstudio version used is printed below.

```
## R version 4.5.1 (2025-06-13 ucrt)
```

```
## Rstudio version 2025.09.2+418
```

Data TALIS 2018 ISCED-2 and sample descriptives

The data available on the TALIS 2018 website and can be found here. Loaded datasets were:

1. BTGAUST3 *Australian secondary school teacher data 2018*
2. BTGAUST2 *Australian secondary school teacher data 2013*
3. BTGENGT3 *English secondary school teacher data 2018*
4. BTGENGT2 *English secondary school teacher data 2013*
5. BTGJPNT3 *Japanese secondary school teacher data 2018*
6. BTGJPNT2 *Japanese secondary school teacher data 2013*
7. BTGNLDT3 *Dutch secondary school teacher data 2018*
8. BTGNLDT2 *Dutch secondary school teacher data 2013*

```
## Teacher TALIS 2018 data Secondary Education.
TAL18.SECED.AUS = read.spss("BTGAUST3.sav", use.value.labels = FALSE,
                            to.data.frame = TRUE)
TAL18.SECED.ENG = read.spss("BTGENGT3.sav", use.value.labels = FALSE,
                            to.data.frame = TRUE)
TAL18.SECED.JPN = read.spss("BTGJPNT3.sav", use.value.labels = FALSE,
                            to.data.frame = TRUE)
TAL18.SECED.NLD = read.spss("BTGNLDT3.sav", use.value.labels = FALSE,
                            to.data.frame = TRUE)

## Teacher TALIS 2013 data Secondary Education.
TAL13.SECED.AUS = read.spss("BTGAUST2.sav", use.value.labels = FALSE,
                            to.data.frame = TRUE)
TAL13.SECED.ENG = read.spss("BTGENGT2.sav", use.value.labels = FALSE,
                            to.data.frame = TRUE)
TAL13.SECED.JPN = read.spss("BTGJPNT2.sav", use.value.labels = FALSE,
                            to.data.frame = TRUE)
TAL13.SECED.NLD = read.spss("BTGNLDT2.sav", use.value.labels = FALSE,
                            to.data.frame = TRUE)
```

Descriptive variables were renamed to give them informative variable names. Example script for Australia is printed below.

```
# AUS 2018
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G01'] <- 'Teacher_Gender'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G09'] <- 'Teacher_Employment_Status'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G10B'] <- 'Teacher_Position'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G03'] <- 'Level_education_completed'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G11B'] <- 'Teacher_Experience'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G17'] <- 'Hours_Teaching'

names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G16'] <- 'Hours_Job'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G18A'] <- 'Hours_Prep'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G18B'] <- 'Hours_Teamwork'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G18C'] <- 'Hours_Mark'
```

```r
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G18D'] <- 'Hours_Couns'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G18E'] <- 'Hours_School_Man'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G18F'] <- 'Hours_GA_work'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G18G'] <- 'Hours_PD'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G18H'] <- 'Hours_Parents'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G18I'] <- 'Hours_extra_activities'
names(TAL18.SECED.AUS)[names(TAL18.SECED.AUS) == 'TT3G18J'] <- 'Hours_Other_Job'

# AUS 2013
names(TAL13.SECED.AUS)[names(TAL13.SECED.AUS) == 'TT2G01'] <- 'Teacher_Gender'
names(TAL13.SECED.AUS)[names(TAL13.SECED.AUS) == 'TT2G06'] <- 'Teacher_Employment_Status'
names(TAL13.SECED.AUS)[names(TAL13.SECED.AUS) == 'TT2G03'] <- 'Teacher_Position'
names(TAL13.SECED.AUS)[names(TAL13.SECED.AUS) == 'TT2G10'] <- 'Level_education_completed'
names(TAL13.SECED.AUS)[names(TAL13.SECED.AUS) == 'TT2G05B'] <- 'Teacher_Experience'
names(TAL13.SECED.AUS)[names(TAL13.SECED.AUS) == 'TT2G17'] <- 'Hours_Teaching'
```

The Teaching and Learning International Survey (TALIS) is a longitundinal trend study, meaning that it studies developments/changes in a series of repeated representative samples of teachers from the same teacher population. Repeated samples, however, do not include the same teachers. TALIS, thus, does not permit the investigation of changes within individual teachers.

Data were selected to optimize the TALIS trend study design. The selection, which is visualized below, ensures that selected teachers all started teaching somewhere between 1983 and 2008. The selection excluded teachers that started before 1983, because teachers that started before this year had reached retirement age in the TALIS 2018 administration. The study excluded teachers starting after 2008, because teachers starting after this year had 5 years or less teaching experience in the TALIS 2013 administration. Beginning teachers, defined as less than 6 years teaching experience were excluded from the study, because many countries including some of the selected countries, have policies that actively stimulate CPL activities for beginning teachers (Schleicher (2016)). Moreover, the CPL activities for beginning teachers are different in terms of its content and didactical approach, and financed from different resources than the CPL activities for experienced teachers.

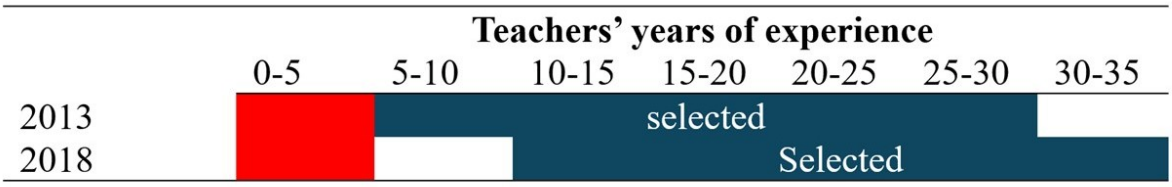


Figure 1: Data selection from the TALIS 2013 and 2018 trend cohorts

Syntax used for data selection in Austalia is printed below.

```r
# Australia
TAL13.SECED.AUS$Teacher_sel <-
  cut(TAL13.SECED.AUS$Teacher_Experience, breaks = c(0, 5, 30, Inf))
TAL13.SECED.exp5_30.AUS <- dplyr::filter(TAL13.SECED.AUS, Teacher_sel == "(5,30]")

TAL18.SECED.AUS$Teacher_sel <-
  cut(TAL18.SECED.AUS$Teacher_Experience, breaks = c(0, 10, 35, Inf))
TAL18.SECED.exp10_35.AUS <- filter(TAL18.SECED.AUS, TAL18.SECED.AUS$Teacher_sel == "(10,35]")
```

descriptive statistics selected teachers

Sample Australia

In Australia the selection included 1322 (P = 0.64) percent of the complete TALIS 2013 sample (n = 2059) and included 1758 (P = 0.49 percent of the complete TALIS 2018 sample (n = 3573). Selected teachers taught within 233 and 123 schools for secondary education. The majority of the teachers was female: (n = 796; P = 0.65) in 2013 and (n = 1134; P = 0.65) in 2018. The selected teachers from TALIS 2013 had 16.43 (SD = 7.47) years of teaching experience and the selected teachers from 2018 had 20.83 (SD = 7.12) years of teaching experience. Selected teachers reported to spent a mean number of 18.69 (SD = 9.24) hours on teaching in 2013 and 18.83 (SD = 9.24) hours on teaching in 2018 and 1.79 (SD = 2.59) hours on professional development in 2018. There was no information about the hours spent on professional development in 2013.

The employment status shows none to limited variation between Australian teachers and administration years. The majority of the teachers in 2013 (n = 1220; P = 0.92) and the majority of the teachers in 2018 (n = 1583; P = 0.9) have a permanent position. Furthermore, the majority of n = 1105 (P = 0.84) teachers worked full-time in 2013 and this slightly increased to (n = 1408 (P = 0.8) in 2018.

Sample England

In England the selection included 1586 (P = 0.64 percent of the complete TALIS 2013 sample (n = 2496) and included 1257 (P = 0.53 percent of the complete TALIS 2018 sample (n = 2376). Selected teachers taught within 149 and 154 schools for secondary education. The majority of the teachers was female: (n = 969; P = 0.65) in 2013 and (n = 812; P = 0.65) in 2018. The selected teachers from TALIS 2013 had 13.78 (SD = 6.3) years of teaching experience and the selected teachers from 2018 had 18.64 (SD = 6.14) years of teaching experience. Selected teachers reported to spent a mean number of 19.41 (SD = 6.53) hours on teaching in 2013 and 19.05 (SD = 8.02) hours on teaching in 2018 and 1 (SD = 1.56) hours on professional development in 2018. There was no information about the hours spent on professional development in 2013.

The employment status shows none to limited variation between English teachers and administration years. The majority of the teachers in 2013 (n = 1536; P = 0.97) and the majority of the teachers in 2018 (n = 1157; P = 0.92) have a permanent position. Furthermore, the majority of n = 1341 (P = 0.85) English teachers worked full-time in 2013 and the proportion teachers working full-time decreased to (n = 949 (P = 0.75) in 2018.

Sample Japan

In Japan the selection included 2274 (P = 0.65 percent of the complete TALIS 2013 sample (n = 3484) and included 1935 (P = 0.54 percent of the complete TALIS 2018 sample (n = 3555). Selected teachers taught within 196 and 192 schools for secondary education. The majority of the teachers was female: (n = 885; P = 0.43) in 2013 and (n = 828; P = 0.43) in 2018. The selected teachers from TALIS 2013 had 18.61 (SD = 7.69) years of teaching experience and the selected teachers from 2018 had 22.78 (SD = 7.55) years of teaching experience. Selected teachers reported to spent a mean number of 17.94 (SD = 6.08) hours on teaching in 2013 and 17.9 (SD = 8.43) hours on teaching in 2018 and 0.6 (SD = 1.53) hours on professional development in 2018. There was no information about the hours spent on professional development in 2013.

The employment status shows none to limited variation between Japanese teachers and administration years. The majority of the teachers in 2013 (n = 1948; P = 0.86) and the majority of the teachers in 2018 (n = 1578; P = 0.82) have a permanent position. In Japan, the overall majority of n = 2187 (P = 0.96) teachers worked full-time in 2013 but the proportion of Japanese teachers working full-time decreased to (n = 1681 (P = 0.87) in 2018.

Sample the Netherlands

In the Netherlands the selection included 1239 (P = 0.65 percent of the complete TALIS 2013 sample (n = 1912) and 1046 (P = 0.56 percent of the complete TALIS 2018 sample (n = 1884). Selected teachers taught within 116 and 127 schools for secondary education. The majority of the teachers was female: (n = 708; P = 0.53) in 2013 and (n = 557; P = 0.53) in 2018. The selected teachers from TALIS 2013 had 15.14 (SD = 7.06) years of teaching experience and the selected teachers from 2018 had 19.84 (SD = 6.85) years of teaching experience. Selected teachers reported to spent a mean number of 17.24 (SD = 6.57) hours on teaching in 2013 and 17.25 (SD = 6.67) hours on teaching in 2018 and 1.72 (SD = 2.84) hours on professional development in 2018. There was no information about the hours spent on professional development in 2013.

The employment status shows none to limited variation between Dutch teachers and administration years. The majority of the teachers in 2013 (n = 1132; P = 0.91) and the majority of the teachers in 2018 (n = 988; P = 0.94) have a permanent position. In the Netherlands, a minority of n = 532 (P = 0.43) teachers worked full-time in 2013 and this did not change in 2018 (n = 430 (P = 0.41)

	N	missing responses	M	Mdn	SD	Min	Max
Australia							
teacher experience (in years)	3573	105	14.51	12	10.72	0	49
weekly hours spent on teaching	3573	157	19.71	19	9.59	0	90
weekly hours spent on Professional Development	3573	219	1.69	1	2.46	0	30
England							
teacher experience (in years)1	2376	60	12.89	12	8.57	0	44
weekly hours spent on teaching1	2376	93	20.21	20	7.84	0	80
weekly hours spent on Professional Development1	2376	148	1.04	1	1.52	0	25
Japan							
teacher experience (in years)2	3555	22	17.25	15	11.77	0	54
weekly hours spent on teaching2	3555	49	18.02	18	8.6	0	96
weekly hours spent on Professional Development2	3555	82	0.67	0	2.18	0	80
Netherlands							
teacher experience (in years)3	1884	16	15.7	14	10.59	0	44
weekly hours spent on teaching3	1884	38	17.25	17	6.57	0	50
weekly hours spent on Professional Development3	1884	65	1.76	1	3.2	0	54

Table 1: Teaching experience and spending of hours (TALIS 2018)

	full-time	part-time 70-90%	part-time 50-70%	part-time <50%
Austrlia				
permanent	1337	160	73	13
fixed-term contract > 1 year	25	7	5	4
fixed-term contract =< 1 year	46	17	4	2
England				
permanent	926	125	87	19
fixed-term contract > 1 year	9	3	1	0
fixed-term contract =< 1 year	14	5	3	5
Japan				
permanent	1534	26	13	5
fixed-term contract > 1 year	77	4	5	7
fixed-term contract =< 1 year	70	24	21	38
Netherlands				
permanent	417	291	221	59
fixed-term contract > 1 year	6	7	5	1
fixed-term contract =< 1 year	7	12	8	3

Table 2: Descriptives Employment status by country ISED-2 Teachers (TALIS 2018)

	N	missing responses	M	Mdn	SD	Min	Max
Australia							
teacher experience (in years)	2059	46	16.59	15	11.11	0	48
weekly hours spent on teaching	2059	58	18.98	19	9.03	0	90
England							
teacher experience (in years)1	2496	85	12.26	10	9.3	0	42
weekly hours spent on teaching1	2496	48	19.8	20	6.3	0	78
Japan							
teacher experience (in years)2	3484	90	17.52	18	10.96	0	53
weekly hours spent on teaching2	3484	32	17.83	18	6.17	0	75
Netherlands							
teacher experience (in years)3	1912	18	15.53	13	10.98	0	48
weekly hours spent on teaching3	1912	25	16.88	17	6.53	0	80

Table 3: Teaching experience and spending of hours (TALIS 2013)

	full-time	part-time 70-90%	part-time 50-70%	part-time <50%
Austrlia				
permanent	1045	87	61	27
fixed-term contract > 1 year	28	5	4	1
fixed-term contract =< 1 year	32	10	11	4
England				
permanent	1310	97	99	30
fixed-term contract > 1 year	10	1	3	1
fixed-term contract =< 1 year	21	2	9	1
Japan				
permanent	1946	1	1	0
fixed-term contract > 1 year	124	1	1	4
fixed-term contract =< 1 year	117	13	14	18
Netherlands				
permanent	504	326	231	71
fixed-term contract > 1 year	8	11	6	2
fixed-term contract =< 1 year	20	29	18	12

Table 4: Descriptives Employment status by country ISED-2 Teachers (TALIS 2013)

Australia

Based on the ratio of questions 17 and 16 the estimated number of hours spent on teaching is 0.41(SD = 0.19). Of the 1758 participating teachers, 198 report to spent above 100% hours on teaching, meaning that the reported hours spent on teaching (question 17) in the last calender week was higher than the reported hours spent on total on the job (question 16). It is unclear how to interpret this result. Another smaller group of 1685, 271 reported to spent less than 10% time on teaching.

A second strategy divides the hours spent on teaching by the hours spent (question 16) on other activities plus the hours on teaching (questions 16 + 18). By definition, this strategy cannot result in estimates of above 100% hours spent on teaching. The distribution of hours spent on teaching as estimated by this strategy is 0.4(SD = 0.19). The correlation between the two methods is high 0.73 but also indicates that the choice for any of the strategies likely impacts on the results.

England

Based on the ratio of questions 17 and 16 the estimated number of hours spent on teaching is 0.4(SD = 0.16). Of the 1257 participating teachers, 114 report to spent above 100% hours on teaching, meaning that the reported hours spent on teaching (question 17) in the last calender week was higher than the reported hours spent on total on the job (question 16). It is unclear how to interpret this result. Another smaller group of 1227, 144 reported to spent less than 10% time on teaching.

A second strategy divides the hours spent on teaching by the hours spent (question 16) on other activities plus the hours on teaching (questions 16 + 18). By definition, this strategy cannot result in estimates of above 100% hours spent on teaching. The distribution of hours spent on teaching as estimated by this strategy is 0.41(SD = 0.17). The correlation between the two methods is high 0.66 but also indicates that the choice for any of the strategies likely impacts on the results.

Japan

Based on the ratio of questions 17 and 16 the estimated number of hours spent on teaching is 0.32(SD = 0.14). Of the 1935 participating teachers, 119 report to spent above 100% hours on teaching, meaning that

the reported hours spent on teaching (question 17) in the last calender week was higher than the reported hours spent on total on the job (question 16). It is unclear how to interpret this result. Another smaller group of 1883, 171 reported to spent less than 10% time on teaching.

A second strategy divides the hours spent on teaching by the hours spent (question 16) on other activities plus the hours on teaching (questions 16 + 18). By definition, this strategy cannot result in estimates of above 100% hours spent on teaching. The distribution of hours spent on teaching as estimated by this strategy is 0.34(SD = 0.16). The correlation between the two methods is high 0.65 but also indicates that the choice for any of the strategies likely impacts on the results.

Netherlands

Based on the ratio of questions 17 and 16 the estimated number of hours spent on teaching is 0.46(SD = 0.16). Of the 1046 participating teachers, 84 report to spent above 100% hours on teaching, meaning that the reported hours spent on teaching (question 17) in the last calender week was higher than the reported hours spent on total on the job (question 16). It is unclear how to interpret this result. Another smaller group of 1026, 104 reported to spent less than 10% time on teaching.

A second strategy divides the hours spent on teaching by the hours spent (question 16) on other activities plus the hours on teaching (questions 16 + 18). By definition, this strategy cannot result in estimates of above 100% hours spent on teaching. The distribution of hours spent on teaching as estimated by this strategy is 0.45(SD = 0.16). The correlation between the two methods is high 0.72 but also indicates that the choice for any of the strategies likely impacts on the results.

Descriptives for teachers' continous professional leanring needs

TALIS question 25 tapped teachers' professorial learning needs. The question stem was: *For each of the areas listed below, please indicate the extent to which you currently need professional learning activities.* The question was followed by a list of areas A to N and an open-ended response option O "other". Teachers responded to the listed aeras on a four point Likert-scale with response options: 1 = *no need at present*, 2 = *low level of need*, 3 = *moderate level of need*, 4 = *high level of need*.

		Australia						England						Japan						The Netherlands					
		freq. level of need				M	SD	freq. level of need				M	SD	freq. level of need				M	SD	freq. level of need				M	SD
area	Item 25: For each of the areas listed below, please indicate the extent to which you currently need professional learning activities	1	2	3	4			1	2	3	4			1	2	3	4			1	2	3	4		
A	Knowledge and understanding of my subject field(s)	546	728	324	61	1.94	0.82	565	426	170	35	1.73	0.81	13	102	790	1001	3.46	0.63	183	424	298	87	2.29	0.87
B	Pedagogical competencies in teaching my subject field(s)	465	816	340	37	1.97	0.76	490	533	152	14	1.74	0.72	14	86	717	1086	3.51	0.62	190	502	264	38	2.15	0.77
C	Knowledge of the curriculum	460	712	395	91	2.07	0.85	455	470	227	40	1.88	0.83	27	392	995	485	3.02	0.72	250	484	227	32	2.04	0.78
D	Student assessment practices	331	728	501	98	2.22	0.83	375	505	274	38	1.98	0.82	15	188	978	717	3.26	0.66	179	348	364	103	2.39	0.90
E	ICT (information and communication technology) skills for teaching	200	555	683	216	2.55	0.87	362	421	342	64	2.09	0.89	27	231	967	673	3.20	0.70	125	310	393	168	2.61	0.91
F	Student behaviour and classroom management	614	757	234	51	1.83	0.78	591	476	104	21	1.63	0.72	29	243	961	670	3.19	0.71	209	439	274	71	2.21	0.85
G	School management and administration	638	644	297	73	1.88	0.85	563	399	191	35	1.75	0.83	129	674	793	304	2.67	0.82	505	318	126	46	1.71	0.86
H	Approaches to individualised learning	251	679	625	102	2.35	0.81	340	513	306	34	2.03	0.81	19	166	938	780	3.30	0.67	124	238	450	183	2.70	0.91
I	Teaching students with special needs	238	629	645	144	2.42	0.84	246	545	343	60	2.18	0.81	23	177	884	816	3.31	0.69	164	368	359	100	2.40	0.88
J	Teaching in a multicultural or multilingual setting	514	660	383	97	2.04	0.88	467	448	224	49	1.88	0.86	108	738	827	229	2.62	0.77	377	444	144	27	1.82	0.78
K	Teaching cross-curricular skills (e.g. creativity, critical thinking, problem solving)	297	631	599	126	2.34	0.86	381	536	236	37	1.94	0.80	36	314	1018	536	3.08	0.72	172	330	369	122	2.44	0.92
L	Analysis and use of student assessments	320	726	502	106	2.24	0.83	400	487	276	31	1.95	0.82	25	268	1059	551	3.12	0.68	265	416	250	61	2.11	0.87
M	Teacher-parent/guardian co-operation	666	714	232	44	1.79	0.78	609	470	99	12	1.59	0.68	37	328	1009	530	3.07	0.72	301	491	177	25	1.93	0.76
N	Communicating with people from different cultures or countries	612	712	283	44	1.85	0.79	572	452	143	24	1.68	0.76	75	628	949	253	2.72	0.74	433	420	115	22	1.72	0.75

Table 5: Descriptives CPL needs per country

		Australia						England						Japan						The Netherlands					
		freq. level of need				M	SD	freq. level of need				M	SD	freq. level of need				M	SD	freq. level of need				M	SD
area	Item 26: For each of the areas listed below, please indicate the extent to which you currently need professional learning activities	1	2	3	4			1	2	3	4			1	2	3	4			1	2	3	4		
A	Knowledge and understanding of my subject field(s)	442	571	209	27	1.86	0.77	787	558	145	29	1.62	0.74	11	79	1050	1117	3.45	0.59	316	455	340	75	2.15	0.89
B	Pedagogical competencies in teaching my subject field(s)	371	619	227	27	1.93	0.75	633	660	204	21	1.75	0.74	9	64	936	1246	3.52	0.57	299	523	317	45	2.09	0.82
C	Knowledge of the curriculum	383	566	255	44	1.97	0.81	690	623	181	24	1.70	0.74	29	406	1383	439	2.99	0.65	348	541	258	39	1.99	0.80
D	Student evaluation and assessment practice	315	593	300	39	2.05	0.79	526	691	269	32	1.87	0.77	17	168	1193	875	3.30	0.64	270	438	411	69	2.23	0.87
E	ICT skills for teaching	125	423	531	166	2.59	0.84	412	570	409	132	2.17	0.93	41	367	1268	580	3.06	0.70	202	330	471	183	2.54	0.95
F	Student behaviour and classroom management	480	572	163	32	1.80	0.76	772	571	143	34	1.63	0.75	15	176	1143	920	3.32	0.64	283	490	334	79	2.18	0.87
G	School management and administration	480	484	231	51	1.88	0.85	667	515	289	49	1.82	0.85	115	731	1084	326	2.72	0.77	650	331	149	57	1.67	0.87
H	Approaches to individualised learning	221	558	406	64	2.25	0.80	353	723	396	48	2.09	0.78	10	159	1218	871	3.31	0.62	200	335	489	164	2.52	0.93
I	teaching students with special needs	243	506	416	86	2.28	0.85	322	686	418	95	2.19	0.84	32	221	1086	913	3.28	0.69	299	404	375	107	2.24	0.93
J	teaching in multicultural settings	547	443	200	56	1.81	0.86	716	482	224	100	1.81	0.92	124	921	990	222	2.58	0.74	618	417	123	30	1.63	0.77
K	teaching cross-curricular skills	310	571	325	40	2.08	0.80	509	686	279	47	1.91	0.80	18	220	1261	759	3.22	0.64	256	388	456	84	2.31	0.89
L	Approaches to developing cross-occupational competencies	448	453	294	51	1.96	0.87	614	529	318	59	1.88	0.87	66	515	1205	468	2.92	0.74	466	410	256	48	1.90	0.88
M	New technologies in the workplace	157	453	493	148	2.51	0.86	359	546	478	139	2.26	0.92	81	631	1203	341	2.80	0.73	284	327	436	136	2.36	0.97
N	Student career guidance and counselling	498	448	242	57	1.89	0.87	659	529	259	74	1.83	0.88	17	149	1140	953	3.34	0.63	366	472	282	61	2.03	0.87

Table 6: Descriptives CPL needs per country

Correlations for teachers' continous professional leanring needs

Correlations were estimated per country. The correlatons matrix serves as input for the circumplex analyses. Multilevel multiple imputation was performed to impute missing values. Procedures followed descriptions as provided here.

An application of three Latent measurement models: Overview and model fit criteria

This section assesses the value of (1) dominance "differences in degree" models, (2) linear unfolding "differences in kind" models, and (3) circular unfolding "differences in kind" models to describe individual differences in teachers' CPL needs. The utility of dominance "differences in degree" models is assessed by fitting a Generalized Partial Credit Model (GPCM) (Muraki, 1992) to the data. The utility of linear unfolding "differences in kind" models is assessed by fitten a Generalized Graded Unfolding Model (GGUM) (Roberts, Donoghue, Service, and Laughlin, 1996) to the data. Finally, the utility of circular unfolding "differences in kind" models is assessed by fitting a circumplex model (Guttman, 1954) to the data. An important consideration for the model choice is model fit. Model fit coefficients describe to extend to which model predicted item responses overlaps with the observed item responses in the data set. The following coefficients for model fit were used:

- **Absolute model fit coefficients:**
  - Root Mean Square Error of Approximation (RMSEA), wherein:
    - $RMSEA \leq 0.05$ = good fit
    - $0.05 < RMSEA \leq 0.08$ = sufficient fit
    - $RMSEA \geq 0.08$ = insufficient fit
  - Comparative Fit Index (CFI), wherein:
    - $CFI \geq 0.95$ = good fit
    - $CFI \geq 0.90$ = sufficient fit
    - $CFI < 0.90$ = insufficient fit
- **Comparative model fit coefficients:**
  - $\frac{\chi^2}{df}$ ratio, wherein:
    - **Rule:** $< \frac{\chi^2}{df}$ means better model fit compared to other models
  - The Bayesian Information Criterion, wherein:
    - **Rule:** $< BIC$ means better model fit compared to other models

The Generalized Partial Credit Model (GPCM)

The Generalized Partial Credit Model (GPCM) (Muraki, 1992) is fitted to the data. The GPCM belongs to the family of dominance models. It models items response probabilities as increasing when the teachers' latent trait level is higher, here CPL needs. For this specific case, the probability on a high need for learning on any specific area is predicted to increase when teachers have an overall high need for CPL. We will not detail the model further as fit of the data with it is insufficient.

```
PCM.AUS.2018 <- mirt::mirt(na.omit(CPL.needs.AUS.2018[, 3:13])-1, 1, itemtype = 'gpcm',
                      IRT.param = TRUE, technical = list(NCYCLES = 2000))
PCM.ENG.2018 <- mirt::mirt(na.omit(CPL.needs.ENG.2018[, 3:13])-1, 1, itemtype = 'gpcm',
                      IRT.param = TRUE, technical = list(NCYCLES = 2000))
PCM.JPN.2018 <- mirt::mirt(na.omit(CPL.needs.JPN.2018[, 3:13])-1, 1, itemtype = 'gpcm',
                      IRT.param = TRUE, technical = list(NCYCLES = 2000))
PCM.NLD.2018 <- mirt::mirt(na.omit(CPL.needs.NLD.2018[, 3:13])-1, 1, itemtype = 'gpcm',
                      IRT.param = TRUE, technical = list(NCYCLES = 2000))
# fit coefficients GPCM
fit.PCM.AUS.2018 <- mirt::M2(PCM.AUS.2018)
fit.PCM.ENG.2018 <- mirt::M2(PCM.ENG.2018)
fit.PCM.JPN.2018 <- mirt::M2(PCM.JPN.2018)
fit.PCM.NLD.2018 <- mirt::M2(PCM.NLD.2018)
```

```
PCM.AUS.2013 <- mirt::mirt(na.omit(CPL.needs.AUS.2013[, 3:13])-1, 1, itemtype = 'gpcm',
                      IRT.param = TRUE, technical = list(NCYCLES = 2000))
PCM.ENG.2013 <- mirt::mirt(na.omit(CPL.needs.ENG.2013[, 3:13])-1, 1, itemtype = 'gpcm',
                      IRT.param = TRUE, technical = list(NCYCLES = 2000))
PCM.JPN.2013 <- mirt::mirt(na.omit(CPL.needs.JPN.2013[, 3:13])-1, 1, itemtype = 'gpcm',
                      IRT.param = TRUE, technical = list(NCYCLES = 2000))
PCM.NLD.2013 <- mirt::mirt(na.omit(CPL.needs.NLD.2013[, 3:13])-1, 1, itemtype = 'gpcm',
                      IRT.param = TRUE, technical = list(NCYCLES = 2000))
# fit coefficients GPCM
fit.PCM.AUS.2013 <- mirt::M2(PCM.AUS.2013)
fit.PCM.ENG.2013 <- mirt::M2(PCM.ENG.2013)
fit.PCM.JPN.2013 <- mirt::M2(PCM.JPN.2013)
fit.PCM.NLD.2013 <- mirt::M2(PCM.NLD.2013)
```

GPCM: Model fit 2018

The GPCM was estimated using the "mirt" package (Chalmers, 2012). Syntax ran in R is printed above. Model fit coefficients were insufficient in absolute terms. RMSEA for the four countries in alphabetical order were: 0.11, 0.139, 0.082, and 0.117. CFI for the four countries in alphabetical ordere were: 0.91, 0.88, 0.91, and 0.82. Because this is the first measurement model explored, conclusions on the relative fit are found in subsequent sections. BIC values were 31355.4, 23044.6, 34540.2, 22379.3. $\frac{\chi^2}{df}$ values ranged between: 17.31, 20.97, 13.16, and 13.28.

GPCM: Model fit 2013

The GPCM was estimated using the "mirt" package (Chalmers, 2012). Syntax ran in R is printed above. Model fit coefficients were insufficient in absolute terms. RMSEA for the four countries in alphabetical order were: 0.171, 0.077, 0.089, and 0.08. CFI for the four countries in alphabetical ordere were: 0.78, 0.96, 0.89, and 0.9. Because this is the first measurement model explored, conclusions on the relative fit are found in subsequent sections. BIC values were 26462.2, 31791, 39774.8, 27788.1. $\frac{\chi^2}{df}$ values ranged between: 35.67, 9.6, 18.4, and 8.1.

GPCM: Interpretation output

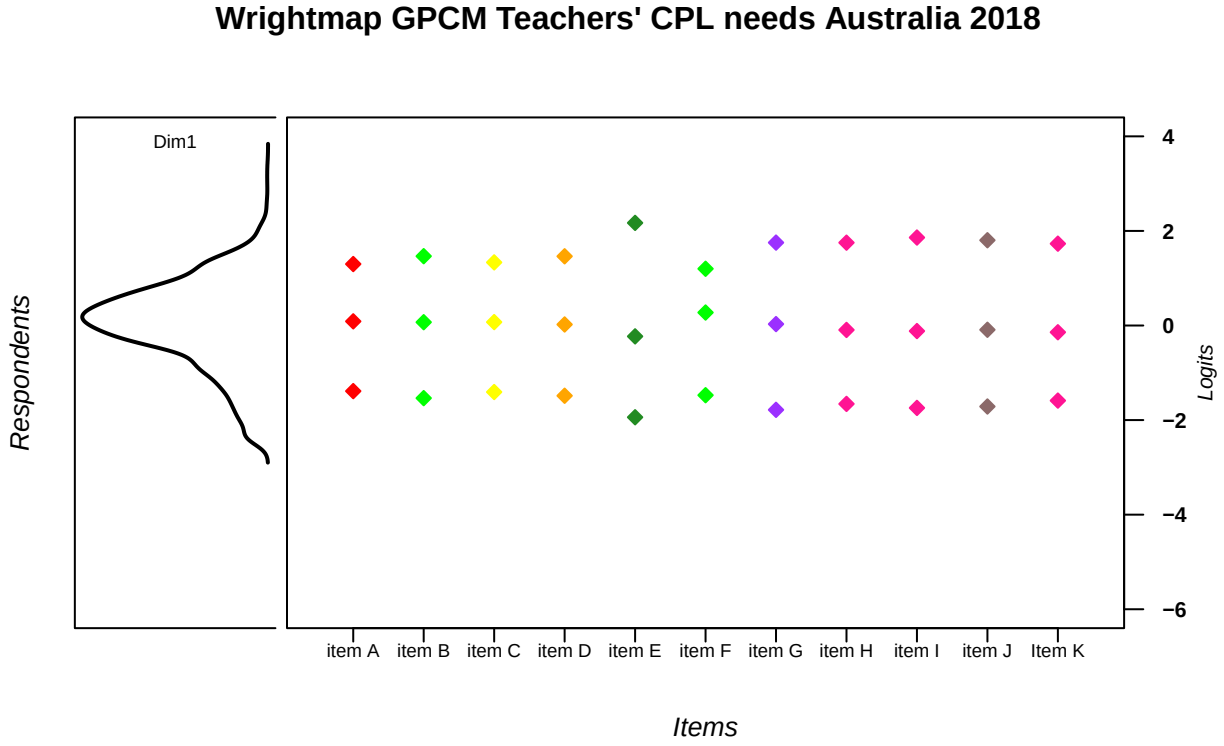
It might be possible to keep a subset of items that fit the GPCM. Item selection is a time consuming process however. Whether such effort might be worthwhile depends on the utility that the GPCM has for identifying individual teachers' CPL needs. We examined Wright map plots to get an impression of its potential utility. In the center of the Wright map plot is the latent continuum plotted vertically. The continuum starts at the top and runs to the bottom. Left side of the vertical continuum the person positions are plotted. Right of the vertical continuum the item locations are plotted. Following the logic of the GPCM, teachers located at the top of the continuum have high probability to mark the item response category "no need at present". Hence, these teachers are estimated to have no or very low levels of CPL need on all of the areas. Teachers at the bottom of the continuum have high probability to mark the item response category "high level of need" on all of the areas. Of most interest is whether areas locations vary over the continuum. Variation would indicate that, although teachers have low or moderate levels of CPL need overall, the probability that they exprese high need for CPL is not uniformly distributed over the areas.

```
person.scores.AUS.2018 <- mirt::fscores(PCM.AUS.2018)

## Make data.frame object to be inserted in the function wrightMap()
item.parameters.AUS.2018 <- as.data.frame(mirt::coef(PCM.AUS.2018,IRTpars = T,
```

```
                                    simplify = T)[[1]][, 2:4])
item.parameters.AUS.2018 <- item.parameters.AUS.2018 - rowMeans(mirt::coef(
                        PCM.AUS.2018,IRTpars = T, simplify = T)[[1]][, 2:4])
rownames(item.parameters.AUS.2018) <- c("item A","item B","item C","item D","item E",
                                    "item F","item G","item H","item I","item J",
                                    "Item K")
```

```
person.scores.AUS.2013 <- mirt::fscores(PCM.AUS.2013)

## Make data.frame object to be inserted in the function wrightMap()
item.parameters.AUS.2013 <- as.data.frame(mirt::coef(PCM.AUS.2013,IRTpars = T,
                                    simplify = T)[[1]][, 2:4])
item.parameters.AUS.2013 <- item.parameters.AUS.2013 - rowMeans(mirt::coef(
                        PCM.AUS.2013,IRTpars = T, simplify = T)[[1]][, 2:4])
rownames(item.parameters.AUS.2013) <- c("item A","item B","item C","item D","item E",
                                    "item F","item G","item H","item I","item J",
                                    "Item K")
```

```
# syntax for plotting Wrightmap
WrightMap.AUS.2018 <- WrightMap::wrightMap(person.scores.AUS.2018, item.parameters.AUS.2018,
          person.side = personDens, show.thr.lab = FALSE,
          main.title = "Wrightmap GPCM Teachers' CPL needs Australia 2018", min.l = -6,
          max.l = 4, item.prop = 0.8, thr.sym.col.fg =
                c(CPL.needs.items[1:11,3],CPL.needs.items[1:11,3],
                  CPL.needs.items[1:11,3]),thr.sym.col.bg =
                c(CPL.needs.items[1:11,3],CPL.needs.items[1:11,3],
                  CPL.needs.items[1:11,3]))
```



We print the syntax to extract the teacher positions and the item locations from the mirt-object "PCM.AUS.2018". Under that code chunk follows the code to generate a Wrightmap plot using the r package "WirghtMap". The wright maps for the GPCM were very similar for all countries. Therefore we plot just one, Australia 2018. On the x-axis are the 11 items "A" to "K". The three vertically plotted dots above the items are our estimates of the item-step locations. The highest dot is the first step. Teacher positioned at the location of the first item step have a probability of 50% to choose the higher response category of the competing categories "no need at present" and a "low level of need", the further teachers position is beyond the item location (thus the lower teachers are positioned at the continuum), the higher the probability is that teachers endorse the higher response category out of these two categories. It can be observed that the GPCM estimates equal distances between the first the second and the third item steps. This result suggests that taking an item step (meaning that the teacher likely will endorse the higher response category $k + 1$) requires a similar increase in teachers' level of CPL need.

What is further apparent from the Wright maps is that the GPCM have no use for matching teachers positions with unique areas in need for CPL. When moving top-down along the continuum then there are three points at which the model predicts that the teacher will take an item step. However, the model predicts that the teacher takes the item step for all areas simultaneously. Again, this is observed in all countries in 2018 and 2013.

The Generalized Graded Unfolding Model (GGUM)

The Generalized Graded Unfolding Model (GGUM) was fitted to the data to test the applicability of the linear unfolding measurement. Unfolding models have the purpose to characterize or typify persons. Conceptually it believes that the probability that teachers endorse a high level of CPL needs peaks for some specific areas (items) but is low for all others. In the Figure 2, the probability peaks at the position of the black triangle. Here, the black triangle represents the location of an item. According to the model estimations, the probability is high that the teacher marks the black triangle item with *a high level of need* while the probability on such mark is lower for the other items. GGUM is a polytomous unfolding model, meaning that like the GPCM it estimates item steps.

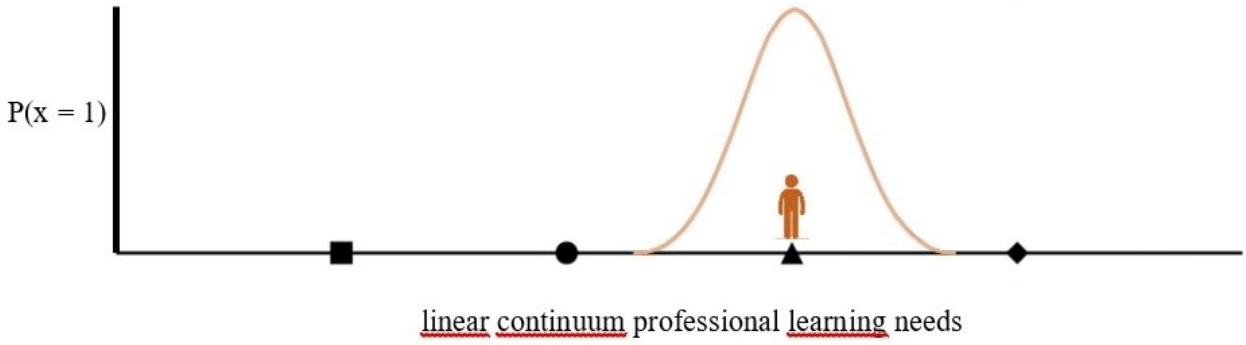


Figure 2: An illustration of the linear unfolding peak probiblity distribution

```
GGUM.AUS.2018 <- mirt::mirt(na.omit(CPL.needs.AUS.2018[, 3:13])-1, 1, itemtype = 'ggum',
                        technical = list(NCYCLES = 5000))
GGUM.ENG.2018 <- mirt::mirt(na.omit(CPL.needs.ENG.2018[, 3:13])-1, 1, itemtype = 'ggum',
                        technical = list(NCYCLES = 5000))
GGUM.JPN.2018 <- mirt::mirt(na.omit(CPL.needs.JPN.2018[, 3:13])-1, 1, itemtype = 'ggum',
                        technical = list(NCYCLES = 2000))
GGUM.NLD.2018 <- mirt::mirt(na.omit(CPL.needs.NLD.2018[, 3:13])-1, 1, itemtype = 'ggum',
                        technical = list(NCYCLES = 2000))

# fit coefficients GGUM
fit.GGUM.AUS.2018 <- mirt::M2(GGUM.AUS.2018)
fit.GGUM.ENG.2018 <- mirt::M2(GGUM.ENG.2018)
fit.GGUM.JPN.2018 <- mirt::M2(GGUM.JPN.2018)
fit.GGUM.NLD.2018 <- mirt::M2(GGUM.NLD.2018)
```

```
GGUM.AUS.2013 <- mirt::mirt(na.omit(CPL.needs.AUS.2013[, 3:13])-1, 1, itemtype = 'ggum',
                        technical = list(NCYCLES = 2000))
GGUM.ENG.2013 <- mirt::mirt(na.omit(CPL.needs.ENG.2013[, 3:13])-1, 1, itemtype = 'ggum',
                        technical = list(NCYCLES = 2000))
GGUM.JPN.2013 <- mirt::mirt(na.omit(CPL.needs.JPN.2013[, 3:13])-1, 1, itemtype = 'ggum',
                        technical = list(NCYCLES = 2000))
GGUM.NLD.2013 <- mirt::mirt(na.omit(CPL.needs.NLD.2013[, 3:13])-1, 1, itemtype = 'ggum',
                        technical = list(NCYCLES = 2000))

# fit coefficients GGUM
fit.GGUM.AUS.2013 <- mirt::M2(GGUM.AUS.2013)
fit.GGUM.ENG.2013 <- mirt::M2(GGUM.ENG.2013)
fit.GGUM.JPN.2013 <- mirt::M2(GGUM.JPN.2013)
fit.GGUM.NLD.2013 <- mirt::M2(GGUM.NLD.2013)
```

GGUM: Model fit 2018

The GGUM was estimated using the "mirt" package (Chalmers, 2012).Fit the of the GGUM ranged between sufficient to insufficient in absolute terms. RMSEA for the four countries in alphabetical ordere were: 0.062, 0.075, 0.078, and 0.076. CFI for the four countries in alphabetical ordere were: 0.99, 0.98, 0.96, and 0.96. Because this is the first measurement model explored, conclusions on the relative fit are found in subsequent sections. BIC values were 31011.6, 23106.8, 34604.1, 22318.4. $\frac{\chi^2}{df}$ values ranged between: 6.25, 6.84, 12.01, and 6.23.

GGUM: Model fit 2013

The GGUM was estimated using the "mirt" package (Chalmers, 2012). Fit the of the GGUM ranged between sufficient to insufficient in absolute terms. RMSEA for the four countries in alphabetical ordere were: 0.08, 0.018, 0.052, and 0.049. CFI for the four countries in alphabetical ordere were: 0.98, 1, 0.98, and 0.98. Because this is the first measurement model explored, conclusions on the relative fit are found in subsequent sections. BIC values were 26539, 31867.4, 39773.2, 27718.9. $\frac{\chi^2}{df}$ values ranged between: 8.57, 1.46, 6.93, and 3.68

Overall, model fit coefficients favor the GGUM model over the GPCM, and fit coefficients for the GGUM were all within the boundaries of what we consider sufficient absolute fit.

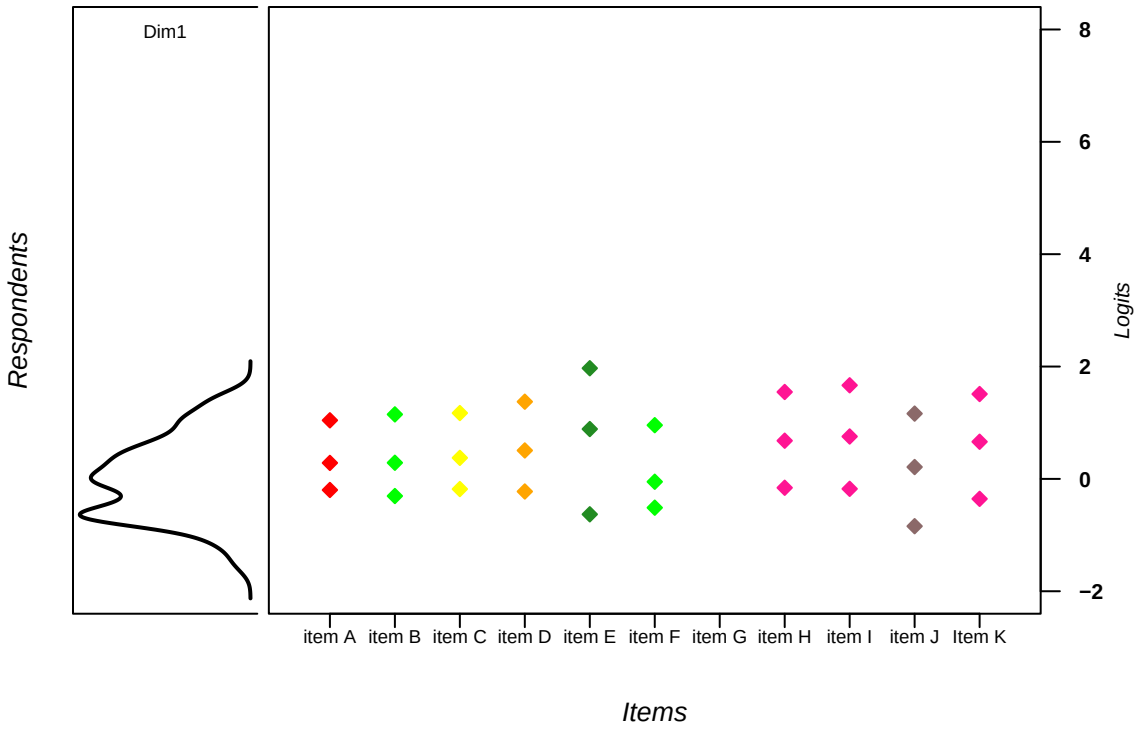
GGUM: Interpretation output

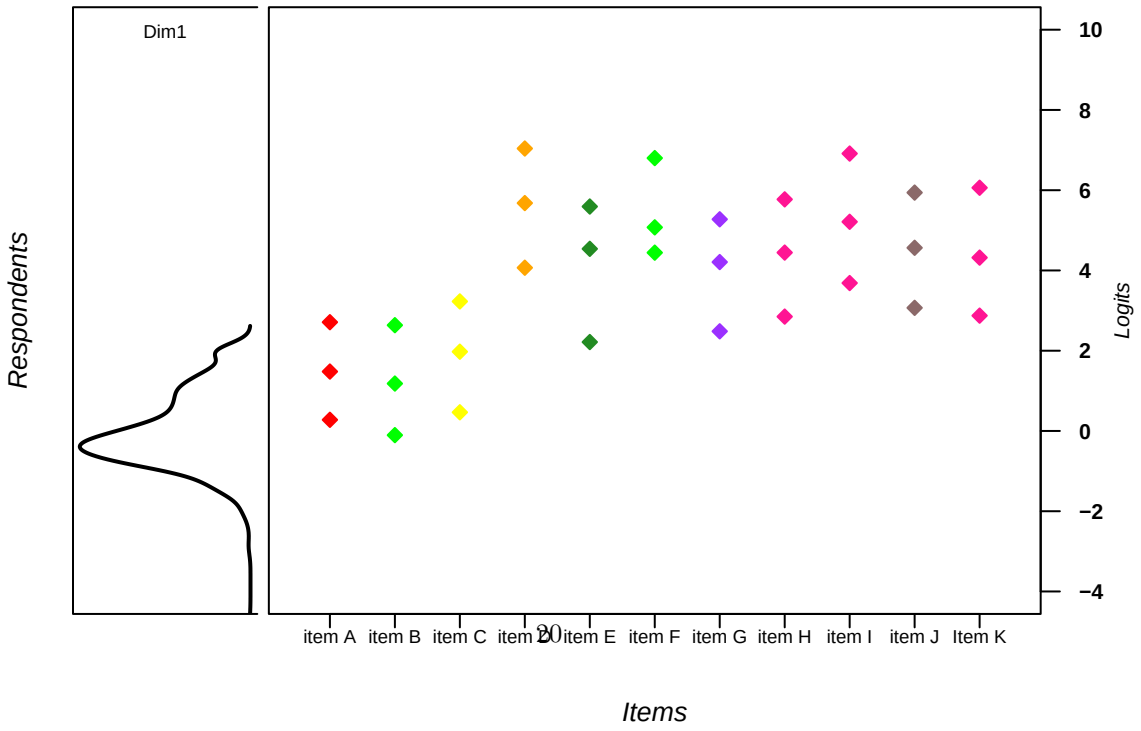
Though the GGUM fits well to the data, Wright map plots indicate modest utility of its outcomes. Again the model outcomes mostly predict no association between the level of need for learning and what area the teacher wants to learn about. Increasing level of need, increases the probability that teachers tick the higher response category, but the increase in probability is uniform over the areas. Only in England in 2013 and in Australia in 2018 do the results connect higher levels of need with varying probability of need for CPL in areas. We plot Australia and England below.

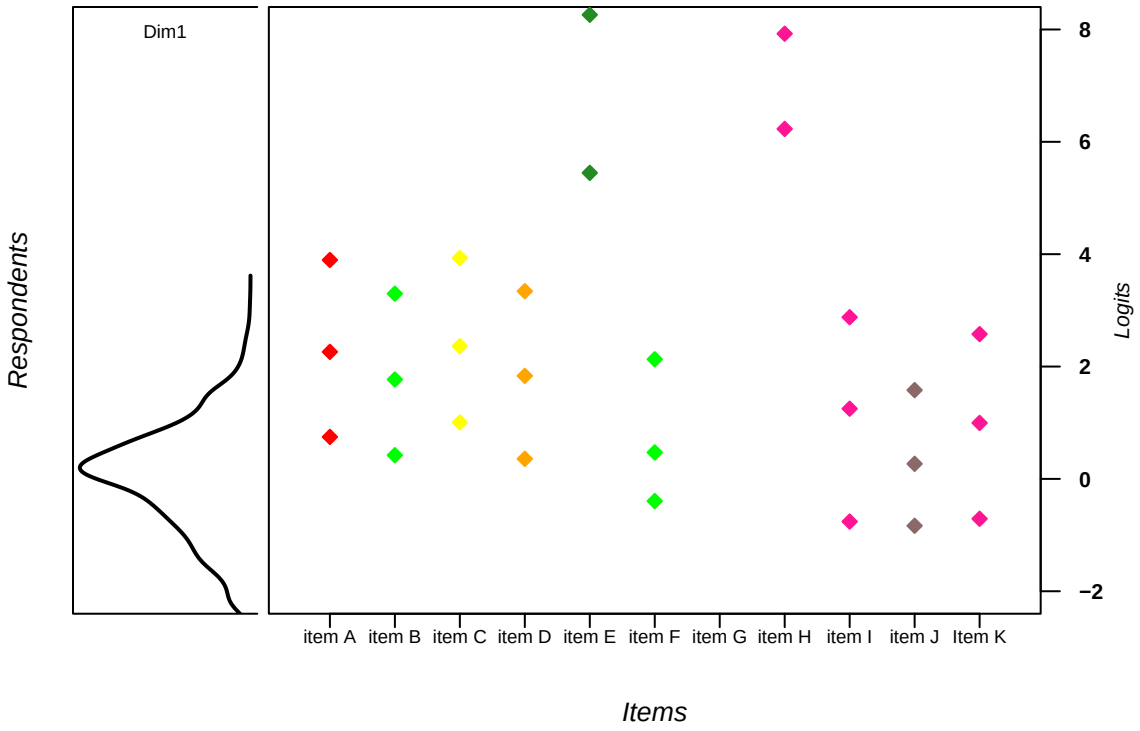
```
person.scores.AUS.2018 <- mirt::fscores(GGUM.AUS.2018)

## Make data.frame object to be inserted in the function wrightMap()
item.parameters.AUS.2018 <- as.data.frame(rbind(mirt::coef(GGUM.AUS.2018)[[1]][3:5],
        mirt::coef(GGUM.AUS.2018)[[2]][3:5], mirt::coef(GGUM.AUS.2018)[[3]][3:5],
        mirt::coef(GGUM.AUS.2018)[[4]][3:5], mirt::coef(GGUM.AUS.2018)[[5]][3:5],
        mirt::coef(GGUM.AUS.2018)[[6]][3:5], mirt::coef(GGUM.AUS.2018)[[7]][3:5],
        mirt::coef(GGUM.AUS.2018)[[8]][3:5], mirt::coef(GGUM.AUS.2018)[[9]][3:5],
        mirt::coef(GGUM.AUS.2018)[[10]][3:5], mirt::coef(GGUM.AUS.2018)[[11]][3:5]))
rownames(item.parameters.AUS.2018) <- c("item A","item B","item C","item D","item E",
                                        "item F","item G","item H","item I","item J",
                                        "Item K")
```

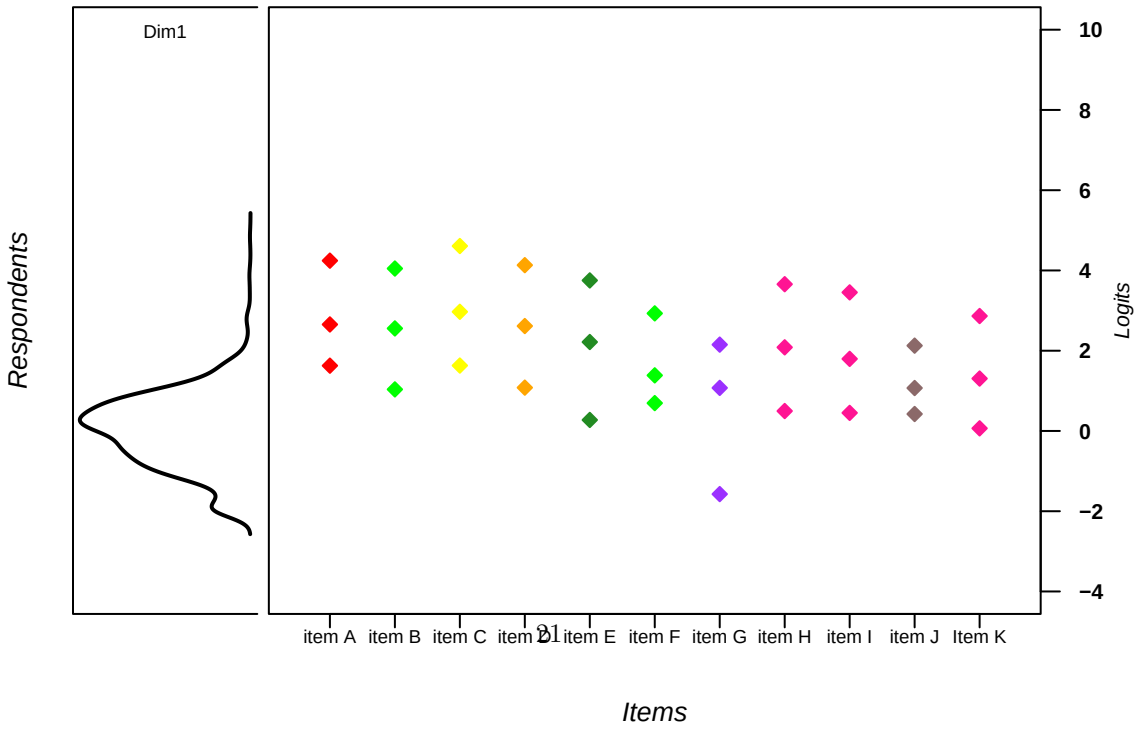
Circumplex Model

The circumplex was estimated using the CIRCUM software (Browne, 1992). Likert Scale scores were re-codes into item steps. In item steps logic, Likert scale scores are dummy coded. We re-coded one matrix for every level of need starting from the low level of need. As we followed the logic of the Adjacent Category Approach, all responses reflecting the matrix defined level of need were coded "1" and all adjacent responses were coded "1". For example, the matrix defining the "low level of need" re-coded all Likert scale scores of "2 = low level of need" into "1", it re-coded the adjacent Likert scale category of "1 = no need" into "1",


Dim1
Respondents
8
6
4
2
0
−2
Logits
item A
item B
item C
item D
item E
item F
item G
item H
item I
item J
Item K
Items


Dim1
Respondents
10
8
6
4
2
0
−2
−4
Logits
item A
item B
item C
item D
item E
item F
item G
item H
item I
item J
Item K
Items


Dim1
Respondents
Logits
8
6
4
2
0
−2
item A
item B
item C
item D
item E
item F
item G
item H
item I
item J
Item K
Items


Dim1
Respondents
Logits
10
8
6
4
2
0
−2
−4
item A
item B
item C
item D
item E
item F
item G
item H
item I
item J
Item K
Items

		no need	low need	moderate need	high need
matrix 1:low need	pattern	1	1	0	0
	rationale	adj	cat		
matrix 2:moderate need	pattern	0	1	1	0
	rationale		adj	cat	
matrix 3:high need	pattern	0	0	1	1
	rationale			adj	cat

Table 7: Coding Adjacent item steps

and it re-coded all higher Likert scales scores of "3 = moderate need" and "4 = high need" into "0"; the matrix defining the "moderate level of need" re-coded all Likert scale scores of "3 = moderate level of need" into "1", it re-coded the adjacent Likert scale category of "2 = low need" into "1", and it re-coded the lowest category "1 = no need" and the highest response category of "4 = high need" both into "0", etc. The idea followed the following pattern:

The correlations for the three matrices were estimated and pooled into one input correlation matrix which was inserted to CIRCUM. Circumplex models were estimated unconstrained and with Minimum Score Correlation (MSC) constrained to 0.00. The constained Circumplex, denoted as Circumplex (C), constrains the locations of the areas such that when two areas are 180 degrees apart, they share a model predicted correlation of 0.00.

The Circumplex (C) is more parsimonious for international comparison, because it ensures that the distances between areas express correlations of similar size in every country. Thus, the distance of 45 degrees reflects a positive correlation of similar size in Japan and the Netherlands, for example.

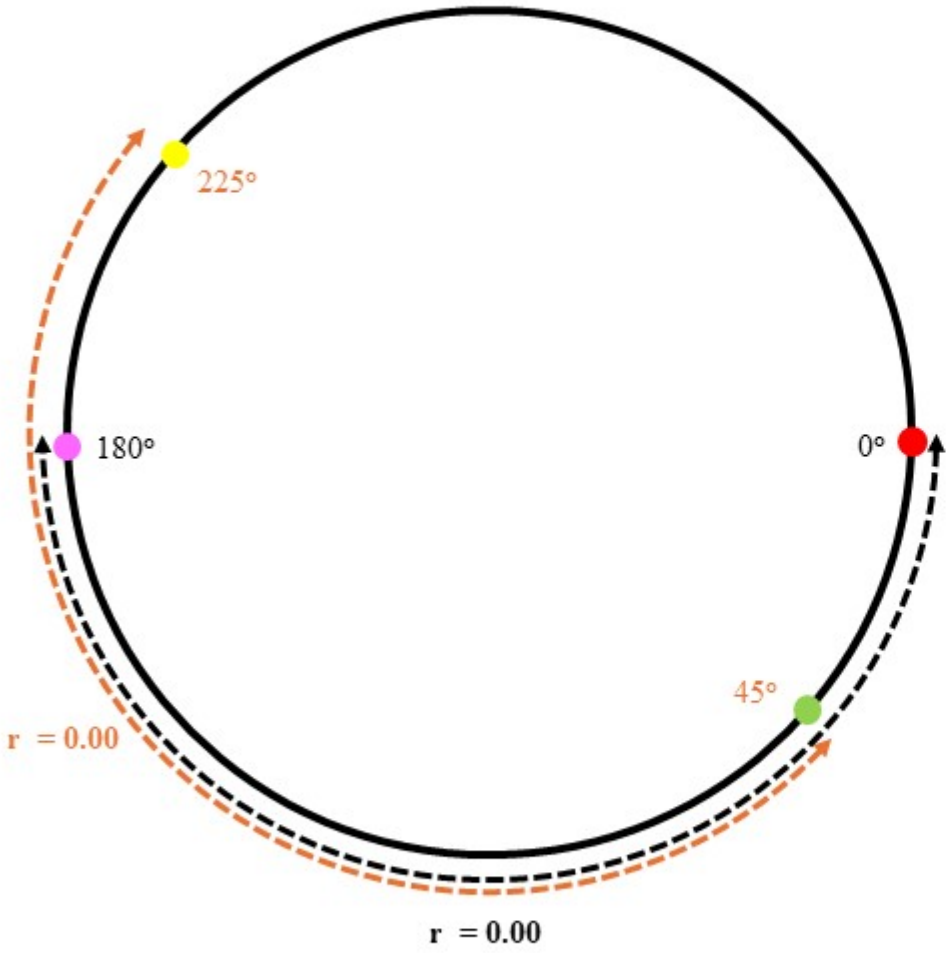


Figure 5: Circumplex with constrained MSC: distance between areas 180 degrees apart reflects their model predicted correlation is r = 0.00

Circumplex Model: Model fit

Fit the of the circumplex was estimated by the Root Mean Square Error of Approximation (RMSEA) and the χ^2. The CFI is misses because it is not clear how to define the null model (Browne (1992)). An estimation of the BIC is given: according to the formula:

$$BIC = \chi^2 + \ln(N)[k(k+1)/2 - df]$$

The unconstrained model had lower χ^2 values and RMSEA indicating less measurement errors. The Constrained circumplex model generally has lower BIC values indicating that its parsimony is preferred over the unconstrained model with more parameters. For the unconstained model RMSEA values for the countries in alphabetical order are: Australia 0.062 with 99.5% CI [0.055-0.069] in 2018 and 0.048 with 99.5% CI [0.04-0.057] in 2013; England 0.047 with 99.5% CI [0.038-0.056] in 2018 and 0.034 with 99.5% CI [0.025-0.042]; Japan 0.067 with 99.5% CI [0.06-0.074] in 2018 and 0.054 with 99.5% CI [0.048-0.061] in 2013; the Netherlands 0.033 with 99.5% CI [0.022-0.044] in 2018 and 0.005 with 99.5% CI [0.031-0.047] in 2013. These values must be compared to the absolute thressholds specified above and to coefficients of alternative unconstrained models like the GPCM and the GGUM. Overall, the RMSEA values of the unconstrained circumplex are well below the 0.08 threshold, lower than the RMSEA values of the GPCM and comparable to the RMSEA values of the GGUM. The $\frac{\chi^2}{df}$ values of the unconstrained circumplex range between 9.7 in Japan 2018 and 1.5 in the Netherlands 2013, which range is close to the general accepted criterion of below 5. The range of the $\frac{\chi^2}{df}$ in the circumplex also is considerably smaller than it is for the GGUM model which ranges from 16.02 in England 2013 to `rround(fit.GGUM.JPN.2018$M2,2)‘` in Japan 2018.

Fit coefficients for the constrained model indicate it has somewhat lower fit, which is consistent with the model having less parameters. The RMSEA values for the countries in alphabetical order are: Australia 0.084 with 99.5% CI [0.077-0.091] in 2018 and 0.056 with 99.5% CI [0.047-0.065] in 2013; England 0.067 with 99.5% CI [0.058-0.076] in 2018 and 0.05 with 99.5% CI [0.043-0.058]; Japan 0.068 with 99.5% CI [0.061-0.075] in 2018 and 0.047 with 99.5% CI [0.041-0.053] in 2013; the Netherlands 0.055 with 99.5% CI [0.045-0.065] in 2018 and 0.056 with 99.5% CI [0.047-0.065] in 2013. All but one of the values are below the 0.08 threshold. Only in Australia in 2018 this is no longer the case. Because this constrained model is more restrictive, it is complex to compare it with the coefficients of the GGUM and GPCM. Alike the RMSEA, the range in $\frac{\chi^2}{df}$ is somewhat higher for the constrained model and ranges from 4.73 in the Netherlands in 2018 to 4.71 in Australia in 2018. Still most values are below or approximate the absolute criterion of 5. The BIC values favor the constrained model over the unconstrained model. In all cases the BIC decreases with more the 100 points. Overall, the study applied the constrained circumplex model because its fit is approximately equal to the unconstrained model while its interpretation is much easier.

model	CFI	RMSEA	RMSEA 5%	RMSEA 95%	M2 / Chi	df	BIC
Austrlia							
GPCM	0.91	0.11	0.1	0.119	380.87	22	31355.4
GGUM	0.99	0.062	0.049	0.077	68.7	11	31011.6
Circumplex	NA	0.062	0.055	0.069	7.71	31	4319.6
Circumplex (C)	NA	0.084	0.077	0.091	12.68	32	4232.9
England							
GPCM	0.88	0.139	0.128	0.15	461.33	22	23044.6
GGUM	0.98	0.075	0.059	0.091	75.24	11	23106.8
Circumplex	NA	0.047	0.038	0.056	3.76	31	4054.8
Circumplex (C)	NA	0.067	0.058	0.076	6.34	32	3896.9
Japan							
GPCM	0.91	0.082	0.074	0.091	289.44	22	34540.2
GGUM	0.96	0.078	0.066	0.09	132.06	11	34604.1
Circumplex	NA	0.067	0.06	0.074	9.7	31	4542.4
Circumplex (C)	NA	0.068	0.061	0.075	9.79	32	4291.8
Netherlands							
GPCM	0.82	0.117	0.105	0.129	292.12	22	22379.3
GGUM	0.96	0.076	0.06	0.094	68.56	11	22318.4
Circumplex	NA	0.033	0.022	0.044	2.11	31	3911.4
Circumplex (C)	NA	0.055	0.045	0.065	4.03	32	3736

Table 8: Fit coefficients for PCM GGUM and Circumplex models ISCED-2 2018

model	CFI	RMSEA	RMSEA 5%	RMSEA 95%	M2 / Chi	df	BIC
Austrlia							
GPCM	0.78	0.171	0.16	0.181	784.69	22	26462.2
GGUM	0.98	0.08	0.065	0.095	94.31	11	26539
Circumplex	NA	0.048	0.04	0.057	4.071	31	4134.3
Circumplex (C)	NA	0.056	0.047	0.065	4.708	32	3910
England							
GPCM	0.96	0.077	0.068	0.087	211.22	22	31791
GGUM	1	0.018	0	0.035	16.02	11	31867.4
Circumplex	NA	0.034	0.025	0.042	2.79	31	4199.3
Circumplex (C)	NA	0.05	0.043	0.058	5.157	32	4022.7
Japan							
GPCM	0.89	0.089	0.082	0.097	404.71	22	39774.8
GGUM	0.98	0.052	0.041	0.063	76.265	11	39773.2
Circumplex	NA	0.054	0.048	0.061	7.69	31	4585
Circumplex (C)	NA	0.047	0.041	0.053	5.88	32	4265
Netherlands							
GPCM	0.9	0.08	0.069	0.091	178.102	22	27788.1
GGUM	0.98	0.049	0.033	0.066	40.53	11	27718.9
Circumplex	NA	0.048	0.031	0.047	1.5	31	4014
Circumplex (C)	NA	0.056	0.047	0.065	4.73	32	3872.5

Table 9: Fit coefficients for PCM GGUM and Circumplex models ISCED-2 2013

Circumplex model: Results

Visual respresentation of area locations in 2013 and 2018

We present results for our adapted version of the constrained circumplex model. The results apply to experienced teachers who started teaching somewhere between 1983 and 20118. This section presents a series of circular figures. The figures only plot the item locations for the countries in 2018 and 2013. Plots can be compared as the use of the MSC constrained model implies that the distances represent the model predicted correlations of the same size. One locations clutter, this means that all the areas are predicted to share a positive correlation of approximately similar size. Areas far apart do not often coincide, meaning that the need for the one is not strongly associated with the need for the other. In Western countries the areas, A "Knowledge and understanding of my subject field(s)", B "Pedagogical competencies in teaching my subject field(s)", and C "Knowledge of the curriculum" typically are situated in a isosceles. This implies that teachers tend to feel a need for learning just one of the areas. A combined need for two (or three) of these areas is relatively rare. Also, any of the combinations A-B, A-C, B-C is equally common. In Japan we don't see this isosceles. Japanese teachers tend to hold holistic pedagogical visions. This translates in them not distancing areas.

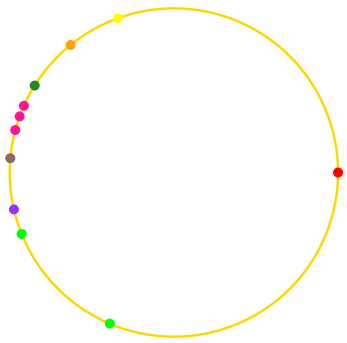


Figure 6: Circular Unfolding Australian secondary education teachers' CPL needs in 2018

letter	professional learning area	angle
A	Knowledge and understanding of my subject field(s)	0
B	Pedagogical competencies in teaching my subject field(s)	113
F	Student behaviour and classroom management	158
G	School management and administration	167
J	Teaching in a multicultural or multilingual setting	185
I	Teaching students with special needs	195
H	Approaches to individualised learning	200
K	Teaching cross-curricular skills (e.g. creativity, critical thinking, problem solving)	204
E	ICT (information and communication technology) skills for teaching	212
D	Student assessment practices	231
C	Knowledge of the curriculum	250

Figure 7: Area locations in angluar degrees for Australia 2018

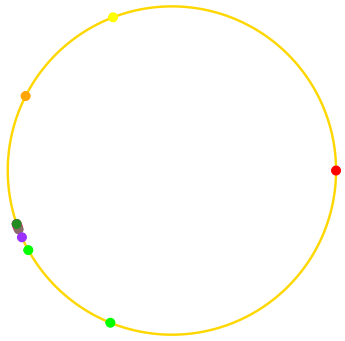
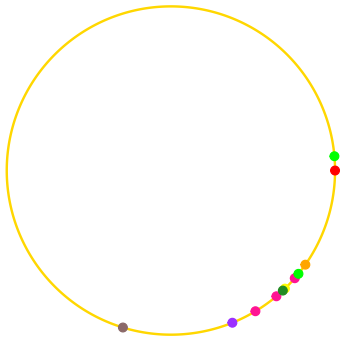


Figure 8: Circular Unfolding English secondary education teachers' CPL needs in 2018

letter	professional learning area	angle
A	Knowledge and understanding of my subject field(s)	0
B	Pedagogical competencies in teaching my subject field(s)	112
F	Student behaviour and classroom management	151
G	School management and administration	156
J	Teaching in a multicultural or multilingual setting	159
H	Approaches to individualised learning	160
K	Teaching cross-curricular skills (e.g. creativity, critical thinking, problem solving)	160
E	ICT (information and communication technology) skills for teaching	161
I	Teaching students with special needs	161
D	Student assessment practices	207
C	Knowledge of the curriculum	249

Figure 9: Area locations in angluar degrees for England 2018



letter	professional learning area	angle
A	Knowledge and understanding of my subject field(s)	0
D	Student assessment practices	35
F	Student behaviour and classroom management	39
H	Approaches to individualised learning	41
C	Knowledge of the curriculum	46
E	ICT (information and communication technology) skills for teaching	47
I	Teaching students with special needs	50
K	Teaching cross-curricular skills (e.g. creativity, critical thinking, problem solving)	59
G	School management and administration	68
J	Teaching in a multicultural or multilingual setting	107
B	Pedagogical competencies in teaching my subject field(s)	355

Figure 10: Circular Unfolding Japanese secondary education teachers' CPL needs in 2018

Figure 11: Area locations in angluar degrees for Japan 2018

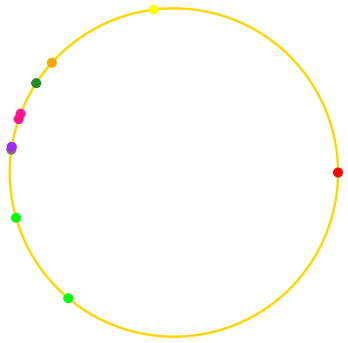
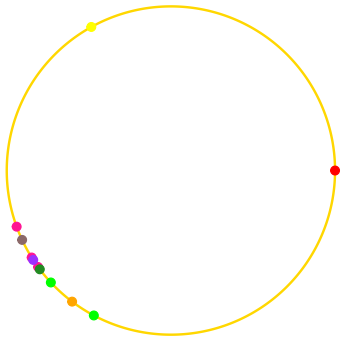


Figure 12: Circular Unfolding Dutch secondary education teachers' CPL needs in 2018

letter	professional learning area	angle
A	Knowledge and understanding of my subject field(s)	0
B	Pedagogical competencies in teaching my subject field(s)	130
F	Student behaviour and classroom management	164
J	Teaching in a multicultural or multilingual setting	188
G	School management and administration	189
I	Teaching students with special needs	189
H	Approaches to individualised learning	199
K	Teaching cross-curricular skills (e.g. creativity, critical thinking, problem solving)	201
E	ICT (information and communication technology) skills for teaching	213
D	Student assessment practices	222
C	Knowledge of the curriculum	263

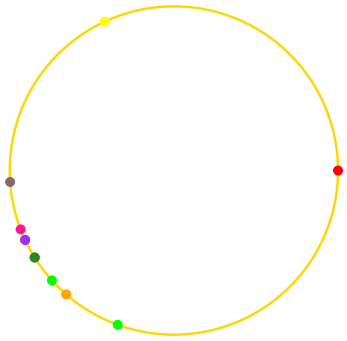
Figure 13: Area locations in angluar degrees for the Netherlands 2018



letter	professional learning area	angle
A	Knowledge and understanding of my subject field(s)	0
B	Pedagogical competencies in teaching my subject field(s)	118
D	Student evaluation and assessment practice	127
F	Student behaviour and classroom management	137
E	ICT skills for teaching	143
K	teaching cross-curricular skills	144
G	School management and administration	147
H	Approaches to individualised learning	148
J	teaching in multicultural settings	155
I	teaching students with special needs	160
C	Knowledge of the curriculum	241

Figure 14: Circular Unfolding australian secondary education teachers' CPL needs in 2013

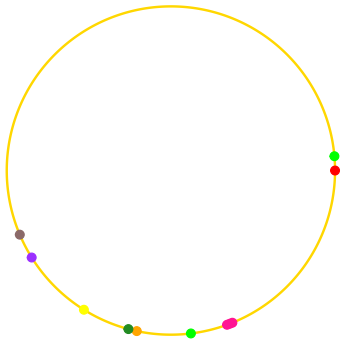
Figure 15: Area locations in angluar degrees for Australia 2013



letter	professional learning area	angle
A	Knowledge and understanding of my subject field(s)	0
B	Pedagogical competencies in teaching my subject field(s)	110
D	Student evaluation and assessment practice	131
F	Student behaviour and classroom management	138
E	ICT skills for teaching	148
H	Approaches to individualised learning	148
G	School management and administration	155
K	teaching cross-curricular skills	155
I	teaching students with special needs	159
J	teaching in multicultural settings	176
C	Knowledge of the curriculum	245

Figure 16: Circular Unfolding English secondary education teachers' CPL needs in 2013

Figure 17: Area locations in angluar degrees for England 2013



letter	professional learning area	angle
A	Knowledge and understanding of my subject field(s)	0
H	Approaches to individualised learning	68
I	teaching students with special needs	69
K	teaching cross-curricular skills	70
F	Student behaviour and classroom management	83
D	Student evaluation and assessment practice	102
E	ICT skills for teaching	105
C	Knowledge of the curriculum	122
G	School management and administration	148
J	teaching in multicultural settings	157
B	Pedagogical competencies in teaching my subject field(s)	355

Figure 18: Circular Unfolding Japanese secondary education teachers' CPL needs in 2013

Figure 19: Area locations in angluar degrees for Japan 2013

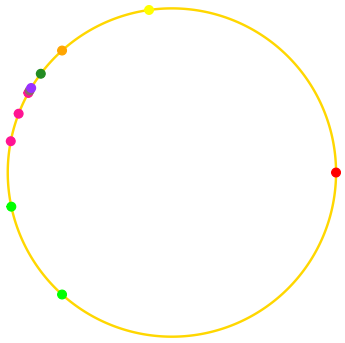


Figure 20: Circular Unfolding Dutch secondary education teachers' CPL needs in 2013

letter	professional learning area	angle
A	Knowledge and understanding of my subject field(s)	0
B	Pedagogical competencies in teaching my subject field(s)	132
F	Student behaviour and classroom management	168
I	teaching students with special needs	191
H	Approaches to individualised learning	201
K	teaching cross-curricular skills	209
J	teaching in multicultural settings	210
G	School management and administration	211
E	ICT skills for teaching	217
D	Student evaluation and assessment practice	228
C	Knowledge of the curriculum	262

Figure 21: Area locations in angluar degrees for the Netherlands 2013

Circumplex model: Assessment of Differential Item Functioning as an indicator of trends in teachers' perceptions

Differential Item Functioning was assessed using the 99.45% Confidence Intervals (99.5%CI). The CI's reflect a Bronferoni correction (0.05 / 11) for the number of items that we assessed DIF for. The same tables with results are also presented in the article. In total seven areas significantly change locations between 2013 and 2018 in Australia, two areas in England, seven areas in Japan, and null areas in the Netherlands.

letter	item	Australia		England		Japan		The Netherlands	
		angle	95% CI	angle	95% CI	angle	95% CI	angle	95% CI
A	Knowledge and understanding of my subject field(s)	0	0 - 0	0	0 - 0	0	0 - 0	0	0 - 0
B	Pedagogical competencies in teaching my subject field(s)	118	109.4 - 126.6	110	98.5 - 121.5	355	348.6 - 1.4	132	119.8 - 144.2
C	Knowledge of the curriculum	241	231 - 251	245	235 - 255	122	112 - 132	262	236.9 - 287.1
D	Student evaluation and assessment practice	127	120.6 - 133.4	131	123.8 - 138.2	102	91.3 - 112.7	228	213 - 243
E	ICT skills for teaching	143	130.8 - 155.2	148	138 - 158	105	92.1 - 117.9	217	198.4 - 235.6
F	Student behaviour and classroom management	137	129.8 - 144.2	138	129.4 - 146.6	83	70.1 - 95.9	168	151.5 - 184.5
G	School management and administration	147	135.5 - 158.5	155	143.5 - 166.5	148	138 - 158	211	185.9 - 236.1
H	Approaches to individualised learning	148	138.7 - 157.3	148	140.1 - 155.9	68	55.8 - 80.2	201	185.2 - 216.8
I	teaching students with special needs	160	143.5 - 176.5	159	150.4 - 167.6	69	54.7 - 83.3	191	176 - 206
J	teaching in multicultural settings	155	142.1 - 167.9	176	161.7 - 190.3	157	144.1 - 169.9	210	192.1 - 227.9
K	teaching cross-curricular skills	144	135.4 - 152.6	155	146.4 - 163.6	70	56.4 - 83.6	209	194 - 224

letter	item	Australia		England		Japan		The Netherlands	
		angle	95% CI	angle	95% CI	angle	95% CI	angle	95% CI
A	Knowledge and understanding of my subject field(s)	0	0 - 0	0	0 - 0	0	0 - 0	0	0 - 0
B	Pedagogical competencies in teaching my subject field(s)	113	104.4 - 121.6	112	100.5 - 123.5	355	348.6 - 1.4	130	117.8 - 142.2
C	Knowledge of the curriculum	250	240 - 260	249	239 - 259	46	36 - 56	263	237.9 - 288.1
D	Student assessment practices	231	224.6 - 237.4	207	199.8 - 214.2	35	24.3 - 45.7	222	207 - 237
E	ICT (information and communication technology) skills for teaching	212	199.8 - 224.2	161	151 - 171	47	34.1 - 59.9	213	194.4 - 231.6
F	Student behaviour and classroom management	158	150.8 - 165.2	151	142.4 - 159.6	39	26.1 - 51.9	164	147.5 - 180.5
G	School management and administration	167	155.5 - 178.5	156	144.5 - 167.5	68	58 - 78	189	163.9 - 214.1
H	Approaches to individualised learning	200	190.7 - 209.3	160	152.1 - 167.9	41	28.8 - 53.2	199	183.2 - 214.8
I	Teaching students with special needs	195	178.5 - 211.5	161	152.4 - 169.6	50	35.7 - 64.3	189	174 - 204
J	Teaching in a multicultural or multilingual setting	185	172.1 - 197.9	159	144.7 - 173.3	107	94.1 - 119.9	188	170.1 - 205.9
K	Teaching cross-curricular skills (e.g. creativity, critical thinking, problem solving)	204	195.4 - 212.6	160	151.4 - 168.6	59	45.4 - 72.6	201	186 - 216

Circumplex model: Teacher positions

This section presents trends in teachers' positions in Australia, England, Japan and the Netherlands. The figures are presented in rows with every row starting with the distribution of teachers having high learning needs, followed by the model presenting the distribution of teachers with only moderate learning needs and completely at the right are the teachers with only low learning needs. The teachers within the grouping of high learning needs have at least one area which they say they feel high need for learning for. Teachers with only moderate learning needs have no area for which they feel a high need for professional learning, but they do feel a moderate level of need to learn about one or more areas. Teacher with only low learning needs have no area for they feel a high need for and no area for which they feel a moderate need for further learning but they do feel a low need for learning at one or more areas.

Pages count two rows of Figures. Every time the top row corresponds with the 2018 trend cohort and the bottom row with the 2013 trend cohort. Broadly looking over the results we observe few differences between teachers with high or those with only low learning needs. We can also observe that the distributions have different shapes in 2013 and 2018. For example in Australia, the distribution in teachers' position is more dispersed in 2018 than in 2013. This shows the trends we noticed in the DIF analysis. However, when one would look at the specific items, then these trends would remain unoticed. The need for "ICT skills" (dark green) is observed in 2013 and 2018. However, in 2013 it is cluttered with the other areas, whereas in 2018 the need is clearly distinguishable from learning needs to other areas.

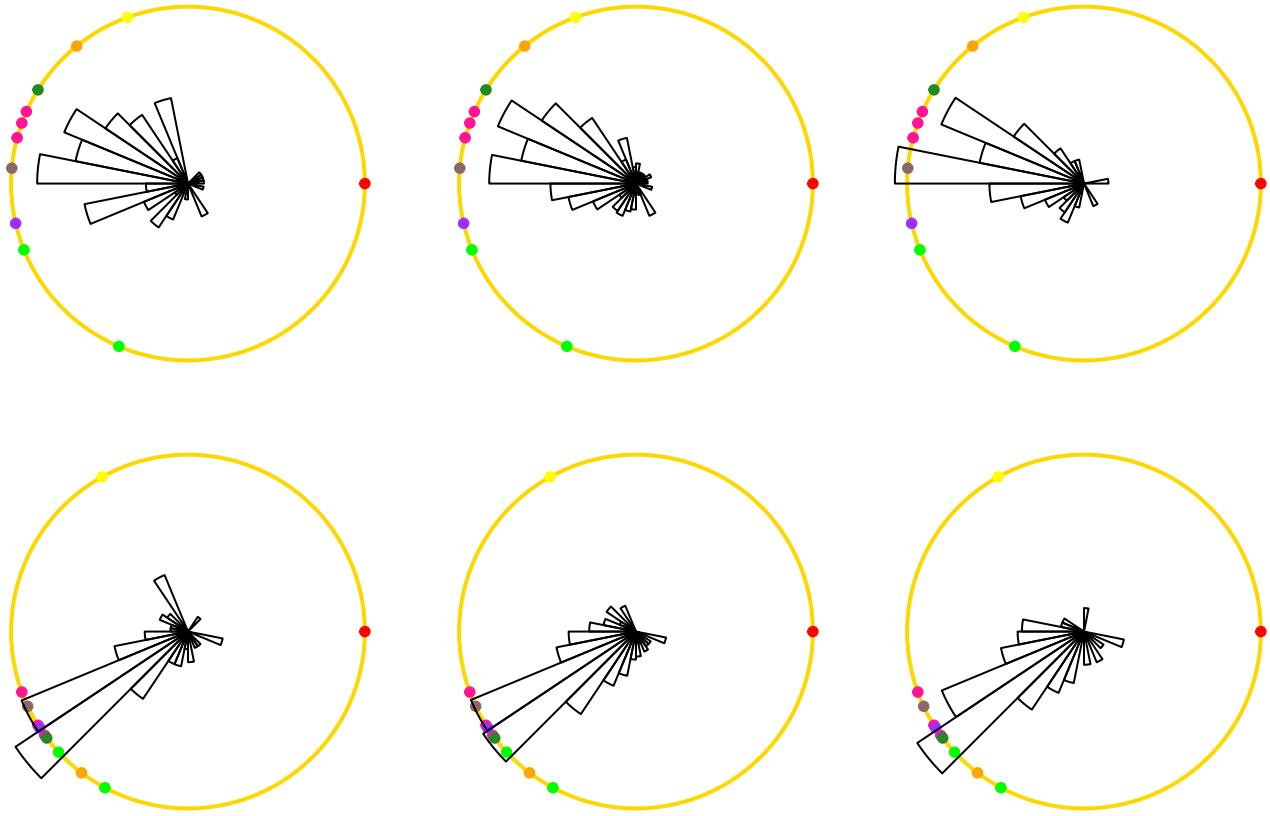


Figure 22: Circular unfolding Australian secondary education teachers' CPL needs; top = 2018, bottom = 2013

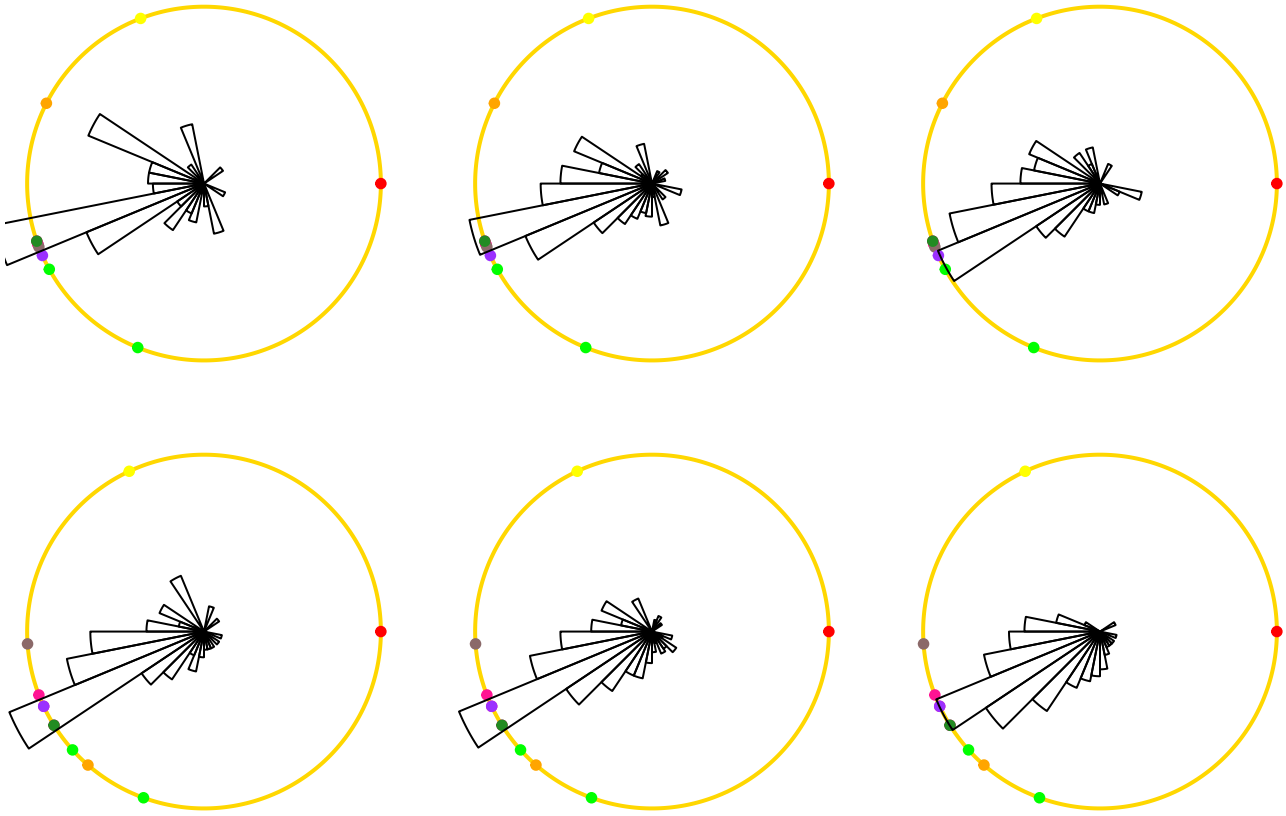


Figure 23: Circular unfolding English secondary education teachers' CPL needs; top = 2018, bottom = 2013

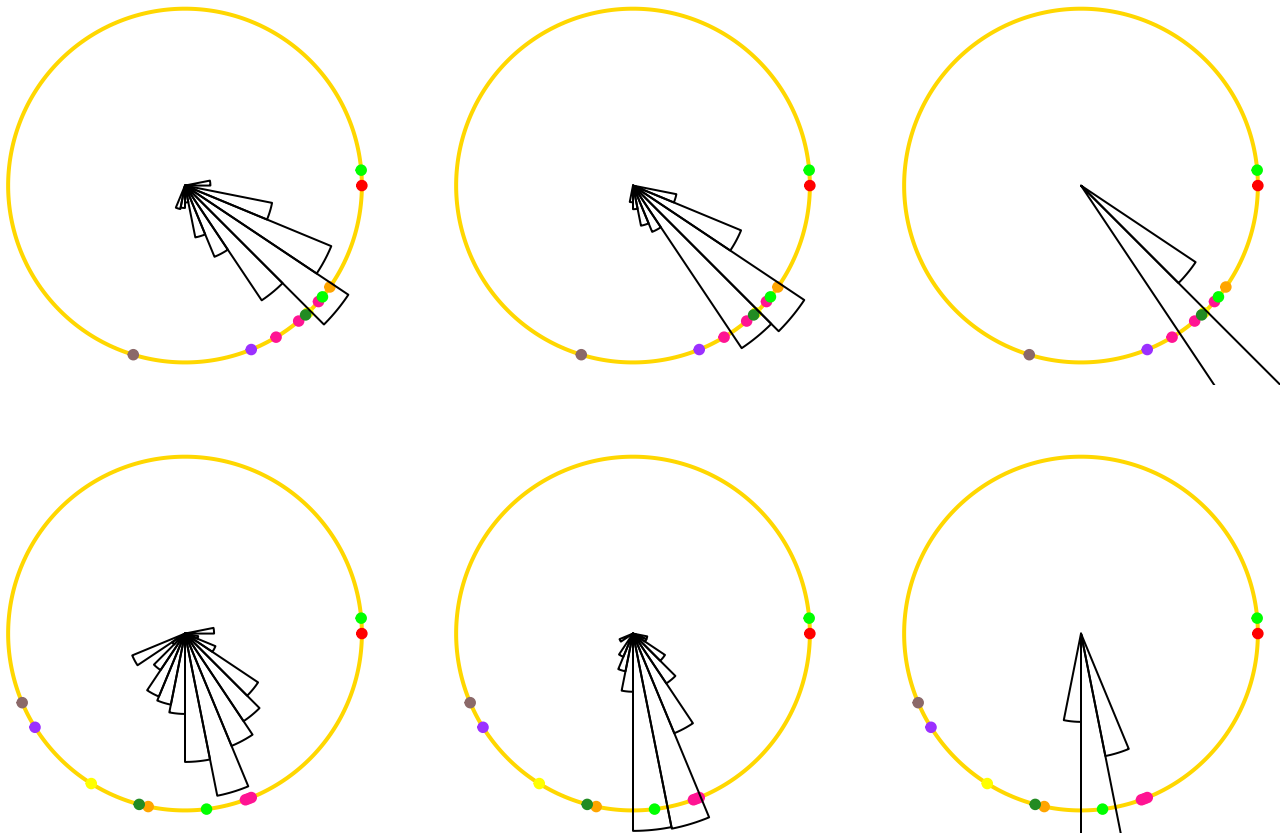


Figure 24: Circular unfolding Japanese secondary education teachers' CPL needs; top = 2018, bottom = 2013

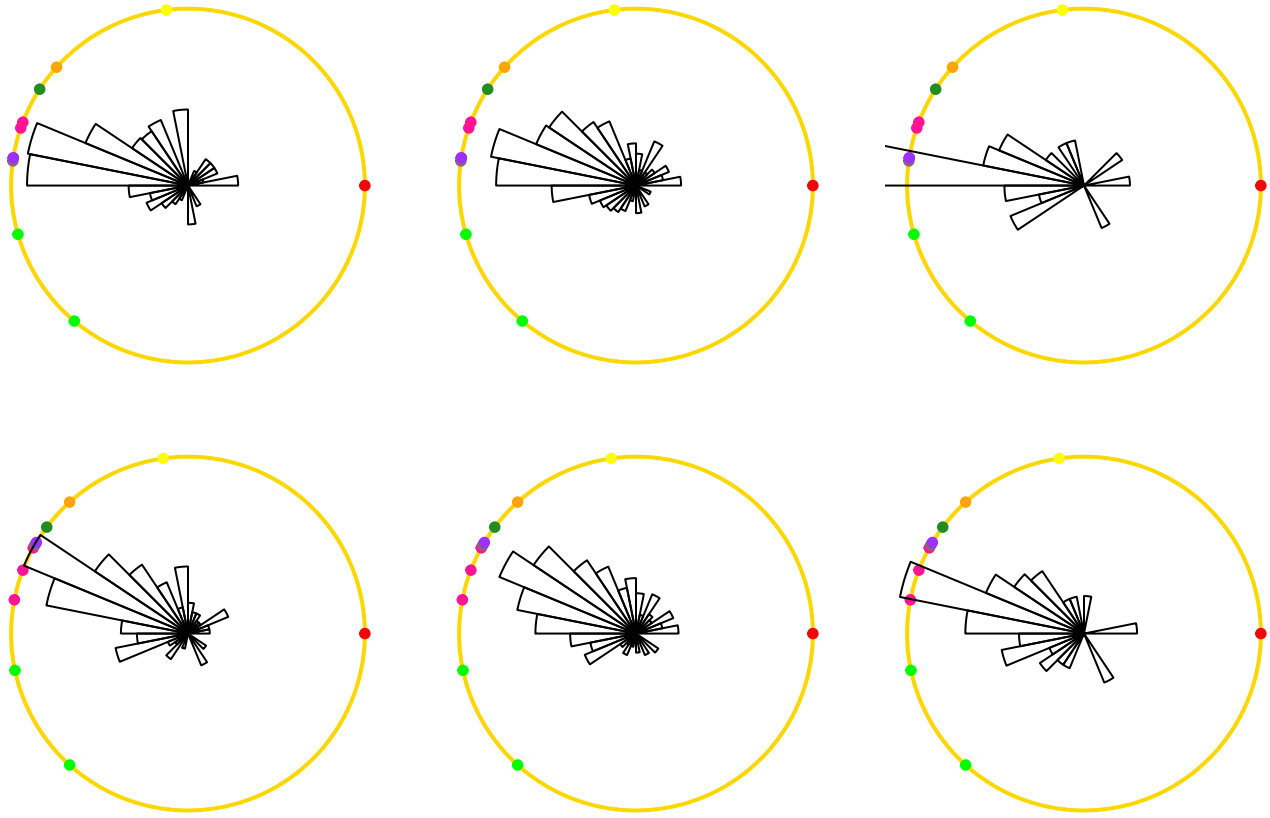


Figure 25: Circular unfolding Dutch secondary education teachers' CPL needs; top = 2018, bottom = 2013

Linear metrics: Differences in teachers' level of need

Below two tables follow with data about the proportion of teachers with high learning needs and the mean level of experience. Because of the data selection, the mean number of years of experience is expected to be 5 years greater in the 2018 cohort. While the means are informative, they are not for comparison between the trend cohorts. The proportions of teachers in the high, moderate and low learning needs categories are comparable between cohorts as they reflect trends occuring in the population of teachers that started between 1983 and 2008.

year	P high	P mod	P low
Austrlia			
2018	0.13	0.56	0.31
2013	0.16	0.56	0.28
England			
2018	0.23	0.57	0.2
2013	0.26	0.52	0.22
Japan			
2018	0.01	0.2	0.79
2013	0.01	0.22	0.77
Netherlands			
2018	0.06	0.46	0.48
2013	0.07	0.52	0.42

Table 10: Proportion of teachers with high, moderate and low CPL need groups in 2013 and 2018

year	M experience low need	SD	M experience mod need	SD	M experience high need	SD
Austrlia						
2018	22.2	6.8	20.5	7	21	7.3
2013	15.8	7.4	16.6	7.5	16.3	7.5
England						
2018	19.1	6.7	18.5	6	18.8	5.9
2013	13.7	6.4	13.6	6.3	14.2	6.4
Japan						
2018	25.1	8.1	24.9	7.3	22.2	7.5
2013	16.8	8.9	20.1	7.3	18.1	7.7
Netherlands						
2018	21	7.7	20.3	6.9	19.4	6.6
2013	15.2	6.9	15.3	7.3	14.7	6.8

Table 11: Teachers' mean experience (in years) for the high, moderate and low CPL need groups in 2013 and 2018

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