

# Development of a German Instrument for Self-Perceived Data Literacy

An Algorithm-based Approach to Scale Development

Leonie Hagitte

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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.

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I dedicate this thesis to

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# Intro

## Background

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 {(carmi2020?)}. 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).

In “Thinking, Fast and Slow,” Kahneman (2011) introduces the two systems of thinking: System 1 and System 2. System 1 operates swiftly, relying on intuition and often succumbing to biases, while System 2 operates more deliberately, engaging in analytical thinking. Kahneman’s exploration extends to the realization that even experts across diverse domains can fall prey to cognitive biases, leading to errors in judgment (Kahneman, 2011). Applying Kahneman’s insights to the realm of data literacy and research questions sheds light on a critical aspect. It underscores the notion that individuals, irrespective of their statistical expertise, remain vulnerable to cognitive biases when interpreting and analyzing data. In the current societal landscape, where data plays an increasingly pivotal role in shaping decisions and policies, acknowledging and addressing these cognitive biases becomes paramount.

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 vs. Information**

The concepts of data and information are foundational in various fields, yet their precise definitions and relationships are often subject to interpretation. In exploring these concepts, it's valuable to consider the insights provided by relevant literature. Is data synonymous with entropy, while information stands in opposition to it? Let's delve deeper into these ideas with insights from scientific literature. 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.

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal*, 27(3), 379-423. Bates, M. J. (2005). An introduction

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## **Measuring 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 selfrating measure!]

## **Conceptual Integration**

finding common ground of the existing theories and

## **Understand and Interpret Data**

## **Contextualize, Evaluate and Critique Data**

## **Integrate Data in One's View of the World**

## **Present/Visualize Data/Information**

## **Manage/Collect/Analyze Data**

## **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).

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## 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 and Katz (1954). The conceptualization of NFC underwent refinement in the mid-1950s through experimental investigations by Cohen and colleagues (e.g., Cohen, Stotland and Wolfe, 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, Wänke, Bohner, Fellhauer and Schwarz, 1994).

## **Self-Efficacy**

-> core self evaluation judge, lock and durham 97 -> heilman und jonas 2010 validation german

The concept of self-efficacy, as formulated by Bandura in 1977 and integral to his social-cognitive theory (Bandura, 1997), revolves around the perceived belief in one’s capability to handle specific situations. While intended as a situation-specific construct, the degree of specificity can vary widely. At one extreme is General SWE, grounded in the assumption that individuals can attribute their experiences of success and failure to themselves and then generalize these experiences. This involves both inductive processes, moving from specific instances to generalizations, and deductive processes, moving from general beliefs to specific situations. The scale used to measure self-efficacy gauges the subjective conviction of an individual’s ability to effectively navigate challenging situations independently. It considers new or difficult situations across various life domains, encompassing barriers that need to be overcome. The overarching aim of Self-Efficacy (SWE) is to predict how individuals cope constructively with the challenges of life (Jerusalem, 1990; Schwarzer, 1994).

## **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

### 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 Self-Efficacy**

### **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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