Applied Psychological Measurement
2018, Vol. 42(7) 523–537

DOI: 10.1177/0146621618758289
journals.sagepub.com/home/apm

A Continuous *a*-Stratification Index for Item Exposure Control in Computerized Adaptive Testing

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IF: 1.326

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Introduction

- Computerized Adaptive Testing (CAT)

practical consideration: prevent items from being overexposed

➡ *a*-stratification method: divide the item bank into *K* strata

an appropriate *K* value ?

- balance exposure control and measurement accuracy
- moderate-size fixed constant (*K* = 4)

the replenishment of item bank ?

- recreate every time
- it is more challenging in high-stakes tests

no need to choose
the number of strata

propose an alternate approach: continuous a-stratification

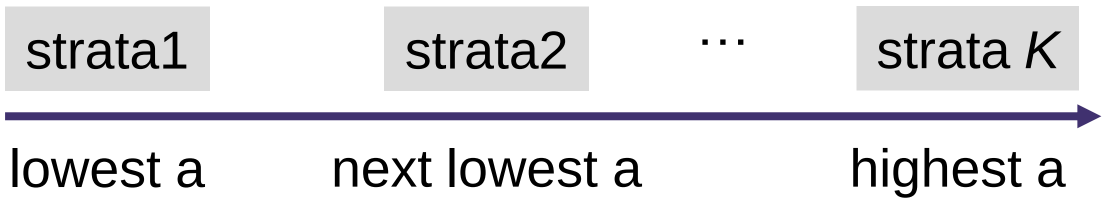
a-Stratification

- One-dimensional IRT model

$$P_j(\theta) = P_j(U = 1|\theta) = c_j + (1 - c_j)\frac{\exp[1.7a_j(\theta - b_j)]}{1 + \exp[1.7a_j(\theta - b_j)]}$$

- Method proceeds

1. Partition the item bank into *K* levels according to item *a* values;
2. Partition the test into *K* stages;
3. J_k items are administered from Stratum *k* ($J_1 + J_2 + \ldots + J_k = J$): e.g. match-*b* / MFI;
4. Repeat Step 3 from *k* = 1, 2, ... ,*K*.



a-Stratification

- Two-dimensional IRT model

$$P_j(\boldsymbol{\theta}) = P_j(U=1|\boldsymbol{\theta}) = \frac{\exp\left[1.7\mathbf{a}_j'(\boldsymbol{\theta} - b_j\mathbf{1})\right]}{1+\exp\left[1.7\mathbf{a}_j'(\boldsymbol{\theta} - b_j\mathbf{1})\right]} \qquad \mathbf{a}_j = \{a_{j1}, a_{j2}\} \quad \boldsymbol{\theta} = \{\theta_1, \theta_2\}$$

➡ use some functions of $\mathbf{a}_j$ for the stratification

What we want to achieve:

- At an early stage: **measure the average** of θ
- As the test progresses: pinpoint the location of θ along **each individual dimension**
- θ_1 and θ_2 should be measurable to the **same degree of precision**

Lee, Ip, & Fuh, 2008 *EPM*

a-Stratification

- Method proceeds

1. Partition the item bank into K levels according to item a values;

strata1 | strata2 | ⋯ | strata K

smallest $|a_1 - a_2|$ → next smallest $|a_1 - a_2|$ → largest $|a_1 - a_2|$

$|a_1 \gg a_2|$ (or $|a_1 \ll a_2|$)

$$D[a_1(\theta_1 - b) + a_2(\theta_2 - b)] \approx D[a_1(\boxed{\theta_1} - b)]$$

individual dimension

$|a_1 - a_2| \approx 0$

$$D[a_1(\theta_1 - b) + a_2(\theta_2 - b)] \approx Da_1[(\theta_1 - b) + (\theta_2 - b)] = 2Da_1\left[\boxed{\frac{\theta_1 + \theta_2}{2}} - b\right]$$

measure the average

– **mimics** the behavior of $|a|$ (equivalently a, because $a > 0$) in a **unidimensional test**

Lee, Ip, & Fuh, 2008 *EPM*

a-Stratification

- Method proceeds

1. Partition the item bank into K levels according to item a values;
2. Divide each level (except the first stratum) into two subsections:
   sub-1($a_1 > a_2$) & **sub-2**($a_1 \le a_2$);
3. Partition the test into K stages;
4. J_k items are administered from Stratum k ($J_1 + J_2 + \ldots + J_k = J$):
   in the first stage: using some psychometric criterion
   after the first stage: select J_{k1} and J_{k2} items from each subsection ($J_{k1} + J_{k2} = J_k$);
5. Repeat Step 4 from $k = 1, 2, \ldots, K$. And keep $\sum_{k=2}^{K} J_{k1} = \sum_{k=2}^{K} J_{k2}$. → same degree of precision

– "match-b": $\hat{b} = \dfrac{a_1\hat{\theta}_1 + a_2\hat{\theta}_2}{a_1 + a_2}$

– D-optimality: $(1.7)^4 \left\{ \sum_{j=1}^{j'+1} a_{j1}^2 P_j(\hat{\boldsymbol{\theta}})\left(1 - P_j(\hat{\boldsymbol{\theta}})\right) \times \sum_{j=1}^{j'+1} a_{j2}^2 P_j(\hat{\boldsymbol{\theta}})\left(1 - P_j(\hat{\boldsymbol{\theta}})\right) - \left(\sum_{j=1}^{j'+1} a_{j1} a_{j2} P_j(\hat{\boldsymbol{\theta}})\left(1 - P_j(\hat{\boldsymbol{\theta}})\right) \right)^2 \right\}$

Lee, Ip, & Fuh, 2008 *EPM*

Continuous a-Stratification

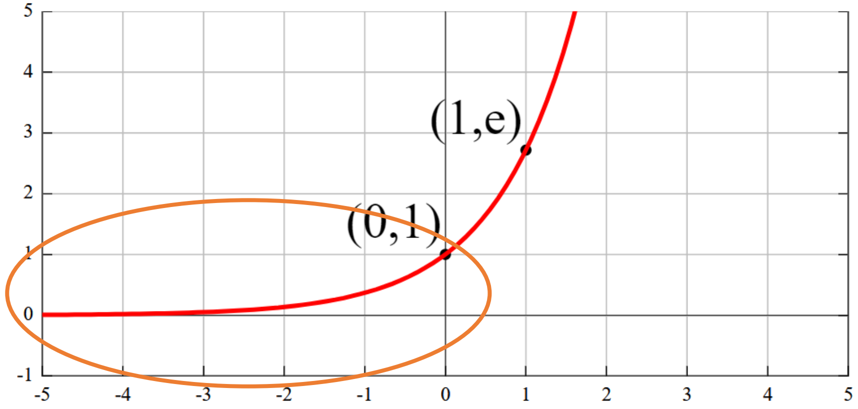
- Continuous a-stratification index (CAI)
  - incorporate exposure control as one building block intrinsic to the index itself
  - item (j' + 1) is selected to **maximize** the quantity:

$$\text{CAI} \times \text{Inf}$$

  - For the 1-DIM case

$$\text{CAI} = \exp\left[-\beta\left(\frac{r(a)}{j'/J} - 1\right)^2\right]$$

β > 0: determines the sensitivity of the discrepancy between j'/J and a



$\frac{r(a)}{j'/J} - 1$: find $r(a)$ as close as possible to j'/J

- ✓ At the beginning of the test: j'/J is small → item with smaller a
- ✓ As the test proceeds: force a to be ascending

Continuous a-Stratification

- Continuous a-stratification index (CAI)
  - For the 2-DIM case

$$\mathrm{CAI} = \exp\left[-\beta\left(\frac{r(\mathbf{a}'\mathbf{a})}{j'/J} - 1\right)^2\right]$$

$\sqrt{\boldsymbol{a}'\boldsymbol{a}}$ is the so-called multidimensional a parameter

  - a second version

$$\left|\frac{r(a)}{j'/J} - 1\right| \quad \text{vs} \quad \left(\frac{r(a)}{j'/J} - 1\right)^2$$

→

Preliminary simulations: did not outperform in any of the test conditions

Simulation Study

- Item selection method
  - CAI method (β = 2)
  - a-stratification method (*K* = 4):

    Maximizing Fisher information (1-DIM) or D-optimality (2-DIM)

    Match-b
  - $\hat{\theta}_0$: selecting randomly within the range -3.5 to 3.5

Case	Length	Test stages for Strata 1/2/3/4
1-DIM	20	(1-5)/(6-10)/(11-15)/(16-20)
	30	(1-7)/(8-14)/(15-22)/(23-30)
2-DIM	40	(1-10)/(11-20)/(21-30)/(31-40)
	60	(1-15)/(16-30)/(31-45)/(46-60)

Note. 1-DIM = one-dimensional; 2-DIM = two-dimensional.

Simulation Study

- 1-DIM Study
  - Item pool structure
    - test length: 20 & 30 items
    - item bank: 500 items
    - $a \sim U(0.0, 1.3)$
    - $b \sim U(-1.3, 1.3)$
    - $c \sim U(0.2, 0.3)$
  - Evaluation criteria
    - $\text{Bias} = \frac{1}{N}\sum_{i=1}^{N}(\hat{\theta}_i - \theta_i)$
    - $\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\hat{\theta}_i - \theta_i)^2$
    - $\chi^2 = \sum_{m=1}^{M}\frac{(er_m - J/M)^2}{J/M}$
  - Examinee generation
    - examinee abilities:

      1. discrete uniform (DU) distribution:

         → from -3.2 to 3.2 by an increment of 0.4 (17 θ × 300 = 5,100)

      2. normal(0,1) distribution: 5,100 examinees
    - theta estimation: grid search (from -3.5 to 3.5, by 0.01)

2×2×3 = 12 total conditions

Simulation Study

- 2-DIM Study
  - Item pool structure
    - test length: 40 & 60 items
    - item bank: 500 items
    - a_1 & a_2 ~ $U(0.0, 1.3)$
    - b ~ $U(-1.3, 1.3)$
  - Examinee generation
    - examinee abilities:
      1. 2-DIM grid:
         → from -2 to 2 by an increment of 0.4 (11 θ_1 × 11 θ_2 × 50 = 6,050)
      2. bivariate normal distribution: 6,050 examinees
         $\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right)$ low: ρ = 0.3; high: ρ = 0.7
    - theta estimation: grid search (from -3.5 to 3.5, by 0.1)
  - Evaluation criteria
    - $\text{Bias} = \frac{1}{N}\sum_{i=1}^{N}\left\{\left(\hat{\theta}_{i1} - \theta_{i1}\right) + \left(\hat{\theta}_{i2} - \theta_{i2}\right)\right\}$
    - $\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left\{\left(\hat{\theta}_{i1} - \theta_{i1}\right)^2 + \left(\hat{\theta}_{i2} - \theta_{i2}\right)^2\right\}$
    - $\chi^2 = \sum_{m=1}^{M}\frac{(er_m - J/M)^2}{J/M}$

2×3×3 = 18 total conditions

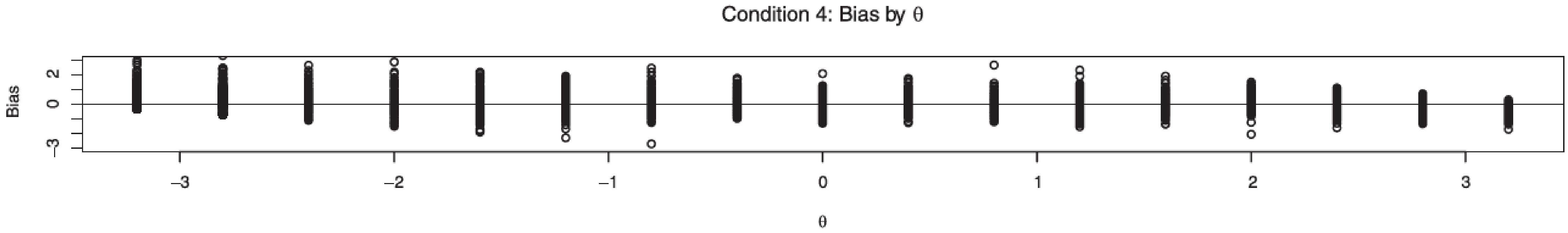
Results: 1-DIM

Condition	Length	Ability	Method	Bias	MSE	χ^2
1	20	*N*(0,1)	SMB	0.076	0.31	83.37
2	20	*N*(0,1)	SMI	0.032	0.22	145.03
3	20	*N*(0,1)	CAI	0.037	0.21	101.01
4	20	DU	SMB	0.085	0.44	115.17
5	20	DU	SMI	0.039	0.33	127.85
6	20	DU	CAI	0.040	0.32	103.47
7	30	*N*(0,1)	SMB	0.042	0.19	69.8
8	30	*N*(0,1)	SMI	0.021	0.14	139.57
9	30	*N*(0,1)	CAI	0.019	0.13	98.54
10	30	DU	SMB	0.057	0.28	105.65
11	30	DU	SMI	0.026	0.23	122.37
12	30	DU	CAI	0.031	0.24	99.48

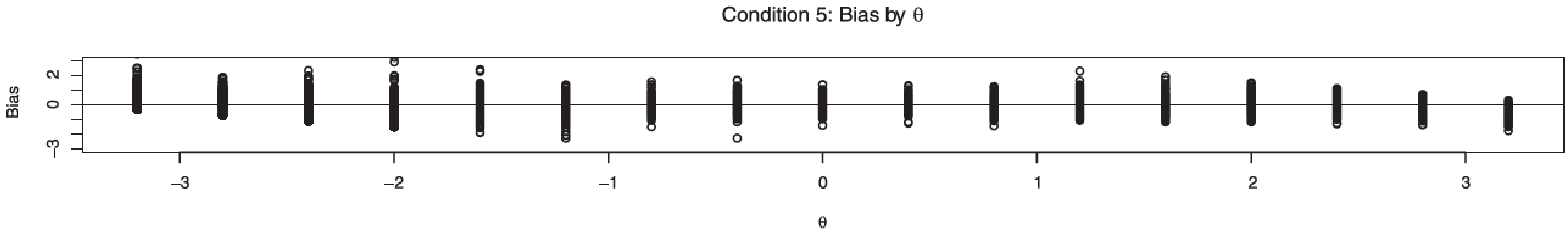
Note. 1-DIM = one-dimensional; MSE = mean squared error; DU = discrete uniform distribution; SMB = *a*-stratification with match-*b* item selection; SMI = *a*-stratification with maximum Fisher information item selection; CAI = continuous *a*-stratification.

Results: 1-DIM

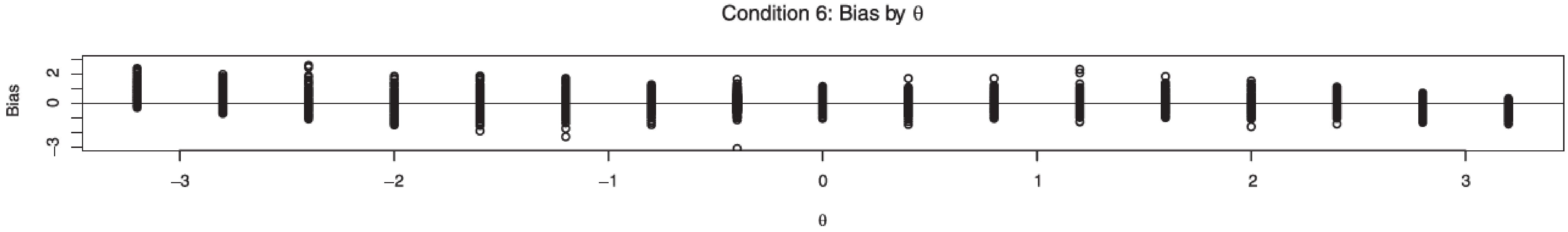
SMB



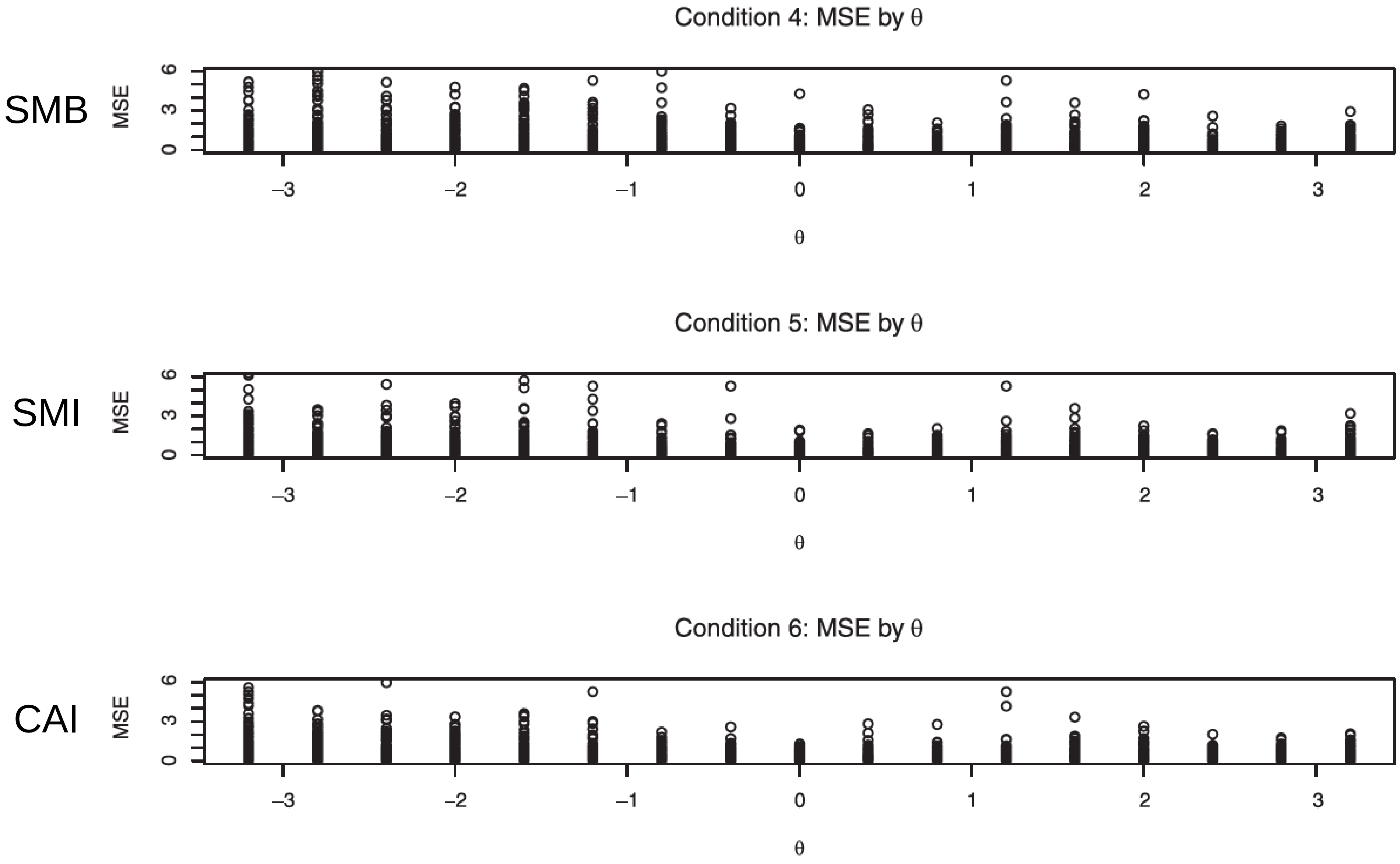
SMI



CAI



Results: 1-DIM



Results: 1-DIM

Condition		Method	Item exposure rates						
			<0.05	0.05-0.10	0.10-0.20	0.20-0.30	0.30-0.40	0.40-0.50	>0.50
1	20 items	SMB	0.825	0.085	0.052	0.015	0.004	0.012	0.006
2		SMI	0.831	0.035	0.048	0.044	0.017	0.012	0.012
3		CAI	0.775	0.062	0.094	0.050	0.010	0.004	0.004
7	30 items	SMB	0.640	0.206	0.098	0.027	0.010	0.008	0.010
8		SMI	0.754	0.048	0.071	0.058	0.029	0.015	0.025
9		CAI	0.696	0.050	0.131	0.092	0.017	0.004	0.010

Note. SMB = *a*-stratification with match-*b* item selection; SMI = *a*-stratification with maximum Fisher information item selection; CAI = continuous *a*-stratification.

Results: 2-DIM

Condition	Length	Ability	Method	Bias	MSE	χ^2
1	40	BN (ρ = .3)	SMB	−0.003	0.37	12.87
2	40	BN (ρ = .3)	SMI	0.001	0.28	86.55
3	40	BN (ρ = .3)	CAI	−0.003	0.26	57.17
4	40	BN (ρ = .7)	SMB	−0.007	0.40	14.15
5	40	BN (ρ = .7)	SMI	0.000	0.30	81.63
6	40	BN (ρ = .7)	CAI	−0.005	0.27	58.61
7	40	Grid	SMB	0.002	0.39	16.77
8	40	Grid	SMI	−0.005	0.31	75.96
9	40	Grid	CAI	−0.008	0.28	51.55
10	60	BN (ρ = .3)	SMB	−0.001	0.24	8.88
11	60	BN (ρ = .3)	SMI	−0.002	0.19	84.83
12	60	BN (ρ = .3)	CAI	0.001	0.17	54.40
13	60	BN (ρ = .7)	SMB	−0.003	0.26	9.50
14	60	BN (ρ = .7)	SMI	−0.004	0.21	78.47
15	60	BN (ρ = .7)	CAI	−0.008	0.19	55.91
16	60	Grid	SMB	−0.004	0.26	13.08
17	60	Grid	SMI	−0.003	0.21	71.60
18	60	Grid	CAI	0.003	0.18	46.56

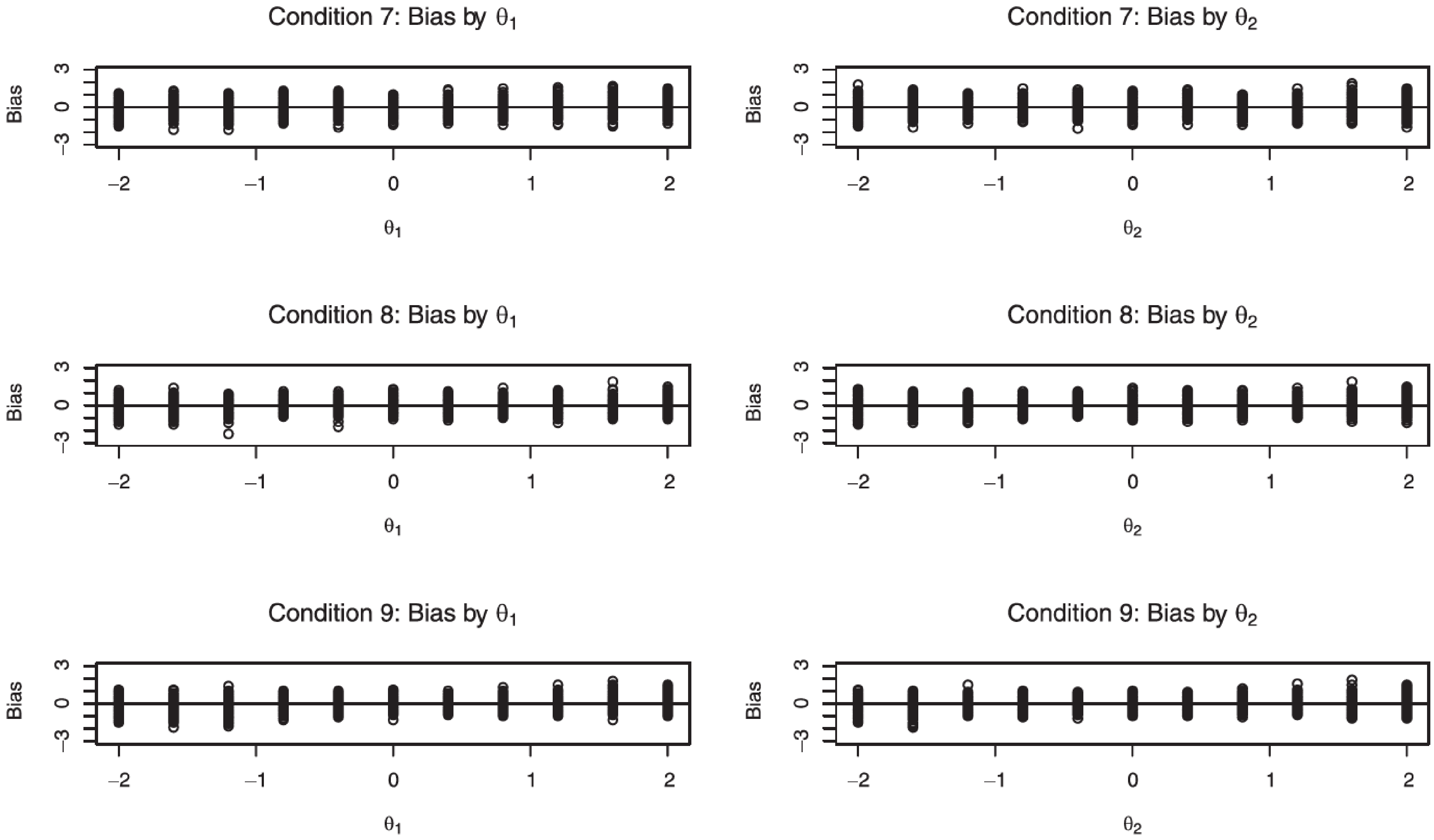
Note. MSE = mean squared error; BN = bivariate normal ability generating distribution with correlation ρ; SMB = *a*-stratification with match-*b* item selection; SMI = *a*-stratification with maximum D-optimality item selection; CAI = continuous *a*-stratification.

Results: 2-DIM

SMB

SMI

CAI

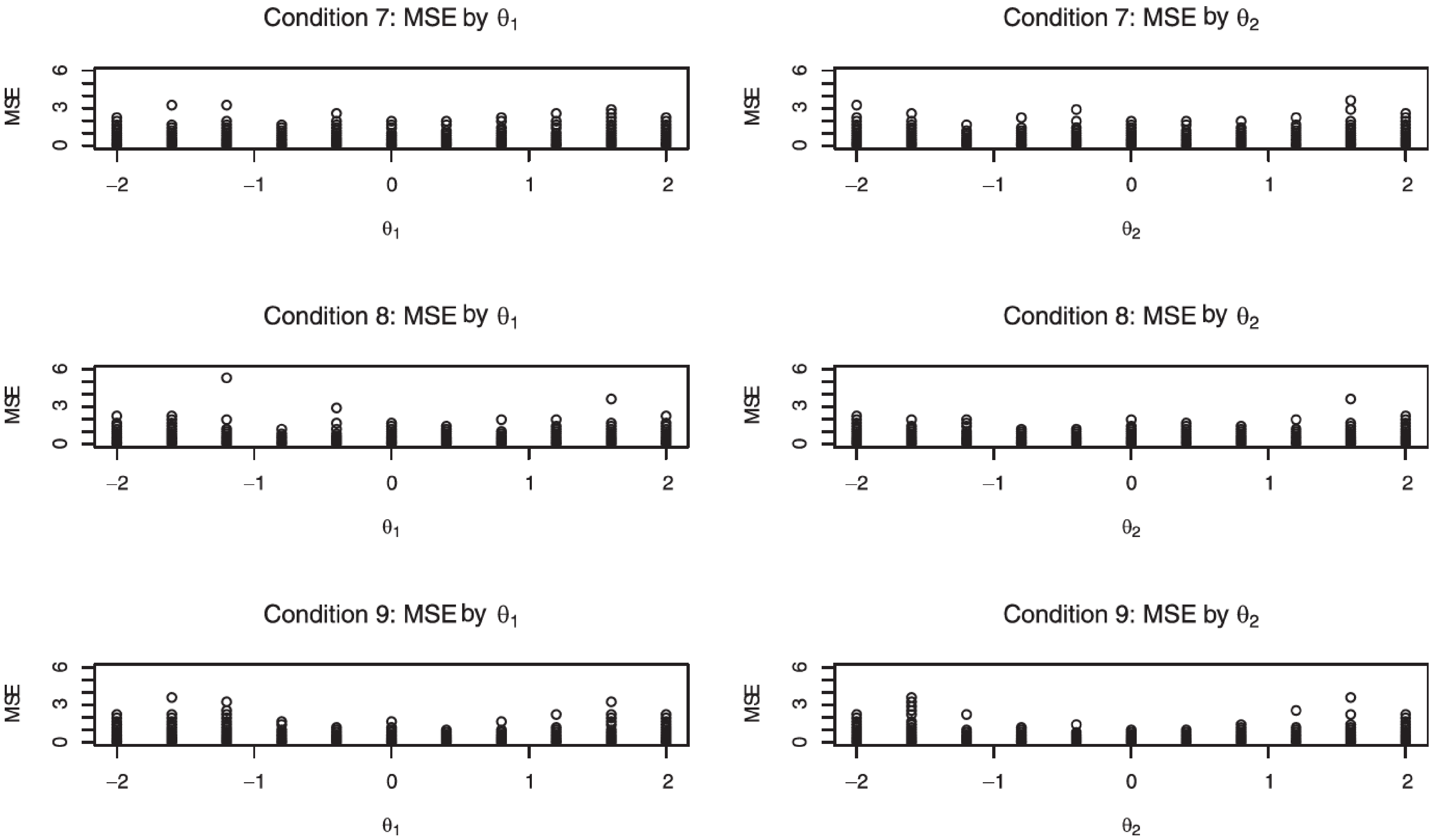


Results: 2-DIM

SMB

SMI

CAI



Results: 2-DIM

Condition		Method	Item exposure rates <0.05	0.05-0.1	0.10-0.20	0.20-0.30	0.30-0.40	0.40-0.50	>0.50
1	40 items	SMB	0.173	0.550	0.271	0.002	0.000	0.000	0.004
2		SMI	0.640	0.069	0.106	0.102	0.060	0.019	0.004
3		CAI	0.531	0.129	0.185	0.112	0.035	0.006	0.000
4		SMB	0.196	0.548	0.250	0.002	0.000	0.000	0.004
5		SMI	0.619	0.088	0.112	0.102	0.056	0.021	0.002
6		CAI	0.540	0.115	0.194	0.106	0.038	0.008	0.000
10	60 items	SMB	0.010	0.262	0.694	0.029	0.000	0.000	0.004
11		SMI	0.494	0.096	0.133	0.133	0.071	0.058	0.015
12		CAI	0.373	0.135	0.235	0.154	0.075	0.021	0.006
13		SMB	0.015	0.296	0.654	0.031	0.000	0.000	0.004
14		SMI	0.477	0.090	0.152	0.140	0.077	0.050	0.015
15		CAI	0.381	0.131	0.221	0.165	0.077	0.021	0.004

Note. BN = bivariate normal ability generating distribution with correlation ρ; SMB = *a*-stratification with match-*b* item selection; SMI = *a*-stratification with maximum D-optimality item selection; CAI = continuous *a*-stratification.

Discussion

- The **SMB** method was shown to be the **best** by far in terms of **item exposure control** but yielded consistently **high MSE**.

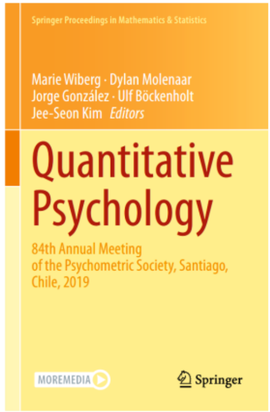
- **CAI** was similar to or **better than that of SMI** in terms of bias and MSE while producing smaller χ^2 values.

- The manner in **which the test is started** may affect the performance of each method.

Limitations

- Only one value was examined for β & only one item bank was simulated for each study & the number of strata was fixed at 4.
- An advantage of the CAI method that may not be readily apparent is its ability to be **extended to more than two dimensions**.
- CAI could be **combined with a method** of maximum exposure control to limit the maximum item exposure rate.
- **Relax** the fact that CAI always forces the discrimination parameters of the selected items to be **strictly ascending**.

Springer Link



The Annual Meeting of the Psychometric Society
IMPS 2019: Quantitative Psychology pp 201-211| Cite as

Performance of the Modified Continuous *a*-Stratification Indices in Computerized Adaptive Testing

Authors

Ya-Hui Su , Yan-Ling Lai

Ya-Hui Su

Introduction

- the maximum item exposure rate: commonly set to 0.2

Condition		Method	<0.05	0.05-0.10	0.10-0.20	Item exposure rates 0.20-0.30	0.30-0.40	0.40-0.50	>0.50
1	20 items	SMB	0.825	0.085	0.052	0.015	0.004	0.012	0.006
2		SMI	0.831	0.035	0.048	0.044	0.017	0.012	0.012
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Note. SMB = *a*-stratification with match-*b* item selection; SMI = *a*-stratification with maximum Fisher information item selection; CAI = continuous *a*-stratification.

➡ **Purpose:** combine the CAI method with item exposure control methods to limit item exposure

Introduction

- the maximum item exposure rate: <u>commonly set to 0.2</u>

					Item exposure rates			
Condition		Method	<0.05	0.05-0.10	0.10-0.20	0.20-0.30	0.30-0.40	0.40-0.50	>0.50
1	20 items	SMB	0.825	0.085	0.052	3.8 %			
2		SMI	0.831	0.035	0.048	8.6 %			
3		CAI	0.775	0.062	0.094	6.9 %			
7	30 items	SMB	0.640	0.206	0.098	5.6 %			
8		SMI	0.754	0.048	0.071	12.7 %			
9		CAI	0.696	0.050	0.131	12.3 %			

Note. SMB = *a*-stratification with match-*b* item selection; SMI = *a*-stratification with maximum Fisher information item selection; CAI = continuous *a*-stratification.

➡ **Purpose:** combine the CAI method with item exposure control methods to limit item exposure

Method

- three modified CAI methods:
  - CAI + exposure
  - CAI + freeze
  - CAI + SHOF

Method

- three modified CAI methods:
  - CAI + exposure
  - CAI + freeze
  - CAI + SHOF

➢ maximum priority index

$$\mathrm{PI}_j = \mathrm{Inf}_i \times \prod_{k=1}^{K} (\omega_k f_k)^{c_{jk}}$$

$$f_k = \frac{1}{r_{\max}} \left(r_{\max} - \frac{s_i}{S} \right)$$

$$= \frac{1}{0.2} (0.2 - \frac{\text{examinees have seen item } i}{\text{examinees have taken the CAT}})$$

$$\Rightarrow \mathrm{CAI}_i \times \mathrm{Inf}_i \times \frac{\left(r_{\max} - \frac{s_i}{S} \right)}{r_{\max}}$$

Method

- three modified CAI methods:
  - CAI + exposure
  - CAI + freeze
  - CAI + SHOF

make popular items appear in a predictable sequence: 1, 6, 11, 16, ...

➢ maximum priority index

$$PI_j = Inf_i \times \prod_{k=1}^{K} (\omega_k f_k)^{c_{jk}}$$

$$f_k = \frac{1}{r_{max}} \left(r_{max} - \frac{s_i}{S} \right)$$

$$= \frac{1}{0.2} \left(0.2 - \frac{\text{examinees have seen item } i}{\text{examinees have taken the CAT}} \right)$$

$$\Rightarrow CAI_i \times Inf_i \times \frac{\left(r_{max} - \frac{s_i}{S} \right)}{r_{max}}$$

➢ freeze control

$$CAI_i \times Inf_i$$

⇒

if reach γ_{max},

not included temporarily

Method

- three modified CAI methods:
  - CAI + exposure
  - CAI + freeze
  - CAI + SHOF

➢ The **Sympson and Hetter** online procedure with freeze (SHOF)

$p(S)$ → the probability that an item is **'selected'**

$p(A)$ → the probability that an item is actually **'administered'**

$$p(A) = p(A|S) \times p(S) \leq r_{\max}$$

to adjust $p(S)$ such that $p(A)$ is less than or equal to r_{max}

a random number is less than $p(A|S)$: administer
otherwise: select next item

→ a series of iterative simulations is needed to find stabilized $p(A|S)$

Method

- The Sympson and Hetter **online procedure with freeze** (SHOF)

$$p(A) = p(A|S) \times p(S) \leq r_{\max}$$

How to update *p*(*A*|*S*) sequentially during the test?

CAI + SHOF

Step 1. Set the initial *p*(*A*|*S*) = 1 for all items in the item pool.

Step 2. Administer CATs to the *j*th examinee as in the SH procedure.

Step 3. Find *p*(*S*) and *p*(*A*) for each item by computing the proportion of times an item has been selected and administered, respectively.

Step 4. Update *p*(*A*|*S*) for each item based on *p*(*S*) and *p*(*A*) as follows:

$$\text{if } p(A) > r_{\max}, \quad \text{then } p(A|S) = 0.0;$$

$$\text{if } p(A) \leq r_{\max} \text{ and } p(S) > r_{\max}, \quad \text{then } p(A|S) = r_{\max}/p(S);$$

$$\text{if } p(A) \leq r_{\max} \text{ and } p(S) \leq r_{\max}, \quad \text{then } p(A|S) = 1.0$$

Step 5. Repeat step 2 until CATs have been administered to all examinees.

Chen, Lei, & Liao, 2008 *BJMSP*

Simulation Study

- Item selection method
  - **CAI** method (β = 2)
  - a-stratification method (*K* = 4):
    SMI: Maximizing Fisher information & **SMB:** Match-b
  - three **modified CAI** methods: CAI + exposure, CAI + freeze, and CAI + SHOF

- Item pool structure
  - test length: 20 & 30 items
  - item bank: 500 items
  - $a \sim U(0.0, 1.3)$
  - $b \sim U(-1.3, 1.3)$
  - $c \sim U(0.2, 0.3)$

- Examinee generation
  - examinee abilities:
    normal(0,1) distribution: 5,100 examinees
  - theta estimation:
    maximum likelihood estimator (MLE)

Simulation Study

- Evaluation Criteria

  - measurement precision

    ➢ $\text{bias} = \frac{1}{N}\sum_{n=1}^{N}\left(\hat{\theta}_n - \theta_n\right)$

    ➢ $\text{RMSE} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(\hat{\theta}_n - \theta_n\right)^2}$

    ➢ $r_{\theta,\hat{\theta}} = \frac{COV_{\theta,\hat{\theta}}}{S_\theta S_{\hat{\theta}}}$

    ➢ $\text{relative efficiency (RE)} = \frac{\text{RMSE}_{\text{SMI}}}{\text{RMSE}_{\text{others}}}$

  - exposure control

    ➢ $\chi^2 = \frac{1}{L/I}\sum_{i=1}^{I}(r_i - L/I)^2$

Results

Table 1 Measurement precision of the six item selection methods under various conditions

Item length	Item selection methods	bias	RMSE	RE	$r_{\theta,\hat{\theta}}$
20	SMB	0.068	0.575	0.858	0.864
	SMI	0.024	0.494	**1.000**	0.901
	CAI	0.018	0.469	1.053	0.912
	CAI + exposure	0.026	0.496	0.996	0.901
	CAI + freeze	0.016	0.461	1.072	0.916
	CAI + SHOF	0.020	0.469	1.054	0.912
30	SMB	0.018	0.397	0.923	0.934
	SMI	−0.001	0.366	**1.000**	0.944
	CAI	0.007	0.363	1.009	0.943
	CAI + exposure	0.016	0.402	0.911	0.933
	CAI + freeze	0.012	0.361	1.013	0.944
	CAI + SHOF	0.011	0.372	0.983	0.940

Results

Table 2 Exposure control of the six item selection methods under various conditions

Test length	Item selection methods	Item exposure rates								Max.	Chi-square statistics
		0	0–0.05	0.05–0.1	0.1–0.2	0.2–0.3	0.3–0.4	0.4–0.5	>0.5		
20	SMB	0.036	0.874	0.012	0.006	0.028	0.026	0.012	0.006	0.79	116.67
	SMI	0.724	0.078	0.044	0.082	0.046	0.012	0.004	0.010	0.81	125.65
	CAI	0.680	0.106	0.070	0.076	0.040	0.016	0.008	0.004	0.78	104.51
	CAI+exposure	**0.058**	0.610	0.306	0.026	–	–	–	–	**0.13**	**9.64**
	CAI+freeze	**0.570**	0.164	0.090	0.176	–	–	–	–	**0.20**	**56.22**
	CAI+SHOF	**0.574**	0.154	0.082	0.190	–	–	–	–	**0.20**	**54.34**
30	SMB	0.028	0.768	0.084	0.006	0.024	0.072	0.012	0.006	0.80	109.59
	SMI	0.658	0.066	0.062	0.084	0.068	0.040	0.012	0.010	0.81	117.84
	CAI	0.600	0.086	0.084	0.116	0.060	0.038	0.006	0.010	0.60	93.97
	CAI+exposure	**0.028**	0.408	0.432	0.132	–	–	–	–	**0.14**	**7.53**
	CAI+freeze	**0.436**	0.186	0.084	0.294	–	–	–	–	**0.20**	**51.30**
	CAI+SHOF	**0.430**	0.188	0.082	0.300	–	–	–	–	**0.20**	**48.75**

Discussion & Future studies

- CAI + exposure method showed **great potential for** monitoring **item exposure**; however, it did not have the best measurement precision.
- Satisfy all the **constraints simultaneously** during item selection.
- The idea of the modified CAI methods can easily be extended to **multidimensional contexts** for item selection.
- The efficiency of item selection methods with different item exposure methods or **test overlap methods**.

Thanks for listening!

Reporter: Yingshi Huang

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