Mental Health Symptom Profiles over Time: A Three-Step Latent Transition Cognitive Diagnosis Modeling Analysis with Covariates

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Abstract

Cognitive diagnostic modeling (CDM) is an item-level analysis that accounts for attribute co-occurrences when characterizing attributes and classifying individuals' attribute profiles. Tan et al. (2023) provided an application for mental health symptom profiles. The current study extends Tan et al. (2023) to demonstrate how intervention and gender affect transition probabilities from one state to another in a three-step latent transition CDM. The sample used in this study consisted of 2,005 college students (34.5% men) who answered 40 items assessing four mental health symptoms (i.e., alcohol-related problems, anxiety, hostility, and depression) at baseline immediately before being randomly allocated to a brief alcohol intervention or control group (pre-test) and at a 12-month follow-up following the intervention (post-test). Participants in the intervention group received personalized feedback on their alcohol use and alcohol-related problems, along with descriptive drinking norms of peers and other personalized and general information aimed at motivating students to change. Results indicated that the selected models showed adequate fit and classification outcomes. Latent logistic regression analysis showed that the intervention helped improve participants' anxiety and depression. Those in the intervention group were more likely to transition from having anxiety and depression attribute profiles at pre-test to not having them at post-test. In addition, male students were more likely to improve anxiety. Although the intervention was not associated with the transition probability from presence to absence for alcohol-related problems, it helped suppress the transition to having the attributes of alcohol-related problems (among men) and hostility (among women) at post-test. However, male students in the intervention were more likely to transition from absence to presence in their depression attribute profile state. The three-step latent transition CDM with covariates showcased in the current study may be an appealing analytical tool for examining and explaining change in mental health symptoms with informative covariates.

1 Introduction

Cognitive diagnosis models (CDMs) have primarily been utilized to understand students' knowledge, thinking processes, and problem-solving strategies in education. Given a set of fine-grained attributes in a specific domain, CDMs can provide diagnostic information on whether or not a given student has mastered the attributes (de la Torre & Minchen, 2014), facilitating teaching and learning. Examples of CDM applications in educational subjects include Ma et al. (2020) in proportional reasoning attributes (Tjoe & de la Torre, 2014), Chen et al. (2022) in second language reading skills, and Liang et al. (2021) in digital literacy skills. However, the utility of CDMs is not limited to educational research. CDMs can also be used to better characterize attribute profiles of mental health symptoms (Tan et al., 2023) or diagnose mental disorders (e.g., de la Torre et al., 2018; Templin & Henson, 2006).

The current study aims to provide an introduction to latent transition CDM as a novel tool for classifying individual attribute profiles of mental health symptoms and their transition over time to illustrate its utility in an actual clinical data application. The current study extended the CDM classification work on mental health symptoms assessed in a single time point (Tan et al., 2023) to examine whether a brief alcohol intervention affects the transition in mental health symptom profiles over time in a longitudinal analysis. In addition, whether the intervention effect on transition is moderated by gender was examined. We used a three-step latent transition CDM with covariates, as shown in Liang et al. (2023b). In the following sections, we introduce CDM, including model formulation of commonly used CDMs and a three-step estimation approach to latent transition CDM with covariates. We then demonstrate an application of the three-step approach to mental health symptoms data and its results in the third and fourth sections, respectively. Finally, this chapter concludes by discussing findings and future directions.

2 Cognitive Diagnosis Modeling

2.1 Model Formulation

CDMs refer to a class of restricted latent class models (LCMs) that can classify or diagnose whether a respondent possesses a given set of *attributes*. In educational research, attributes may represent specific skills or cognitive processes that examinees must master to answer an item correctly. In mental health research, attributes can be the mental health problems or disorders measured by clinical assessment tools (e.g., de la Torre et al., 2018; Tan et al., 2023). In this mental health research setting, the presence or absence of an attribute can be interpreted as having or not having a symptom, problem, or disorder.

Various CDMs exist in the literature (von Davier & Lee, 2019). One of the most often cited CDMs is the generalized deterministic inputs, noisy and gate (G-DINA; de la Torre, 2011) model. The G-DINA model is a general CDM, from which several other general CDMs and commonly used reduced CDMs can be obtained by using different link functions and setting proper constraints, respectively. For instance, the G-DINA model under the logit link is equivalent to the log-linear CDM (Henson et al., 2009). Examples of the reduced CDMs that the G-DINA model can subsume include (1) the DINA model (Junker & Sijtsma, 2001), which assumes that only the individuals with all the attributes (or disorders) measured by the item are expected to endorse the item; (2) the deterministic inputs, noisy or gate (DINO; Templin & Henson, 2006) model, which assumes that the individuals with at least one attribute measured by the item are expected to endorse the item; and (3) the additive-CDM (A-CDM; de la Torre, 2011), which assumes that the probability of an item endorsement is related to additive main effects of the attributes that an individual possesses. Moreover, the additive models with the log and logit links are equivalent to the reduced reparameterized unified model (R-RUM; Hartz, 2002) and the linear logistic model (LLM; Maris, 1999), respectively. Within the G-DINA model framework, the reduced CDMs can be compared against the saturated G-DINA model for each item to determine whether a more parsimonious model can be selected (Ma et al., 2016).

As with item response theory models, CDM implementation requires response data stored in an $N \times J$ matrix, where N is the number of respondents (i.e., sample size). For dichotomous CDMs, the response data contain each respondent's responses to J items, where 1s represent item endorsement and 0s otherwise. In addition to response data, most CDMs require a Q-matrix (Tatsuoka, 1983, 2009), which delineates the relationships between the items and the attributes. A Q-matrix is an essential component and provides input for a CDM analysis. In most practical applications, it is usually constructed by domain experts (e.g., Tjoe & de la Torre, 2014). A Q-matrix is typically a $J \times K$ matrix of 1s and 0s, where J is the number of items and K is the number of attributes. The entry of the jth row and kth column in a Q-matrix is 1 if attribute k is measured by item j and 0 otherwise.

Each respondent's attribute profile is estimated by fitting CDMs to response data with a Q-matrix linking items to attributes. A respondent is assigned to a latent class by a binary attribute vector or profile, where 1 and 0 represent the presence and absence of attribute k, respectively. Typically, K attributes produce 2^K latent classes. For example, when $K = 3$, there are $2^3 = 8$ latent classes, namely, (0, 0, 0), (1, 0, 0), (0, 1, 0), (0, 0, 1), (1, 1, 0), (1, 0, 1), (0, 1, 1) and (1, 1, 1), where an attribute profile (0, 0, 0) indicates the respondent does not have any of the three attributes. In contrast, an attribute profile (1, 0, 1) indicates that the respondent has the first and the third attributes but not the second.

When the G-DINA model is used, the probability of respondent i with attribute profile $\boldsymbol{\alpha}_i$ endorsing item j can be written as

$$P\left(Y_{ij} = 1|\boldsymbol{\alpha}_i\right) = \delta_{j0} + \sum_{k=1}^{K_j} \delta_{jk}\alpha_{ik} + \sum_{k'=k+1}^{K_j} \sum_{k=1}^{K_j-1} \delta_{jkk'}\alpha_{ik}\alpha_{ik'} + \cdots + \delta_{j12\ldots K_j} \prod_{k=1}^{K_j} \alpha_{ik}\,, \tag{1}$$

where K_j is the number of attribute(s) measured by item *j*; δ_{j0} represents the baseline probability of item *j*; δ_{jk} is the main effect of attribute *k*; $\delta_{jkk'}$ is the two-way interaction effect between attribute *k* and k'; and $\delta_{j12\ldots K_j}$ is the highest-order interaction effect of all measured attributes. In short, Equation 1 expresses a fully saturated model of all possible effects, including terms for main effects, lower-order interaction effects, and the highest-order interaction effect.

A Q-matrix is validated and revised by empirically fitting data with CDMs, discussing results with domain experts, and revising the Q-matrix accordingly (de la Torre & Chiu, 2016; Tjoe & de la Torre, 2014). With the revised Q-matrix, we can compare the reduced CDMs (e.g., DINA, DINO, A-CDM, LLM, and R-RUM) against the saturated G-DINA model. Items potentially measuring multiple attributes can be examined using the Wald test or likelihood ratio test (Ma et al., 2016) to determine whether one of the interpretable reduced models can be used instead of the saturated model. Lastly, the selected CDMs fit response data to obtain item parameter estimates and respondents' attribute profiles. The following fit statistics can evaluate the absolute fit of CDMs: the residual between observed and predicted transformed correlation (*r*) and the log-odds ratios of item pairs (*l*) (Chen et al., 2013), the limited information root mean square error approximation ($RMSEA_2$; Maydeu-Olivares & Joe, 2014), and the M_2 statistic (Hansen et al., 2016; Liu et al., 2016; Ma, 2020). Classification accuracy can be estimated to ascertain the utility of applying CDMs to data (Wang et al., 2015).

2.2 Three-step Latent Transition CDM with Covariates

Latent transition analysis (LTA), also referred to as a latent or hidden Markov model (Baum & Petrie, 1966), is a longitudinal analog of the latent class model (LCM). It has been developed to model the transitions of latent class membership over time, where LCM serves as the measurement model (Collins & Lanza, 2010). To distinguish LTA from LCM, we refer to the respondents' temporal state at each time point as a latent "state" rather than a latent class in the current study.

LTA or LCM can further incorporate informative covariates to investigate the association of covariates with latent transition or class membership using a one-step or three-step approach via latent logistic regression (e.g., Humphreys & Janson, 2000; Iaconangelo & de la Torre, 2016; Lanza et al., 2010; Reboussin et al., 1998; Vermunt, 2010; Vermunt et al., 1999). The one-step approach (e.g., Clogg, 1981; Dayton & Macready, 1988; Lanza et al., 2013) simultaneously estimates both the measurement and the logistic regression (structural) models. The one-step approach provides precise estimates of the measurement and structural components. However, it has one notable disadvantage: any modifications to either model require refitting the entire model, which is computationally inconvenient and potentially tricky, especially with high dimensional data. In contrast, a three-step approach (e.g., Bolck et al., 2004; Di Mari et al., 2016; Iaconangelo & de la Torre, 2016; Lu & Thomas, 2008; Vermunt, 2010) is more flexible because the measurement and structural models are estimated in separate sequential steps. They are CDM estimation (step 1), latent state assignment (step 2), and logistic regression analysis (step 3). However, the stepwise three-step estimation approach can yield biased estimates of covariate effects (Bolck et al., 2004; Vermunt, 2010) when classification errors are unaccounted for by directly regressing the estimated attribute status or profile on covariates. To avoid this bias in stepwise estimation, correction weights can be added to latent state assignments in subsequent logistic regression analyses (Bolck et al., 2004; Iaconangelo & de la Torre, 2016; Vermunt, 2010). Recent studies have extended this approach to LTA (Di Mari et al., 2016) and latent transition CDMs (Liang et al., 2023b). In the current study, the *three-step approach* implies that classification error probabilities (CEP) were taken into account. Methodological research on incorporating covariates into longitudinal CDMs is quite limited in the literature. Liang et al. (2023b) recently proposed a three-step approach for latent transition CDMs with covariates under a general CDM framework (i.e., the G-DINA model framework) to strengthen the three-step estimation of latent transition CDM with covariates. In the present study, we adopted this three-step approach shown in Liang et al. (2023b). We examined the transition of respondents' mental health symptoms before and after intervention, and explored how informative covariates, such as intervention membership, affect latent states and their transitions over time.

2.3 Technical Details

The three-step approach proceeds as follows. In the first step, the repeated response data from the same respondents are treated as independent data sets at each time point and estimated separately using the G-DINA model. In this step, Q-matrix validation and modification, model selection, and item parameter estimation are completed. Note that item parameters are constrained to be equal across time points to ensure longitudinal measurement invariance. Imposing constraints can help avoid classification problems and allow interpretable results over time. In the second step, respondents are classified into latent (discrete) states given their responses at each time point using the expected a posteriori (EAP; Huebner & Wang, 2011) method. The associated CEP at each time point is also computed in this step. Lastly, in the third step, the latent transition CDM corrected with the CEP obtained from step 2 is estimated to derive regression coefficients.

Formally, details of the three-step latent transition CDM with covariates can be presented as follows. Let T denote the number of time points, Y_{it} the respondent i's response at time t, $t = 1, \dots, T$, $\boldsymbol{Y}_t$ the response data at time t, and $\boldsymbol{Y}$ the full response data at T time points. Denote the attribute profile and attribute status of α_k at time *t* by $\boldsymbol{\alpha}^{(t)}$ and $\alpha_k^{(t)}$, respectively. The set of covariates related to the classification of latent state membership at time t is denoted by $\boldsymbol{Z}_t$, and the full set of covariates at all T time points is denoted by $\boldsymbol{Z}$. The latent transition CDM specifying the item response probabilities at pre-and post-tests, given the time-specific covariates, is formulated as

$$P(\boldsymbol{Y}|\boldsymbol{Z}) = \sum_{\alpha_k^{(t=1)}=0}^{1} \sum_{\alpha_k^{(t=2)}=0}^{1} P\left(\alpha_k^{(t=1)}\middle|\boldsymbol{Z}_1\right) P\left(\alpha_k^{(t=2)}\middle|\alpha_k^{(t=1)}, \boldsymbol{Z}_2\right) \prod_{t=1}^{T=2} P\left(\boldsymbol{Y}_t\middle|\boldsymbol{\alpha}^{(t)}\right), \tag{2}$$

where $P\left(\boldsymbol{Y}_t\middle|\boldsymbol{\alpha}^{(t)}\right)$ is the G-DINA measurement model estimating the latent state membership at each time point from the response data, $P\left(\alpha_k^{(t=1)}\middle|\boldsymbol{Z}_1\right)$ is the initial state probability, and $P\left(\alpha_k^{(t=2)}\middle|\alpha_k^{(t=1)}, \boldsymbol{Z}_2\right)$ is the transition probability between pre-and post-tests, given covariates at each time point. Note that covariates can be time-invariant or time-varying depending on the research questions. In the current study, the covariates were time-invariant (e.g., intervention vs. control group; see Figure 1). The initial state probabilities and transition probabilities are associated with the covariates through logistic regression, which can be written as

$$P\left(\alpha_k^{(t=1)} = 1\middle|\boldsymbol{Z}_1\right) = \frac{\exp\left(\beta_{0k}^{(t=1)} + \boldsymbol{\beta}_k'^{(t=1)}\boldsymbol{Z}_1\right)}{1 + \exp\left(\beta_{0k}^{(t=1)} + \boldsymbol{\beta}_k'^{(t=1)}\boldsymbol{Z}_1\right)} \tag{3}$$

and

$$P\left(\alpha_k^{(t=2)}\middle|\alpha_k^{(t=1)}, \boldsymbol{Z}_2\right) = \frac{\exp\left(\beta_{0k}^{(t=2)} + \boldsymbol{\beta}_k'^{(t=2)}\boldsymbol{Z}_2\right)}{1 + \exp\left(\beta_{0k}^{(t=2)} + \boldsymbol{\beta}_k'^{(t=2)}\boldsymbol{Z}_2\right)}, \tag{4}$$

respectively, where β_{0k} is the intercept and $\boldsymbol{\beta}_k$ is a vector of remaining regression coefficients. For attribute-level transitions, the transition probability matrix of α_k at two time points for binary states is a 2 × 2 matrix (see Table 1).

Table 1. Transition Probability Matrix of α_k.

	Post-test	
Attribute state	0	1

Pre-test	0	$1 - P\left(\alpha_k^{(t=2)} = 1 \middle| \alpha_k^{(t=1)} = 0, \boldsymbol{Z}_2\right)$	$P\left(\alpha_k^{(t=2)} = 1 \middle| \alpha_k^{(t=1)} = 0, \boldsymbol{Z}_2\right)$
	1	$P\left(\alpha_k^{(t=2)} = 0 \middle| \alpha_k^{(t=1)} = 1, \boldsymbol{Z}_2\right)$	$1 - P\left(\alpha_k^{(t=2)} = 0 \middle| \alpha_k^{(t=1)} = 1, \boldsymbol{Z}_2\right)$

To obtain correction weights, a CEP matrix needs to be computed. A CEP matrix estimates the degree of misclassification in the measurement model conditional on the true or latent attribute state status. Denote the estimated attribute status by α_q and the true attribute presence status by α_k. The attribute-level CEP at each time point is a 2 × 2 matrix representing the probabilities of the true attribute presence status α_k (rows) being classified into the observed attribute status α_q (columns), which is calculated as

$$P\left(\alpha_q^{(t)} \middle| \alpha_k^{(t)}, \boldsymbol{Y}_t\right) = \frac{\frac{1}{NT}\sum_{i=1}^{N} \sum_{t=1}^{T} P\left(\alpha_{ik}^{(t)} \middle| \boldsymbol{Y}_{it}\right) I\left[\alpha_{iq}^{(t)} = \alpha_{ik}^{(t)}\right]}{P\left(\alpha_k^{(t)} \middle| \boldsymbol{Y}_t\right)}, \quad (5)$$

where $P\left(\alpha_k^{(t)} \middle| \boldsymbol{Y}_t\right)$ is the posterior proportion of α_k estimated by the G-DINA model at time *t*, and *I*[•] is an indicator function equal to 1 if α_{iq} is equal to α_{ik} at time *t*, and 0 otherwise.

For example, consider a 2 x 2 CEP matrix for attribute *k* at time point *t*:

$$P\left(\alpha_q^{(t)} \middle| \alpha_k^{(t)}, \boldsymbol{Y}_t\right) = \begin{bmatrix} 0.88 & 0.12 \\ 0.24 & 0.76 \end{bmatrix}.$$

In this example, at time point *t*, 88% of the respondents who do not possess attribute *k* (first row) will be correctly classified as not having the attribute (first column), whereas 12% will be incorrectly classified as possessing the attribute. Similarly, 76% of the respondents who possess attribute *k* (second row) will be correctly classified as having the attribute (second column), whereas 24% will be incorrectly classified as not possessing the attribute. Note that the row elements of the CEP matrix sum up to 1. In addition, overall classification accuracy is influenced by the marginals. For didactic purposes, let us assume that the true number of respondents who possess the attribute is $N_+ = \frac{1}{4}N$ and the true number of respondents who do not possess the attribute is $N_- = \frac{3}{4}N$. In such a scenario, only $(88\% \times N_-)/(88\% \times N_- +$

$24\% \times N_{+}) = 92\%$ of respondents who were classified as not possessing attribute *k* do not, in fact, possess the attribute. Similarly, only 68% of respondents who were classified as possessing attribute *k* do, in fact, possess the attribute. Under ideal situations, the diagonal elements of CEP approximate 1.0, and the off-diagonal elements approximate 0.0, indicating that the respondents are near-perfect classification. In practice, the misclassification rates need to be considered in subsequent analyses.

To do so, the correction weight of respondent *i* is the element of the CEP matrix at the α_{kt}-th row and α_{iqt}-th column, and is given by

$$w_{\alpha_{iq}^{(t)}}^{\alpha_k^{(t)}} = P\left(\alpha_{iq}^{(t)} \middle| \alpha_k^{(t)}, \boldsymbol{Y}_t\right). \tag{6}$$

Using the above example, for a respondent classified as possessing α_k attribute at time point *t*, the correction weights for, in fact, not having and having this attribute are $w_{\alpha_{iq}^{(t)}=1}^{\alpha_k^{(t)}=0} = 0.12$ and $w_{\alpha_{iq}^{(t)}=1}^{\alpha_k^{(t)}=1} = 0.76$, respectively (the second column of the above CEP matrix). These correction weights are used in the latent logistic regression in the final third step of estimation.

Finally, in the third step, we estimate the parameters of the structural model (i.e., $\boldsymbol{\beta}$ in Equations 3 and 4) by maximizing the below objective function:

$$L_{step3} = \sum_{i=1}^{N} \log \sum_{\alpha_k^{(t=1)}=0}^{1} \sum_{\alpha_k^{(t=2)}=0}^{1} P\left(\alpha_k^{(t=1)} \middle| \boldsymbol{Z}_1\right) \prod_{t=2}^{T} P\left(\alpha_k^{(t=2)} \middle| \alpha_k^{(t=1)}, \boldsymbol{Z}_2\right) \prod_{t=1}^{T=2} w_{\alpha_{iq}^{(t)}}^{\alpha_k^{(t)}}. \tag{7}$$

Note that it is possible to further improve this three-step latent transition CDM by updating classification results using Bayes' theorem on the classification information obtained from the first step of CDM estimation and information from the third step, logistic regression (see Sun & de la Torre, 2020). The updated posterior probability of respondent i having α_k at time t is given by

$$P\left(\alpha_{ik}^{(t)}\middle|\boldsymbol{Y}_{it},\boldsymbol{Z}_{it}\right)=\frac{L\left(\boldsymbol{Z}_{it}\middle|\alpha_{ik}^{(t)}\right)P\left(\alpha_{ik}^{(t)}\middle|\boldsymbol{Y}_{it}\right)}{\sum_{\alpha_{ik}^{(t)}=0}^{1}L\left(\boldsymbol{Z}_{it}\middle|\alpha_{ik}^{(t)}\right)P\left(\alpha_{ik}^{(t)}\middle|\boldsymbol{Y}_{it}\right)}, \tag{8}$$

where $P(\alpha_{ik}^{(t)}|\boldsymbol{Y}_{it})$ is the marginal posterior probability obtained using the G-DINA model. We followed this and updated the results as an ad hoc step.

3 Methods

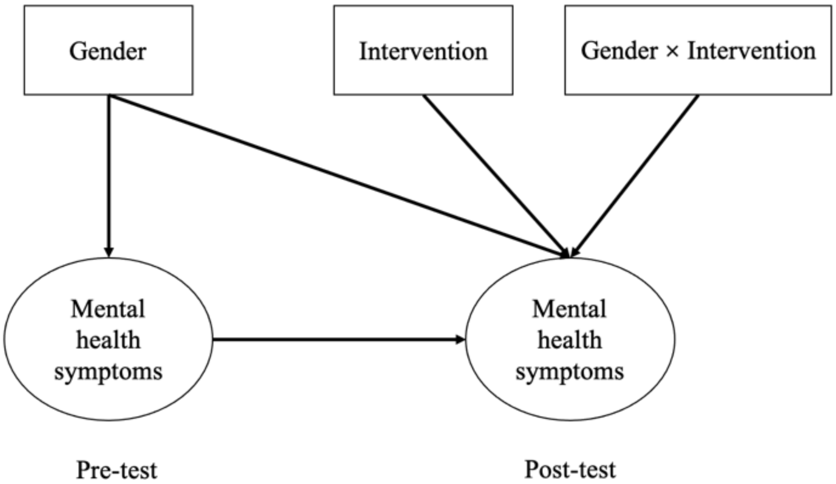
3.1 Sample

Data were collected from 4,241 respondents (38.0% men) from three university campuses in the USA at two time points 12 months apart (Larimer et al., 2007; Mun et al., 2015). All three universities utilized the same study design and intervention. Tan et al. (2023) reported baseline data before intervention at one of the three universities, a subset of the current sample. In the current study, we analyzed complete response data from 2,005 respondents (34.5% men) after excluding missing item responses at both time points. In this final sample, 48.8% of the respondents received a brief alcohol intervention at baseline (pre-test) and were followed up after 12 months (post-test). The sample size by gender and intervention status is shown in Table 2. Gender was used as the covariate at pre-test, and gender and intervention status as well as their interaction were used as covariates at post-test in this analysis (see Figure 1).

Table 2. Sample Size by Gender and Intervention Status.

Group	Female	Male
Control	661	366
Intervention	652	326
Total	1313	692

Figure 1. Covariates at Pre- and Post-Test



3.2 Measures

3.2.1 Alcohol-Related Problems

Participants' alcohol-related problems were assessed by the Rutgers Alcohol Problem Index (RAPI; White & Labouvie, 1989), a widely-used questionnaire for adolescent and young adult problem drinking. The RAPI is a 23-item self-reported instrument measuring the frequency of consequences experienced while drinking alcohol or as the result of alcohol use using a five-point scale ranging from 0 (= never) to 4 (= more than 10 times). Cronbach's α and ω for the RAPI with the current sample were 0.90 and 0.91, respectively, at both pre-and post-tests.

3.2.2 Psychological Symptoms

Anxiety (6 items), hostility (5 items), and depression (6 items) were measured by the Brief Symptom Inventory (BSI; Derogatis, 1975), a widely used self-reported assessment to identify clinically relevant psychological symptoms in adolescents and adults. Respondents were asked, "During the past 7 days, how much were you distressed by," using a five-point scale ranging from 0 (= not at all) to 4 (= extremely). Based on the current sample, Cronbach's α and ω for the Anxiety items were 0.84 and 0.87, respectively, at pre-test, and 0.85 and 0.88, respectively, at post-test; Cronbach's α and ω for the Hostility items were 0.81 and 0.86, respectively at pre-test, and 0.82 and 0.87, respectively at post-test; and Cronbach's

α and ω for the Depression items were 0.90 and 0.92, respectively at both pre-and post-tests.

3.3 Data Analysis

The original five-point scaled responses (0 - 4) were dichotomized into non-zero (= 1) and zero (= 0) responses in the current study. It is reasonable to dichotomize responses since over 82% of the responses were zero, with limited variation in non-zero responses. We analyzed an inventory of 40 items that measured four attributes, namely, alcohol-related problems (AP), anxiety (AN), hostility (HO), and depression (DE). We used the Q-matrix (Table 3), which was empirically validated by Tan et al. (2023). As per Tan et al. (2023), we also used the selected CDMs (i.e., A-CDM for item 29; R-RUM for items 21 and 28; LLM for items 26 and 27; and the saturated G-DINA model for the remaining items). The item parameters were obtained for illustration purposes in this longitudinal study. We imposed a monotonicity constraint when fitting the CDMs.

Table 3. Q-matrix of the 40-item Measure.

Item and a brief description	AP	AN	HO	DE
1. Not able to do homework or study	1	0	0	0
2. Got into fights or did mean things	1	0	0	0
3. Missed out on other things	1	0	0	0
4. Went to work or school drunk	1	0	0	0
5. Caused shame to someone	1	0	0	0
6. Neglected responsibilities	1	0	0	0
7. Relative avoided you	1	0	0	0
8. Needed more alcohol than before	1	0	0	0
9. Tried to control drinking	1	0	0	0
10. Had withdrawal symptoms	1	0	0	0
11. Noticed a change in personality	1	0	0	0
12. Felt you had an alcohol problem	1	0	0	0
13. Missed school or work	1	0	0	0
14. Tried to cut down or quit drinking	1	0	0	0
15. Found yourself in a place you don't remember	1	0	0	0
16. Passed out suddenly	1	0	0	0
17. Had a fight or argument with a friend	1	0	0	0
18. Had a fight or argument with a family member	1	0	0	0
19. Kept drinking when meant not to	1	0	0	0

20. Felt going crazy	1	0	0	0
21. Had a bad time	1	0	1	0
22. Felt physically or psychologically dependent	1	0	0	0
23. Told to stop or cut down on drinking	1	0	0	0
24. Nervousness inside	0	1	0	0
25. Feeling scaled for no reason	0	1	0	0
26. Feeling fearful	0	1	0	1
27. Feeling tense	0	1	0	1
28. Spells of terror or panic	0	1	0	1
29. Feeling restless	0	1	1	0
30. Feeling annoyed or irritated	0	0	1	0
31. Temper outburst	0	0	1	0
32. Having urges to harm someone	0	0	1	0
33. Having urges to break things	0	0	1	0
34. Getting into arguments	0	0	1	0
35. Thoughts of ending life	0	0	0	1
36. Feeling lonely	0	0	0	1
37. Feeling blue	0	0	0	1
38. Feeling no interest in things	0	0	0	1
39. Feeling hopeless	0	0	0	1
40. Feeling worthlessness	0	0	0	1

Note. 1 = an item measures the attribute; 0 = an item does not measure the attribute. AP = alcohol-related problems, AN = anxiety, HO = hostility, DE = depression.

The detailed procedures for analyzing respondents' mental health symptoms over time are demonstrated as follows. First, we fitted selected CDMs to the pre-test and post-test data separately, with item parameters constrained to be equal across time to ensure longitudinal measurement invariance. Second, based on the measurement model estimation, we assigned respondents to latent states (i.e., mental health symptom profiles) at each time point and computed the associated CEP and correction weights. Third, we estimated the latent transition CDM with the correction weights to obtain regression coefficients. A quasi-Newton optimization method, namely, Broyden-Fletcher-Goldfarb-Shanno (BFGS; Nash, 1990) with box constraints (i.e., L-BFGS-B; Byrd et al., 1995), was used to maximize the objective function given in Equation 7. Lastly, the classification results were updated based on Equation 8.

Given the updated classification results, the transition probabilities of mental health symptoms can be computed by the following logistic regression function:

$$\text{logit}(P) = \beta_0 + \beta_1 \times \text{Gender} + \beta_2 \times \text{Intervention} + \beta_3 \times \text{Gender} \times \text{Intervention}, \quad (9)$$

where P is the transition probability in Equation 4. We included binary covariates in the logistic regression so that Gender = 1 indicates males (0 = female) and Intervention = 1 (0 = control) indicates intervention group. The logit of transition probabilities by gender and intervention status can be shown in Table 4. The significance of the intervention effect on transition probabilities amongst females can be revealed by β_2.

Table 4. Logit of Transition Probability by Gender and Intervention Status (Gender = 1 for Males).

Gender	Intervention status	Logit(P)
Male	Intervention	$\beta_0 + \beta_1 + \beta_2 + \beta_3$
	Control	$\beta_0 + \beta_1$
Female	Intervention	$\beta_0 + \beta_2$
	Control	β_0

Note. $\text{Logit}(P) = \beta_0 + \beta_1 \times \text{Gender} + \beta_2 \times \text{Intervention} + \beta_3 \times \text{Gender} \times \text{Intervention}$.

Note that males in the control and intervention groups can be directly compared by switching the coding of the gender variable (i.e., in this case, Gender = 1 for females and 0 for males). In doing so, we can also test whether the transition probabilities between intervention and control groups amongst males differ by testing the new β_2. We can easily obtain the logit of transition probability by swapping the positions of "Male" and "Female" in the "Gender" column in Table 4. Annotated computer code in R and data utilized in the current paper are available at Mendeley Data (https://doi.org/10.17632/kpjp3gnwbt.1; Liang et al., 2023a).

4 Results

4.1 Model fit, Classification without Correction, and CEP Matrix (Steps 1 and 2)

In Step 1, the measurement model (i.e., the selected CDMs) showed adequate absolute fit with an $RMSEA_2 = 0.04$ (< 0.05; Maydeu-Olivares & Joe, 2014) at both pre-and post-tests. In addition, classification accuracy was estimated to ascertain the utility of using the selected CDMs for the data. The classification accuracy indices at the attribute level ranged from 0.91 to 0.96 at both pre-and post-tests. The probability of 0.9 or above in accurately classifying respondents' four mental health symptom attributes would be considered high. The hostility attribute had the lowest (0.91), and alcohol-related problems (0.96) had the highest classification accuracy for both time points. These classification accuracy indices indicate the measurement models at both time points were appropriate for analyzing the data.

In Step 2, respondents were classified into latent states based on the measurement model estimated at each time point. In addition, the CEP matrices for each attribute at both time points were also computed. Table 5 displays the CEP matrices of the attribute of alcohol-related problems at pre-and post-tests. At pre-test, 97% of the participants without alcohol-related problems were correctly classified as not having the attribute; similarly, 93% of the participants with alcohol-related problems were classified as having the attribute. Similar results were obtained at post-test. Appendix A shows the CEP matrices of the remaining attributes.

Table 5. The CEP Matrices of the Attribute of Alcohol-Related Problems at Pre- and Post-Tests.

	Estimated	
True	0	1
Pre-test		
0	0.97	0.03
1	0.06	0.93
Post-test		
0	0.97	0.03
1	0.07	0.94

Note. Row totals may not add up to 1.00 due to rounding.

4.2 Latent Logistic Regression (Step 3)

In the third step, the model shown in Figure 1 was estimated. Table 6 shows the regression coefficients of the latent logistic regression for the initial state and transition probabilities of the four attributes of mental health symptoms from pre- to post-test. At the initial state (pre-test), gender was negatively related to anxiety (AN) and positively associated with hostility (HO). Specifically, the odds of males being classified as having the anxiety attribute were odds ratio (*OR*) = 0.56 (= $e^{-0.58}$; $p < 0.001$, $d = -0.32$) times of females, indicating that females were 79% (= 1/0.56 = 1.79) more likely to have the anxiety attribute at pre-test. Males were more likely to be classified as having the hostility attribute than females, in particular, $OR = 1.23$ (= $e^{0.20}$; $p < 0.05$, $d = 0.11$) times females.

Multiple logistic regressions were conducted at post-test to examine how transition probabilities were associated with covariates. We investigated participants' transition for each attribute from 0 to 1 (i.e., from not possessing to possessing the attribute) and from 1 to 0 (i.e., from possessing to not possessing the attribute). For the transition from 0 to 1 (see Table 6; the middle row block), gender was significantly related to the transition probabilities for the alcohol-related problems and depression attributes. A significant interaction term between gender and intervention status was also observed for alcohol-related problems and depression. Specifically, in terms of alcohol-related problems, amongst males, their odds of transitioning from 0 to 1 in the intervention group were 0.45 (= $e^{\beta_2 + \beta_3} = e^{0.09 - 0.88}$) times of those in the control group; and amongst females, their odds of transitioning from 0 to 1 in the intervention group were 1.09 (= $e^{\beta_2} = e^{0.09}$) times those in the control group. With regard to depression, the odds of males transitioning from 0 to 1 in the intervention group were 1.14 (= $e^{\beta_2 + \beta_3} = e^{-0.28 + 0.41}$) compared to those in the control group, and the odds of females transitioning from 0 to 1 in the intervention group were 0.75 (= $e^{\beta_2} = e^{-0.28}$) compared to those in the control group. Participants who received the intervention were less likely to transition from 0 to 1 for the attribute of hostility.

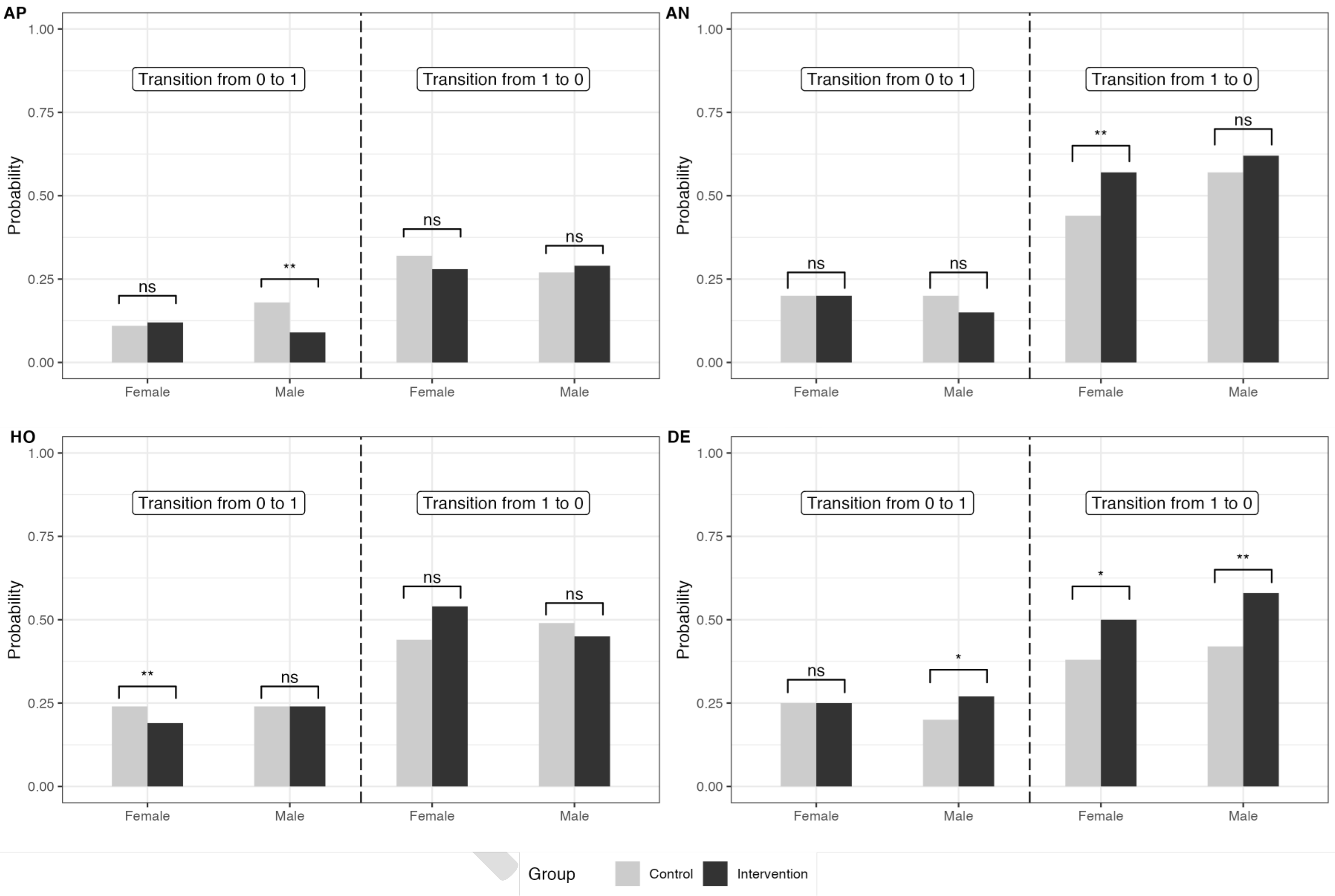
Concerning the transition from 1 to 0 (see Table 6; bottom row block), men were more likely to transition from 1 to 0 compared to women for the anxiety attribute. Participants in the intervention (vs. control) group were more likely to transition from having anxiety and depression attributes to not having them.

Table 6. Coefficients of the Latent Logistic Regression Obtained in Step 3.

	AP			AN			HO			DE		
	β	*OR*	*d*	β	*OR*	*d*	β	*OR*	*d*	β	*OR*	*d*
Initial state												
Intercept (β_0)	-0.81	0.44	-0.45	-0.83	0.43	-0.46	-0.81	0.45	-0.44	-0.61	0.55	-0.33
Gender (β_1)	0.00	1.00	0.00	-0.58**	0.56	-0.32	0.20*	1.23	0.11	0.03	1.03	0.02
Transition from Absence (0) to Presence (1)												
Intercept (β_0)	-2.12	0.12	-1.17	-1.36	0.26	-0.75	-1.18	0.31	-0.65	-1.10	0.33	-0.61
Gender (β_1)	0.60**	1.82	0.33	-0.04	0.96	-0.02	0.01	1.01	0.01	-0.28*	0.75	-0.16
Intervention (β_2)	0.09	1.09	0.05	-0.06	0.94	-0.03	-0.30**	0.74	-0.17	-0.01	0.99	-0.01
Gender × Intervention (β_3)	-0.88**	0.41	-0.49	-0.25	0.78	-0.14	0.30	1.34	0.16	0.41*	1.51	0.23
Transition from Presence (1) to Absence (0)												
Intercept (β_0)	-0.78	0.46	-0.43	-0.26	0.77	-0.14	-0.24	0.79	-0.13	-0.49	0.62	-0.27
Gender (β_1)	-0.23	0.80	-0.13	0.54**	1.71	0.30	0.20	1.22	0.11	0.15	1.16	0.08
Intervention (β_2)	-0.19	0.83	-0.10	0.53**	1.69	0.29	0.39	1.47	0.21	0.47*	1.60	0.26
Gender × Intervention (β_3)	0.29	1.33	0.16	-0.33	0.72	-0.18	-0.56	0.57	-0.31	0.18	1.20	0.10

Note. Gender = 0 for females, and =1 for males; Intervention = 0 for control group, and = 1 for intervention group; AP = alcohol-related problems, AN = anxiety, HO = hostility, DE = depression; *d* = Cohen's $d = \beta \times \frac{\sqrt{3}}{\pi}$ (Sánchez-Meca et al., 2003); *OR* = Odds Ratio $= \exp(\beta)$; *$p < 0.05$, **$p < 0.01$.

Figure 2. Transition Probabilities of Mental Health Symptoms by Gender and Intervention Status.



Note. AP = alcohol-related problems, AN = anxiety, HO = hostility, DE = depression; ns $p > 0.05$, *$p < 0.05$, **$p < 0.01$.

Because gender and intervention status variables were considered clinically informative covariates in this study, the transition probabilities were calculated using the regression coefficients by gender and intervention status based on Table 6 (see Figure 2). The significance of the intervention effects amongst females or males can be examined using the coefficients of intervention (β_2). Table 6 shows the regression coefficients obtained when Gender = 1 for males (see Appendix B for the results when Gender = 1 for females). Figure 2 shows intervention effects for each attribute and each transition separately for males and females. Overall, the intervention effect on the transition from 1 to 0 was more likely to occur than the transition from 0 to 1. Of the transition from 1 to 0, the intervention benefited both males and females who had depression at the initial time point; however, the intervention effect on anxiety was found only among females. In contrast, the transition from 0 to 1 was more common for those in the control group than those who received the intervention (i.e., alcohol-related problems among males and hostility among females). However, depression among men showed the opposite pattern - men in the intervention group were more likely to transition from 0 to 1 than those in the control group.

The updated latent state membership was computed using Equation 8, from which the attribute prevalences and the transition probabilities of the mental health symptoms in Table 7 were computed. Not surprisingly, the probabilities of transitioning from 1 to 0 were substantially greater than the corresponding probabilities of transitioning from 0 to 1. Regarding the transition probabilities between the control and intervention groups, except for depression, participants in the intervention group were less likely to transition from 0 to 1 compared to those in the control group. Except for alcohol-related problems, participants in the intervention group were more likely to transition from 1 to 0 than those in the control group. Taken together, the results suggest that the brief alcohol intervention positively affected the transitions of all four attributes by either alleviating existing mental health symptoms or preventing them from developing. However, the beneficial effects may have to be examined for men and women more carefully.

Table 7. The Corrected and Updated Attribute Prevalence of the Mental Health Symptoms at Pre-/Post-Test and the Marginal Transition Probabilities

	Attribute			
	AP	AN	HO	DE
Attribute prevalence (%)				
Pre-test	27.63	20.70	25.49	34.16
Post-test	27.93	20.80	24.74	33.62
Transition probability (total sample)				
From 0 to 1	0.10	0.14	0.15	0.22
From 1 to 0	0.25	0.52	0.47	0.44
Transition probability (by intervention status)				
From 0 to 1 (control group)	0.11	0.15	0.16	0.20
From 0 to 1 (intervention group)	0.09	0.12	0.14	0.24
From 1 to 0 (control group)	0.26	0.46	0.42	0.39
From 1 to 0 (intervention group)	0.24	0.57	0.51	0.50

Note. AP = alcohol-related problems, AN = anxiety, HO = hostility, DE = depression. For transition probabilities from 0 to 0 and from 1 to 1, please refer to Table 1.

5 Discussion

This study demonstrated how to analyze the transition of mental health symptoms over time with a model that accounts for the covariates' effects on both the initial state and transition probabilities within a CDM analytic framework. We demonstrated the use of a three-step latent transition CDM with covariates (Liang et al., 2023b) in this data application, which extends the work by Tan et al. (2023) to transitions and the effects of covariates on transitions. We walked through the three-step estimation procedure, where CDM parameters (measurement model) and regression coefficients (structural model) can be flexibly estimated while maintaining classification accuracy through correction. The current study showcases the first application of CDMs for longitudinal clinical data.

The three-step approach in this study disentangled the relationships between covariates and each mental health symptom. This approach can answer the question of which covariates are associated with the transition of which constructs at the attribute level. It allows researchers to understand the mental health symptoms at the most granular level of information and enables evaluation of intervention effects. This fine-grained approach may assist with developing better intervention designs. Specifically, by testing intervention group membership as a covariate, we can probe whether respondents in the intervention group exhibited a higher transition probability from one state to another. For example, in the present study, the intervention did not have any significant effects on respondents' transition from presence to absence with respect to alcohol-related problems and hostility. However, it had "spillover" effects on anxiety and depression, in the sense that the intervention was not designed to improve anxiety and depression. This suggests that the brief alcohol intervention tested may have a broader range of health effects, while its targeted effect may need to be strengthened.

Note that we utilized the three-step approach to latent transition CDM. Because each step is separately estimated, it is possible to examine an additional set of covariates or different sets of covariates without fitting the entire model again. With the advent of powerful computing capacity, it may be helpful to assess clinical and non-clinical endpoints more broadly to assess the health benefits of brief alcohol interventions across time.

The current study adopted Bayes' Theorem to integrate the classification information obtained from the first step of CDM estimation and information from the latent logistic regressions to update the posterior probability. This procedure was demonstrated by Sun and de la Torre (2020), which incorporated covariates into CDMs and updated posterior probabilities at a single time point. This procedure may be useful to improve the classification of respondents even if covariates are not related to attributes. Future studies could investigate to what extent using covariates and updating posterior probabilities in longitudinal CDMs can improve the classification of individuals at multiple time points.

Despite the utility of the three-step latent transition CDM approach, this study has several potential limitations worth mentioning. First, this study dichotomized polytomous responses for model simplicity. Dichotomization may lead to information loss and affect structural and item parameter estimation. Based on the pre-test mental health data from the same project, Tan et al. (2023) conducted a sensitivity analysis of the polytomous data using a sequential G-DINA model (Ma & de la Torre, 2016). They showed that the patterns of results obtained with polytomous data were similar to those with dichotomized data. Therefore, it is quite likely that the current results would be similar even with polytomous response data. In the existing literature, most methodological developments (e.g., the three-step approach) and analysis procedures (e.g., absolute model fit evaluation and classification accuracy evaluation) are developed based on dichotomous CDMs. Future research should consider extending the dichotomous CDM methodologies to polytomous CDMs in longitudinal studies and proposing appropriate procedures for polytomous CDMs. For instance, future large sample studies can examine the three-step approach of latent transition CDM with covariates in polytomous response data.

Second, we analyzed the complete response data in this study, consistent with Tan et al. (2023). However, complete response data are not necessary for CDM analysis, and response data with some missing values can also be analyzed using the approach demonstrated in this study. The presence of missing data could lead to biased parameter estimation in psychometric models (e.g., De Ayala et al., 2001; Pohl et al., 2014). However, in the CDM literature, it remains an outstanding task to systematically examine how different patterns of missing data may affect model estimation and classification (Pan & Zhan, 2020; Shan & Wang, 2020; Xu & von Davier, 2006). Only a few studies have empirically evaluated various approaches for handling missing data in CDM applications (e.g., Dai et al., 2018;

Ömür Sünbül, 2018). Because respondents with missing data do not receive any diagnostic feedback when a complete case analysis is employed, researchers may want to utilize the response data with missing data. In such cases, we suggest that researchers identify the missing data mechanisms and employ proper analytic approaches to missing data.

Third, only two binary covariates were used in this study, and they were expected to be unrelated due to randomization. However, latent transition CDM can accommodate continuous covariates (for example, see Liang et al., 2023b). When continuous covariates are used, they may be associated. When the number of covariates in the model increases, however, multicollinearity may become an issue in empirical studies, just as it is a common concern in generalized linear mixed models. In such situations, variable selection and regularization may be considered. Iaconangelo and de la Torre (2017) incorporated the correction weights with the latent-class lasso as a variable selection procedure for CDMs at a single time point, which led to a more helpful subset of non-redundant variables. This variable selection may result in more helpful structural parameter estimation. However, developing variable selection methods for the three-step latent transition CDM with covariates remains a future challenge to address.

Lastly, the present study used the same measurement model with item parameter constraints at different time points to ensure measurement invariance – this may degrade assessment flexibility. Most longitudinal CDM methodologies were developed under such constraints. However, theoretically, using identical test forms and fixing item parameters across time points are not necessary. For different test forms with common items at different time points, multiple-group CDMs (e.g., multiple-group-GDINA; Ma et al., 2021) can be used to detect whether items function differentially across different time points and determine item parameters for each time point separately. Moreover, measurement models could be different across time points. We suggest that the feasibility of using different measurement models at multiple time points (Asparouhov & Muthén, 2014) be explored, as this allows researchers to select the most appropriate CDMs for each time point. Di Mari et al. (2016) also noted that the three-step approach for LTA can be adapted to allow time-specific measurement models by performing the first and second steps separately at each time point.

In closing, the current paper demonstrated the utility of CDM for classifying and understanding transition in attributes in longitudinal item-response data. Individual-focused profiles can serve as the basis for tailored or personalized learning or treatment. For example, Wu (2019) developed an online personalized tutor program based on the CDM diagnostic profiles and found that the personalized program outperformed traditional remedial instruction. In addition, the program benefited all students by improving their learning outcomes. The same promise may be possible in clinical settings with more appropriate and specific intervention programs that can be tailored to individuals' diagnostic profiles. To this end, novel analytical techniques, such as CDM, in conjunction with technology, are promising in facilitating the successful implementation of tailored interventions.

References

Asparouhov, T., & Muthén, B. (2014). Auxiliary variables in mixture modeling: Three-step approaches using Mplus. *Structural Equation Modeling*, *21*(3), 329–341. https://doi.org/10.1080/10705511.2014.915181

Baum, L. E., & Petrie, T. (1966). Statistical inference for probabilistic functions of finite state Markov chains. *The Annals of Mathematical Statistics*, *37*(6), 1554–1563. http://www.jstor.org/stable/2238772

Bolck, A., Croon, M., & Hagenaars, J. (2004). Estimating latent structure models with categorical variables: One-step versus three-step estimators. *Political Analysis*, *12*(1), 3–27. https://doi.org/10.1093/pan/mph001

Byrd, R. H., Lu, P., Nocedal, J., & Zhu, C. (1995). A limited memory algorithm for bound constrained optimization. *SIAM Journal on Scientific Computing*, *16*(5), 1190–1208. https://doi.org/https://doi.org/10.1137/0916069

Chen, H., Cai, Y., & de la Torre, J. (2022). Investigating second language (L2) reading subskill associations: A cognitive diagnosis approach. *Language Assessment Quarterly*, 1–24. https://doi.org/10.1080/15434303.2022.2140050

Chen, J., de la Torre, J., & Zhang, Z. (2013). Relative and absolute fit evaluation in cognitive diagnosis modeling. *Journal of Educational Measurement*, *50*(2), 123–140. https://doi.org/10.1111/j.1745-3984.2012.00185.x

Clogg, C. C. (1981). New developments in latent structure analysis. In D. J. Jackson & E. F. Borgatta (Eds.), *Factor analysis and measurement in sociological research* (pp. 215–246). Sage Publications.

Collins, L. M., & Lanza, S. T. (2010). *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences*. Wiley. https://doi.org/10.1002/9780470567333

Dai, S., Svetina, D., & Chen, C. (2018). Investigation of missing responses in Q-Matrix validation. *Applied Psychological Measurement*, *42*(8), 660–676. https://doi.org/10.1177/0146621618762742

Dayton, C. M., & Macready, G. B. (1988). Concomitant-variable latent-class models. *Journal of the American Statistical Association*, *83*(401), 173–178. https://doi.org/10.2307/2288938

de la Torre, J. (2011). The generalized DINA model framework. *Psychometrika*, *76*(2), 179–199. https://doi.org/10.1007/s11336-011-9207-7

De Ayala, R. J., Plake, B. S., & Impara, J. C. (2001). The impact of omitted responses on the accuracy of ability estimation in item response theory. *Journal of Educational Measurement*, *38*(3), 213–234. https://doi.org/10.1111/j.1745-3984.2001.tb01124.x

de la Torre, J., & Chiu, C. Y. (2016). A general method of empirical Q-matrix validation. *Psychometrika*, *81*(2), 253–273. https://doi.org/10.1007/s11336-015-9467-8

de la Torre, J., & Minchen, N. (2014). Cognitively diagnostic assessments and the cognitive diagnosis model framework. *Psicologia Educativa*, *20*(2), 89–97. https://doi.org/10.1016/j.pse.2014.11.001

de la Torre, J., van der Ark, L. A., & Rossi, G. (2018). Analysis of clinical data from a cognitive diagnosis modeling framework. *Measurement and Evaluation in Counseling and Development*, *51*(4), 281–296. https://doi.org/10.1080/07481756.2017.1327286

Derogatis, L. R. (1975). *Brief symptom inventory*. MD: Clinical Psychometric Research.

Di Mari, R., Oberski, D. L., & Vermunt, J. K. (2016). Bias-adjusted three-step latent Markov modeling with covariates. *Structural Equation Modeling*, *23*(5), 649–660. https://doi.org/10.1080/10705511.2016.1191015

Hansen, M., Cai, L., Monroe, S., & Li, Z. (2016). Limited-information goodness-of-fit testing of diagnostic classification item response models. *The British Journal of Mathematical *and Statistical Psychology*, *69*(3), 225–252. https://doi.org/10.1111/bmsp.12074

Hartz, S. M. (2002). *A Bayesian framework for the unified model for assessing cognitive abilities: Blending theory with practicality* [Doctoral dissertation, University of Illinois at Urbana-Champaign].

Henson, R. A., Templin, J. L., & Willse, J. T. (2009). Defining a family of cognitive diagnosis models using log-linear models with latent variables. *Psychometrika*, *74*(2), 191–210. https://doi.org/10.1007/s11336-008-9089-5

Huebner, A., & Wang, C. (2011). A note on comparing examinee classification methods for cognitive diagnosis models. *Educational and Psychological Measurement*, *71*(2), 407–419. https://doi.org/10.1177/0013164410388832

Humphreys, K., & Janson, H. (2000). Latent transition analysis with covariates, nonresponse, summary statistics and diagnostics: modelling children's drawing development. *Multivariate Behavioral Research*, *35*(1), 89–118. https://doi.org/10.1207/S15327906MBR3501_4

Iaconangelo, C., & de la Torre, J. (2016, July 11-15). *Three-step estimation of cognitive diagnosis models with covariate* [Paper presentation]. 81st International Meeting of the Psychometric Society, Asheville, NC, United States.

Iaconangelo, C. (2017). *Uses of classification error probabilities in the three-step approach to estimating cognitive diagnosis models* [Doctoral dissertation, Rutgers, The State University of New Jersey]. https://doi.org/doi:10.7282/T3W95D95

Junker, B. W., & Sijtsma, K. (2001). Cognitive assessment models with few assumptions, and connections with nonparametric item response theory. *Applied Psychological Measurement*, *25*(3), 258–272. https://doi.org/10.1177/01466210122032064

Lanza, S. T., Patrick, M. E., & Maggs, J. L. (2010). Latent transition analysis: Benefits of a latent variable approach to modeling transitions in substance use. *Journal of Drug*

Issues, *40*(1), 93–120. https://doi.org/10.1177/002204261004000106

Lanza, S. T., Tan, X., & Bray, B. C. (2013). Latent class analysis with distal outcomes: A flexible model-based approach. *Structural Equation Modeling*, *20*(1), 1–26. https://doi.org/10.1080/10705511.2013.742377

Larimer, M. E., Lee, C. M., Kilmer, J. R., Fabiano, P. M., Stark, C. B., Geisner, I. M., Mallett, K. A., Lostutter, T. W., Cronce, J. M., Feeney, M., & Neighbors, C. (2007). Personalized mailed feedback for college drinking prevention: A randomized clinical trial. *Journal of Consulting and Clinical Psychology*, *75*(2), 285–293. https://doi.org/10.1037/0022-006X.75.2.285

Liang, Q., de la Torre, J., Larimer, M. E., & Mun, E.-Y. (2023a). Mental health symptom profiles over time: A three-step latent transition cognitive diagnosis modeling analysis with covariates. *Mendeley Data*. https://doi.org/10.17632/kpjp3gnwbt.1

Liang, Q., de la Torre, J., & Law, N. (2023b). Latent transition cognitive diagnosis model with covariates: A three-step approach. *Journal of Educational and Behavioral Statistics*. (in press) https://doi.org/10.3102/10769986231163320

Liang, Q., de la Torre, J., & Law, N. (2021). Do background characteristics matter in Children's mastery of digital literacy? A cognitive diagnosis model analysis. *Computers in Human Behavior*, *122*, Article 106850. https://doi.org/10.1016/j.chb.2021.106850

Liu, Y., Tian, W., & Xin, T. (2016). An application of M2 statistic to evaluate the fit of cognitive diagnostic models. *Journal of Educational and Behavioral Statistics*, *41*(1), 3–26. https://doi.org/10.3102/1076998615621293

Lu, I. R. R., & Thomas, D. R. (2008). Avoiding and correcting bias in score-based latent variable regression with discrete manifest items. *Structural Equation Modeling*, *15*(3), 462–490. https://doi.org/10.1080/10705510802154323

Ma, W. (2020). Evaluating the fit of sequential G-DINA model using limited-information measures. *Applied Psychological Measurement*, *44*(3), 167–181. https://doi.org/10.1177/0146621619843829

Ma, W., & de la Torre, J. (2016). A sequential cognitive diagnosis model for polytomous responses. *The British Journal of Mathematical and Statistical Psychology*, *69*(3), 253–275. https://doi.org/10.1111/bmsp.12070

Ma, W., Iaconangelo, C., & de la Torre, J. (2016). Model similarity, model selection, and attribute classification. *Applied Psychological Measurement*, *40*(3), 200–217. https://doi.org/10.1177/0146621615621717

Ma, W., Minchen, N., & de la Torre, J. (2020). Choosing between CDM and unidimensional IRT: The proportional reasoning test case. *Measurement: Interdisciplinary Research and Perspectives*, *18*(2), 87–96. https://doi.org/10.1080/15366367.2019.1697122

Ma, W., Terzi, R., & de la Torre, J. (2021). Detecting differential item functioning using multiple-group cognitive diagnosis models. *Applied Psychological Measurement*, *45*(1), 37–53. https://doi.org/10.1177/0146621620965745

Maris, E. (1999). Estimating multiple classification latent class models. *Psychometrika*, *64*(2), 187–212. https://doi.org/10.1007/BF02294535

Maydeu-Olivares, A., & Joe, H. (2014). Assessing approximate fit in categorical data analysis. *Multivariate Behavioral Research*, *49*(4), 305–328. https://doi.org/10.1080/00273171.2014.911075

Mun, E., de la Torre, J., Atkins, D. C., White, H. R., Ray, A. E., Kim, S., Jiao, Y., Clarke, N., Huo, Y., Larimer, M. E., Huh, D., & The Project INTEGRATE Team. (2015). Project INTEGRATE: An integrative study of brief alcohol interventions for college students. *Psychology of Addictive Behaviors*, *29*(1), 34–48. https://doi.org/10.1037/adb0000047

Nash, J. C. (1990). *Compact numerical methods for computers : linear algebra and function minimisation* (2nd ed.). Adam Hilger.

Ömür Sünbül, S. (2018). The Impact of Different Missing Data Handling Methods on DINA Model. *International Journal of Evaluation and Research in Education (IJERE)*, *7*(1), 77. https://doi.org/10.11591/ijere.v7i1.11682

Pan, Y., & Zhan, P. (2020). The impact of sample attrition on longitudinal learning diagnosis: A prolog. *Frontiers in Psychology*, *11*, Article 1051. https://doi.org/10.3389/fpsyg.2020.01051

Pohl, S., Gräfe, L., & Rose, N. (2014). Dealing with omitted and not-reached items in competence tests: Evaluating approaches accounting for missing responses in item response theory models. *Educational and Psychological Measurement*, *74*(3), 423–452. https://doi.org/10.1177/0013164413504926

Reboussin, B. A., Reboussin, D. M., Liang, K.-Y., & Anthony, J. C. (1998). Latent transition modeling of progression of health-risk behavior. *Multivariate Behavioral Research*, *33*(4), 457–478. https://doi.org/10.1207/s15327906mbr3304_2

Sánchez-Meca, J., Marín-Martínez, F., & Chacón-Moscoso, S. (2003). Effect-size indices for dichotomized outcomes in meta-analysis. *Psychological Methods*, *8*(4), 448–467. https://doi.org/10.1037/1082-989X.8.4.448

Shan, N., & Wang, X. (2020). Cognitive diagnosis modeling incorporating item-level missing data mechanism. *Frontiers in Psychology*, *11*, Article 564707. https://doi.org/10.3389/fpsyg.2020.564707

Sun, Y., & de la Torre, J. (2020). Improving attribute classification accuracy in high dimensional data: A four-step latent regression approach. In H. Jiao & R. W. Lissitz (Eds.), *Innovative psychometric modeling and methods* (pp. 17–44). Information Age.

Tan, Z., de la Torre, J., Ma, W., Huh, D., Larimer, M. E., & Mun, E.-Y. (2023). A tutorial on cognitive diagnosis modeling for characterizing mental health symptom profiles using existing item responses. *Prevention Science*, *24,* 480-492.

https://doi.org/10.1007/s11121-022-01346-8

Tatsuoka, K. K. (1983). Rule space: An approach for dealing with misconceptions based on item response theory. *Journal of Educational Measurement*, *20*(4), 345–354. https://doi.org/10.1111/j.1745-3984.1983.tb00212.x

Tatsuoka, K. K. (2009). *Cognitive assessment: An introduction to the rule space method*. Routledge. https://doi.org/10.4324/9780203883372

Templin, J. L., & Henson, R. A. (2006). Measurement of psychological disorders using cognitive diagnosis models. *Psychological Methods*, *11*(3), 287. https://doi.org/10.1037/1082-989X.11.3.287

Tjoe, H., & de la Torre, J. (2014). The identification and validation process of proportional reasoning attributes: An application of a cognitive diagnosis modeling framework. *Mathematics Education Research Journal*, *26*(2), 237–255. https://doi.org/10.1007/s13394-013-0090-7

Vermunt, J. K. (2010). Latent class modeling with covariates: Two improved three-step approaches. *Political Analysis*, *18*(4), 450–469. https://doi.org/10.1093/pan/mpq025

Vermunt, J. K., Langeheine, R., & Bockenholt, U. (1999). Discrete-time discrete-state latent Markov models with time-constant and time-varying covariates. *Journal of Educational and Behavioral Statistics*, *24*(2), 179–207. https://doi.org/10.3102/10769986024002179

von Davier, M., & Lee, Y.-S. (Eds.). (2019). *Handbook of diagnostic classification models* (1st ed.). Springer Cham. https://doi.org/https://doi.org/10.1007/978-3-030-05584-4

Wang, W., Song, L., Chen, P., Meng, Y., & Ding, S. (2015). Attribute-level and pattern-level classification consistency and accuracy indices for cognitive diagnostic assessment. *Journal of Educational Measurement*, *52*(4), 457–476. https://doi.org/10.1111/jedm.12096

White, R. H., & Labouvie, E. W. (1989). Towards the assessment of adolescent problem drinking. *Journal of Studies on Alcohol*, *50*(1), 30–37. https://doi.org/10.15288/jsa.1989.50.30

Wu, H. M. (2019). Online individualised tutor for improving mathematics learning: A cognitive diagnostic model approach. *Educational Psychology*, *39*(10), 1218–1232. https://doi.org/10.1080/01443410.2018.1494819

Xu, X., & von Davier, M. (2006). Cognitive diagnosis for NAEP proficiency data. *ETS Research Report Series*, *2006*(1), i–25. https://doi.org/10.1002/j.2333-8504.2006.tb02014.x

Appendix A. The CEP Matrices of the Other Three Mental Health Symptoms at Pre-and Post-tests.

	Pre-test		Post-test	
	Estimated			
True	0	1	0	1
AN				
0	0.98	0.03	0.97	0.03
1	0.19	0.81	0.19	0.81
HO				
0	0.95	0.06	0.94	0.06
1	0.15	0.84	0.15	0.86
DE				
0	0.97	0.03	0.97	0.03
1	0.06	0.93	0.06	0.94

Note. AN = anxiety, HO = hostility, DE = depression. Row totals of each CEP matrix may not add up to 1.00 due to rounding.

Appendix B. Coefficients of the Latent Logistic Regression Obtained in Step 3 when Gender = 1 for Females.

	AP			AN			HO			DE		
	β	*OR*	*d*	*β*	*OR*	*d*	*β*	*OR*	*d*	*β*	*OR*	*d*
Initial state												
Intercept (β_0)	-0.82	0.44	-0.45	-1.42	0.24	-0.78	-0.60	0.55	-0.33	-0.58	0.56	-0.32
Gender (β_1)	0.00	1.00	0.00	0.58**	1.79	0.32	-0.20*	0.82	-0.11	-0.03	0.97	-0.02
Transition from 0 to 1												
Intercept (β_0)	-1.49	0.22	-0.82	-1.43	0.24	-0.79	-1.17	0.31	-0.64	-1.41	0.24	-0.78
Gender (β_1)	-0.62**	0.54	-0.34	-0.01	0.99	-0.01	-0.01	0.99	-0.01	0.30	1.35	0.16
Intervention (β_2)	-0.74**	0.48	-0.41	-0.37	0.69	-0.20	-0.01	0.99	0.00	0.38*	1.47	0.21
Gender × Intervention (β_3)	0.83**	2.28	0.46	0.25	1.28	0.14	-0.30	0.74	-0.17	-0.41	0.67	-0.22
Transition from 1 to 0												
Intercept (β_0)	-0.97	0.38	-0.53	0.21	1.23	0.11	-0.04	0.96	-0.02	-0.37	0.69	-0.20
Gender (β_1)	0.20	1.22	0.11	-0.59**	0.56	-0.32	-0.20	0.82	-0.11	-0.13	0.88	-0.07
Intervention (β_2)	0.13	1.14	0.07	0.07	1.08	0.04	-0.18	0.84	-0.10	0.62**	1.86	0.34
Gender × Intervention (β_3)	-0.32	0.73	-0.18	0.37*	1.45	0.21	0.55**	1.74	0.31	-0.17	0.85	-0.09

Note. Gender = 0 for males, and =1 for females; Intervention = 0 for control group, and = 1 for intervention group; AP = alcohol-related problems, AN = anxiety, HO = hostility, DE = depression; *d* = Cohen's $d = \beta \times \frac{\sqrt{3}}{\pi}$ (Sanchez-Meca et al., 2003); *OR* = Odds Ratio $= \exp(\beta)$; *$p < 0.05$, ** $p < 0.01$.