Utilizing Multidimensional Item Response Theory to Examine Social Capital

By

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B.S., Soochow University, 2013

Submitted to the graduate degree program in Educational Psychology and the Graduate Faculty of the University of Kansas in partial fulfillment of the requirements for the degree of Master of Science in Education.

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Date Defended: 6 December 2018

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Abstract

This study introduces the use of mixed-format multidimensional item response theory (MIRT) analysis for assessing the latent factor structure of the Social Capital Rating Scale (SCRS). The rating scale, an instrument developed for measuring the parent involvement and the peer network of high school students, contains twenty-two items selected from the student questionnaire of the National Educational Longitudinal Study (NELS:88) Database. The psychometric properties and dimensionality of the scale are evaluated with MIRT framework. Using the sample of grade eight students from NELS:88 (N = 27,394), the two-factor structure of the SCRS (factor 1: within-family social capital; factor 2: peer social capital) was confirmed with the two-parameter IRT model (*2PL*): *RMSEA* = 0.049, *CFI* = 0.915, *TLI* = 0.905, *SRMSR* = 0.057. Discussion includes methodological implications for social capital scale, focusing on assessment of measurement invariance in differential item functioning etc.

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Chapter 1: Introduction

Recently a greater focus has been placed on understanding the impacts of the social capital of high school students on educational outcomes as well as school dropout rates. Some of the mechanisms linking family characteristics to the educational attainment of children, adolescents, and young adults seem clear. Higher income parents can invest more in the education of their children than can low income parents, and parents with more education have expectations and experiences that encourage their children to attain education more so than do parents with low levels of education (Sandefur, Meier, & Campbell, 2006).

"Parental involvement" has been believed as a component of "successful" program by administrators of college preparation programs and researchers and policy analysts (Laura Walter Perna& Titus, 2005). A 1999 survey by the College Board revealed that more than two third (70%) of college preparation programs that target historically underrepresented minority groups report having a parental involvement component; for one third of all programs, parents of participating students are required to participate (Laura W. Perna, 2002).

Though social capital has gained wide acceptability as a crucial predictor of high school students' academic achievement (Israel, Beaulieu, &Hartless, 2001; Lee & Bowen, 2006; Sui-Chu &Willms, 1996), social competence (Kohl, Lengua, & McMahon, 2000) and other educational outcomes, the definition of social capital is long debated. It was originally defined as those patterns of social interrelationships that enable people to coordinate action to achieve the desired goals (Helliwell & Putnam, 2007). Even though social capital is considered as multidimensional entity, few previous research have utilized multidimensional IRT method to examine social capital measurement. In this study, multidimensional graded response model was utilized to analyze the scale. The new measurement contains parental involvement subscale (Kohl et al., 2000) and peer networks subscale (Robert K. Ream &Rumberger, 2008).

Item response theory (IRT) plays a very important role in model psychometric test development, but the use of IRT has been limited in social capital measurement. One specific potential application of IRT methods is for developing measures and evaluating items selected from the public database. A basic concept in IRT is the item characteristic curve (ICC), which is essentially a non-linear regression on ability of probability of a correct response to a given item. IRT theory and methods also are applicable at the test or scale level. The test characteristic curve (TCC) represents a non-linear regression of overall test score on ability. The TCC can be a very useful tool for evaluating the range of measurement error and the degree of discrimination at different points of the latent trait continuum.

There are two purposes for this study. The primary one is to introduce the mixed-format multi-dimensional multidimensional IRT framework for reliability analysis and model selection process. The secondary one was to offer a new measurement tool based upon items from National Education Longitudinal Study of 1988 (NELS:88). A new measurement is necessary because, as Paxton (1999) noted, there is 'wide gap between the concept of social capital and its measurement' (Paxton, 1999). Social capital is ordinarily operationalized as a composite of the frequency of discussions between the parent and child about school-related activities (Laura Walter Perna& Titus, 2005). Recent studies also consider *peer network* as another influential dimension of social capital, indicated by the number of friends of children who drop out of the school (Ream, 2008; Stewart, 2008).

Inspired by previous studies of family involvement and peer network (Dunham & Wilson, 2007a; Ream, 2008), the scale consists of 22 items picked from the student questionnaires of National Education Longitudinal Study of 1988 (*NELS:88*). This study aims to assess the latent factor structure of social capital of 8th grade high school students, and to provide a statistic tool for measuring social capital to future research.

Chapter 2: Literature Review

2.1 Two Perspectives of Social Capital

Despite that social capital has been a successful concept that "exports" from sociology to other fields during the last two decades, its definition is still ambiguous. The first theoretical confusion is social scientists from different disciplines define social capital from different perspectives. Historically, social capital could be considered as both group-level and individual-level construct.

Studies focusing on individual-level social capital examined how individuals access and use resources embedded in social networks to gain returns in instrumental actions or preserve gains in expressive actions (Goddard, 2003; McNeal Jr, 1999). The focal points for analysis in this perspective are how individuals (1) invest in social relations, and (2) capture the embedded resources in the relations to generate a return (Lin, 1999). The original theoretical development of the concept by the French sociologist Pierre Bourdieu (1980) and the American sociologist James Coleman (1993) were centered on this perspective with some significant variations. Bourdieu's concept of social capital was instrumental. He claimed that people intentionally built their relations for the benefits that they would bring later (Bourdieu, 1986). The key idea is that social capital could be traded for each other and require such trades for their development. Without the investment of some material resources and the possession of some cultural knowledge, social capital can hardly be acquired. Also, the interaction between human capital, social capital, and cultural capital are significant for the individuals to establish relations with others. Coleman defined social capital by its function – "It is not a single entity but a variety of different entities, with two elements in common: they all consist of some aspect of social structures, and they facilitate certain actions of actors – whether persons or corporate actors – within the structure."

Another perspective focuses on social capital at the group level (Israel, Beaulieu, & Hartless, 2001; Reynolds, Weissberg, & Kasprow, 1992). In this perspective, social capital is a feature of communities rather than individuals. This perspective mainly discusses (1) how certain groups develop and maintain social capital as a collective asset, and (2) how such a collective asset enhances group member's life chances. In contrast to individual-level social capital, this perspective emphasizes on community ties as an important role in the community itself. Coleman (1998) provided an example by indicating that old people could walk on the streets at night without fear, and children could be sent to play outside if the tight community controls guaranteed their safety(Coleman, 1988). A pattern of community activeness builds social capital in that the networks developed during past activities provide a foundation for new community efforts to address educational or other needs (Lloyd, 1985). Social capital at community level may benefit much more to the cluster as a whole in the form of reduced crime rates, lower official corruption, and better governance than to individuals (Portes, 2000). For instance, using data from the National Education Longitudinal Survey (NELS), Israel et al. (2001) asserts that process and structural attributes of community social capital could help youths to excel (Israel et al., 2001).

Though social capital is mostly regarded as a property of students in the education field, this perspective suggests that social capital may have multiple levels of analysis in a different context. However, compared to the individual-level, the community-level social capital is hardly measured and assessed for the following reasons. First, this transition of conceptualization from individual resource to collective resources was never explicitly theorized because of the current state of confusion about the definition of social capital. McNeal JR (1999), for instance, claims that social capital could be the assets of students in intact families with high parent-school involvement (McNeal Jr, 1999); other studies claimed that it was an attribute of social networks

of traders, and social capital became the explanatory variable of good governance and economically success of one city (Leyden, 2003; Woolcock, 1998). The divergent perspectives indicate that social capital is becoming synonymous with any other relevant concepts that are positive in social life. Second, the causes and consequences of collective social capital were never well explained. Third, the need for alternative indicators of social capital arises when collective social capital can be hardly measured by its consequences.

2.2 The dimensionality of Social Capital

After reviewing journal articles, book chapters, conference papers, and electronic resources published between 1986 and 2001 in which social capital was used as an explanatory variable in the education field, Dika (2002) concluded that most of the work in this area relied on Coleman's rater vague and metaphorical concept of social capital, while others began investigating social networks and social reproduction theories for more theoretically refined models (Dika & Singh, 2002). Finally, the increasing focus on psycho-social outcomes such as school engagement and locus of control has the potential to contribute to a richer understanding of students' school experiences. Although there is a wealth of research on social capital, the dimensionality of social capital has not been well examined (Laura, 2005). The complexity comes both from the vague theoretical definitions and from inconsistent measurement tools. In previous studies, the indicators of social capital include activities, relations between parents, students, institutions, and teachers. Moreover, those subscales have varied link with educational outcomes. For example, Dika (2002) reviewed fourteen of the studies investigating the link between social capital with educational attainment, and found that dropout rates are positively related to nontraditional family structure and number of siblings and negatively related to parental expectations and aspirations, parent-teen interactions/discussion, parent monitoring, number of moves, parent communication with school, parent-school involvement, church

attendance, involvement in other activities, and inter-generational closure. Some indicators of social capital are also positively associated with high school graduation and college enrollment. Also, strong help network of the parent, number of friends known by parent, how often seeing close friends, and friend's educational expectations, teacher's expectations will also affect dropout rates of schools. Other studies investigating the relationship between social capital and years of schooling assert that the influence of factors outside the family is also significant, including discussions about jobs and education with other adults, teachers' expectations and influence, and teacher interest in student (Dunham & Wilson, 2007b).

2.3 Family Social Capital

Parental Involvement (PI) was the most important indicator of social capital used by previous research including varied types of the relationship of parents (Ryan & Ream, 2016), and parent-child relationships form the building blocks for social capital development within the family(Coleman, 1991).

To examine the dimensionality of social capital, one must first adequately define and measure parent involvement. Family social capital used in this study as known as parent involvement has been defined and measured inconsistently across previous studies (Kohl, Lengua, & McMahon, 2000). Grolnich and Slowiaczek (1994) conceptualized three dimensions of parents' school involvement: (a) behavior (participation in school actives and helping with school work at home); (b) cognitive-intellectual (exposing the child to intellectually stimulating activities); and (c) personal (staying informed about the child's schooling). Eccles and colleagues (1996) delineated five dimensions of parent-initiated involvement in their Michigan Childhood and Beyond Study: (a) monitoring (how parents respond to the teacher's requests for helping their children with school work such as checking homework or listening to them read); (b) volunteering (parents' level of participation in activities at school including Parent-Teacher

Organization [PTO]); (c) involvement (parents' involvement in their children's daily activities related to homework); (d) contacting the school about their children's progress; and (e) contacting the school to find out how to give extra help. The dimensions in the Grolnick and Slowiaczek (1994) model are very broad, encompassing many different behaviors within a given factor(Grolnick& Slowiaczek, 1994), whereas the dimensions in Eccles and colleagues' model are quite narrowly defined, creating different dimensions from apparently similar behaviors (Eccles & Harold, 1996).

The first question of all research on family social capital is how parental involvement can be conceptualized within the framework of social capital. First, to be conceptualized as social capital, parental involvement should be considered as one form of a social network with strong or weak ties. The social network of parental involvement involves dyadic relationships between the parent and the child, the teacher, or another parent. These dyadic social relationships of parents are often symbolic of an extended social network. The strong and weak ties they represent are a dimension of structural form that provides significant amounts of social capital to individual members of the network. Those ties play different roles affecting the social capital on educational outcomes. The social relationship could be the network among students' parents. For instance, Carbonaro (1998) found that the chances of a child dropping out of high school declined as the number of the child's friends' parents with whom a parent reported talking (i.e. strong ties) increased, after controlling for background characteristics, parental expectations, and such measures of behavior as skipping school, suspensions, and number of friends who had dropped out. The financial relationship of parents are also related to the educational outcome of students. Hofferth et al. (1998) found that weak ties, defined as parents' access in an emergency to financial and other assistance from friends, were positively related to college attendance for students from high-income families, whereas strong ties, defined as parents' access in an

emergency to financial and other assistance from relatives, were unrelated to college attendance regardless of family income. Second, the kinship base between parents and children could be thought of as the norms of obligation and reciprocity inherent in parent-child and parent-school relationships. It will be quite severe if not abiding by the social norm of investment and care for your child (e.g., child neglect, abandonment), including a loss of social ties.

The third characteristic of family social capital is the existence and degree of resources. Family-related resources like parents' education, parent-child discussion, and parents' investment in children's education have varied levels, such as physical capital, human capital, and cultural capital. Ralph (1999) further pointed out that the potential benefit of social capital is likely relative and dependent upon the parent's position in the social hierarchy.

To sum up, parent involvement in school activities and a child's relationship with his or her parents is the most important factor within-family source of school-based social capital. Some studies have suggested that within-family factors would have a strong impact on school success more than school variables (Dunham & Wilson, 2007b; Eccles & Harold, 1996; Kohl et al., 2000). Despite a wealth of studies, empirical findings seem most inconsistent in relationships among parenting practices, academic achievement, and educational attainment. More specifically, the relationship between parent involvement and various outcomes during adolescence remains unclear.

2.4 Peer Social Capital

Instead of within-family factors, peer network is another important indicator of social capital construct. A growing body of recent research has focused on the role of adolescents' peer networks in school performance and students' outcomes (Ream 2005; South &Haynie 2004; Stanton-Salazarand Spina, 2005), including school completion and dropout (Croninger and Lee 2001; Teachman at al. 1996). Peer social capital could be regarded as one type of resources

within friendship networks, which are accumulated and exchanged in a manner that influences educational processes and subsequent outcomes.

Using NELS:88 database, Ream (2005), for instance, indicated the upside and potential downside influence of same-age friends on dropout behavior according to their comparative availability across groups, especially paid special attention to the way in which disparate and often-competing characteristics of adolescent's friends influence students, specifically with regard to their ability to complete school on time(Ream, 2005). He also claimed that social capital has a mediator effect between student engagement on dropout rates. The results suggest that student engagement has a impact on competing for friendship networks in predictably obverse ways, at once promoting school-oriented friendships and the same time affect students' tendency to nominate those who drop out of school as friends. In short, the behavioral and social aspects of schooling are dynamically interlinked within the overall process of school completion or dropout.

2.5 Graded Response Model

The graded response model (GRM) was introduced by Samejima (1969, 1972, 1995) to handle ordered polytomous categories such as letter grading, A, B, C, D, and F and polytomous responses to attitudinal statements (such as a Likert scale). The study utilized GRM to fit mixed-format indicators of social capital.

A graded response model is a IRT measurement model in which an item has m_j ordered response categories (Samejima, 1997). The examinee is permitted to select only one of the categories. Just as there are to Item Response Functions (IRFs) for a dichotomous item, it is possible to specify m_j category response functions (CRFs) for each graded response, where m_j is

the number of response categories for the item j. The CRF describes $P_{jk}(\theta)$, which is the probability of response k to item j as a function of θ (Cohen, Kim, & Baker, 1993). Each category has a response weigh associated with it so that an examinee's true score is defined as

$$T_i = \sum_{j=1}^{n} \sum_{k=1}^{m_j} u_{jk} P_{jk}(\theta) \qquad (1)$$

where k denotes an item response category of item j; m_j is the number of response categories of item j – therefore, $1 \leq k \leq m_j$; and u_{jk} is the weight allocated to the response category.

The estimation of the item parameters under the graded response model involves the use of m_j -1 boundary curves representing the cumulative probability of selecting response categories greater than and including the response category of interest. The boundary curves are characterized by an item discrimination parameter, a_j, and by the m_j -1 step parameters, b_{jk}. The step parameters for each item are ordered, typically from low ($k = 1$) to high (k = m_j). Take a 4-category item for example. There should be one discrimination parameter and 3 step parameters for this item. That is, for a given item, discrimination should be the same over all boundary curves (Baker, 1992). As a result, the probability of choosing a given response category is given by the following expressions:

when $1 < k < m_j$,

$$P_{jk}(\theta_i) = \hat{P}_{j,k-1}(\theta_i) - \hat{P}_{jk}(\theta_i) \qquad (2)$$

and when k =1,

$$P_{j1}(\theta_i) = 1 - \hat{P}_{j1}(\theta_i) \qquad (3)$$

and when k = m_j,

$$P_{jm_j}(\theta_i) = \hat{P}_{j1,m_j-1}(\theta_i) \qquad (4)$$

where $\hat{P}_{jk}(\theta_i)$ are the cumulative probabilities obtained from the boundary curves. In this study, multidimensional graded response models would be implemented because each item in the scale are ordinal-response items.

Chapter 3: Method

3.1 Participants and Procedures

Participants in this study come from the public database of National Educational Longitudinal Study of 1988 (NELS:88). NELS:88 was launched in the spring of the 1987-88 school year with an initial sample of 24,599 participating eighth graders, one parent of each student participant, two of their teachers, and their school principal. It was frequently used for the study of social capital for two reasons: first, it is nationally longitudinal study of 8^{th} grader which allows for examining the relationship between family and school environment with educational outcomes in the long term; Second, surveys of students reported on school, work, home experiences, educational resources and support. The large item bank makes it possible to create a new measure of social capital. Third, student's teachers, parents, and school administrators were also surveyed so that measurement from varied perspectives could be compared. However, the drawback of NELS:88 is the items related to parent involvement and peer network were not well structured.

To be included in this study, participants must have been attending public schools and have filled the student questionnaire at the baseline year. Participants are also needed to report their parent's information and peer network information. As Table 1 shows, there are 27,394 eighth grade pupils in total, with 12,241 males (44.6%) and 12,358 females (45.1%). After removing the missing values, the final sample consists of 1,527 Asian/Pacific Islander (5.57%), 3,171 Hispanic (11.57%), 3,009 black (10.98%), 16,317 whites (59.56%), and 299 American Indians (1.09%).

Table 1 Descriptive Statistics for Samples

	N	%
Gender		
Male	12,241	44.6%
Female	12,358	45.4%
Race		
Asian or Pacific Islander	1,527	5.57%
Hispanic	3,171	11.57%
Black	3,009	10.98%
White	16,317	59.56%
American Indian or Alaskan Native	299	1.09%

3.2 Measures

Though previous studies have offer external validity evidences for the social capital measurement, they were conducted within the framework of classical test theory and principal component analysis (Dunham & Wilson, 2007; McNeal Jr, 1999). For instance, McNeal Jr (1999) indicated that parent involvement and monitoring are associated with reduced likelihoods of truancy and dropping out, while being inversely related to science achievement (McNeal Jr, 1999). However, the reliability analysis was based within classical test theory assuming tau-equivalent design as well as unidimensional latent factor structure, which can be hardly held.

The hypothesized two-dimensional model will be specified based on previous studies (Bourdieu, 1986; Coleman, 1991). The family social capital consists of 16 items which could be grouped into five categories: *Parental Monitoring* (PM), *Parent-student Discussion* (PSD), *Educational Support Strategies* (ESS), *Parent-teacher Organization Involvement* (PTOI), and *Peer Social Capital* (PSC).

Parental Monitoring items were aimed to tap into Coleman's notion of positive social control: "How often do your parents check homework/ require that chores be done/ limit time

spent watching TV" (Dunham & Wilson, 2007b). Items in this subscale were coded as "1 = often, 2= sometimes, 3= rarely and 4 = never", with lower scores representing closer parental monitoring. The items' scores were reverse coded so that higher scores represent closer monitoring.

Parental-student discussions items measure Coleman's notion of information channels: "discussing school programs with parents", "discussing school actives with parents", "discussing things studies in class with parents", "talked to the father about planning the high school program" and "talk to the mother about planning the high school program". Items in *Parent-student discussions* measures the degree to which parents and children actively engage in conversation about education. The items were recoded "1 = not at all, 2 = once or twice, 3 = 3 or more times" with higher scores representing parents discuss with students about school more frequently, and family social capital then higher.

Items of *Parent-teacher organization involvement* (PTOI) were conceptualized as a key mechanism in adolescent development because of the shared information that extended parent networks allow. It includes 4 items: "parent belongs to the Parent-teacher organization (PTO)", "attend PTO meeting", "take part in PTO activities", and "volunteer at the school." The scale of each item in this dimension is binary, 0 = no, 1 = yes. Answering "yes" represents more shared information between parents and teachers.

The fourth sub-dimension of family social capital is called *Educational Support Strategies*, which taps into the direct parental involvement in the educational process, was measured by three items, "parent will attend at school meeting, talk to teachers/counselors," "visit the student's class." Each item was coded as 0 = no, 1 = yes, with "yes" representing higher parental involvement in the educational process.

Peer social capital, recommended by Ream (2008), was measured by 6 items. Those items measured students' perception of their friends: "Among the friends you hang out with, how important is it to attend class regularly, study, get good grades, finish high school, and continue education past high school." The first five items were coded as "1 = not important, 2 = somewhat important, 3 = very important", with a higher value representing friends value education higher. The last item "Altogether, how many of your close friends have dropped out of school without graduating?" has 4 categories from 0 = "None of them" to 3 = "All of them". Peer social capital subscale operationalized the potential resources embedded in student's social network.

Table 2 Social Capital Rating Scale Items

Item	Labels
Family Social Capital	
1. parents check homework	PM1
2. require that chores be done	PM2
3. limit time spent watching television	PM3
4. Discussing school programs with parents	PSD1
5. Discussing school activities with parents	PSD2
6. Discussing things studied in class with parents	PSD3
7. Talked to father about planning the high school program	PSD4
8. Discussing school programs with parents	PSD5
9. Parent's attendance at school meeting	PTOI1
10. Parents talk to teachers/counselors	PTOI2
11. Parents visiting the student's class	PTOI3
12. Belong to a parent-teacher organization	PTOI4
13. Attend meetings of a parent-teacher organization	PTOI5
14. Take part in the activities of a parent-teacher organization	ESS1
15. Act as a volunteer at the school	ESS2
16. Belong to any other organization with several parents from your eighth grader's school	ESS3
Peer Social Capital	
17. Among the friends you hang out with, how important is it to attend class regularly	PSC1
18. Among the friends you hang out with, how important is it to study	PSC2
19. Among the friends you hang out with, how important is it to get good grades	PSC3
20. Among the friends you hang out with, how important is it to finish high school	PSC4

21. Among the friends you hang out with, how important is it to continue education past high school	PSC5
22. How many of your close friends have drop out of school	PSC6

3.3 Plan of Analysis

Psychometric assessment for the extent to which two latent traits of social capital could describe the pattern of association among these 22 items was conducted using *mirt* package in R (R Core Team, 2017). For all models, parameters were estimated with full information maximum likelihood.

The hypothesized models use a cumulative link function (i.e., logit or probit) and a conditional multinomial response distribution, in which 3-category outcomes are predicting using 3 binary sub-models: $Link(y_{is} > 0) = a_{i1}(F_s - b_{i1})$, $Link(y_{is} > 1) = a_{i2}(F_s - b_{i2})$, $Link(y_{is} > 0) = a_{i2}(F_s - b_{i2})$. In each model, b_i is an item-specific and category-specific step parameters that give the level of trait at which the probability of choosing a higher category will be just greater than that of choosing a lower category. a_{i1} is a *discrimination* parameter which stands for the relationship between the latent trait and the item response. Item discrimination influences the steepness of the slope of the IRT curves.

In this study, one-dimensional 1PL/2PL GRM were initially specified as the baseline model to examine whether one single entity could explain the associations among indicators. A theory-based two-dimensional IRT model was then specified in which item 1 to item 16 indicated family social capital, item 17 to item 22 indicated peer social capital. The initial model was compared to a two-dimensional model. If the proposed two-dimensional model did not fit significantly better than the baseline model, this was deemed an indication that the proposed model should be rejected or be modified. Both the *two-parameter logistic* (2PL) and *three-parameter* logistic version (3PL) for each model were fitted to examine whether additional

parameters would improve the global model fit. One-parameter model (1PL) was not included in this study because of bad model fit in initial exploratory analyses. Since the 2PL model is nested within the 3PL model, they could be compared using Log likelihood ratio tests. All models use Z-scored identification method in which factor means were fixed to 0 and factor variances were fixed to 1. Latent factor variances and covariances, factor loadings, item error variances were freely estimated in the IRT models.

The following indicators were required to examine absolute model fit: Root Mean Square Error of Approximation (RMSEA) is acceptable if < 0.08 and satisfactory if < 0.05; the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) are higher than 0.9 (Hu&Bentler, 1999). The effect size of item discrimination was assessed by determining the extent to which items correlate more highly with the hypothesized dimensions rather than with the other dimensions (Campbell & Fiske, 1959).

The model comparison among nested models was conducted with a log-likelihood ratio test ($\Delta\chi 2$). Two models are considered as nested when one model has freely estimated parameters whereas those parameters are constrained in the comparison model. The deviance statistic (chi-square) changes as parameters are added or deleted from the model, and changes in fit between nested models can be statistically tested.

3.4 Category Response Curves (ICC)

One objective of IRT model is to examine the relation between latent trait with the probability of categorical item responses, which is nonlinear logistic regression. The probability of endorsing a response category is graphically depicted by an *item characteristic curves* (ICC, also referred to as an item response function, or IRF). ICCs reflect the nonlinear (logit) regression of a response probability on the latent trait level (Brown, 2014). The ICC is a good

summary of an item and is frequently used in test development, DIF studies, model-data fit evaluations.

ICCs are different for two-parameter versus three-parameter as well as polytomous items versus dichotomous items. For two-parameter logistic (2PL) model, two item properties - *difficulty* (b) and *discrimination* (a) – would determine the steepness and location of ICCs. The item difficulty parameter represents the level of latent trait required for an individual to have a .50 chance of endorsing the item in the keyed direction (Crocker &Algina, 1991). The second psychometric property is *discrimination*, which describes how well an item can differentiate examinees whose abilities below the item location and those have abilities above the item location. In other words, item discrimination decides on whether one item could differentiate between students with high level of social capital and those with low level. This property essentially reflects the steepness of the item characteristic curve in its middle section. The steeper the curve, participants with higher ability level will have more probability to endorsing higher categories. Otherwise, the flatter the curves are, the probability of high-ability participants answer higher category would be close as those with high ability levels. It should also be noted that these two properties say nothing about whether the item really measures some facet of the underlying ability or not; that is a question of validity. These two properties simply describe the form of the item characteristic curve.

In the three-parameter logistic (3PL) model, there are another property called guessing parameter (c). Guessing parameter means even for individuals with lowest trait level, there is still some chances of answer the items correctly. The probability of endorsing one specific category given the latent ability level (or attribute level) are decided by discrimination parameter *a*, difficulty parameter *b,* and pseudo-guessing parameter c, which is modelled as

$$P(\theta) = c + \frac{1-c}{1+\exp(-a(\theta-b))} \quad (4)$$

3.5 Reliability Analysis

The amount of information for measurement is a concept due to Sir R. A. Fisher and is the reciprocal of the variance of an estimate. The larger the variance of interest is, the less precise the estimate of θ and the less information one has as to an examinees' unknown ability level (Baker & Kim, 2004). In present study, the amount of information contributed by an individual dichotomous item is given by:

$$I_i(\theta) = \frac{[P_i'(\theta)]^2}{P_i(\theta)Q_i(\theta)} \qquad (5)$$

Where $P_i(\theta)$ is obtained by evaluating the item characteristic curves at θ, and $P_{\mathrm{i}}'(\theta)$ is $\partial P_{\mathrm{i}}(\theta)/\partial\theta$.

The reliability for the test is examined using the test information function (TIF) which is the sum of all item information functions. TIF is a curve describing how information from the scale is distributed over different levels on the two dimensions of social capital. It provides a measure of how precisely the *n* items are estimating ability at any point along the ability scale (Baker & Kim, 2004). This function plays a role within IRT analogous to that of reliability in classical test theory. However, it has distinct advantage over the latter as it provides a measure of precision at each ability level of interest rather than a global measure. TIF are composed of the amount of information shares of the item response categories. The shape of the test information function will depend upon the mix of values of the parameters of the items in the test. The peaks of TIF represent the largest amount of information the test could provide given the latent level of interest or the least standard measurement error. Moreover, if the "target" test information function is specified over a narrow ability range of interest, it may suggest the test is not reliable for most participants. Another important feature of test information function is that the more items a test has, the greater the amount of information (Baylari & Montazer, 2009). The greater

the amount of information at a given ability level, the closer the maximum likelihood estimates of ability will be clustered around the true but unknow ability level and, hence, the estimate is more precise (Baker & Kim, 2004).

Chapter 4: Results

4.1 Descriptive Statistics

Table 3 below provides the descriptive statistics regarding mean, standard deviations, minimum and maximum of 22 items in the scale. For *Parental Monitoring*, item 2 - "require that chores be done" has the highest mean (M = 3.528, SD = 0.746). It suggests means compared to other monitoring, parents will require 8th graders to finish their chores more frequently. This may be due to the high frequency for the category 4 and the low frequency for category 1 (see Table 3). On the other hand, item 3 "limit time spend watching television" has the lowest observed mean due to the relatively high frequency for category 1. For Parent-Student Discussion subscale, the average scores appear pretty close across the items. For Educational Support Strategies subscale, the item "parents talk to teachers/ counselors" has highest mean (M = 0.67, SD = 0.47) and the item PTOI2 "Attend meetings of a parent-teacher organization" has highest mean in parent-teacher organization involvement (M = 0.385, SD = 0.487). Finally, for Peer Social Capital subscale, the item "how important is it to finish high school" has the highest mean than other items (M = 2.785, SD = 0.462). In summary, the response pattern of items meets the requirement of the IRT models.

Table 3 Descriptive Statistics of 22 Items

Item	Category					Min	Max	Mean	SD
	1	2	3	4	0				
PM1	2395	4102	7210	10707		1	4	3.074	0.997
PM2	611	1919	5837	16025		1	4	3.528	0.746
PM3	8573	6209	5768	3798		1	4	2.197	1.084
PSD1	3597	11115	9421			1	3	2.241	0.694
PSD2	2147	8195	13840			1	3	2.484	0.654
PSD3	2730	8651	12793			1	3	2.416	0.685

PSD4	6062	10048	7685		1	3	2.068	0.757
PSD5	2632	8855	12588		1	3	2.414	0.679
ESS1	12404			8882	0	1	0.583	0.493
ESS2	14426			7007	0	1	0.673	0.469
ESS3	7010			15537	0	1	0.311	0.463
PTOI1	7243			14535	0	1	0.333	0.471
PTOI2	8377			13396	0	1	0.385	0.487
PTOI3	5942			15731	0	1	0.274	0.446
PTOI4	4523			17050	0	1	0.21	0.407
PTOI5	5365			16332	0	1	0.247	0.431
PSC1	689	6667	10060		1	3	2.538	0.572
PSC2	1469	9361	6564		1	3	2.293	0.613
PSC3	980	7681	8605		1	3	2.442	0.6
PSC4	387	2953	13976		1	3	2.785	0.462
PSC5	1378	6536	9439		1	3	2.465	0.638
PSC6	41	317	3912		1	3	2.907	0.322[1]

4.2 Dimensionality

To examine the dimensionality of the rating scale, four competitive models were specified - unidimensional 2PL model, unidimensional 3PL model, two-dimension 2PL model,

[1] PM: 1=often, 2= sometimes, 3=rarely, 4=never; PSD: 1=not at all, 2=once or twice, 3=3 or more times; ESS&PTOI: 0=NO, 1=Yes; PSC1-PSC5: 1 = not important, 2 = somewhat important, 3 = very important; PSC6: 1 = most of them, 2 = some of them, 3 = none of them

and two-dimension 3PL model. The global model fit indices and Chi-square difference test are shown in *Table 4*.

Table 4 Model fit indices and Model comparison for IRT models

	M2	df	p value	RMSEA	SRMSR	TLI	CFI	$\Delta\chi^2$	p value
One-factor (2PL)	41944.3084	192	< 0.01	0.091	0.078	0.718	0.747		
One-factor (3PL)	25510.295	184	< 0.01	0.072	0.067	0.818	0.844	3381.28	< 0.01
Two-factor (2PL)	12758.986	191	< 0.01	0.049	0.057	0.905	0.915		
Two-factor (3PL)	6549.055	183	< 0.01	0.036	0.047	0.950	0.957	2666.227	< 0.01

The hypothesized 2PL unidimensional model (*Model 1*) in which one factor explained the response pattern converged after 30 iterations with $\chi^2_{(H_0)}$= -359573.44. As shown in row 1 of Table 4, this model resulted in poor absolute model fit (*M2* = 41993.58, *p*< 0.01, Comparative Fit Index (*CFI*) = 0.711, Tucker-Lewis Index (*TLI*) = 0.678, Root Mean Square Error of Approximation (*RMSEA*) = 0.09, Standardized Root Mean Square Residual (*SRMSR*) = 0.08. The results may suggest that one general latent factor could not adequately describe the covariance pattern across items. Moreover, relatively larger positive residual covariances were observed among subscale items, indicating that these items were more related than was predicted by the single-factor model. Modification indices corroborated this pattern, further suggesting additional remaining relationships among the subscale items as well.

Next, a unidimensional 3PL model (*Model 2*) was specified to examine the necessity of adding a "pseudo" guessing parameter for each item. Model 2 converged after 154 iterations with $\chi^2_{(H_0)}$= -357882.80. Results of the model fit are displayed in the second row of Table 4. It turns out that adding more parameters provides better global model fit than the 2PL model (*CFI* = 0.823, *TLI* = 0.795, *RMSEA* = 0.072, *SRMSR* = 0.067) but is still considered unacceptable. The model comparison test (see *Table 4*) showed that this model fits the data significantly better

than the 2PL model. Thus, adding guessing parameters could significantly improve the model fit of this unidimensional model.

The necessity of separated social capital factor was tested by specifying a two-dimension 2PL model (*Model 3*), in which items 1 to 16 indicated Family Social Capital (FSC), and items 17 to 22 indicated Peer Social Capital (PSC). Convergence was reached after 90 iterations with $\chi^2_{(H_0)}$ = -349800.34. The absolute goodness of fit suggests that model 3 provided better model fit (*CFI* = 0.907, *TLI* = 0. 896, *RMSEA* = 0.05, *SRMSR* = 0.06). In addition, the estimated factor correlation between FSC with PSC was moderate in magnitude (0.243). Thus, the covariance pattern of these 22 items appeared to be explained by two separate, but related constructs.

Finally, for comparison to the hypothesized model, the two-dimension 3PL model (*Model 4*) converged after 82 iterations with a log-likelihood value of -348467.22. Results suggested this model provided better global model fit than previous model (*CFI* = 0.95, *TLI* = 0.944, *RMSEA* = 0.04, *SRMSR* = 0.05). Also, -2LL difference test results indicated that model 4 (the two-dimensional 3 PL model) was significantly better than 2PL ($\Delta\chi^2$= 2630.71, Δdf = 8, p< 0.01). Even though 3PL two-dimension model fits significantly better than 2PL model, it makes no sense adding guessing parameter for the social capital items. Thus, the two-factor structure of the SCRS (factor 1: within-family social capital; factor 2: peer network) was confirmed by IRT analysis.

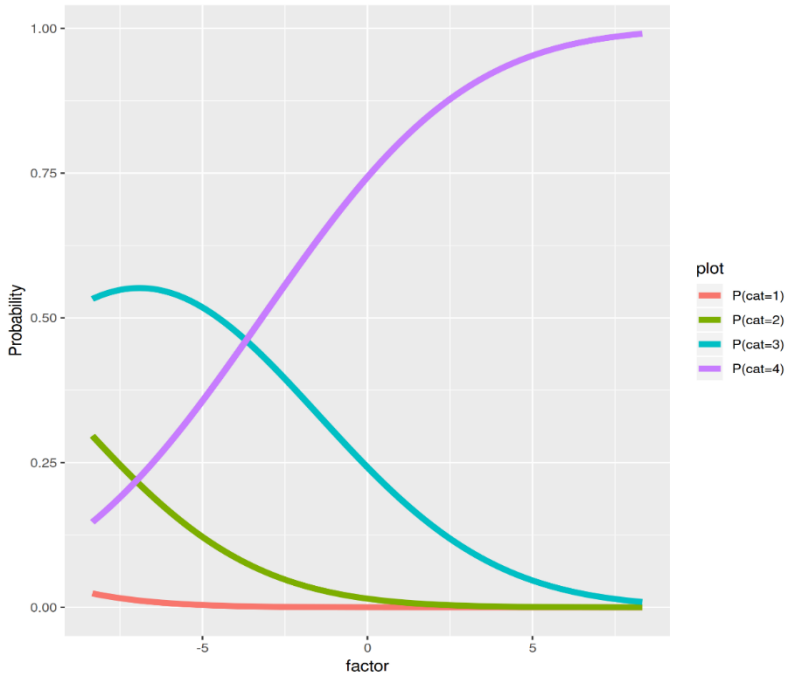
To sum up, two-dimensional models fit significantly better than unidimensional models. Two-factor structure may explain the response pattern of twenty-two items better than one-factor structure. However, M2 statistics suggest that none of the four model is satisfactory. Two-factor 2PL model is selected as final model because of better relative model fit and stronger theoretical base.

4.3 Item Quality

The ICC plots indicated that items within the same subscale had similar shapes of curves because of the similarity of responses pattern (see Appendix I). Item 1, 2 and 3, for instance, have 4 ordinal categories from 1 = often to 4 = never and use the same stem question "*How often do your parents or guardians do the following?*", so the ICC plots have 4 curves in which the difficulty parameter represents the trait at which the probability of choosing a higher category is same as of choosing a lower category.

The ICCs of the 22 items for *Model 3* aim to examine the items' psychometric quality. The results (Appendix I) indicated that all items except item 2 and item 22 show acceptable quality. For instance, the ICC of item 1 "*parents check homework*", as shown in Appendix I, displays the predicted probability of 8th graders choosing each category on different level of the latent attribute. To be specific, the orange line represents the probability of choosing "often". It indicates that students with a family involvement level lower than -4.8 SD from average most

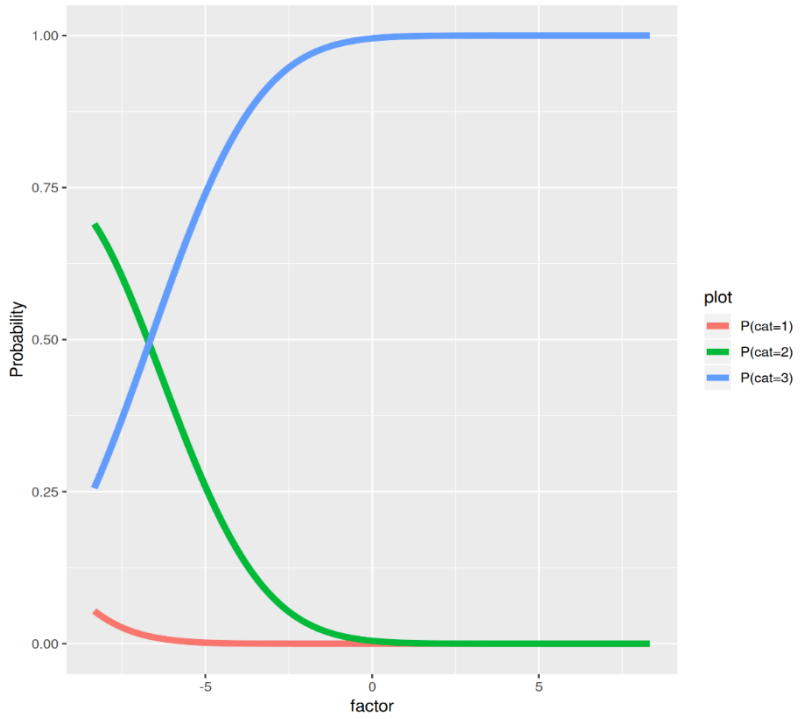
Figure 1 ICC for Item 2



likely responded that their parents never check their homework. The green line represents the probability of choosing "sometimes", which means students with a theta of -4.8 to -2.2 SDs on the family social capital subscale would be most likely to respond that their parents rarely check their homework. The blue line is the probability of a respondent choosing "sometimes", suggesting that students whose family social capital theta ranges from -2.2 to 0.55 SDs will most likely think their parents will sometimes check homework. Lastly, the purple line reflects the probability of a respondent choosing "never". Similarly, this means any student whose family social capital was higher than 0.55 SD will most likely agree that their parents often check homework.

Compared to item 1 (PM1), item 2 (PM2) has a relatively low discrimination parameter (a = 0.204), which means this item could not differentiate the students with varied levels of family involvement. Moreover, because of the low *difficulty parameter* ($b_1 = -18.018, b_2 = -10.619, b_3 = -3.197$), any students with family social capital higher than -3 SD from average were expected to choose category 4 *never*. In other words, item 2 could not measure students'

Figure 2 ICC for item 22



social capital precisely. Similarly, item 22 also shows relatively low discrimination parameter (a = 0.39), which means the item response categories can hardly discriminate between examinees who choose adjacent responses. The location indexes of the item response categories would be $b_1 = -12.46, b_2 = -6.65$. This indicates that the ordinal item response categories are not spread out along the latent attribute continuum but clustered on the low levels. That is to say, item 22 was too "easy" for participants. In this context, it means most respondents will answer "None of them" for this question (*How many of your close friends have drop out of school*).

Table 5 IRT Parameters for Family Social Capital Subscale

	Loading (a)		Difficulty (b_1)		Difficulty (b_2)		Difficulty (b_3)	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
PM1	0.476	0.015	-4.839	0.0224	-2.226	0.015	0.549	0.013
PM2	0.204	0.016	-18.018	0.0411	-10.619	0.021	-3.197	0.013
PM3	0.522	0.015	-1.224	0.0142	0.909	0.014	3.417	0.018
PSD1	1.041	0.023	-2.008	0.0238	0.516	0.016		
PSD2	1.037	0.022	-2.631	0.0285	-0.327	0.016		
PSD3	1.023	0.022	-2.359	0.0257	-0.119	0.016		
PSD4	1.103	0.024	-1.199	0.0196	0.832	0.018		
PSD5	1.247	0.028	-2.103	0.0307	-0.083	0.017		
ESS1	1.280	0.029	-0.325	0.0307				
ESS2	0.480	0.018	-1.576	0.0224				
ESS3	0.570	0.019	1.498	0.018				
PTOI1	1.434	0.039	0.671	0.015				
PTOI2	1.219	0.034	0.502	0.016				
PTOI3	1.695	0.050	0.849	0.022				
PTOI4	1.296	0.035	1.328	0.019				
PTOI5	0.944	0.026	1.388	0.030				

Table 6 IRT Parameters for Peer Social Capital Subscale

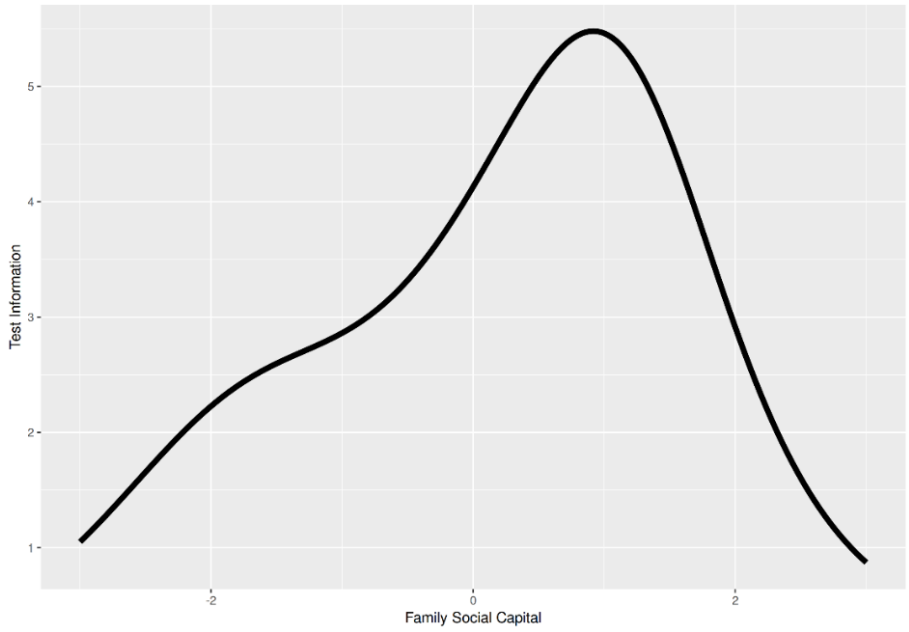
	Discrimination (a)		Difficulty (b_1)		Difficulty (b_2)	
	Estimate	SE	Estimate	SE	Estimate	SE
PSC1	2.750	0.052	-2.096	0.089	-0.221	0.032
PSC2	3.059	0.060	-1.570	0.079	0.365	0.037
PSC3	3.221	0.065	-1.793	0.097	0.012	0.034
PSC4	3.022	0.070	-2.352	0.133	-0.984	0.063
PSC5	2.256	0.040	-1.781	0.055	-0.131	0.027
PSC6	0.390	0.060	-12.458	0.163	-6.650	0.069

4.4 Item Information Function

As shown in Appendix I, all items except item 2 and item 22 have steep information curves for the students with low levels of social capital. Item 1, for instance, has the most information when the family social capital of students is near -1.5 unit. To be compared, item 2 and item 22 have low information and a high standard error in general. In other words, it is expected that these two items are not able to precisely measure 95% percent of students.

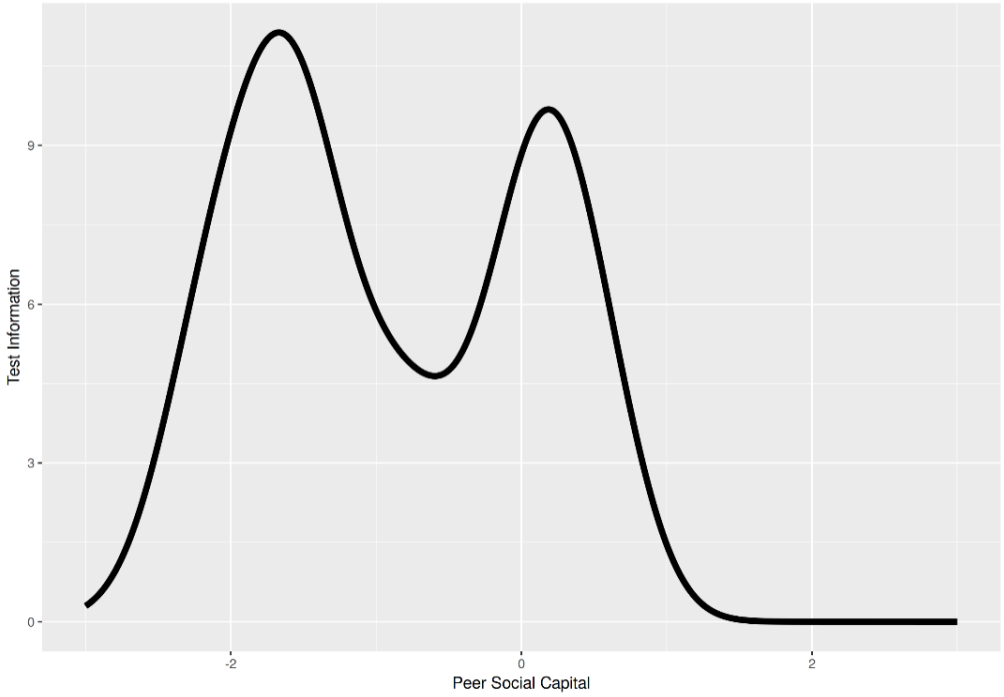
It should be noted that the ICC for polytomous items in this study have two or more peaks. To illustrate, the curves for item 17 peaks when students' peer social capital is at near -2 or 0, but the information decreases quickly when the level of latent attribute nears -1, below -2 or larger 0. In summary, it is ideal that item has relatively high information when latent attribute level ranges from -3 to 3, so that the social capital for most of the students could be estimated precisely.

Figure 3 Test Information for Parent Involvement



Sum of information across items within a scale is called the *Test information function (TIF)*. Figure 3 displays the two-dimensional TIF curves for Factor 1 (Family Social Capital) and Factor 2 (Peer Social Capital). The test information of factor 1 peaks around -1, meaning students whose theta level near -1 SD will be the most reliable; the test information of factor 2 has two peaks suggesting that the students with factor scores near 1 or -1 will be most reliable. The TIF curve indicates that two dimensions of the measurement are adequate for students at the levels between -2 and 2 on the 3PL model.

Figure 4 Test Information for Peer Network



For ease of interpretation, the test information function was converted to a traditional measure of reliability that ranges from 0 to 1 (see ***Error! Reference source not found.*** and ***Error! Reference source not found.***). The figures below show that this parent involvement subscale has high reliability (larger than .8) for people with a latent trait level from 0 to 1.5 SD, and the peer network scale has high reliability for those with trait level from -2 to 1 SD. Thus,

this scale appears to measure people with mid-range family social capital and low-level peer social capital best.

Figure 5 Reliability for Parent Involvement

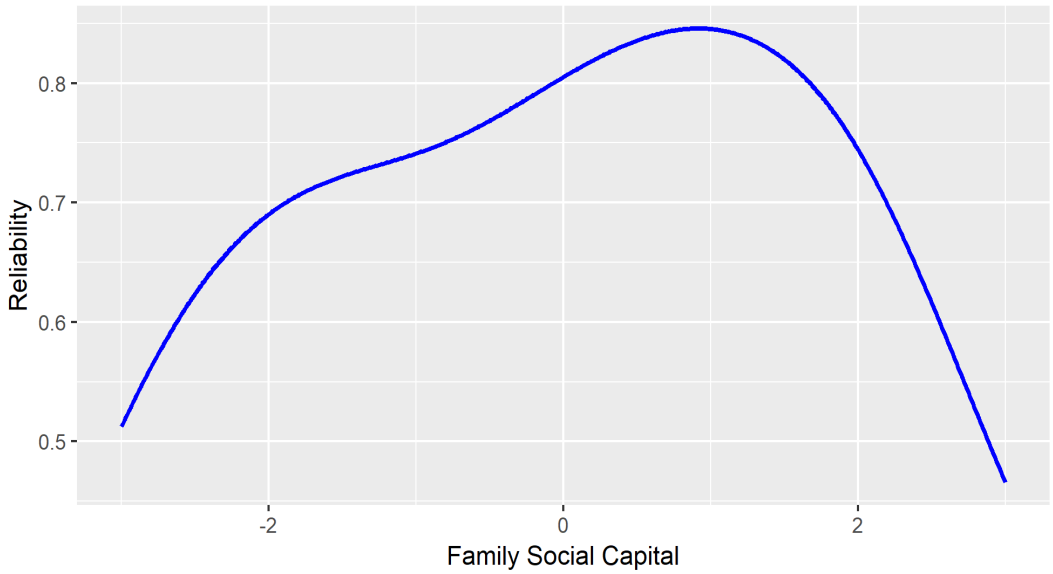
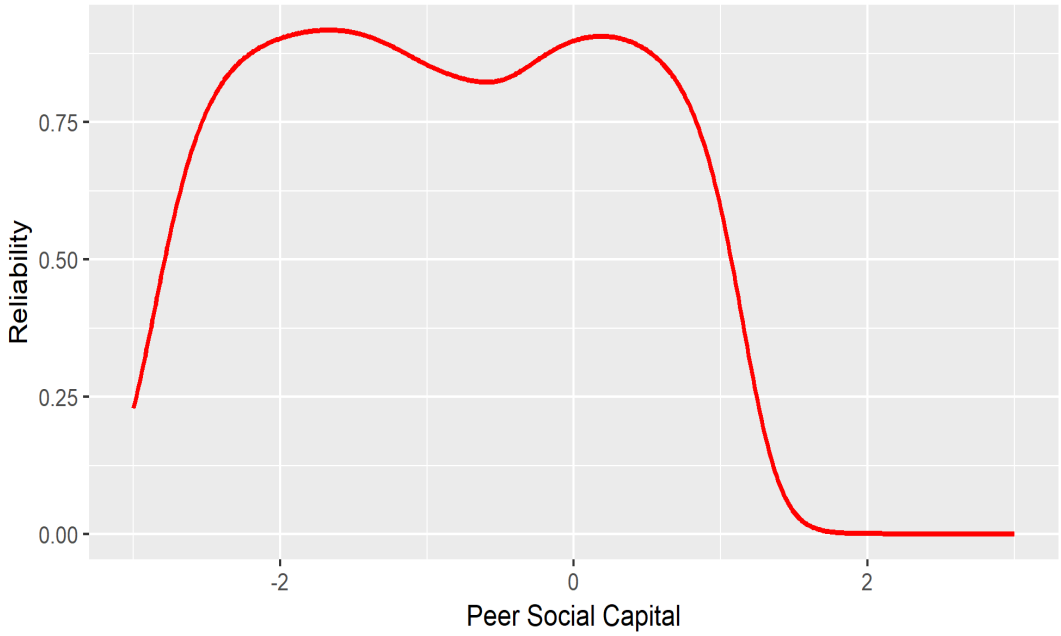


Figure 6 Reliability for Peer Network



Chapter 5: Discussion

5.1 Dimensionality and Reliability

This study designs a new scale for social capital incorporating both parent involvement and peer network. With the final model two-dimension 2PL model, the current work confirmed the 2-factor structure of social capital. This scale considers the variability of social capital for students by including parent involvement (factor 1) and peer network (factor 2). The likelihood ratio test indicated that the hypothesized two-factor 2PL model fits to the sample data significantly better than one-factor 2PL model. Also, even though 3PL two-factor model fits significantly better than 2PL model, it was found to be hard to embed guessing parameters in the social capital scale. Moreover, this study confirms there is the moderate correlation between parental involvement and peer network (Eccles & Harold, 1996). The results indirectly proved that social capital as a construct may be affected by family factors as well as social network. Future research should consider both family involvement and peer network as social capital for a comprehensive conclusion.

The rating scale modified in this particular study has proven acceptable reliability for high student with mid-range family social capital and peer social capital. To be specific, most of the item information curves peaks in the range of -2 to 2 SD except for item 2 and item 22. It is because the "easiness" of item 2 "*require that chores be done*" makes it hardly differentiate students at varying levels of social capital. Item 22, "Altogether, how many of your close friends have dropped out of school without graduating? (Do not include those who have transferred to another school)", also had low discrimination and location indexes indicating that this item could not measure peer social capital of 8th graders precisely. The four categories of this item include: 1 = "None of them" to 4 = "All of them". As noted in the descriptive statistics, 91.6% participants chose category 1 (*None of them*). Thus, item 22 did not provide enough information

about the latent attribute as other items did. In term of the item information curves, item 1, item 5, item 6, item 17, item 18, item 19 and item 20 provided the highest information when students are at lower level of latent attributes. The information provided by item 11, item 12, item 13, item 14, item 15, and item 16 peaks for those with higher level of latent attribute. Item 9 was ideal since it provided the highest information when latent trait was near zero, which was the mean of latent factor. Since the number of students clustered at the average is highest, this item will precisely estimate the latent trait for most of the participants. To sum up, these items together could measure social capital precisely for children along the trait continuum.

Finally, it should be noted that these two components (parent involvement and peer network) may have different functioning for students from varied ethnicity. For example, specific dimensions of involvement mat have greater effects for more affluent and white students (McNeal Jr, 1999). However, it depends on the purpose of study whether one should integrate family social capital and peer social capital into one dimension or to assess the dimensions separately. For example, when predicting academic performance or school dropout, an overall score would probably be more feasible and practical. On the other hand, when the purpose is to investigate the relationship among components of social capital of students and their different functioning, it will provide more information conducting multidimensional IRT model.

5.2 Direction

In conclusion, this rating scale could be utilized as a tool for examining high students' social capital with some considerations. First, item 2 and item 22 should be excluded from this scale given their poor psychometric qualities. Second, some items' categories are not proper. For instance, item 4 to 8 only has three categories. The highest category is "3 or more times". For those who discuss school program with parents more than 5 times per week will choose same

category with those with only 3 times per week. The responses to this item then will have ceiling effects. Finally, depend on the response pattern of items in this study, mixed-format IRT models is a more proper way rather than confirmatory factor analysis or classical test theory. Otherwise, the results may be biased.

For those who want to design a new measure of social capital, the results argue against a unidimensional understanding of social capital of high school schools and support the view of the family and peer as two main resources students could utilize to aggregate social capital. Thus, the measure of social capital should include both family involvement and peer network as two separate but related dimensions.

5.3 Limitation

This study has several limitations. First, this study does not examine method effect. One assumption of IRT models is that the items display local independence. It requires that given their relationship to the underlying construct being measured, there is no additional systematic covariance among the items. Local dependence (LD) can potentially arise among subsets of items that have a similar stem. In this study, there are several items sharing one stem. There's not appropriate way for polytomous items to identify the LD in *mirt* package. In the framework of CFA, if there are strongly LD for several items, it may be the indicate for adding a new latent factor. The standardized residual covariance shows that the residual covariance among items sharing same stem is higher than items not sharing. However, the modification indices within MIRT framework does not exist in most IRT software. It indicates that to some degree LD exists in this sample but hard to fixed.

Second, item difficulty parameters could not be compared among items with various categories. The number of difficulty parameters depends on the number of categories for each item. Since the items in this scale were originally selected from different subscales in NELS:88,

the scales are different from each other, which leads to different interpretation for difficulty parameters.

Finally, differential item functioning (DIF) analysis was not included in this study. Some past research (Walker & GocerSahin, 2017) has indicated that multidimensionality and the correlation between the primary and the secondary dimensions would influence the significance test of DIF. Future research should explore DIF issue among varied race groups in the multidimensional mixed-format IRT model. Moreover, the samples used in this study are 8th grade students so the results may not be generalized to students from lower or higher grades or from other cultures.

Figure 7 Unidimensional Model Diagram

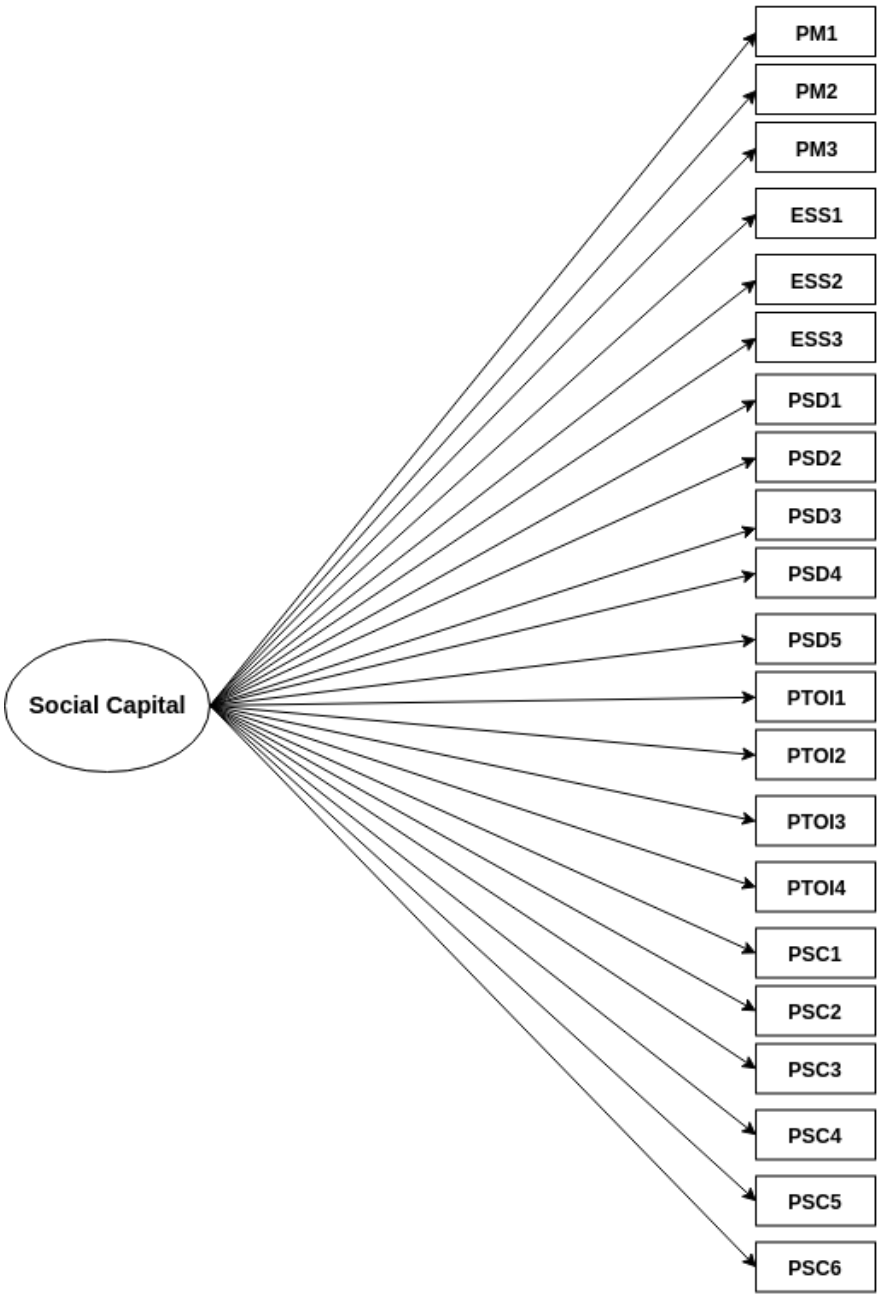
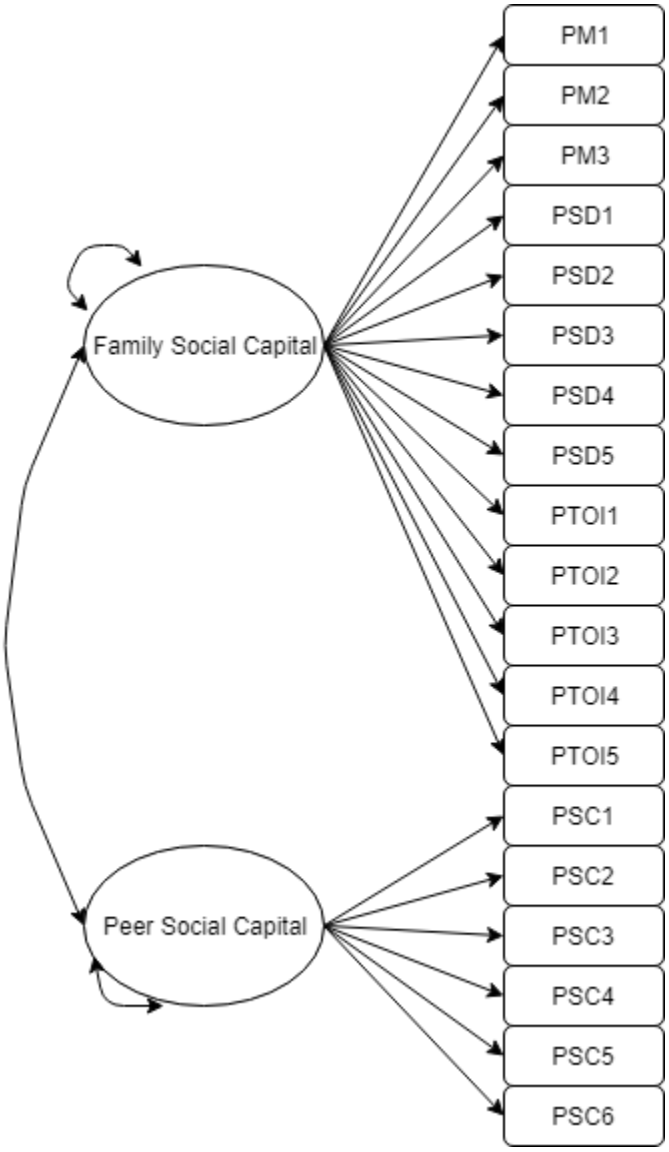


Figure 8 Two-dimensional Model Diagram



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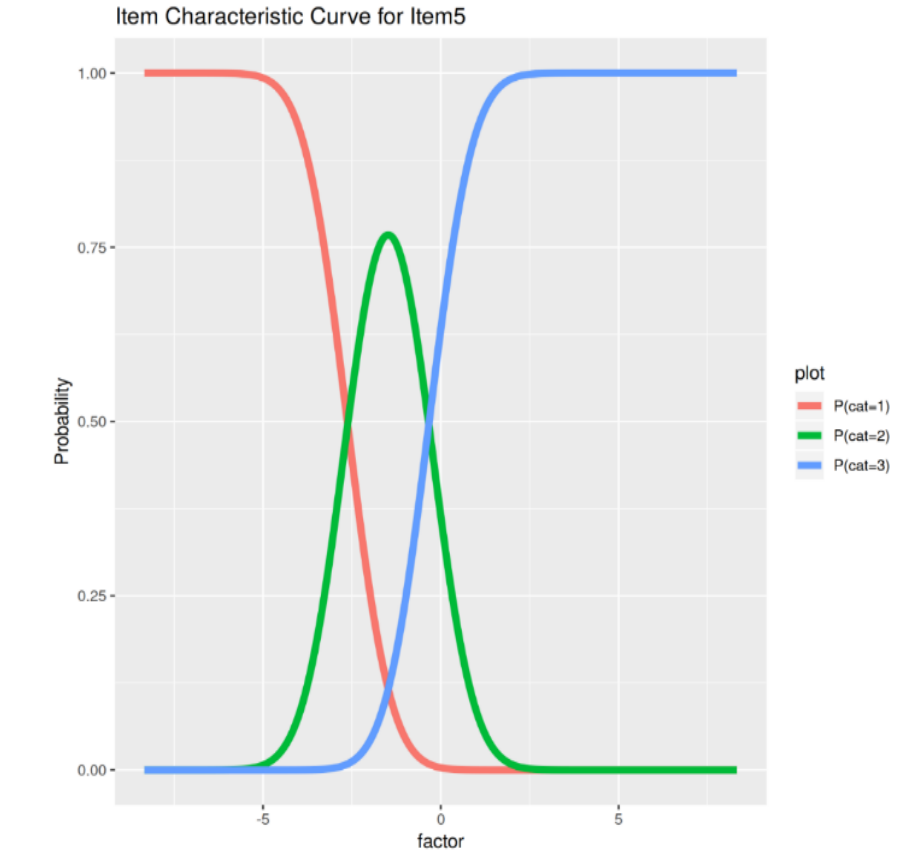
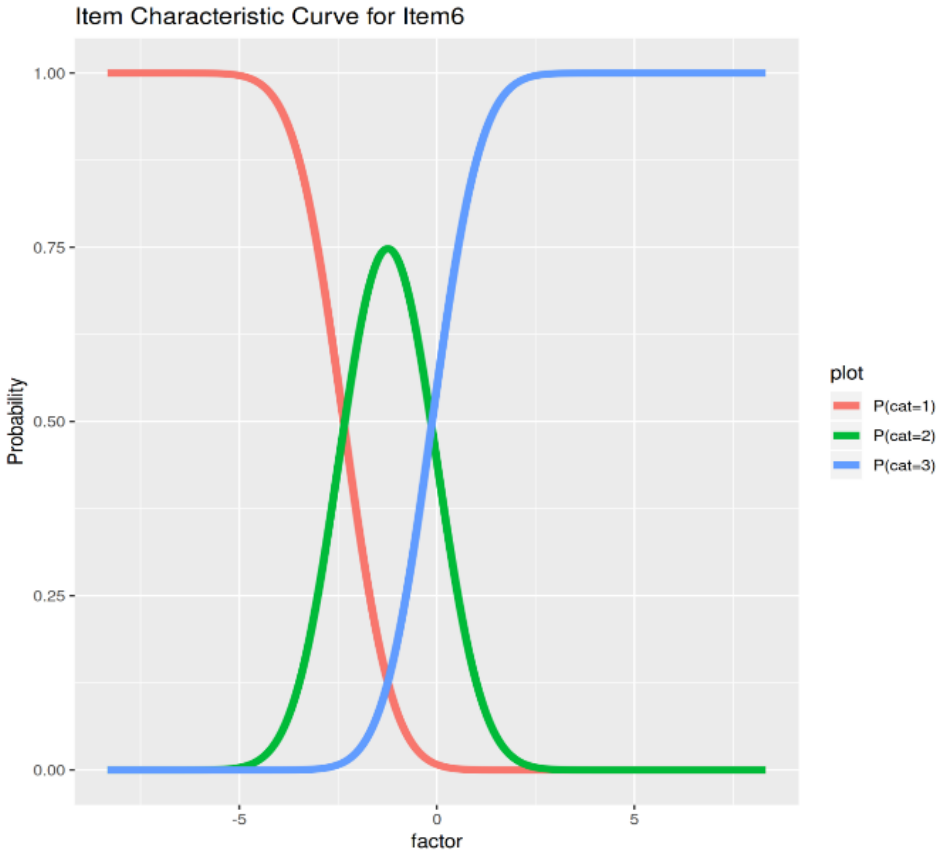
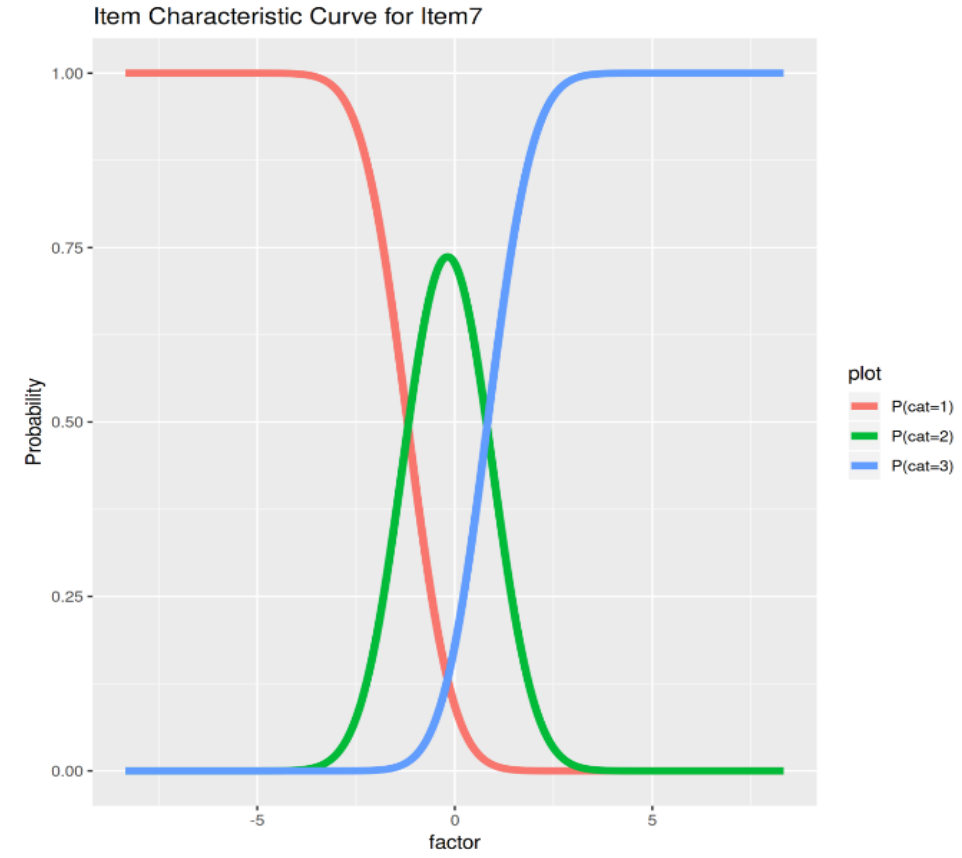
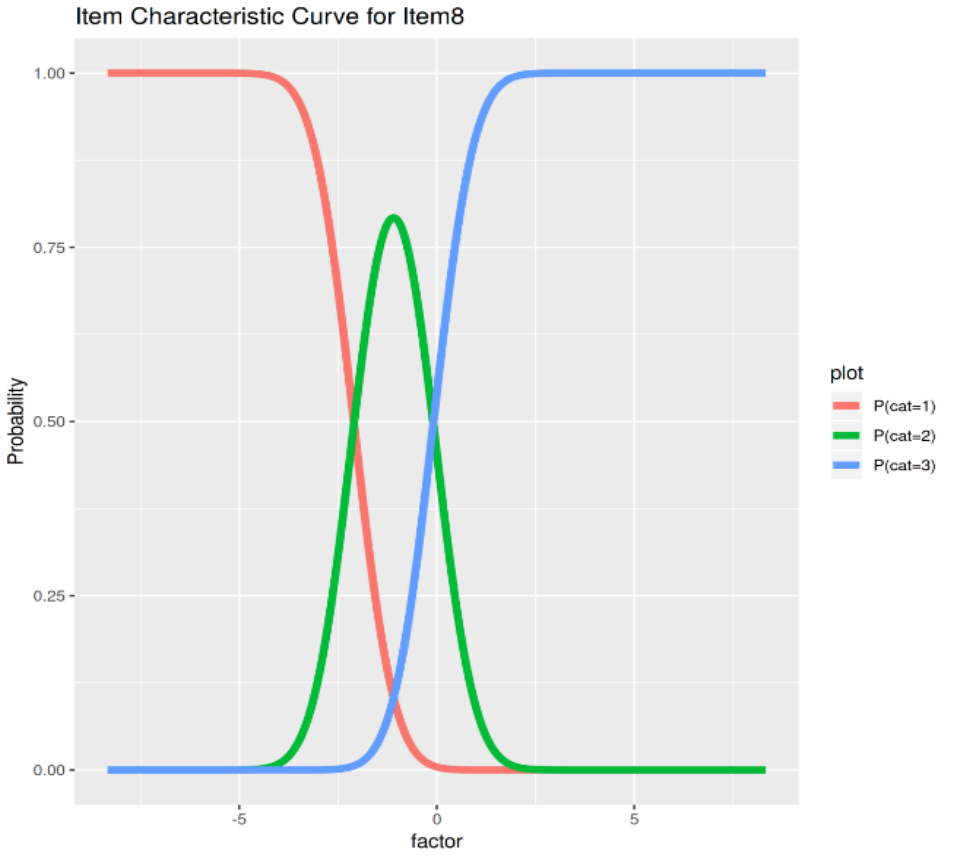
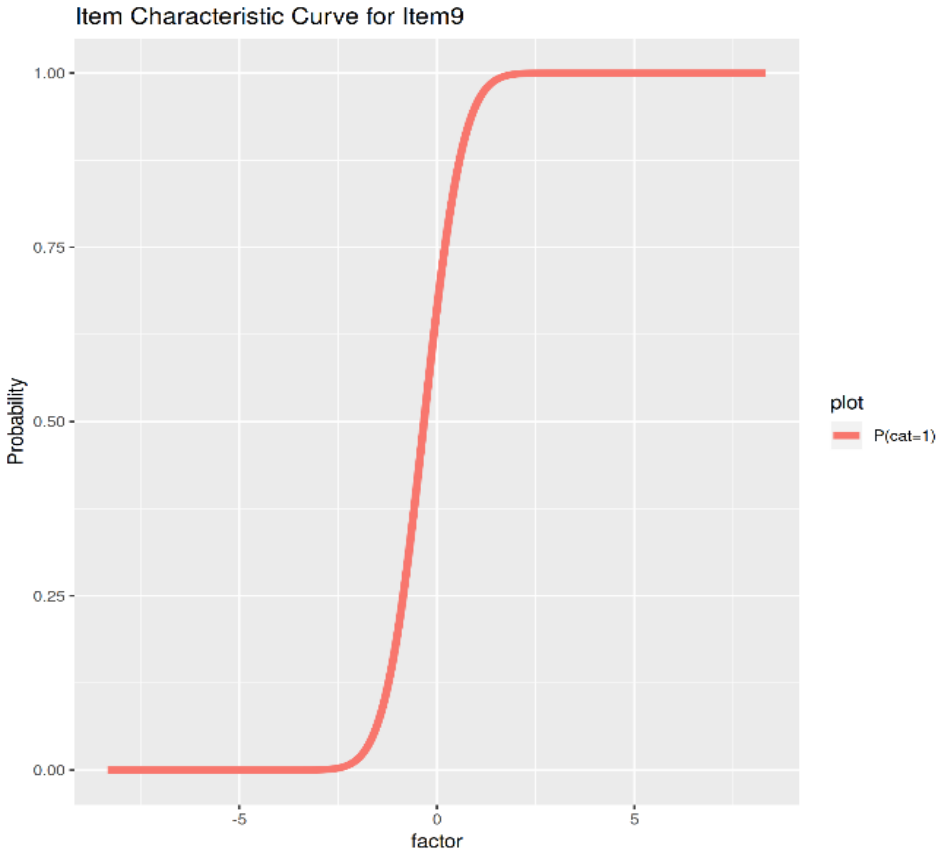
Appendix I

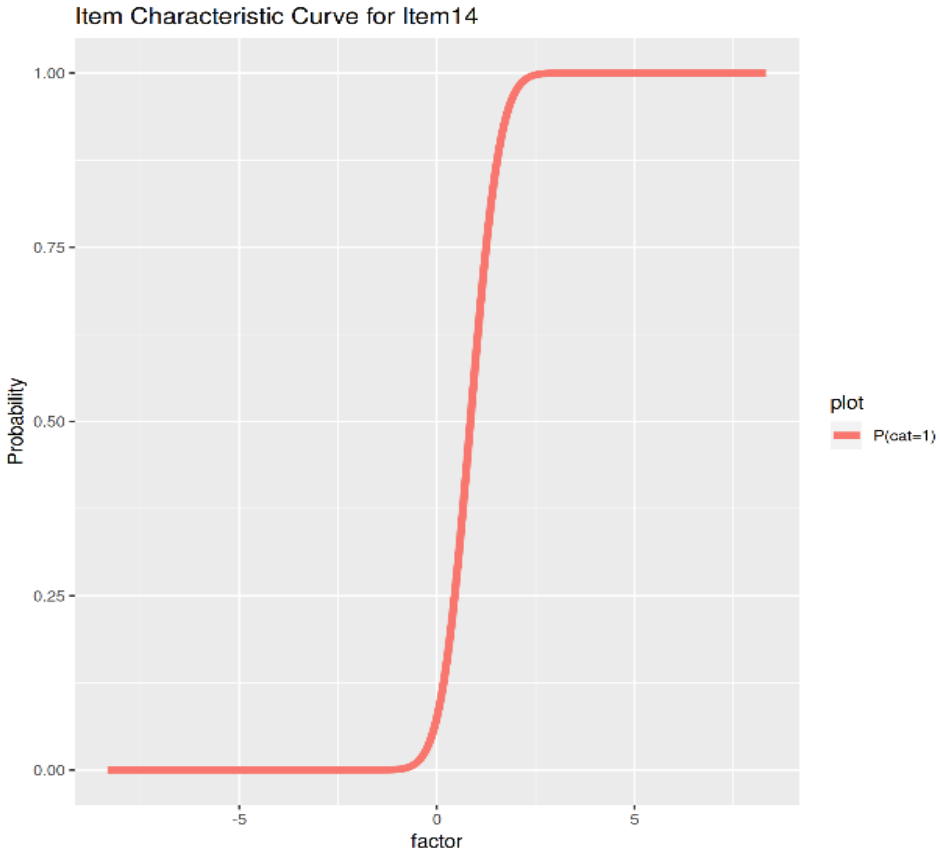

Item Characteristic Curve for Item5
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)
P(cat=2)
P(cat=3)

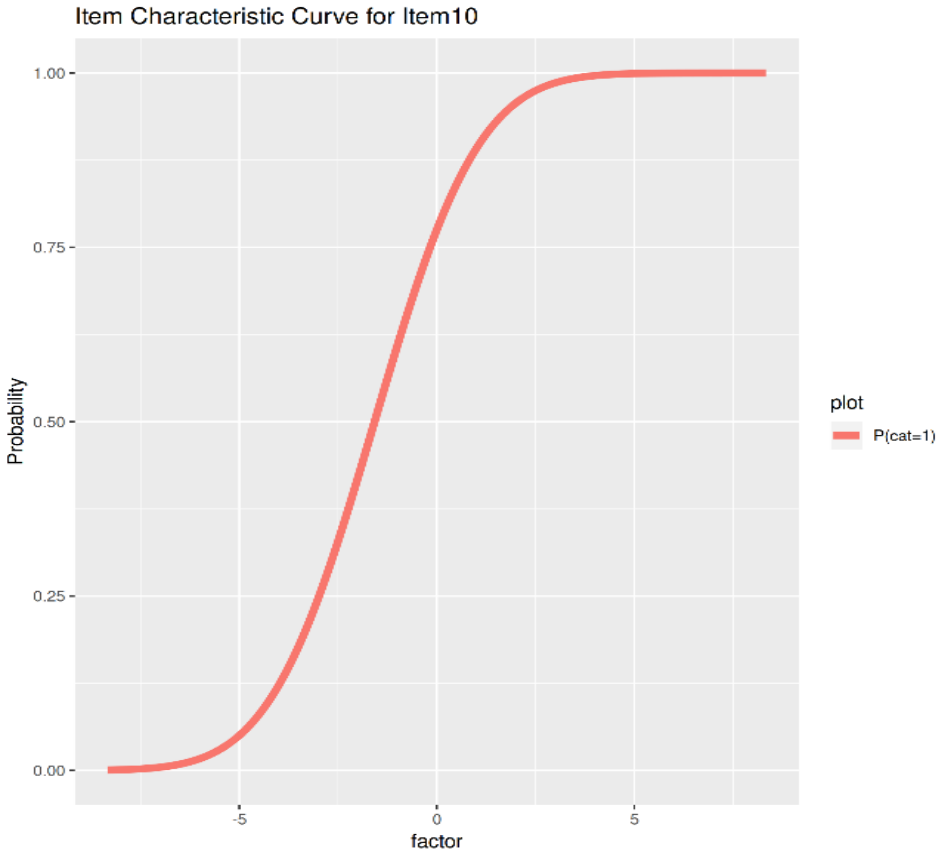

Item Characteristic Curve for Item6
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)
P(cat=2)
P(cat=3)

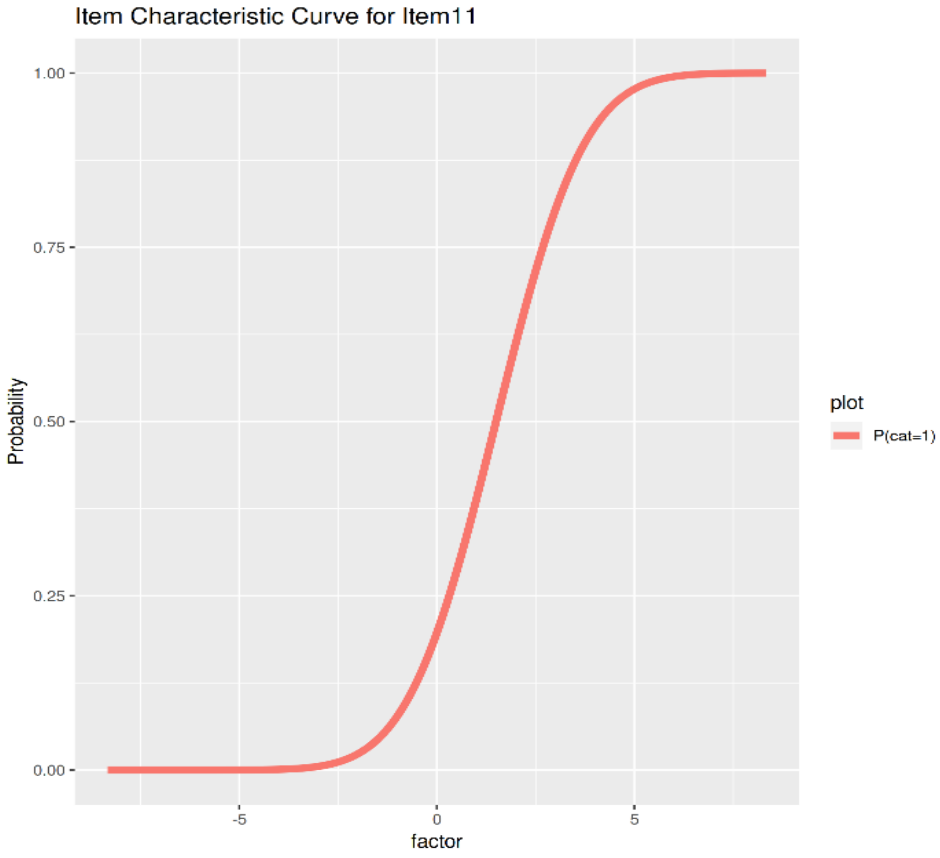

Item Characteristic Curve for Item7
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)
P(cat=2)
P(cat=3)

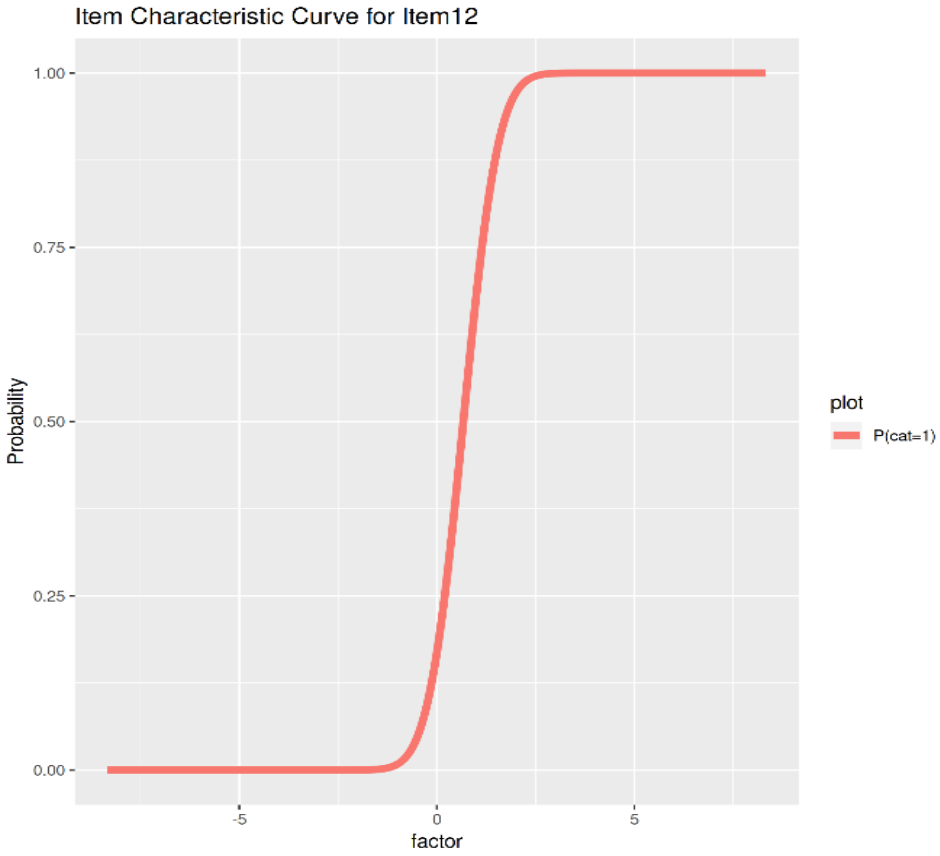

Item Characteristic Curve for Item8
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)
P(cat=2)
P(cat=3)

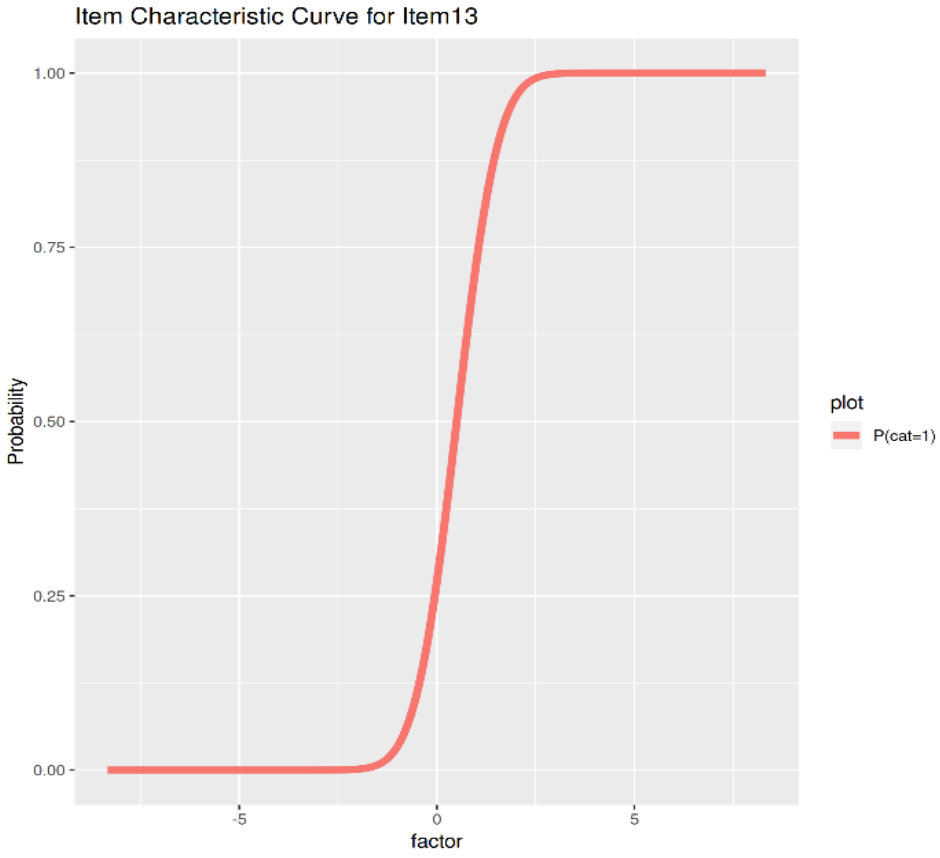

Item Characteristic Curve for Item9
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)

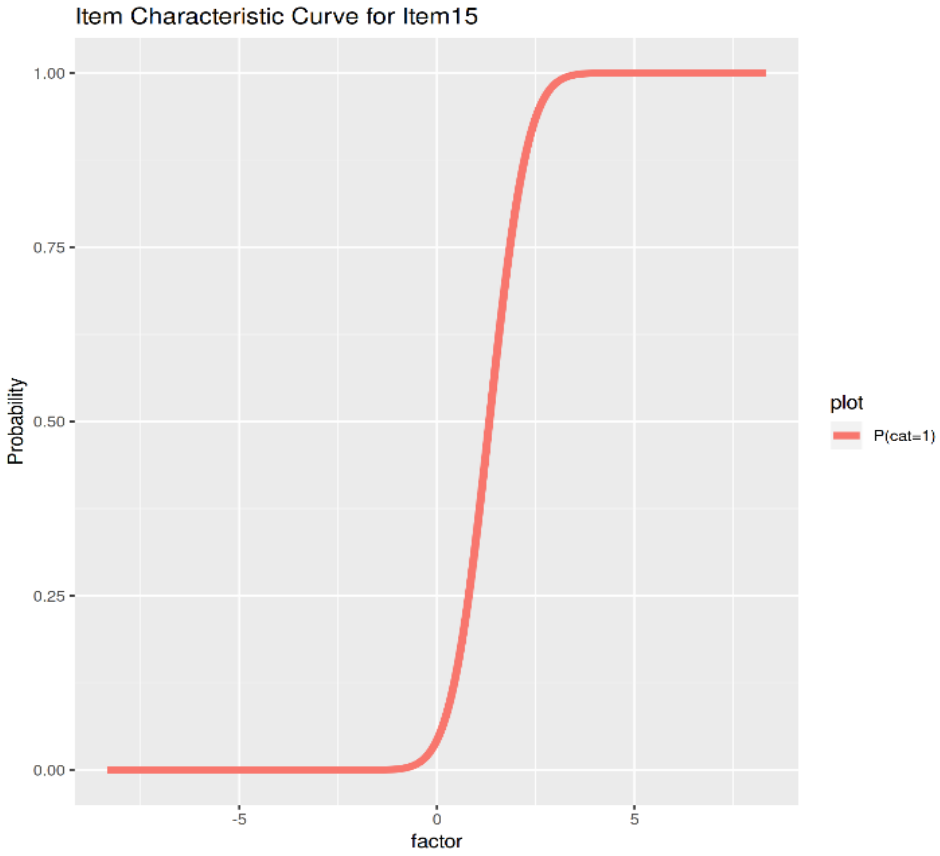

Item Characteristic Curve for Item14
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)

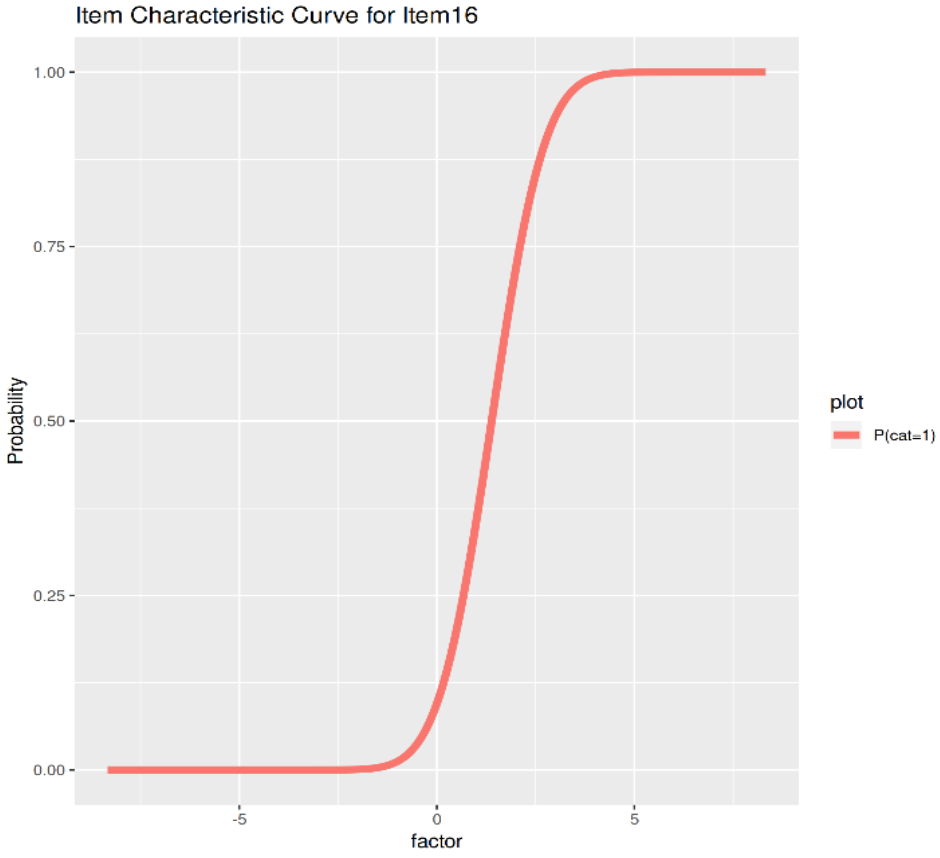

Item Characteristic Curve for Item10
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)

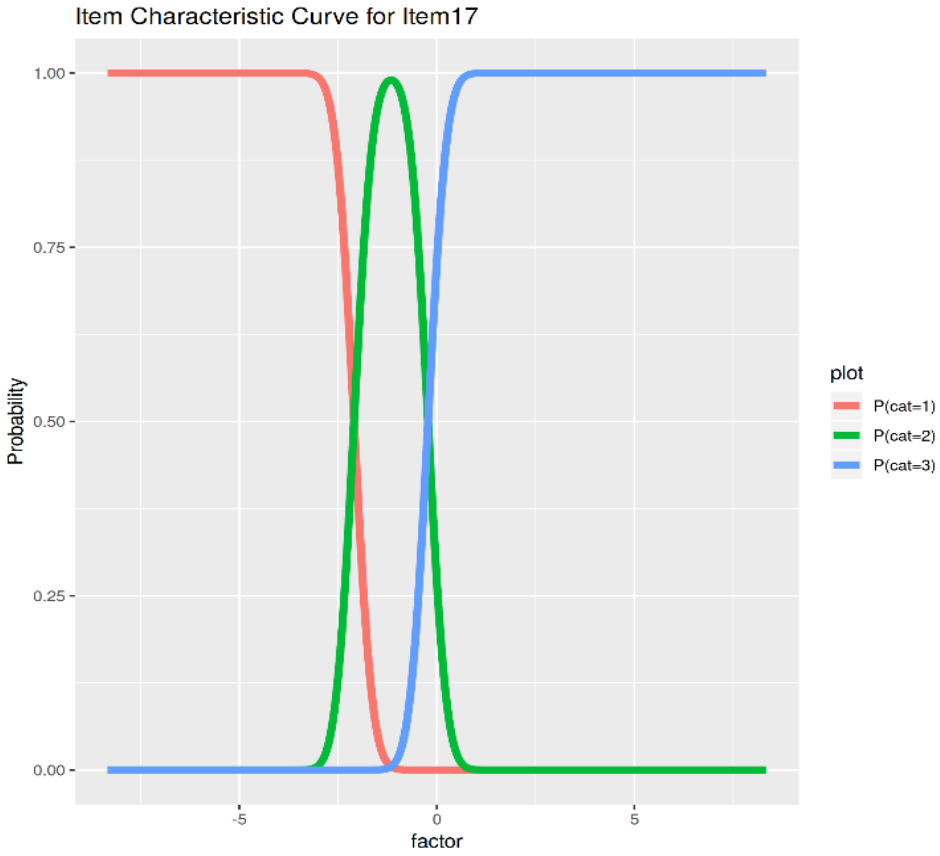

Item Characteristic Curve for Item11
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)

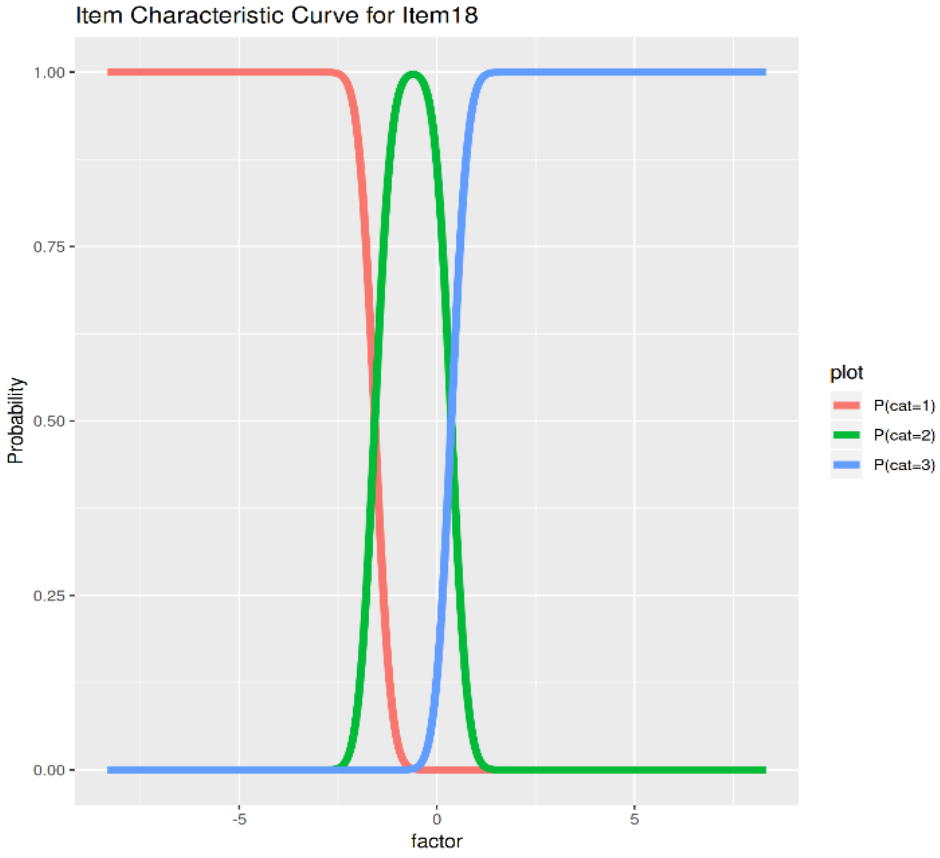

Item Characteristic Curve for Item12
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)

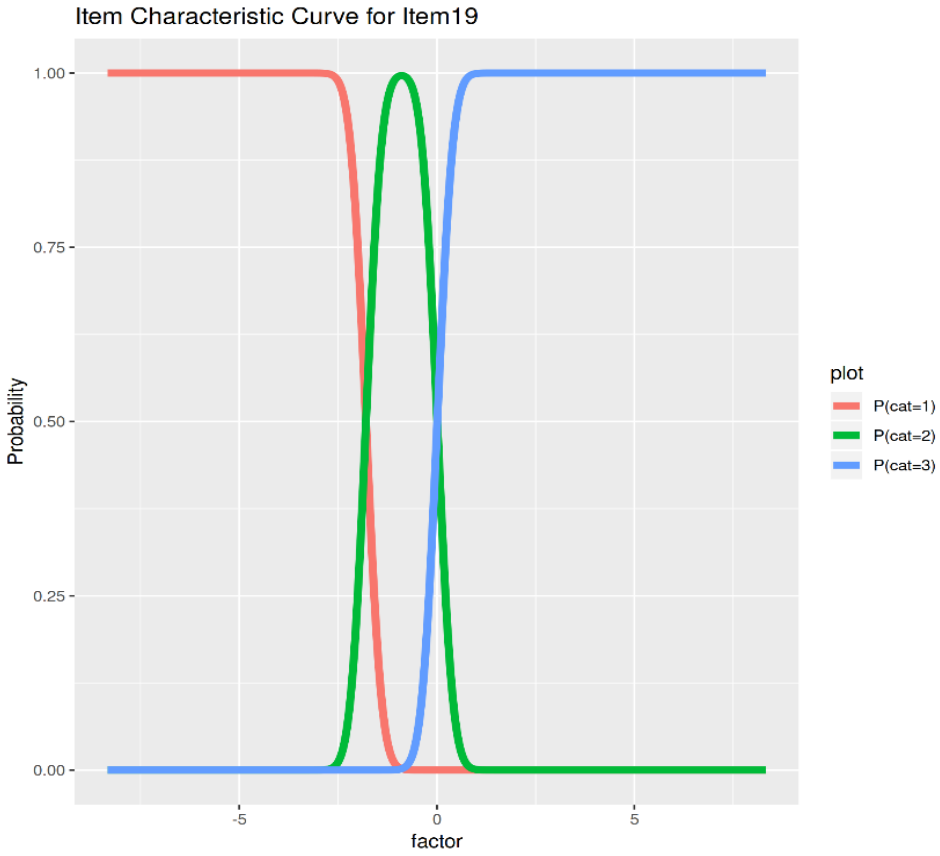

Item Characteristic Curve for Item13
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)

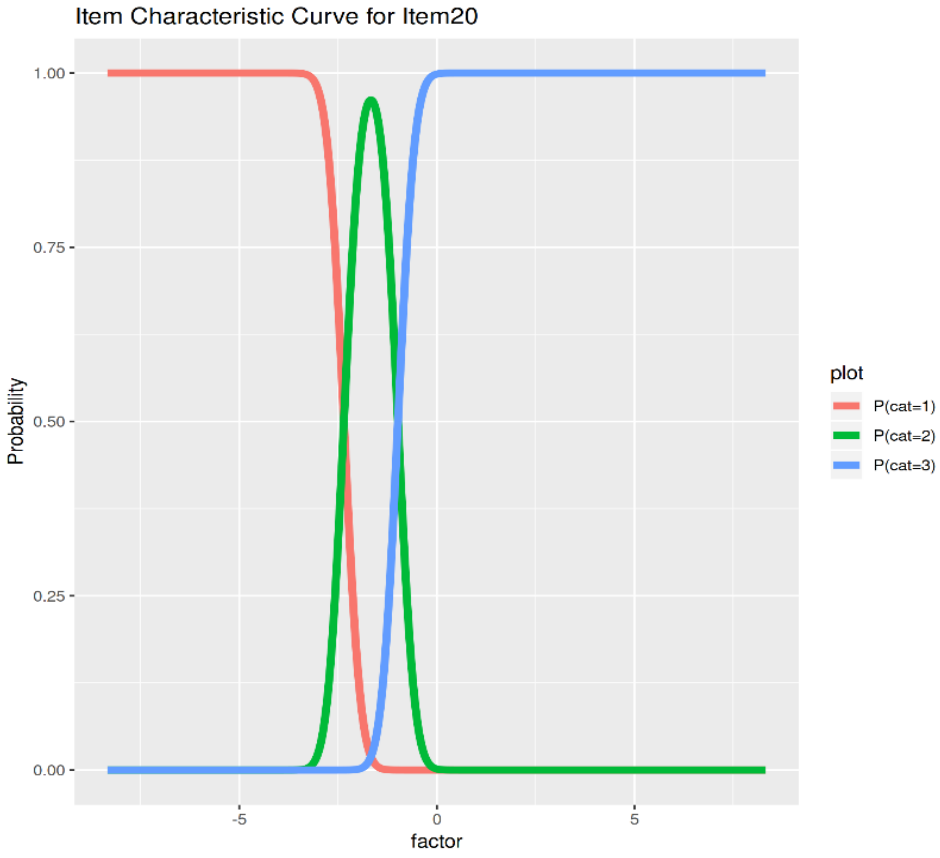

Item Characteristic Curve for Item15
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)

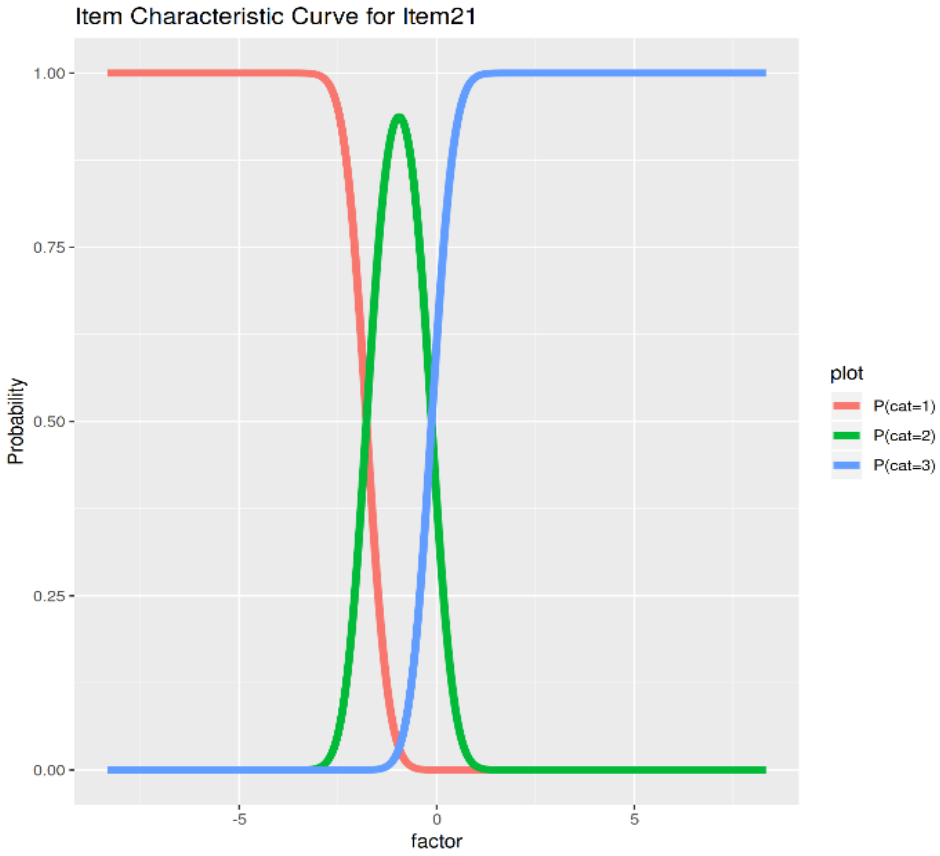

Item Characteristic Curve for Item16
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)

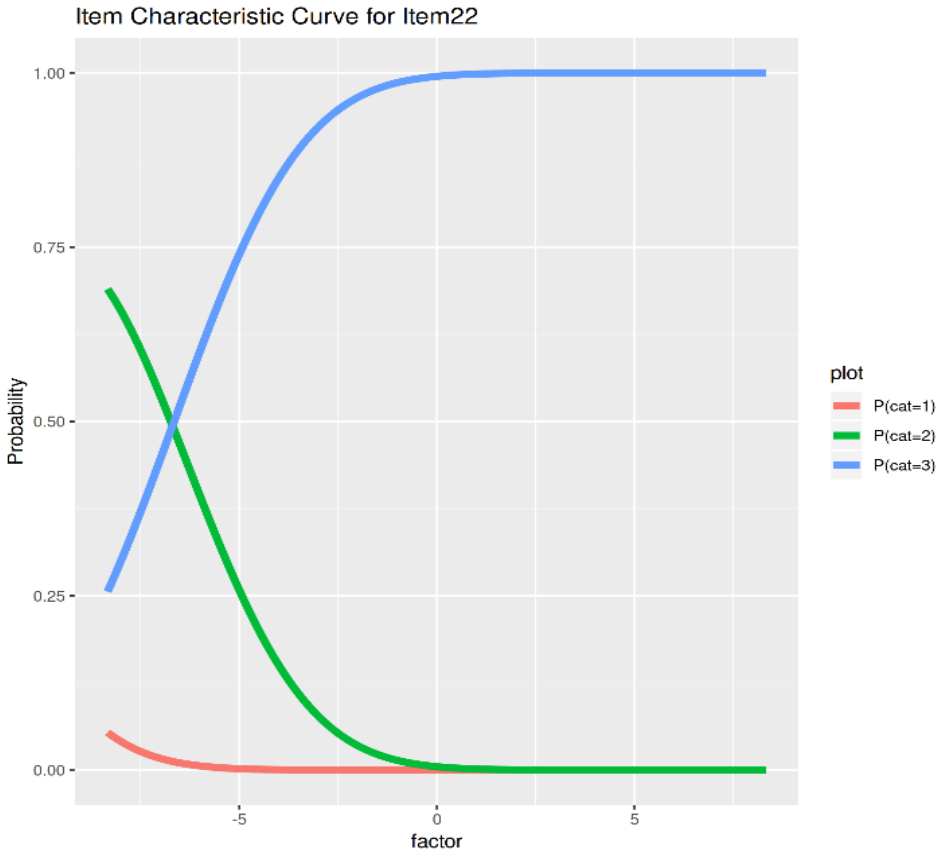

Item Characteristic Curve for Item17
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)
P(cat=2)
P(cat=3)

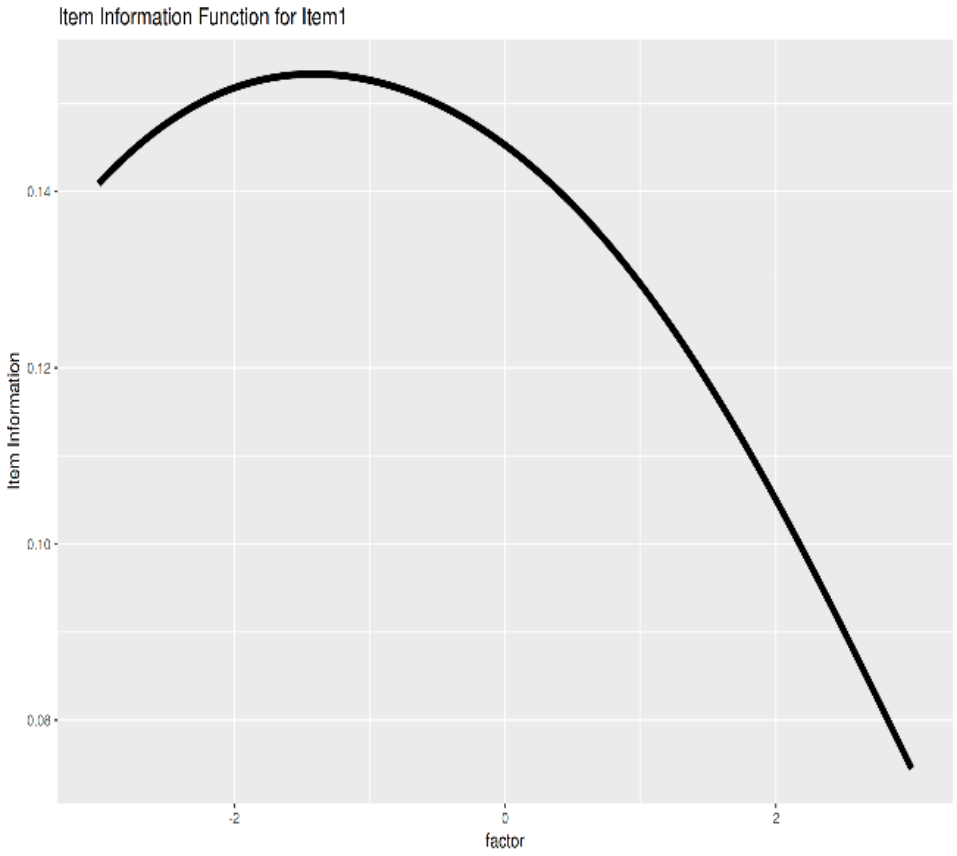

Item Characteristic Curve for Item18
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)
P(cat=2)
P(cat=3)

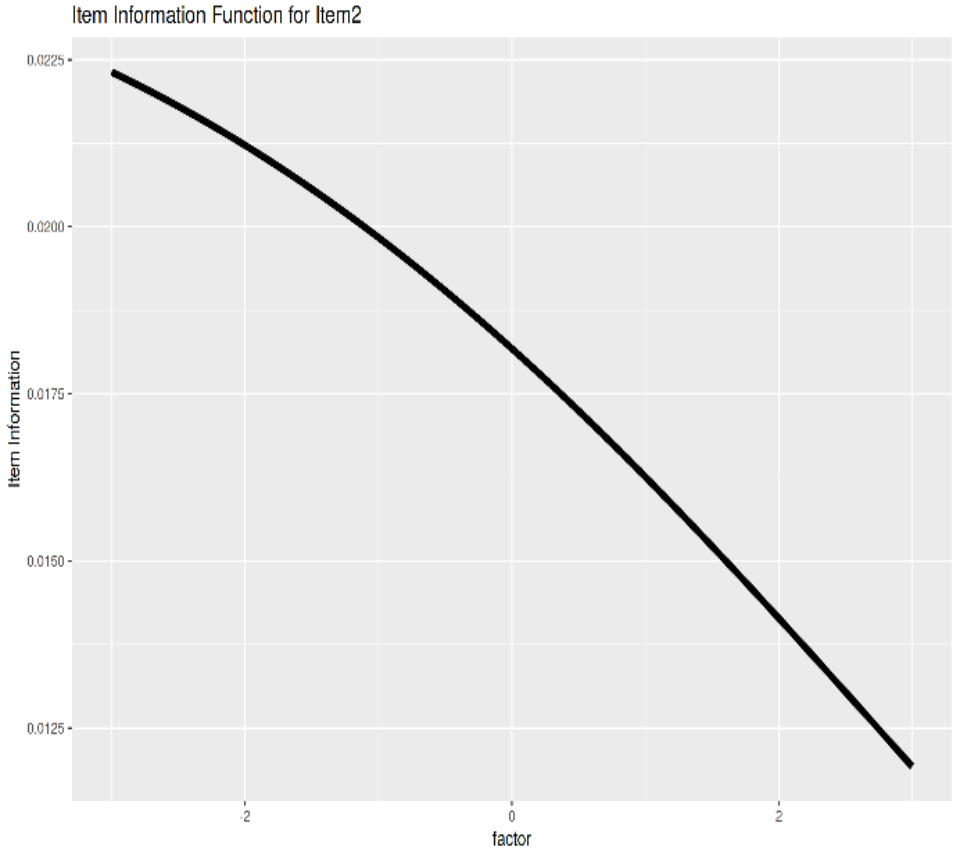

Item Characteristic Curve for Item19
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)
P(cat=2)
P(cat=3)

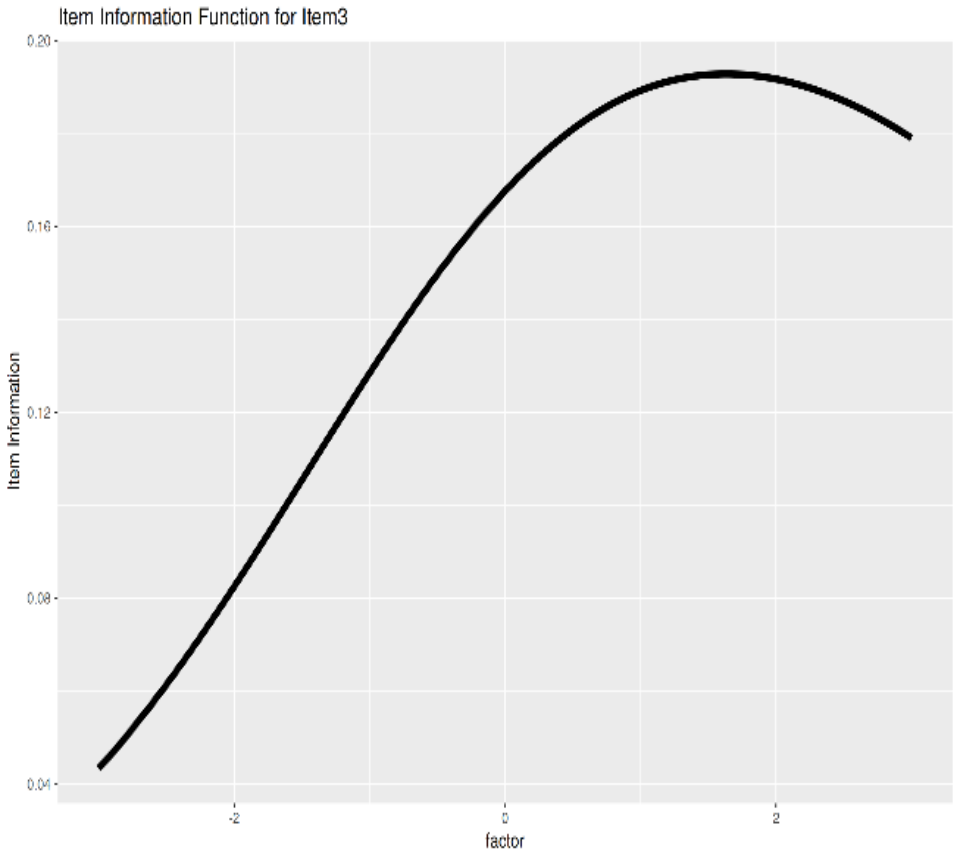

Item Characteristic Curve for Item20
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)
P(cat=2)
P(cat=3)

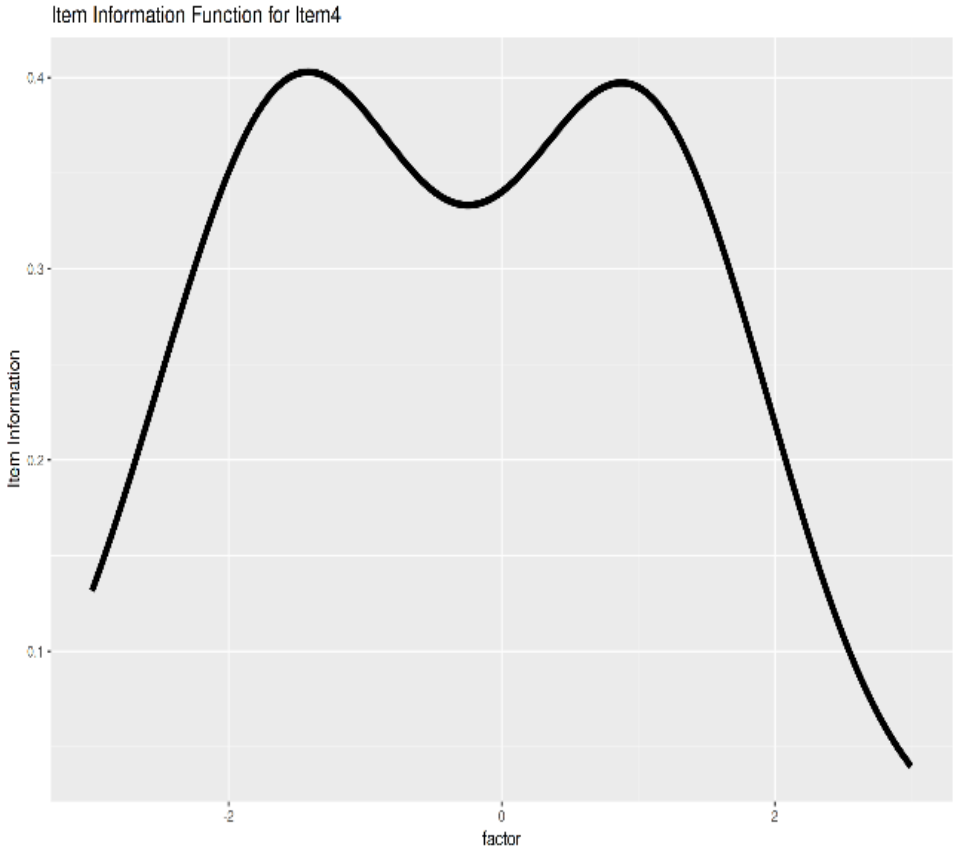

Item Characteristic Curve for Item21
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)
P(cat=2)
P(cat=3)

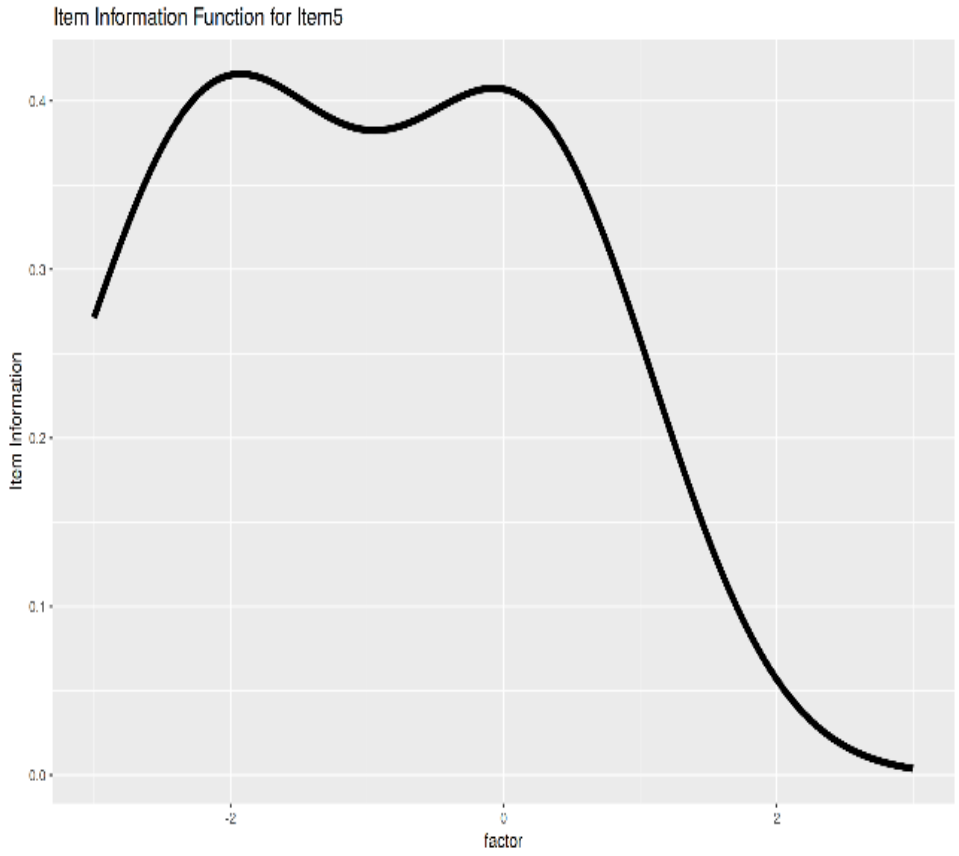

Item Characteristic Curve for Item22
1.00
0.75
0.50
0.25
0.00
Probability
-5
0
5
factor
plot
P(cat=1)
P(cat=2)
P(cat=3)

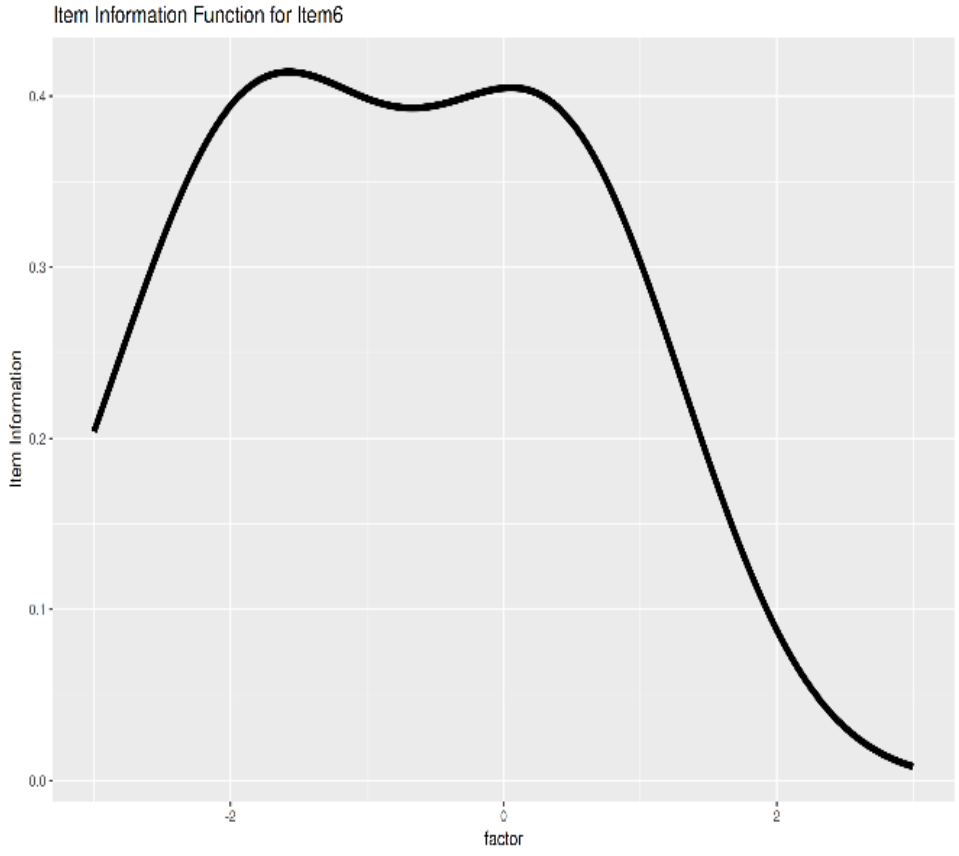

Item Information Function for Item1
Item Information
0.14
0.12
0.10
0.08
-2
0
2
factor

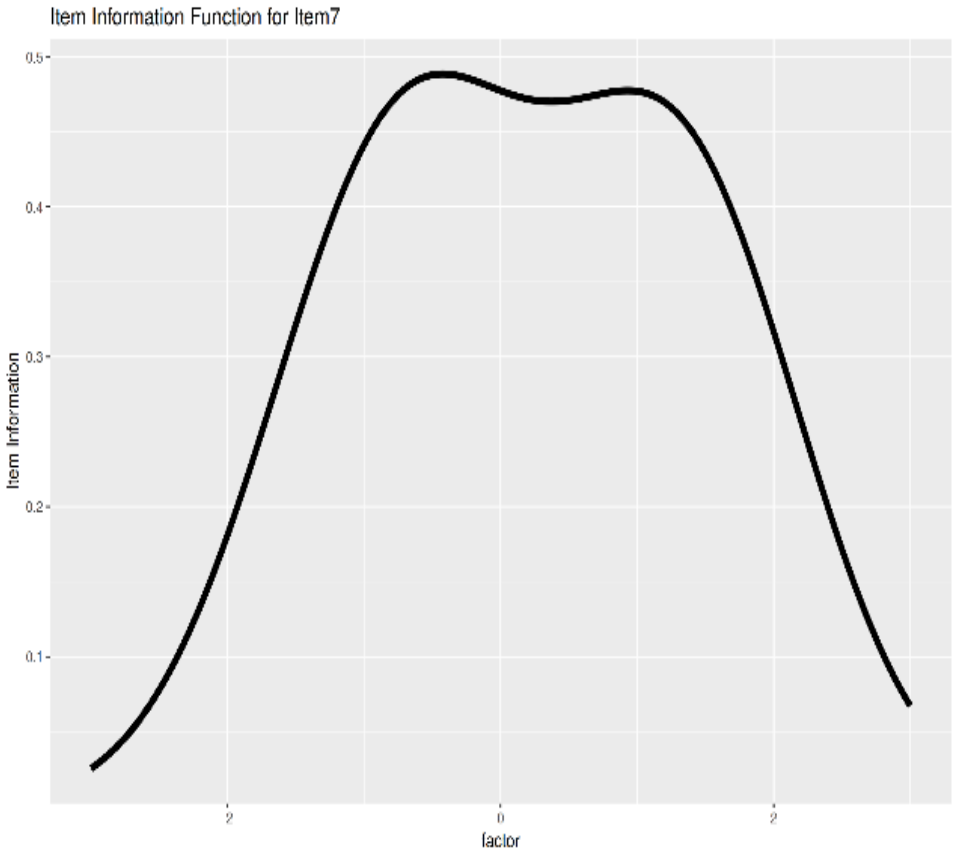

Item Information Function for Item2
Item Information
0.0225
0.0200
0.0175
0.0150
0.0125
-2
0
2
factor

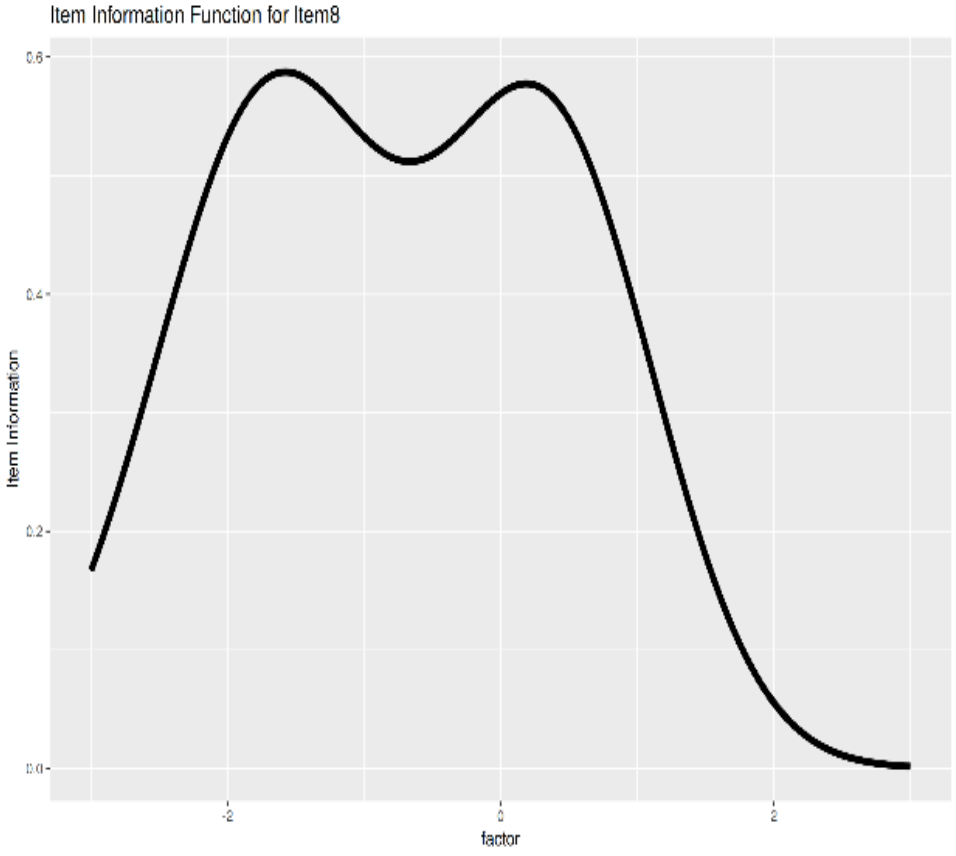

Item Information Function for Item3
0.20
0.16
0.12
0.08
0.04
Item Information
-2
0
2
factor

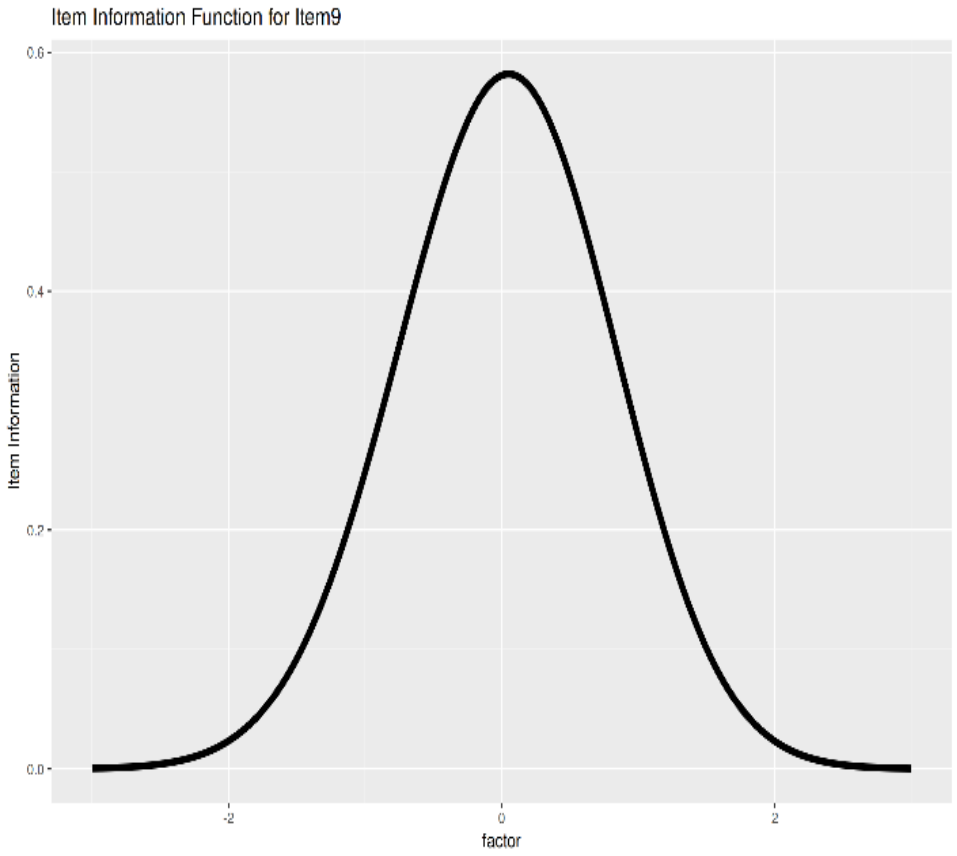

Item Information Function for Item4
0.4
0.3
0.2
0.1
Item Information
-2
0
2
factor

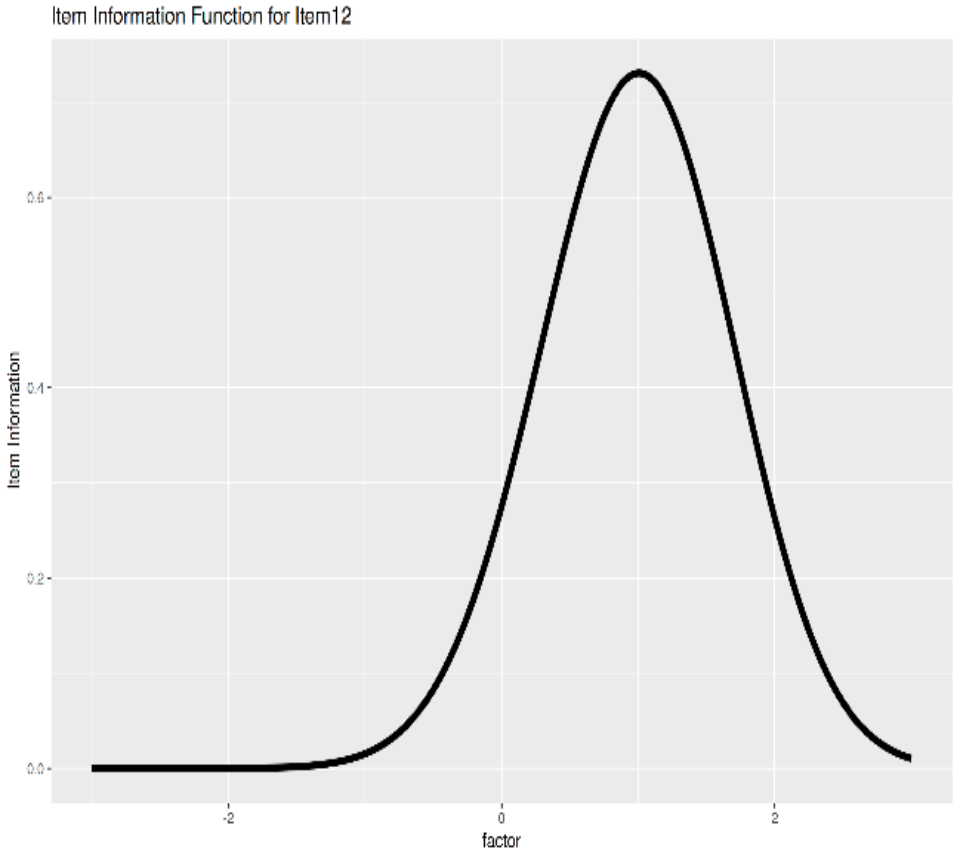

Item Information Function for Item5
Item Information
0.0
0.1
0.2
0.3
0.4
-2
0
2
factor

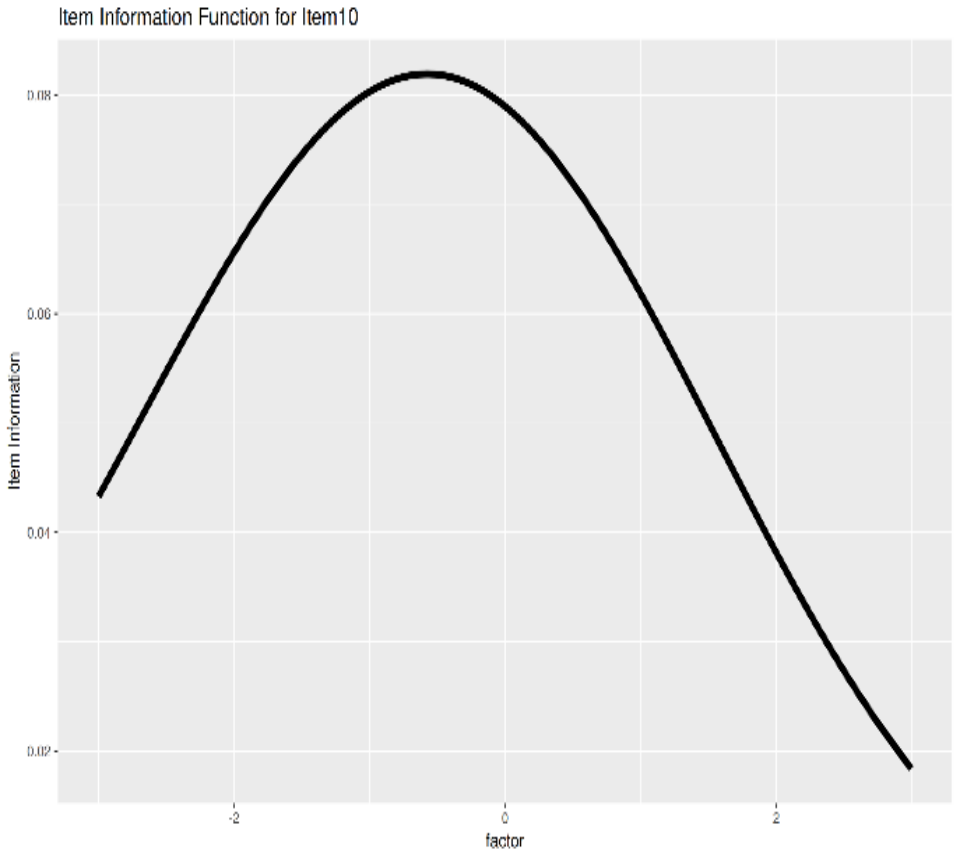

Item Information Function for Item6
Item Information
0.0
0.1
0.2
0.3
0.4
-2
0
2
factor

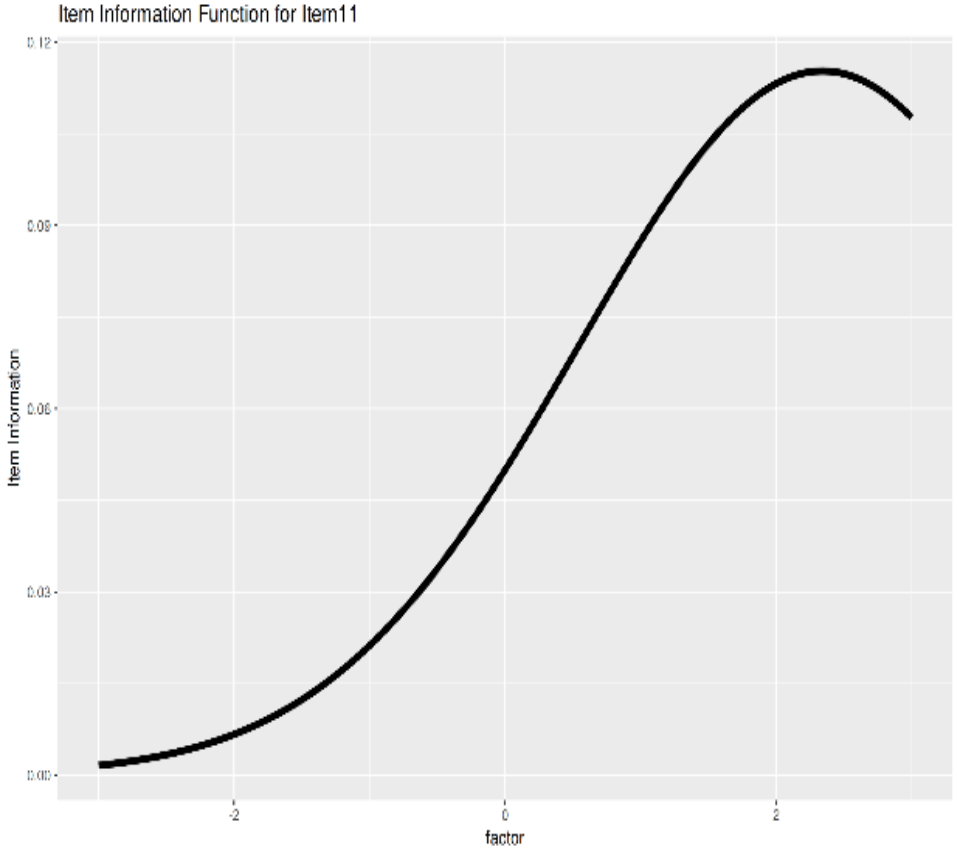

Item Information Function for Item7
Item Information
0.5
0.4
0.3
0.2
0.1
2
0
2
factor

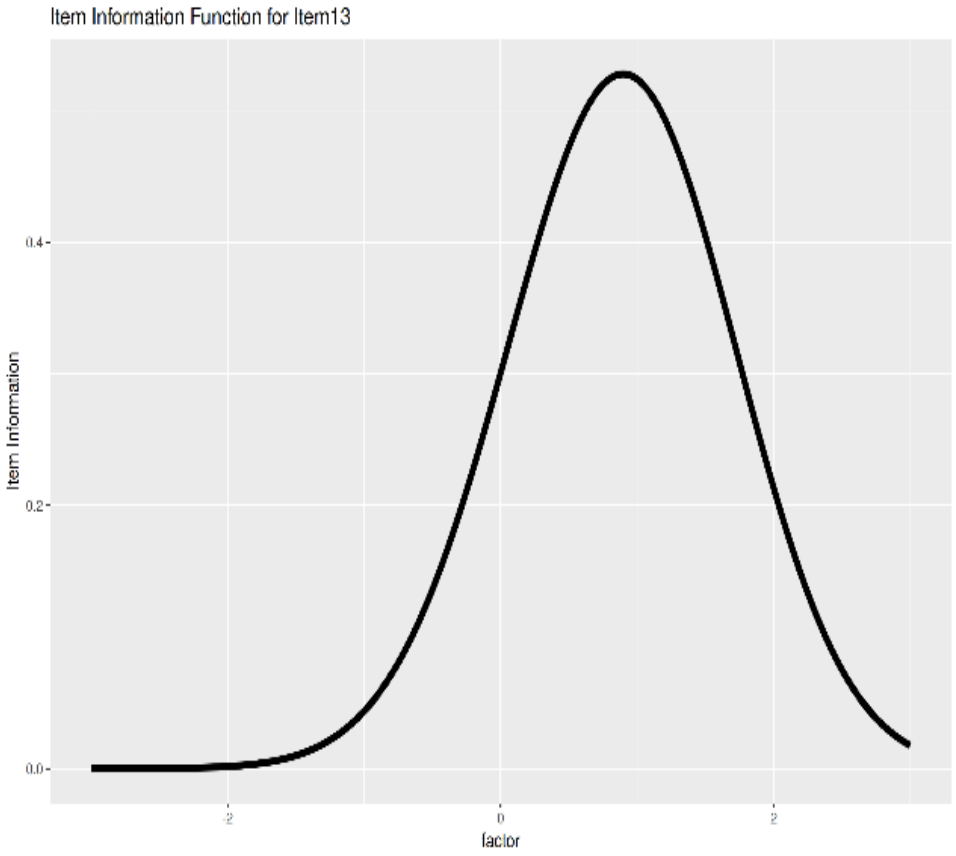

Item Information Function for Item8
Item Information
0.6
0.4
0.2
0.0
-2
0
2
factor

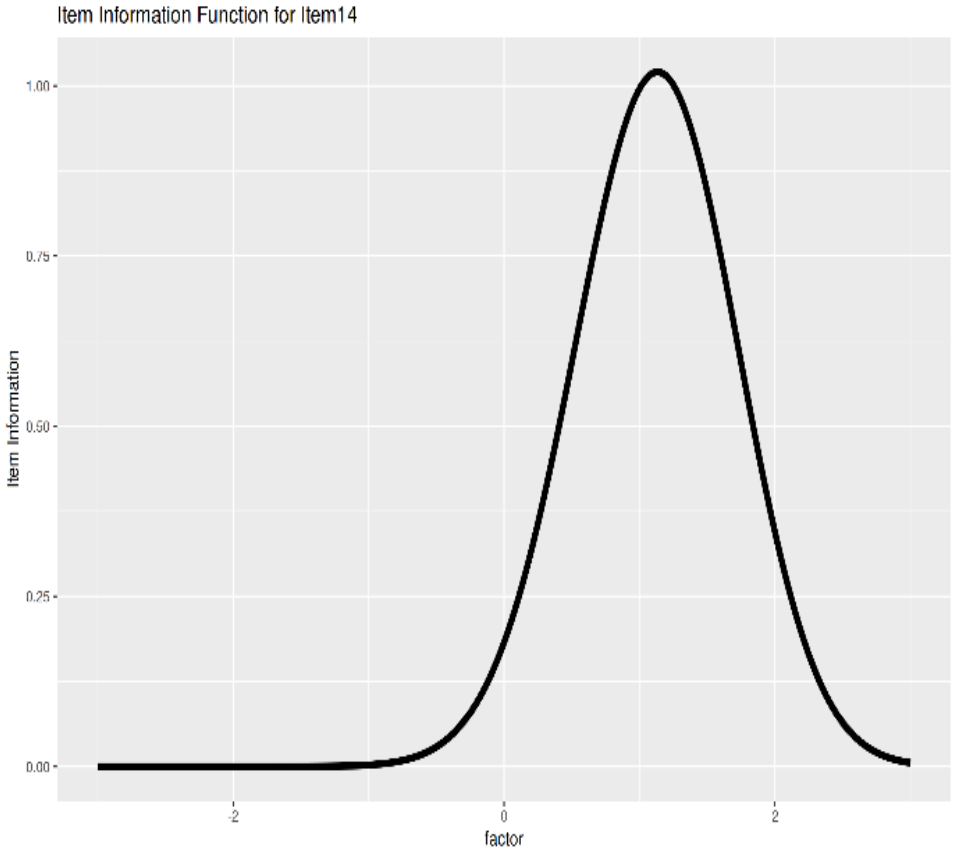

Item Information Function for Item9
Item Information
0.6
0.4
0.2
0.0
-2
0
2
factor


Item Information Function for Item12
Item Information
0.6
0.4
0.2
0.0
-2
0
2
factor

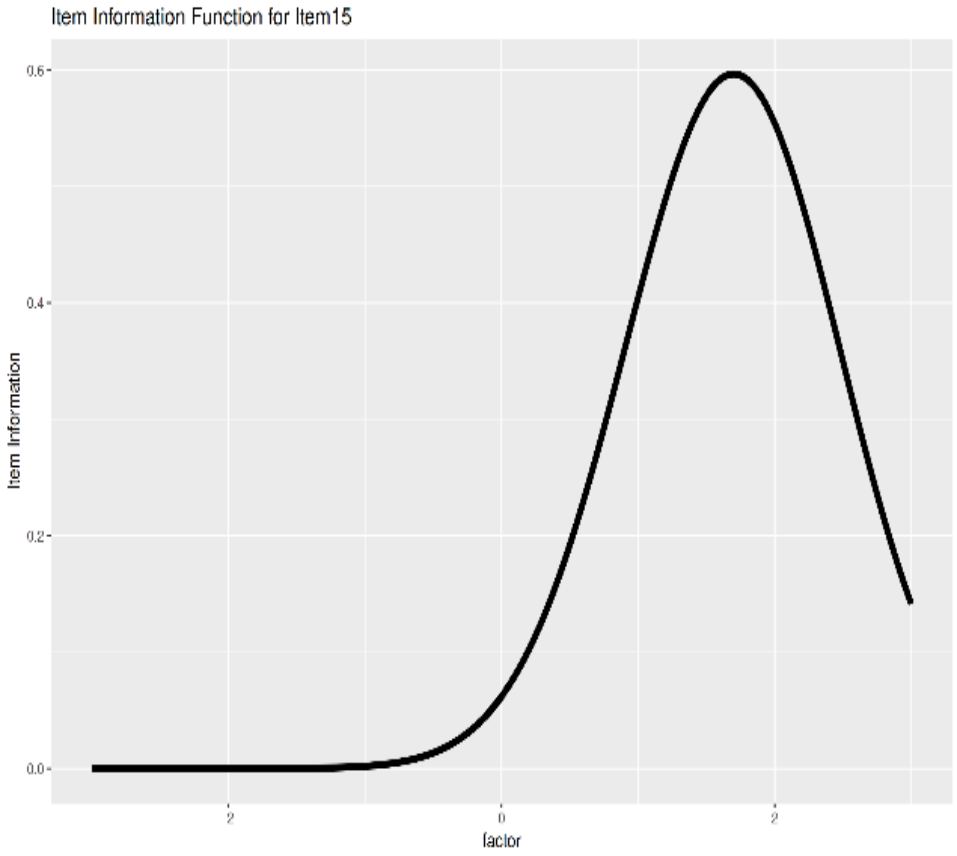

Item Information Function for Item10
0.08
0.06
0.04
0.02
Item Information
-2
0
2
factor

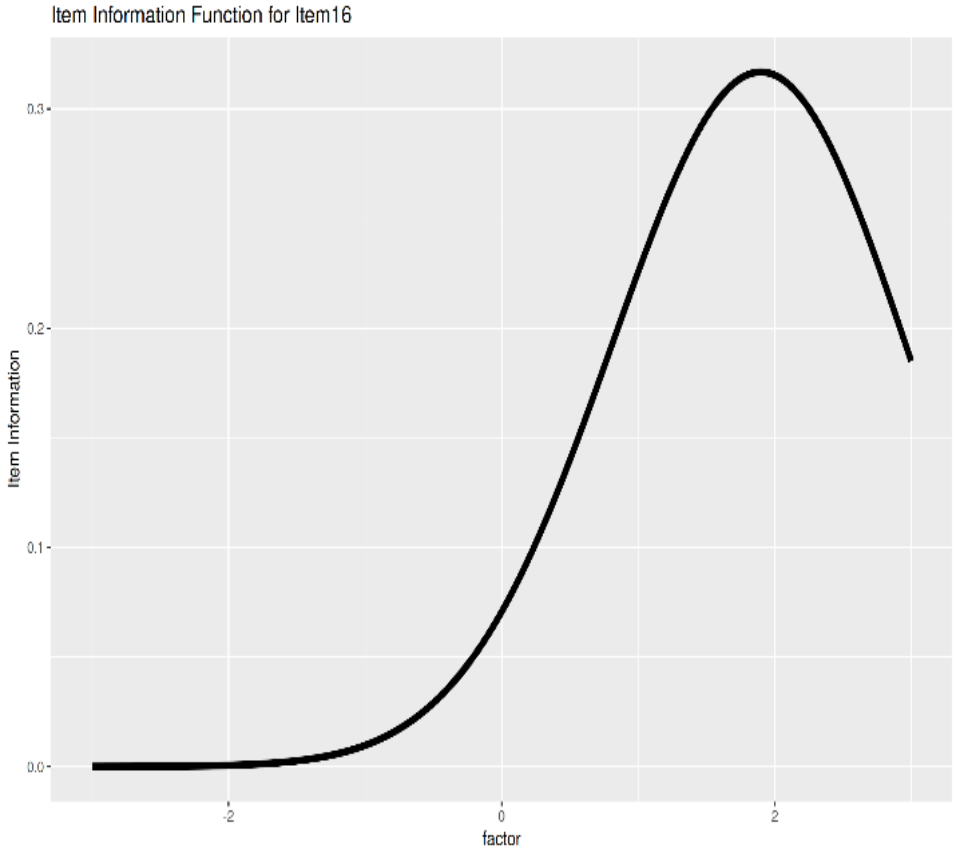

Item Information Function for Item11
0.12
0.09
0.06
0.03
0.00
Item Information
-2
0
2
factor

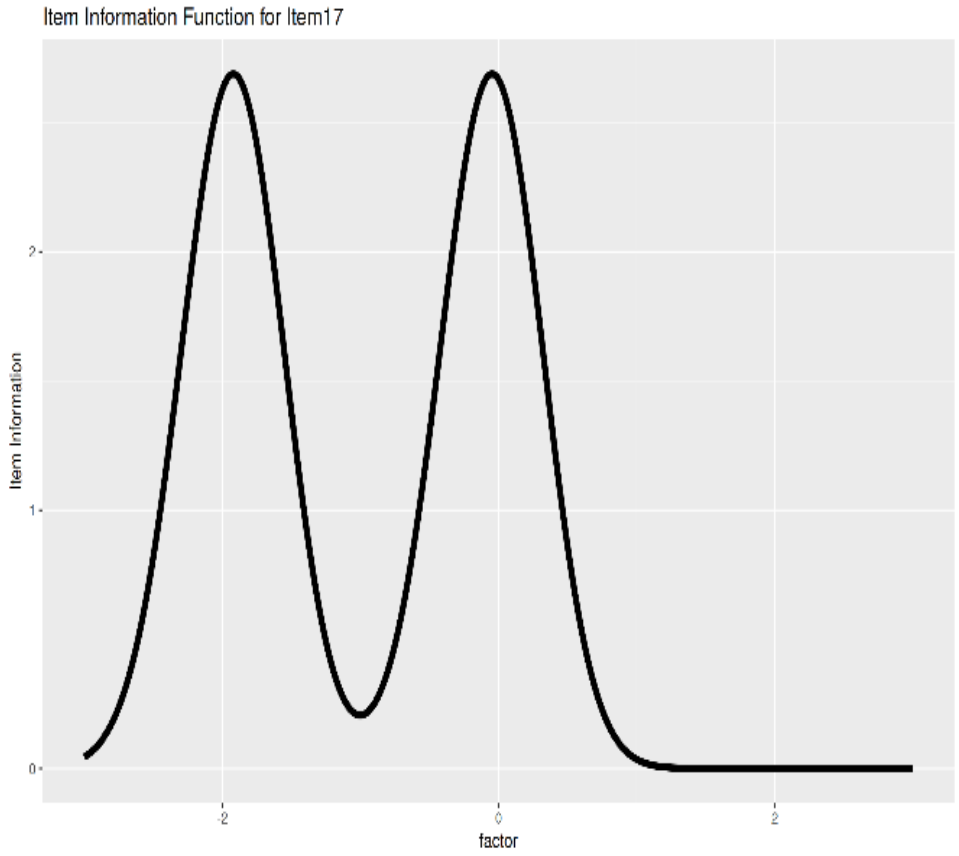

Item Information Function for Item13
Item Information
0.4
0.2
0.0
-2
0
2
factor

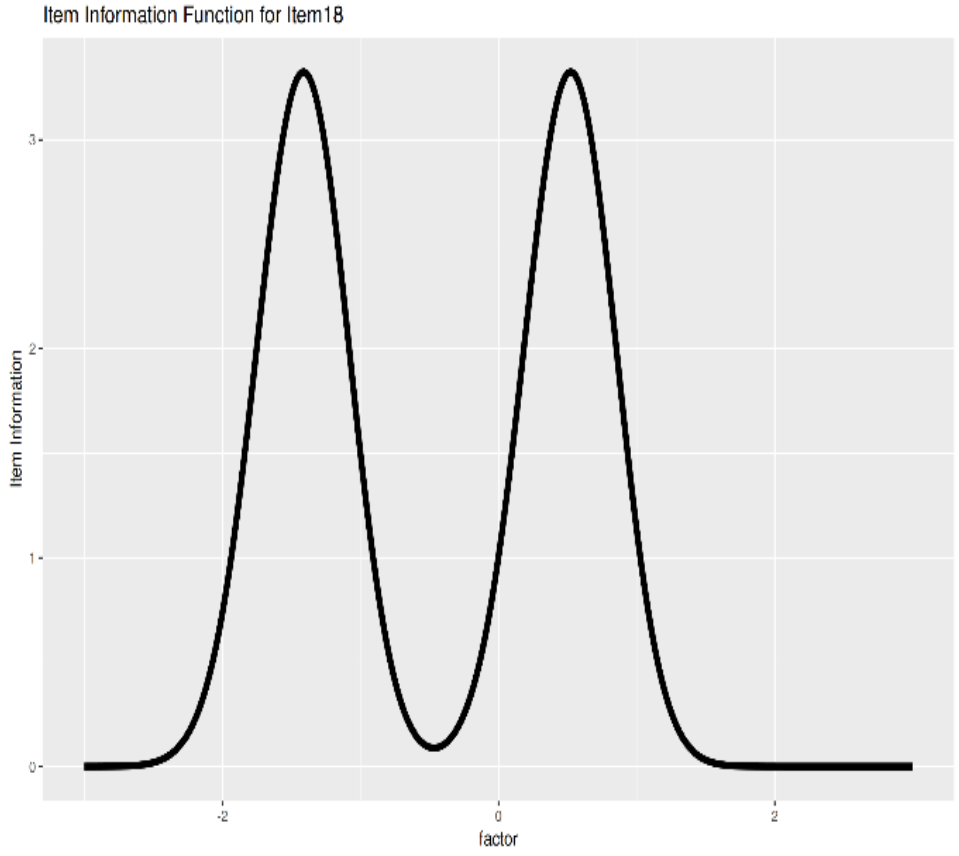

Item Information Function for Item14
Item Information
1.00
0.75
0.50
0.25
0.00
-2
0
2
factor

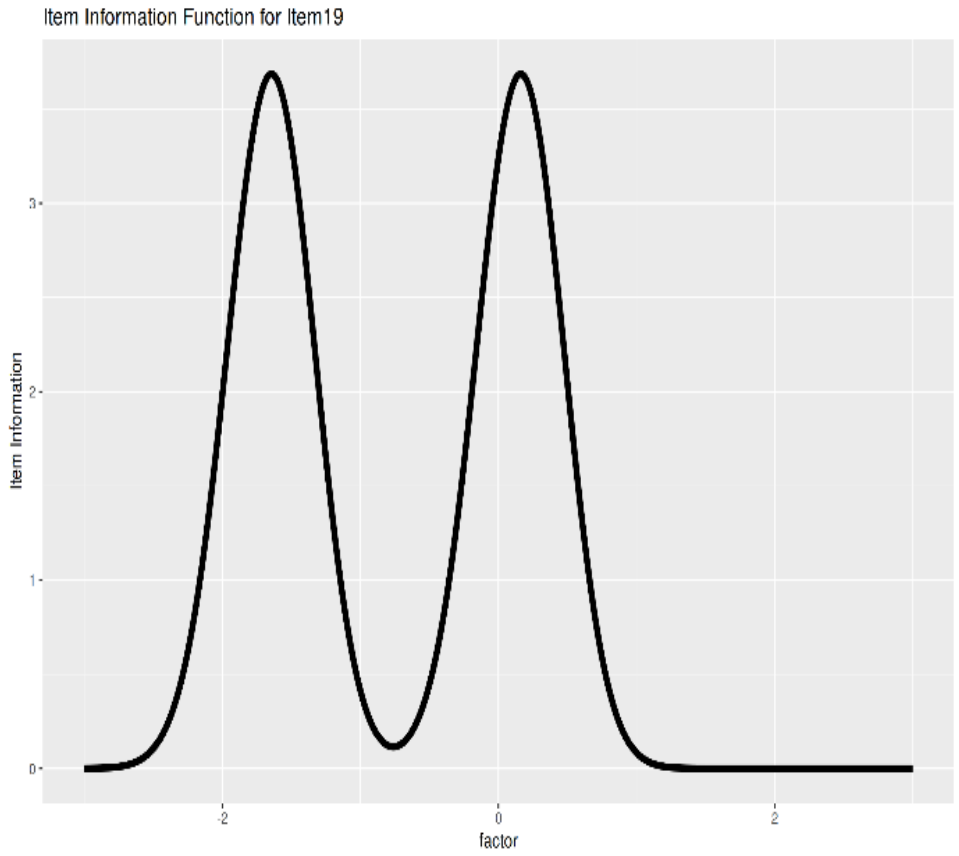
Appendix II

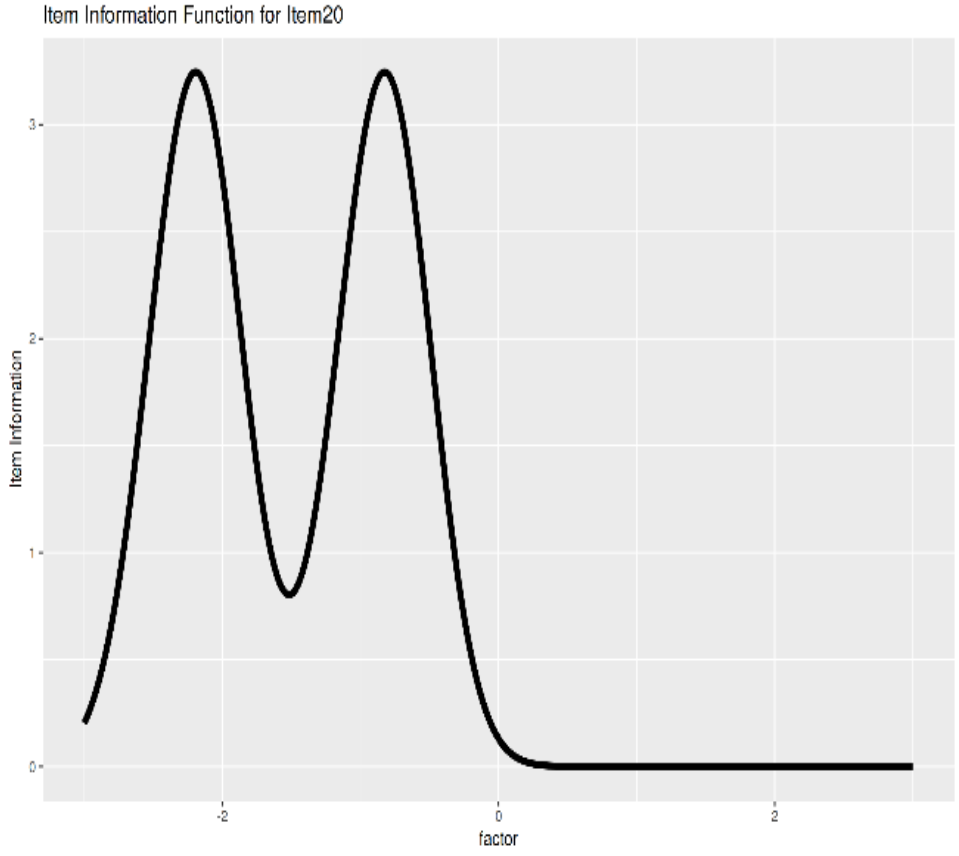

Item Information Function for Item15
Item Information
0.6
0.4
0.2
0.0
2
0
2
factor

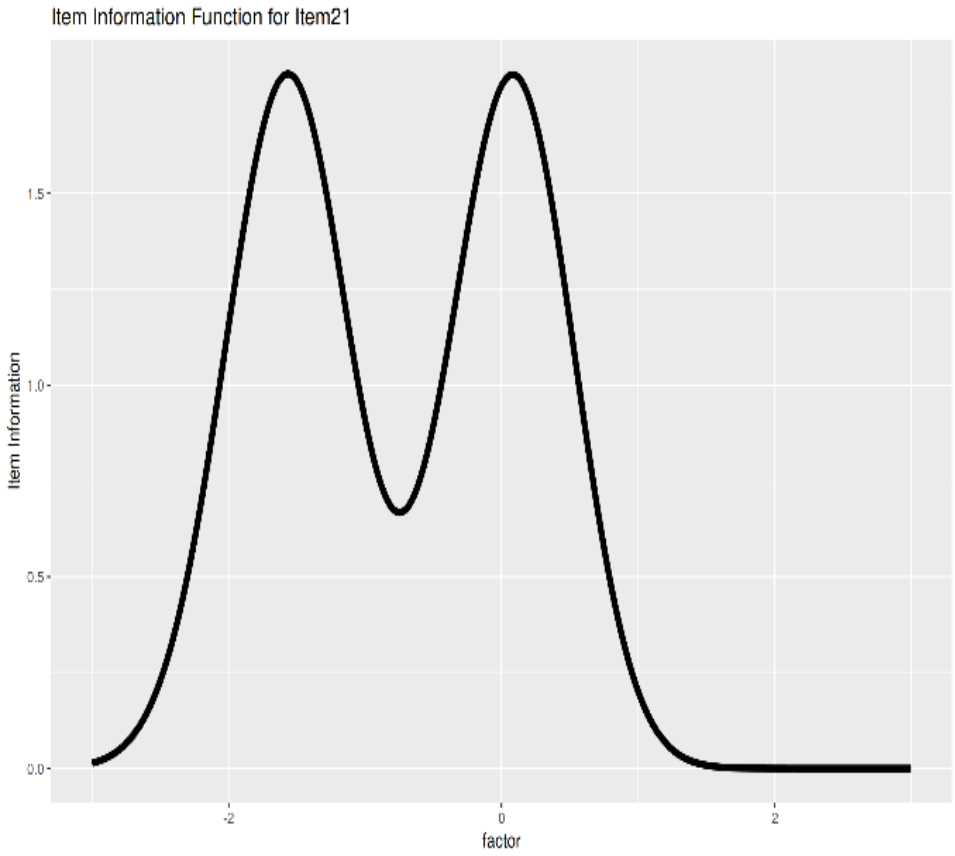

Item Information Function for Item16
Item Information
0.3
0.2
0.1
0.0
-2
0
2
factor

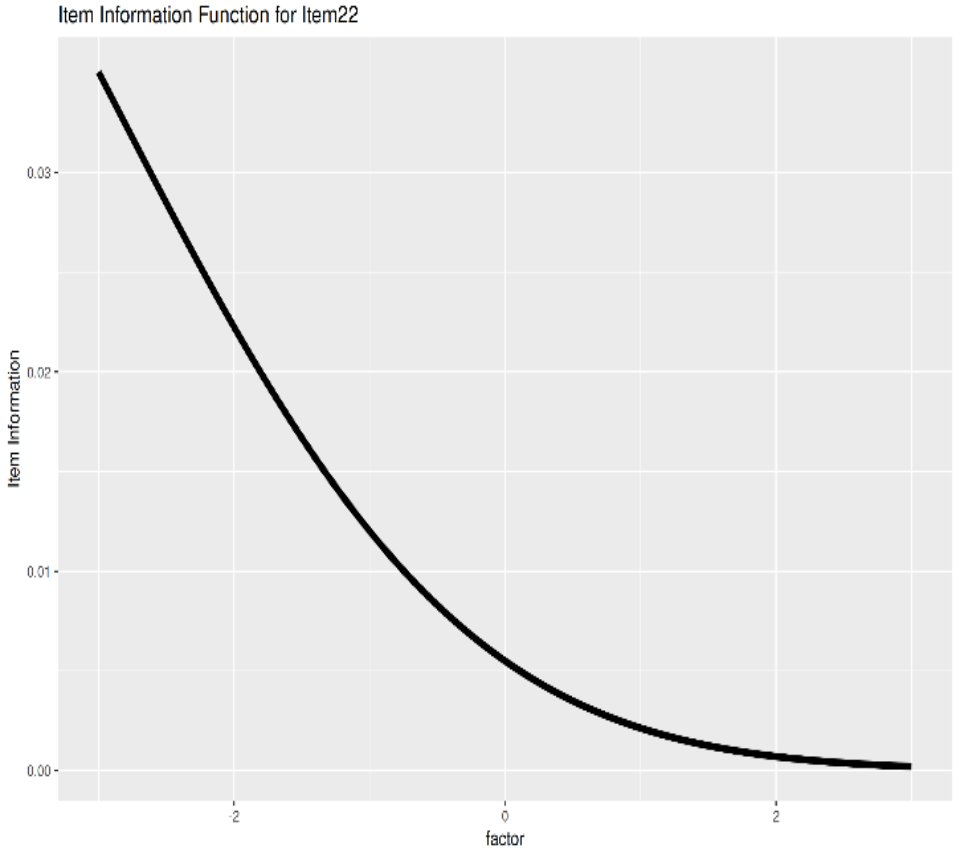

Item Information Function for Item17
Item Information
2
1
0
-2
0
2
factor


Item Information Function for Item18
Item Information
3
2
1
0
-2
0
2
factor


Item Information Function for Item19
Item Information
3
2
1
0
-2
0
2
factor


Item Information Function for Item20
Item Information
3
2
1
0
-2
0
2
factor


Item Information Function for Item21
Item Information
1.5
1.0
0.5
0.0
-2
0
2
factor


Item Information Function for Item22
Item Information
0.03
0.02
0.01
0.00
-2
0
2
factor

Appendix III

```
library(mirt)
item_data <- data_pooled[c("PM1", "PM2", "PM3", "PSD1", "PSD2",
"PSD3", "PSD4", "PSD5", "ESS1", "ESS2", "ESS3", "PTOI1", "PTOI2",
"PTOI3", "PTOI4", "PTOI5", "PSC1", "PSC2", "PSC3", "PSC4", "PSC5",
"PSC6")]
## remove empty rows
item_data <- item_data[rowSums(is.na(item_data)) != ncol(item_data),]
mirt1PLsyntax = "
  Factor = 1-22
  COV = 1
"
item.list = c(rep("graded",8),  rep("2PL",8),rep("graded",6))
model_1f_2PL = mirt(data = item_data, model = mirt1PLsyntax, itemtype = item.list)
item.list2 = c(rep("graded",8),  rep("3PL",8),rep("graded",6))
model_1f_3PL = mirt(data = item_data, model = mirt1PLsyntax, itemtype = item.list2)
fit_1f_2PL = M2(model_1f_2PL, impute = 10)
fit_1f_3PL = M2(model_1f_3PL, impute = 10)
## 2PL/3PL 2-factor Model
mirt2fsyntax = "
  Factor1 = 1-16
  Factor2 = 17-22
  COV = Factor1*Factor2
"
item_list_2PL = c(rep("graded",8),  rep("2PL",8),rep("graded",6))
model_2f_2PL = mirt(data = item_data, model = mirt2fsyntax, itemtype = item_list_2PL, SE = TRUE)
item_list_3PL = c(rep("graded",8),  rep("3PL",8), rep("graded",6))
model_2f_3PL = mirt(data = item_data, model = mirt2fsyntax, itemtype = item_list_3PL)
fit_2f_2PL = M2(obj = model_2f_2PL, impute = 10)
fit_2f_3PL = M2(obj = model_2f_3PL, impute = 10)
```