Development of a German Instrument for Self-Perceived Data Literacy

An Algorithm-based Approach to Scale Development

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Abstract

The increasing relevance of competent and critical handling of data in society not only makes it possible to record this competence, but also makes self-perception with regard to this competence increasingly clear. Previous approaches consider this competence primarily against the specific background of individual target groups, jobs or roles (Cui et al., 2023). In addition, only a few explicitly refer to the general population (Carmi et al., 2020; Cui et al., 2023). In view of the various theoretical approaches, there is a need for a uniform definition of data literacy in order to create comparability. Our aim is therefore to derive a holistic definition based on these approaches and to develop a questionnaire for self-perception of one's own data literacy. To this end, the decisive factors for the construct from previous definitions and operationalizations in various disciplines are brought together. Cognitive interviews are conducted iteratively to create and refine the items. The items are then selected using algorithm-based item selection. The facets of data literacy are comprehensively tested for factorial, discriminant, convergent and congruent incremental validity in order to promote a differentiated understanding of the construct. Construct and criterion validity are tested using correlations and hierarchical regression analyses, while cross-validation checks the robustness of the instrument. Based on a cross-sectional online questionnaire study, we first examine a representative sample of people from the general population. Limitations arise from the cross-sectional design and the heuristic item reduction, which limit predictions of predictive validity. The heterogeneous nature of the construct makes global instrument development and understanding of all participants difficult. The self-assessment questionnaire promotes a holistic assessment of competence and its perception for further research, for example by comparing self-assessment and actual performance.

Acknowledgements

I dedicate this thesis to

I want to thank my advisers, Prof. Martin Schultze, Prof. Timo Lorenz, and Prof. Manuel Völkle for their time and patience, and my friends for their resourceful advice:

Introduction

The relevance of data literacy in today's society becomes evident as it serves as a potent tool in navigating the complex data-driven environment. In a world characterized by information overload and rapid technological advancements, individuals equipped with strong data literacy skills can discern patterns, critically evaluate information, and make informed decisions

The exploration of citizens' interaction with media and the cultivation of their agency has traditionally centered around concepts such as written literacy, media literacy, information literacy, and digital literacy. In more recent discussions, Data Literacy has been approaching relevance among discussed competencies regarding what is necessary for agency in the current society (Carmi et al., 2020). Deficiency in data literacy not only exposes individuals to various risks and harms on personal, social, physical, and financial levels but also constrains their capacity to actively engage as informed citizens within an evolving, data-driven society (Carmi et al., 2020). Thus, Data Literacy is a competency that is becoming increasingly important to everyone. And research has acknowledged this in recent years, as more and more research is being done in that direction (Cui et al., 2023); And in praxis there are Training programmes and Workshops sprouting to enhance ones Data Literacy as well (QUELLE).

Background

Data Literacy involves the ability to effectively collect, manage, evaluate, and apply data in a critical manner. According to Wolff et al. (2016), it means being able to ask and answer everyday questions using both small and large datasets while considering ethical aspects. This includes skills such as selecting, cleaning, analyzing, visualizing, criticizing, and interpreting data, as well as communicating insights from data and using data for various purposes. (Frank, 2016) distinguish between cognitive skills, like data collection and analysis, and social skills, which involve trusting data while maintaining skepticism. (Calzada Prado & Marzal, 2013) outline five dimensions of Data Literacy: understanding data, acquiring data, interpreting and evaluating data, managing data, and using data. Understanding data includes knowing their types, roles, and significance, while acquiring data involves evaluating and selecting sources. Interpreting and evaluating data encompass understanding different presentation methods and data interpretation. Using data involves preparation, analysis, communication, and ethical considerations. Managing data includes storage, management, and reuse. This highlights one prominent feature of Data Literacy - It is a heterogeneous concept. Every subject or profession seems to hold their own definition or framework of Data Literacy (Cui et al., 2023). While that most certainly is good for assessing specific skills (e.g. in an Recruitment test), it limits the generalizability and comparability of Data Literacy across individuals with different background. It furthermore limits the accuracy of communication about the topic as two people with different background might hold different definitions on Data Literacy. In the study from (Cui et al., 2023) it also becomes apparent, that one group seems to be underrepresented in the research on Data Literacy: citizens or the general public. Although there seem to be several definitions of Data literacy for citizens (Wolff et al., 2016), most studies focus on other groups of people. On the first look this appears as a massive oversight, as citizens or the general public is forming the largest group by far, compared to professions like researchers, librarians, students or education provider (Cui et al., 2023). But when taking a closer look into the concept and its comprising factors,it becomes clear that many of those tend to speak to professionals rather than laypeople. In their Framework (Schüller, 2020) highlight the different roles in Data Literacy: Some of the facets or skills regard data-consumption, whereas the most are skills that data-producers would have. This is also reflected when taking a look into related concepts. The definition proposed by Wolff et al. (2016) suggests that data literacy shares some common competencies with statistical and information literacies. Information literacy, often studied in library sciences, overlaps with data literacy in terms of accessing, critically evaluating, and using data sources (Calzada Prado & Marzal, 2013; Shields, 2005), Wolff et al. (2016) also emphasize the importance of the data inquiry process, starting from identifying problems, designing studies, acquiring data, conducting analysis, to drawing data-based conclusions. In comparison, Gould (2017) argued that data literacy is essentially the same as statistical literacy but with additional competencies needed due to the increasing importance of data. These added competencies include understanding who collects the data, how and why data is collected, and understanding data privacy and ownership. However, while statistical literacy focuses on quantitative data and basic statistics, data literacy extends to the ability to understand, access, evaluate, and use arguments and decision-making based on both quantitative and qualitative data (Cui et al., 2023). The framework of (Schüller, 2020) shows that citizens are mainly covering roles where they consume data/ data products or informations. Thus, they are most likely to find tasks or items regarding the producing facets like providing or exploiting data more difficult to answer. This would systematically impair the fairness of tests and questionnaires regarding Data Literacy. Kubinger & Proyer (2005) define fairness as the condition where test measurements or values do not discriminate against specific groups of people who are relevant to the test. In the case of Data Literacy it is to be expected, that the item-difficulties in the producing factors would not be evenly distributed.

Aim of the Study

We noticed several gaps in the current research that we want to try addressing with this study. For once the target groups for Data Literacy are currently each having their own definition of the construct it seems (Cui et al., 2023). This not only makes comparisons impossible but also makes a general understanding of the topic as well as communication in the community and science communication to the public harder.

Data and Information

When speaking of Data Literacy, the respective self-perception and how to define and measure both constructs, one naturally has to think about what data is. What is information, how are they different to each other and what extents do they share? And what role does the process of interpretation play? Does one interpret data to make sense of it? And if so, does that mean that data is entropy while information stands in opposition to it?

The concepts of data and information are foundational in various fields, yet their precise definitions and relationships are often subject to interpretation. According to Shannon's seminal work on information theory (Shannon, 1948), data can be understood as raw, unprocessed symbols or observations, devoid of inherent meaning. It is through a process of interpretation and organization that data transforms into information, as elucidated by Bates (2005). Bates emphasizes that information emerges when data is structured and presented in a way that is comprehensible and relevant to a particular context or purpose.

Entropy, a concept borrowed from thermodynamics and applied in information theory, plays a crucial role in understanding the relationship between data and information. In his landmark paper, Shannon (1948) defines entropy as a measure of uncertainty or disorder in a system. In the realm of information theory, entropy is often associated with the amount of unpredictability or randomness in a set of data. However, it's essential to note that entropy can also be viewed as a measure of information content within a system. This perspective is articulated by Brillouin (1953), who suggests that low entropy corresponds to a high concentration of meaningful information. Similarly, the work of Jaynes (1957) highlights the connection between entropy and information, proposing that information can be quantified in terms of the reduction of uncertainty or entropy in a system. Thus, we can refine our understanding of the relationship between data, entropy, and information. While data serves as the raw material from which information is derived, it's the reduction of entropy through organization and interpretation that gives rise to meaningful information. Thus, rather than viewing data as synonymous with entropy, it's more accurate to consider information as emerging from the structured representation of data, leading to a deeper understanding of the underlying phenomena.

Self-Perceived Data Literacy

instances have underscored the extent to which citizens may lack awareness regarding the potential uses and misuses of their data. [argumentation for self-rating measure!]

Conceptual Integration

Conceptual integration was employed to find common grounds of the existing theories and studies. By synthesizing heterogeneous definitions and perspectives into cohesive, unified representations and selectively incorporating relevant features while establishing cross-disciplinary connections, conceptual integration enables researchers to create comprehensive latent factors that capture the complexity of the construct.

Data Comprehension and Interpretation

This factor encompasses skills related to understanding and critically evaluating data and information. It involves the ability to comprehend various forms of data presentation, detect inconsistencies, interpret data comprehensively, and identify logical fallacies. Individuals with high scores on this factor demonstrate a strong aptitude for processing and making sense of complex information across different formats, enabling them to draw accurate conclusions and insights.

Contextualize, Evaluate and Critique Data

This factor involves skills related to critically evaluating information sources and discerning between facts and opinions. It encompasses the ability to assess the credibility and reliability of information, considering factors such as the reputation of the source and the context in which the information was presented. Individuals scoring high on this factor demonstrate a keen awareness of potential biases or vested interests in information sources.

Data-Informed Worldview

This factor relates to the ability to integrate data-driven insights into one's worldview and values. It involves actively seeking comprehensive understanding of various topics, engaging with diverse perspectives, and consciously incorporating data-driven insights. Individuals high in this factor adapt their opinions based on new data, prefer evidence-based information, and ensure their values align with reliable data. They engage with information and perspectives that challenge their existing views, showing a willingness to reassess their opinions and positions based on new data.

Data Communication Proficiency

This factor revolves around the skill to effectively communicate and present data through various means, including visual formats, verbal explanations, and written descriptions. It requires translating complex data into clear and impactful formats, ensuring comprehension by varied audiences. Proficiency in data communication is essential for facilitating understanding, aiding informed decision-making, and prompting action based on data-driven insights. This proficiency includes the ability to translate data into simple visualizations, present findings confidently, and articulate complex information effectively in written and visual as well as verbal formats. It involves adeptly summarizing extensive datasets, engaging in professional discussions, and using advanced visual elements to convey specialized results to target audiences.

Data Management and Analysis

This factor covers skills related to managing and analyzing data effectively. It involves proficiency in organizing and analyzing data using software tools, conducting statistical analyses, and understanding research methodologies. It includes skills such as organizing and managing data using software tools, conducting interviews or surveys for data collection, performing basic statistical analysis and recognizing trends in graphical representations. Individuals scoring high on this factor exhibit competence in statistical methods, enabling them to effectively analyze data and interpret findings.

Statistical Literacy

Statistical literacy, as defined by Gal (2002), encompasses five knowledge dimensions: literacy skills, statistical knowledge, mathematical knowledge, contextual knowledge, and critical reflection skills, along with two dispositional dimensions: beliefs and attitudes, and a critical mindset. It involves understanding written, spoken, or graphical information, knowing why data are needed, grasping basic statistical concepts, understanding probability, and drawing statistical inferences. It also includes basic mathematical operations, interpreting information within a context, and critically questioning the validity of information, particularly in media. Statistical literacy requires a critical attitude and the perception of oneself as competent in statistical reasoning.

Reference: Gal, I. (2002). Adult numeracy and statistical literacy: Concepts, research, and a challenge. Journal of Statistics Education, 10(3). Retrieved from https://www.tandfonline.com/doi/abs/10.1080/10691898.2002.11910562

Information Literacy

Information literacy is the ability to recognize when information is needed and to effectively locate, evaluate, and use that information (American Library Association (2000). Information Literacy Competency Standards for Higher Education. http://www.ala.org/acrl/standards/informationliteracycompetency). It empowers individuals to determine the extent of information needed, access it efficiently, critically evaluate information and their sources, incorporate information into their knowledge base, and use it effectively for specific purposes. Additionally, information literacy involves understanding the legal, economic, and social aspects of information use and ensuring ethical and legal access and use of information. Furthermore, Information literacy is not static; it involves a commitment to lifelong learning and adaptation to evolving information technologies and practices. This definition already highlights the closeness of Information literacy to Data Literacy. Another possible way to describe it is suggested by Johnson and Webber (2003): "Information literacy is the adoption of appropriate information behaviour to obtain,through whatever channel or medium, information well fitted to information needs,together with critical awareness of the importance of wise and ethical use of information in society." (Johnston & Webber, 2003, p.336)

Also similar to Data Literacy, is its heterogeneous nature. This already becomes apparent when looking at the different frameworks for Information literacy. In the UK, the seven Pillars of IL model was published in 1999 by the SCONUL Advisory Committee on Information Literacy. In 2001, the Australian and New Zealand Institute for Information Literacy developed its IL framework, which was revised in 2004 by Bundy. A year later, Mexican standards for IL in higher education were established, influenced significantly by the Association of College and Research Libraries (ACRL) Standards published in 2000. Work on the Scottish IL framework began in 2004, as documented by Irving in 2011. IL was also a focal point in a European project aimed at revitalizing the European library and information science curriculum, identifying essential topics and teaching methods (Virkus, S., Boekhorst, A.K., Gomez-Hernandez, J.A., Skov, C., & Webber, S. (2005). Information literacy: Conceptions, context and the formation of a discipline.).

Moral Attentiveness

- moral disengagement scale

Moral Attentiveness (Reynolds, 2008) is a concept that delves into the inherent differences individuals display when it comes to engaging with ethical considerations. Some individuals naturally exhibit a genuine interest and attentiveness to ethical matters, while others may find the subject mundane or remain indifferent, and in extreme cases, appear unresponsive. This inclination toward or against ethics appears to be deeply ingrained, persisting across diverse contexts and proving resistant to various ethics interventions, whether constructive or detrimental. Importantly, acknowledging one's interest in ethics does not imply inherent moral virtue or vice, nor does it suggest that behavior is rigid and unchangeable. Rather, it highlights an observation familiar to many practitioners — that certain individuals inherently pay more attention to moral matters. These individuals contribute to making organizational interventions more interactive, enjoyable, and presumably more beneficial compared to those less attuned to such ethical considerations. Within the field, an implicit assumption is that the variance in individual moral attentiveness can be explained by two existing constructs: moral awareness and moral sensitivity. Moral awareness involves an individual's recognition that a situation possesses moral implications, while moral sensitivity refers to their capacity to achieve such moral awareness. In essence, the unspoken argument is that an individual's level of attention to moral matters can be attributed to their moral awareness, moral sensitivity, or a combination of both.

Critical Thinking

The conceptualization of Critical Thinking (CrT) has evolved along three main branches: philosophical, psychological, and educational (Rear, 2019). In the philosophical view, which centers on the mental process of thought, a critical thinker is someone adept at logically evaluating and questioning both the assumptions of others and their own. On the psychological front, which delves into the processes driving action, a critical thinker possesses a combination of skills enabling them to assess a situation and determine the most appropriate course of action. The educational approach aligns more closely with the psychological perspective, relying on frameworks and learning activities tailored to enhance students' CrT skills and subsequently assess their proficiency in these skills (Payan Carreira et al., 2022).

Need for Cognition

The personality trait known as Need for Cognition (NFC) originated in social psychology during the 1940s and 1950s, the concept of NFC, representing an inclination for joyful thinking, is evident in the works of Maslow (1943), Murphy (1947), Asch (1952), and Sarnoff & Katz (1954). The conceptualization of NFC underwent refinement in the mid-1950s through experimental investigations by Cohen and colleagues (Cohen et al., 1955). They defined NFC as "a need to structure relevant situations in meaningful, integrated ways. It is a need to understand and make reasonable the experiential world" (Cohen et al., 1955, p. 291). The concept captures individual variations in the engagement and enjoyment of thinking tasks (Bless et al., 1994).

Core self evaluation

Core Self-Evaluations (CSE) is a comprehensive personality trait that encompasses fundamental appraisals of one's worthiness, effectiveness, and capability as a person (Judge et al., 2003). This construct, initially introduced by Judge et al. (1997), integrates four traits: self-esteem, emotional stability, generalized self-efficacy, and locus of control, all of which contribute to individuals' perceptions of themselves and their agency (Judge & Bono, 2001).

The study by Chang et al. (2012) further emphasizes the role of CSE in individuals' assessments of their own worthiness and capabilities. These assessments, rooted in self-esteem, emotional stability, generalized self-efficacy, and locus of control, form the core components of CSE (Judge et al., 2003). Self-esteem, as established by Rosenberg (1965), provides a foundation for positive self-perceptions, while emotional stability (low neuroticism) characterized by confidence and steadiness (Goldberg, 1990) enhances individuals' resilience. Generalized self-efficacy, reflecting beliefs about one's ability to perform across diverse situations (Locke et al., 1996), and locus of control, which pertains to individuals' beliefs about the causes of events in their lives (Rotter, 1966), further shape individuals' perceptions of their capabilities and control over their environment.

Openness towards technology

The widespread integration of information and communication technology (ICT) in various aspects of daily life, notably accelerated by the COVID-19 pandemic lockdown (Richter and Mohr, 2020; Rizun and Strzelecki, 2020), has underscored the significance of individuals' self-perceived ICT competence. This self-perception extends beyond a general assessment to encompass specific competence domains, referred to as ICT self-concept (ICT-SC). ICT-SC reflects individuals' mental representations and evaluations of their ICT competences shaped by experiences, feedback, and interactions with the environment.

Research findings indicate that when the objective demands of competence encompass multiple dimensions, the corresponding self-concepts are likewise structured in a multidimensional fashion (Brunner et al., 2010). Examining the European Digital Competence Framework for Citizens (DigComp) and its updated versions, DigComp 2.0/2.1 (Carretero et al., 2017; Vuorikari et al., 2016), reveals a comprehensive structure. This framework not only integrates previous models of ICT competence but also extends its scope, incorporating models such as the Canadian Digital Skill Framework (Chinien and Boutin, 2011) and components of ICT literacy by Katz (2007), among others (e.g., Eshet-Alkalai, 2004; Ferrari, 2012; Martin and Grudziecki, 2006). Within DigComp and its subsequent versions, ICT competence is systematically organized across five competence domains: information and data literacy, communication and collaboration, digital content creation, safety, and problem-solving. These domains encompass a total of 21 competences, providing a comprehensive and nuanced perspective on the multifaceted nature of ICT competence.

Methods

1. Stage One: Conceptualization and Item Pool Generation

- Review relevant literature to develop a theory-driven conceptualization of constructs.
- Ensure diversity in the sample regarding age and occupation.
- Integrate theory and interview results to generate an initial item pool.
- Include a member of the majority group in the item creation process.
- Present original items to a diverse group for comprehensibility and content validity assessment.
- Exclude items as necessary, resulting in a refined item pool.

2. Stage Two: Item Selection and Construct Validity

- Conduct a quantitative survey including the original item pool, demographics, and validation measures.
- Utilize automated item selection procedures to reduce the item pool.
- Cross-validate findings using a split-sample approach.
- Hypothesize relationships between the newly created measure and related constructs.
- Use distinct but conceptually similar instruments for validation purposes.

3. Stage Three: External and Construct Validity Testing

- Perform bivariate correlational analyses with relevant work-related constructs to establish external validity.
- Investigate construct validity through multiple regression analysis, controlling for other variables.
- Discuss specific hypotheses regarding associations between the measure and related constructs.

The general procedure outlined in the text can be extracted as follows:

Item Selection Procedure:

1. Utilize an algorithm to select items from the original item pool and develop the final version of the scale.
2. Create an initial population by randomly generating a predefined number of chromosomes from the original item pool.
3. Use an algorithm implemented in the R package "stuart" with predefined datasets split into training and test datasets.
4. Evaluate solutions against an objective function consisting of model fit criteria and composite reliability.
5. Validate findings using k-fold cross-validation with the test dataset.

Evaluation of Model Fit, Measurement Invariance, and External Validity:

1. Evaluate model fit using standard recommendations proposed by Hu and Bentler (1999), including χ^2 significance testing and fit indices.
2. Conduct confirmatory factor analysis (CFA) with the R package "lavaan."
3. ggf. Account for non-normal distribution using a robust maximum likelihood estimator (MLR).
4. Validate the selected scale using k-fold cross-validation to examine measurement invariance assumptions.
5. Evaluate divergent and convergent validity of the scale using Pearson's correlation coefficients with other relevant measures.
6. Assess correlations to determine the strength of associations.

Sample

The sample for this study comprised XXX participants (M=, SD=). Within the sample, XXX% identified as female, XXX% as male, and xxx% did not identify with binary gender categories. All participants were aged 18 and above. Regarding education, all participants exhibited a [insert educational level- specifying the range or types of educational levels observed in the sample]. Among the participants, n= reported higher knowledge on items x, x, x, leading to their selection for an additional set of items as a preliminary survey for factors four and five. The study encompassed every sector within the occupational classification (Bundesagentur für Arbeit, 2020), ensuring comprehensive representation. Conducted in German, the participation in the study was entirely voluntary, with no external incentives provided. The recruitment of participants was carried out through a combination of personal and professional networks, along with outreach on various online social media platforms.

Our study sample serves as a focal point for comparison against the demographic landscape of the general public in Germany. In 2022, the mean age of the German population was 44.6 years, with 45,457,000 individuals engaged in employment. Educational backgrounds varied (XXX), and for gender distribution, the split was nearly 50/50 (41,616,473 males and 42,816,197 females) according to the Statistisches Bundesamt (source: https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bevoelkerung/Bevoelkerungsstand/Tabellen/liste-zensus-geschlecht-staatsangehoerigkeit.html#651186).

Analyzing our sample against these benchmarks provides a comprehensive understanding of any distinctions or parallels in age, employment, education, and gender. This comparison enhances the applicability of our findings to the broader German population.

Preregistration

Instruments

Measuring Moral Attentiveness

To assess moral attentiveness, we employed the perceptual moral attentiveness scale derived from the German Moral Attentiveness Scale by Pohling et al.(2014); adapted from Reynolds, 2008). This subscale comprises four items, including statements such as “I am regularly confronted with decisions that have significant ethical consequences.” The scale comprises a seven-point Likert-type scale with fully labeled options, ranging from strongly disagree (1) to strongly agree (7).

Measuring Critical Thinking

Measuring Need for Cognition

Measuring Core self evaluation

-> heilman und jonas 2010 validation german

Measuring Openness towards technology

ICT-SC was measured, using the ICT-SC25g. The ICT-SC25 is a self-administered questionnaire designed to assess ICT self-concept (ICT-SC) on both a general scale (items 1-5) and a domain-specific scale (items 6-25). Responses to items are provided on a six-point Likert-type scale with fully labeled options, ranging from strongly disagree (1) to strongly agree (6). The questionnaire has undergone validation in German (ICT-SC25g). Its applicability extends across the adult population, spanning ages 18 to 69, and diverse contexts including work, private life, and education.

Item Creation

After drafting a set of items, those items were being reviewed in cognitive interviews in an iterative manner. The idea was to go through the items with different people and ask them if the items are comprehensive, whether it is clear to them what is being asked with the items and what everyone associates with the item and so on. After every interview, the remarks made by the Person interviewed get worked into the items and then the reworked item set is presented in the next interview and so on.

Berücksichtigung von z.b. Trennschärfe etc. item schwierigkeit

Analysis

We employed an automated item selection algorithm to craft the [insert name] scale. The process of scale development, involving the strategic selection of items to ensure psychometric soundness, is conceptualized as a combinatorial problem (Kerber et al., 2022). Combinatorial problems, exemplified by the knapsack problem (Schroeders et al., 2016), entail identifying a discrete and finite solution within predefined constraints (Hoos and Stützle, 2005).

Contemporary approaches to address these combinatorial problems leverage automatic optimization algorithms, such as Genetic Algorithms (GA; Holland, 1975), Ant Colonization Algorithms (ACO; XXX), brute force (XXX), or random sampling(XXX). (Schultze, 2022). Unlike classical approaches that consider items based on their individual merits, heuristic item selection algorithms aim to enhance the psychometric properties of a set of items within predetermined constraints (Schultze, 2017). Noteworthy is the inherent approximate, rather than deterministic, nature of metaheuristics (Schultze & Lorenz ,2023; Blum and Roli, 2003). Wich makes brute force approaches the preferred choice, if applicable (Schultze & Lorenz ,2023). Nevertheless, as brute force often isnt fesable because of timely and computational costs, approximate algorithms are indispensable for obtaining near-optimal solutions to complex combinatorial problems in a timely or computationally efficient manner (Schultze & Lorenz ,2023; Dorigo and Stützle, 2010).

residuals correlates or the residuals for the adjacent constructs

Results

Discussion

- what to optimize the scale for?
- dynamic fit indices
- factors 4 and 5
  - adaptive testing/ IRT
    - dimensionality assumption and computationally intense
  - CART - tree based adaptive testing (classification trees) always binary split
    - gini index to identify the cut off
    - POMP method - for differing number of answer formats

- residuals correlates
- heterogeneity of construct

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