Development of the data literacy scale in social sciences: A validity and reliability study

Çağrı Demirtaş[1]

1 Department of Social Studies Education, Education Faculty, Adıyaman University, Adıyaman, Türkiye

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ABSTRACT

The present study will provide important information for future educational strategies and intervention programs by revealing the current status of undergraduate students in data literacy. The current research is a scale development study. The study group consisted of undergraduate students from 20 universities in Türkiye. Data validity and construct analysis were performed using exploratory and confirmatory factor analyses. Whereas the Kaiser–Meyer–Olkin (KMO) value of 0.967 indicated that the sample was perfect, Bartlett's test confirmed that the correlations between the items were adequate. Cronbach's alpha value of 0.973 indicated a very high internal consistency. Furthermore, high reliability was provided with the inter-form correlation of 0.853, the Spearman-Brown coefficient of 0.920, and the Guttman split-half coefficient of 0.919. The exploratory factor analysis revealed that the scale consisted of three sub-dimensions and explained 64.056% of the total variance. The items showed factor loadings above 0.40. The CFA results confirmed that the model represented the three sub-dimensions of data literacy well, and the RMSEA, CFI, IFI, and RFI fit indices were high. Compared with the available scales in the literature, this study makes a significant contribution by presenting a customized, comprehensive measurement tool in the context of the social sciences.

KEYWORDS: Education; Data literacy; Social sciences; Undergraduate students; Technology

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1. Introduction

CERN's mission is explained in the following way: "At CERN, our work helps to uncover what the universe is made of and how it works" (The CERN Council, 2024a). At CERN, experiments are designed to produce large particles, such as the Higgs boson or the top quark, using the Large Hadron Collider (The CERN Council, 2024b). Scientists design and conduct studies to learn what was happening in the universe, even before they existed, to increase understanding of matter and the universe's origins by measuring its properties. To this end, they plan extensive research with many participants, spend large sums of money, and continue it for years. The main purpose is to reach the "first data," the "notion" regarding how the universe or world is formed. It can be stated that data existed before humanity and gradually grew to gigantic proportions. When the increasing impact of digitalization is added to the growing amount of data every second, huge volumes of data are generated.

A significant increase in worldwide data volume and the rapid development of data-processing technologies have attracted attention. This has caused a greater need to conduct studies addressing and examining data and, therefore, categorizing, analyzing, combining, making meaningful, and using

Corresponding author: cagridemirtass@mail.com

data. In this respect, it is critical to examine data, the first step in reaching the data, information, knowledge, and wisdom (DIKW) scheme (Ackoff, 1989), and data literacy, which refers to reading data. To this end, it is necessary to first define the data and then determine its characteristics and boundaries.

1.1. Literature Review

The dictionary definitions of data are as follows: (1) Factual information used as a basis for reasoning, discussion, or calculation; (2) digital information that can be transmitted or processed digitally; (3) something provided by a device or organ that includes useful, irrelevant, or redundant information and must be processed to be meaningful (Merriam-Webster, 2024).

The literature states that data consist of symbols, simple, unrefined, and usually unfiltered things that include the characteristics of objects and events (Amidon, 1997; Ackoff, 1989; Davenport & Prusak, 2000; Kelley, 2002; Liew, 2007). Data represent the characteristics of not only objects or events but also living beings, ideas, emotions, times, places, and many other phenomena in the world. Data are nothing unless they concern you; once they begin to concern you, data may be everything (Gencer & Altun, 2021). In general terms, as stated by Demirtaş (2022), data can be expressed as simple, unrefined numbers, symbols, words, records of events, calculations, images, observations, numerical or verbal expressions, etc., obtained by individuals through experiments, observations, or by chance.

As the data definitions indicate, they have many forms and characteristics. In this data universe, it has become necessary for individuals to know which data, where, how, and by what means they will obtain it, and under what principles they will use it in their daily or business lives. This requires individuals to be able to read data. Literacy, specifically data literacy, comes to the forefront at this stage. In an interdisciplinary context, literacy can be defined as the ability to define, understand, interpret, create, calculate, and communicate using visual, auditory, and digital materials (Demirtaş, 2022). In addition to knowing, literacy involves displaying developed/advanced/high-level skills and/or abilities in that direction, and developing behaviors toward awareness (İnan, 2021).

Regarding data literacy, Schield (2004) described it as a set of skills, including accessing, evaluating, manipulating, summarizing, and presenting data. As defined by Qin and D'Ignazio (2010), data literacy is the ability to understand, use, and manage data. According to another definition, data literacy is "a person's level of understanding of how to find, evaluate, and use data to know how to teach" (Mandinach & Gummer, 2016). By contrast, data literacy involves formulating hypotheses, identifying problems, interpreting data, and planning, thereby enabling data to be converted into information and, ultimately, into actionable knowledge. According to Calzada Prado and Marzal (2013), data literacy enables individuals to access, interpret, critically evaluate, manage, process, and use data ethically. Another aspect of data literacy involves understanding what data mean, including critically evaluating data, knowing how to read graphs and tables appropriately, drawing correct conclusions from data, and recognizing when data are used in misleading or inappropriate ways (Carlson et al., 2011; Koltay, 2015). In general terms, data literacy can be expressed as a set of skills, including obtaining data (from whom, by what means, and under what conditions data are collected); evaluating, interpreting, and using data; and carrying out this process within the framework of ethical principles.

Definitions of data literacy also reveal a framework for data literacy. This framework or indicator reveals the dimensions considered important for a data-literate individual to acquire. Although the content of these dimensions may differ slightly depending on the relevant subject or field, different researchers have revealed similar structures. Considering this structure, D'Ignazio and Bhargava (2015) categorized data literacy as follows: reading data; working with data; analyzing data; arguing with data. Calzada Prado and Marzal (2013) indicated the following five dimensions of data literacy: understanding data; finding and/or obtaining data; reading, interpreting, and evaluating data; managing data; using data. Deahl (2014) expressed six dimensions of data literacy: understanding data, finding data, collecting data, interpreting data, visualizing data, and supporting arguments using data.

Based on the literature, a simple and comprehensive structure for data literacy can be presented, including the following dimensions: defining data; detecting/accessing data; collecting data; organizing data; using data; and the ethical dimension of data.

The rapidly changing technological and scientific environment requires individuals to understand, interpret, and use the data effectively. In this regard, the education system will inevitably play a role in ensuring that students acquire data literacy skills. Measuring data literacy skills is as important as ensuring that students acquire them. This reveals the need for an appropriate measurement tool to determine the current status of data literacy skills.

Advancements in science and technology have transformed the concepts of assessment and evaluation in parallel with changes in our century's understanding of the learning-teaching process. In addition to these activities carried out with a student-centered education approach, assessment and evaluation practices have also evolved to allow students and their peers to evaluate their own work. Thus, students can actively participate in the evaluation process and perceive themselves and their environment from a personal perspective. This creates an environment in which they can analyze their strengths and weaknesses and succeed in life (Çalışkan, 2012).

Upon examining the literature, two scales have been developed to assess the data literacy status of associate degree students and teachers. Kim et al. (2023) conducted a study to explore how college students in the United States of America evaluate their data literacy and to examine demographic and education/career progression differences in self-evaluated data literacy levels among 573 students at four community colleges. The researchers developed a three-factor, 24-item "data literacy scale" with reliability and construct validity. Trantham et al. (2021) developed the "NU Data Knowledge Scale (NUDKS)" to reliably evaluate educators' data-usage skills and determine teachers' data literacy for in-class data use. The scale development process was tested for its suitability for the Rasch model.

When the existing scales in the literature are examined, they primarily aim to measure individuals' self-perceived data literacy levels within specific contexts, such as community college students or in-service teachers' classroom data use. For instance, the scale developed by Kim et al. (2023) focuses on university students' self-evaluations of their data literacy skills, whereas the NU Data Knowledge Scale (Trantham et al., 2021) assesses educators' competencies in using data for instructional purposes. These instruments provide valuable contributions by operationalizing data literacy within their respective target groups and professional contexts. However, a scale specifically designed to conceptualize and measure data literacy within the social sciences at the undergraduate level appears to be scarce in the literature. Therefore, the present study aims to address this gap by developing a data literacy scale grounded in the theoretical dimensions of data literacy and tailored to the epistemological and methodological characteristics of social sciences.

1.2. Purpose

The present study aims not only to develop a valid and reliable data literacy scale but also to establish a theoretically grounded and empirically validated multidimensional framework of data literacy within the context of social sciences. By modeling data literacy as a higher-order construct, the study seeks to contribute to conceptual clarification in the field and to provide a psychometrically robust instrument for future research, curriculum development, and educational policy implementation.

2. Method

2.1. Study Group

The study group consisted of students enrolled in the 1st, 2nd, 3rd, and 4th grades at 20 universities in Türkiye. A purposive sampling method was employed, and within this framework, criterion sampling was adopted. The inclusion criterion was defined as being an actively enrolled undergraduate student at the time of data collection.

Cohen and Cohen (1983) stated that a minimum of ten participants should be included in each variable. As a general rule, it was suggested that the minimum sample size should be at least five times the number of variables to be analyzed, and that a more acceptable ratio is 10:1 (Hair et al., 2014). In the present study, 381 individuals were included, which is more than 11 times the number of variables for exploratory factor analysis (EFA). It is usually stated that sample sizes of at least 200, 250, or 500 people, or 3, 6, or 20 times the number of variables, should be used for confirmatory factor analysis (CFA) (De Winter et al., 2009; Uyumaz & Sırgancı, 2020). In this study, 200 individuals, approximately six times the number of variables, were included. Table 1 lists participants' information.

Table 1 ***EFA-CFA Participant Information***

Group	Male	Female	1st Grade	2nd Grade	3rd Grade	4th Grade
EFA (N=381)	106	275	83	90	78	130
CFA (N=200)	49	151	18	65	37	80

2.2. Data Collection and Analysis

Clark and Watson (1995) stated that scale development is a process that includes a clear definition of the target structure, carefully creating an item pool, testing the items in the pool on a representative sample, and assessing dimensionality and discriminant validity with inter-item correlation and factor analysis (as cited in Koyuncu & Kılıç, 2019). In this study, the process was carried out with these stages in mind.

In this research, content and construct validity were examined as part of the validity studies. To ensure content validity, a literature review was conducted, as specified above, and statements on the scale were presented to experts. Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were conducted to examine construct validity.

In exploratory factor analysis (EFA), researchers aim to determine the most appropriate number of factors, reveal whether the measured variables (items) are reasonable indicators of latent dimensions, and elucidate the theoretical structure (Goodwin, 1999; Brown, 2015). Confirmatory factor analysis (CFA) tests the fit of a hypothetical factor structure to the observed covariance structure of the measured variables and provides empirical support for theoretical assumptions (Goodwin, 1999; Jöreskog, 1971; Floyd & Widaman, 1995; Koyuncu & Kılıç, 2019; Uyumaz & Sırgancı, 2020). Prior to factor analysis, the suitability of the data obtained from undergraduate students for factor analysis was examined using the Kaiser-Meyer-Olkin (KMO) coefficient and Bartlett's test of sphericity.

Corrected item-total correlation coefficients, Cronbach's alpha internal consistency coefficients, and Guttman split-half coefficients were calculated within the scope of reliability studies.

2.3. Ethical Considerations

This study was conducted in accordance with established ethical principles. Prior to data collection, ethical approval was obtained from the Adıyaman University Social and Humanities Ethics Committee (decision dated 14.05.2024 and numbered 53). The approved research protocol was reviewed and authorized by the committee. As the data were collected from undergraduate students, the official ethics committee approval was secured before the study commenced, and the approval document was presented to the participants during the research process.

3. Findings

3.1. Scale Development Steps

When developing the scale form, the literature on data, literacy, and data literacy was first reviewed, and the theoretical framework for data literacy and its dimensions was created. The dimensions were used to avoid overlooking any points when writing the items.

Within the scope of the dimensions identified in the literature, a pool of 45 items to measure undergraduate students' data literacy perceptions was created. To evaluate the items in the pool for content validity, they were presented to 10 academicians and experts in data literacy, and experts' feedback was received using the Lawshe form. In line with the experts' opinions, 11 items were removed from the scale form, leaving 34 items. Table 3 presents the findings on the items, including content validity ratios and indices specified in the literature, as evaluated by domain experts using the Lawshe technique (Lawshe, 1975). Within the scope of the experts' suggestions for other items, the scale items were corrected for language consistency, in line with the assessment and evaluation criteria. Two language expert academicians were consulted to evaluate the clarity and comprehensibility of the items in terms of meaning. The items were corrected within the scope of the suggestions provided by domain experts.

The scale was pre-applied to 20 undergraduate students who were not included in the intervention. Necessary corrections were made to the scale form, which was finalized in line with the undergraduate students' suggestions and expert evaluations. The final version of the scale included 34 items. Each item in the scale form was rated on a Likert-type scale ranging from (5) strongly agree, (4) agree, (3) no idea, and (2) disagree to (1) strongly disagree. The scale was applied to undergraduate students studying at 20 universities in Türkiye. Table 1 lists the students' demographic information. Data obtained from the intervention were analyzed.

3.2. Findings Regarding Content Validity

Table 2 presents the minimum content validity criteria (CVC) that items should meet, based on the total number of experts who expressed their opinions, as specified by Veneziano and Hooper (1997).

Table 2 ***Content Validity Criteria (Veneziano & Hooper, 1997)***

Number of Experts	Minimum Value
5	0.99
6	0.99
7	0.99

Number of Experts	Minimum Value
8	0.78
9	0.75
10 (present study)	0.62

Opinions in the expert evaluation form were analyzed and interpreted using Lawshe's technique. After obtaining expert opinions through the expert evaluation form, content validity ratios (CVRs) for the items were obtained, and the scale's content validity index (CVI) was calculated. Ultimately, the final form was created based on the items' CVRs, and the scale's CVI was calculated from the items' CVRs.

Table 3 ***Content Validity Rates***

Items	N Experts	Essential	Not Necessary	CVR
Item 1	10	9	1	0.8
Item 2	10	9	1	0.8
Item 3	10	9	1	0.8
Item 4	10	10	0	1
Item 5	10	9	1	0.8
Item 6	10	9	1	0.8
Item 7	10	9	1	0.8
Item 8	10	9	1	0.8
Item 9	10	10	0	1
Item 10	10	10	0	1
Item 11	10	9	1	0.8
Item 12	10	10	0	1
Item 13	10	9	1	0.8
Item 14	10	10	0	1
Item 15	10	10	0	1
Item 16	10	9	1	0.8
Item 17	10	10	0	1
Item 18	10	9	1	0.8
Item 19	10	10	0	1

Items	N Experts	Essential	Not Necessary	CVR
Item 20	10	10	0	1
Item 21	10	9	1	0.8
Item 22	10	9	1	0.8
Item 23	10	10	0	1
Item 24	10	9	1	0.8
Item 25	10	9	1	0.8
Item 26	10	10	0	1
Item 27	10	10	0	1
Item 28	10	10	0	1
Item 29	10	9	1	0.8
Item 30	10	10	0	1
Item 31	10	10	0	1
Item 32	10	10	0	1
Item 33	10	10	0	1
Item 34	10	10	0	1
				CVR = 31.4 | CVI = 0.92

As shown in Table 3, the CVR values for the items in the draft form ranged from 0.8 to 1.00. The CVR was calculated to be 31.4. The content validity index (CVI) was obtained from the total CVR averages of the items significant at $\alpha = 0.05$, and included in the final form. The CVI value of 0.92 indicates that the scale is statistically significant (Lawshe, 1975).

3.3. Findings Regarding Validity Studies

3.3.1. Exploratory Factor Analysis

Exploratory factor analysis (EFA) was performed to determine the construct validity of the Data Literacy Scale (DLS) and to reveal the factor structure. The Kaiser-Meyer-Olkin (KMO) sample adequacy value was 0.967, indicating that the sample size was adequate for EFA (Field, 2009; Nikkhah et al., 2018). The lowest KMO value calculated for each item was 0.941, confirming that the sample size was adequate. Additionally, Bartlett's test found $\chi^2(561) = 11048.951$; $p < .05$, and this finding demonstrated that the inter-item correlations were sufficiently large for EFA.

A Cronbach's alpha value of 0.973 indicates very high internal consistency. This shows that the 34 items of the scale are highly consistent with each other and that the scale is a reliable measurement tool. In social sciences, Cronbach's alpha value above 0.70 is generally considered acceptable; the value between 0.80–0.89 is considered good; the value of 0.90 and above is considered excellent. In this respect, a value of 0.973 indicates that the scale has excellent internal consistency and that all items are compatible with the overall structure (DeVellis, 2012; Hair et al., 2014; Sarmento & Costa, 2017).

After the data were deemed suitable for factor analysis, an exploratory factor analysis was conducted to assess the scale's construct validity. Principal components and the direct oblimin method were employed. The principal component method was selected to reduce dimensionality, strengthen interpretation, and prevent information loss. Because these factors are theoretically related, the direct oblimin method was selected. Oblique rotations allow correlated factors rather than maintaining independence among the rotated factors (Hair et al., 2014). Worthington and Whittaker (2006) argued that the minimum factor loadings should be as high as possible; thus, this would reduce cross-loading. Hair et al. (2014) reported that factor loadings in the range of ±.30 and ±.40 meet the minimum level for interpreting the structure. This study determined the minimum factor loading to be 0.40. In the analysis, all the items had values greater than 0.40. Therefore, the analysis continued without deleting any items.

Table 4 ***Total Variance Explained***

Comp.	Total	% of Var.	Cum. %	Total	% of Var.	Cum. %	Rot. Total[a]
1	18.388	54.083	54.083	18.388	54.083	54.083	16.862
2	2.047	6.021	60.104	2.047	6.021	60.104	12.306
3	1.344	3.952	64.056	1.344	3.952	64.056	10.099

Note. Extraction Method: Principal Component Analysis. [a] When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

The EFA determined that the 34-item Data Literacy Scale has three subdimensions (factors). According to the Kaiser criterion, components have eigenvalues higher than 1 (Braeken & Van Assen, 2017). Hence, these three components were considered in the analysis. These three factors account for 64.056% of the total variance. Furthermore, it was revealed that the first sub-dimension explained 54.083% of the variance, the second explained 60.104%, and the third explained 64.056%. Accordingly, we concluded that the "Data Literacy Scale" was valid. The rotation sums yield a more balanced distribution of variance by accounting for correlations among the components.

Table 5 ***Item-Total Statistics***

Item	Scale Mean if Deleted	Scale Var. if Deleted	Corrected Item-Total r	α if Item Deleted
i1	136.74	395.441	.635	.973
i2	136.86	394.969	.604	.973
i3	137.01	395.616	.518	.973
i4	136.87	392.105	.634	.973
i5	136.79	392.833	.641	.973
i6	136.76	392.711	.639	.973

Item	Scale Mean if Deleted	Scale Var. if Deleted	Corrected Item-Total r	α if Item Deleted
i7	136.82	392.866	.658	.973
i8	136.92	391.812	.632	.973
i9	136.88	392.068	.646	.973
i10	136.61	392.291	.759	.972
i11	136.81	391.740	.655	.973
i12	136.60	389.035	.789	.972
i13	136.83	389.005	.708	.972
i14	136.83	388.503	.763	.972
i15	136.79	388.075	.764	.972
i16	136.62	389.352	.792	.972
i17	136.81	388.712	.714	.972
i18	136.94	389.765	.661	.973
i19	136.67	389.765	.782	.972
i20	136.65	388.560	.795	.972
i21	136.70	389.669	.773	.972
i22	136.72	388.414	.790	.972
i23	136.73	389.614	.784	.972
i24	136.96	391.906	.589	.973
i25	136.72	389.164	.789	.972
i26	136.87	389.190	.708	.972
i27	136.68	388.156	.794	.972
i28	136.75	390.022	.744	.972
i29	136.69	389.719	.725	.972
i30	136.62	390.894	.757	.972
i31	136.58	390.013	.755	.972
i32	136.57	390.871	.771	.972

Item	Scale Mean if Deleted	Scale Var. if Deleted	Corrected Item-Total r	α if Item Deleted
i33	136.71	388.892	.698	.973
i34	136.61	388.643	.757	.972

Evaluation of Item-Total Statistics: Corrected Item-Total Correlation — the correlation values for all the items varied between 0.518 and 0.795. This indicates that all items are in good agreement with the scale's overall structure and support its reliability. Cronbach's alpha if an item was deleted remained between 0.972 and 0.973 when any item was deleted, indicating that deleting any item from the scale does not significantly impact the overall reliability.

Three factors emerge, given that Hair et al. (2014) stated that factors with eigenvalues greater than 1 should be taken into account (Scree Plot Analysis). Hence, the analysis considers the first three components.

Table 6 ***Items' Distribution by Factors and Factor Loadings***

Item	Factor 1 Data Collection	Factor 2 Data Processing	Factor 3 Ethics
i1	.708		
i2	.754		
i3	.696		
i4	.752		
i5	.732		
i6	.658		
i7	.712		
i8	.597		
i9	.487		
i10		.555	
i11		.652	
i12		.576	
i13		.586	
i14		.462	
i15		.493	
i16		.719	
i17		.652	

Item	Factor 1 Data Collection	Factor 2 Data Processing	Factor 3 Ethics
i18		.653	
i19		.758	
i20		.758	
i21		.731	
i22		.910	
i23		.858	
i24		.667	
i25		.827	
i26		.615	
i27		.788	
i28		.810	
i29			.656
i30			.680
i31			.660
i32			.727
i33			.702
i34			.653

Note. The 'minimum residual' extraction method was used in combination with an 'oblimin' rotation. Factor loading values below 0.40 are not given in the table.

As seen in Table 6, the first sub-dimension comprised nine items (items 1–9), the second comprised 19 items (items 10–28), and the third comprised six items (items 29–34). The lowest factor loading is 0.462. Therefore, since factor loadings of 0.40 or higher are considered ideal (Field, 2009), the items were considered to contribute significantly to the factors. Furthermore, the factors were named as "Data Collection," "Data Processing," and "Ethics" respectively.

Table 7 ***Factor Names and Reliability***

No.	Factor Name	No. of Items	Cronbach's α
1	**Data Collection**	9	0.902
2	**Data Processing**	19	0.964
3	**Ethics**	6	0.940

No.	Factor Name	No. of Items	Cronbach's α
Total		34	**0.973**

Table 7 shows the number of items and Cronbach's alpha reliability coefficients for the Data Collection, Data Processing, and Ethics factors. High Cronbach's alpha values indicated that the scale had high internal consistency and reliability.

Table 8 ***Component Correlation Matrix***

Component	1	2	3
1	1.000	0.651	0.573
2	0.651	1.000	0.383
3	0.573	0.383	1.000

The component correlation matrix shows that Component 1 and Component 2 had a moderate positive correlation (r = 0.651), indicating that these two factors overlapped to some extent. Component 1 and Component 3 showed a moderate positive correlation (r = 0.573). Components 2 and 3 showed a lower but positive correlation (r = 0.383).

3.3.2. Reliability Statistics

Table 9 ***Reliability Statistics***

Measure	Part 1	Part 2	Total	Corr. Between Forms	Spearman-Brown (Equal)	Spearman-Brown (Unequal)	Guttman Split-Half
α Value	0.945	0.961	0.853	0.853	0.920	0.920	0.919
No. Items	17	17	34				

Cronbach's alpha values higher than 0.9 in both parts (Part 1: 0.945; Part 2: 0.961) indicate that the scale had high internal consistency. A high correlation between the forms (r = 0.853) indicates that the two parts are quite similar and that the scale has a consistent structure. The high Spearman-Brown coefficient (0.920) for both equal and unequal lengths supports the scale's reliability and consistency. The high Guttman split-half coefficient (0.919) indicates that the scale is highly reliable, even when split in half.

3.3.3. Confirmatory Factor Analysis

A confirmatory factor analysis (CFA) was performed to confirm the factor structure. Whereas EFA investigates the factor structure of how variables are related within a group, the results of the CFA conducted using LISREL confirm the factor structure extracted from EFA.

Table 10 ***Pre- and Post-Modification CFA Fit Indices***

Fit Index	Pre-Modification	Post-Modification	Criteria
χ^2/df	2.49 (1306.47/524)	2.25 (1170.49/520)	≤ 2.5 = perfect fit
RMSEA	0.086	0.077	≤ 0.05 = perfect fit; ≤ 0.06 = good fit

Fit Index	Pre-Modification	Post-Modification	Criteria
CFI	0.97	0.97	≥ 0.90 = good fit
RMR	0.037	0.035	≤ 0.05 = perfect fit
IFI	0.97	0.97	≥ 0.90 = acceptable fit
TLI	0.94	0.97	≥ 0.90 = acceptable fit
RFI	0.94	0.95	≥ 0.90 = acceptable fit
Std. RMR	0.064	0.060	≤ 0.05 = perfect fit

The fit indices presented in Table 10 indicate that the model provided a good-to-perfect fit both before and after modification. The χ^2/df value improved from 2.49 to 2.25, both within the perfect fit criterion of ≤ 2.5. RMSEA improved from 0.086 to 0.077; CFI and IFI remained at 0.97 in both cases, indicating a good fit. RMR improved from 0.037 to 0.035; TLI improved from 0.94 to 0.97; and RFI improved from 0.94 to 0.95. As a result of the first analysis, the modifications suggested by the program for items 6–5, 12–10, 22–21, and 28–27 were implemented by the researcher for the items within the same dimension.

Factor loadings indicate that the main factor "data literacy" relates to its sub-dimensions as follows: Data Collection (λ = 0.80), Data Processing (λ = 1.02), and Ethics (λ = 0.85). These loadings demonstrate that data literacy has three sub-dimensions that are strongly related to the main factor.

4. Discussion

The Kaiser-Meyer-Olkin (KMO) sample adequacy value was 0.967, indicating that the sample size was adequate for EFA. The Kaiser-Meyer-Olkin values between 0.00–0.49 are classified in the "unacceptable" category, values between 0.50–0.70 are classified in the "mediocre" category, values between 0.70–0.80 are classified in the "good" category, values between 0.80–0.90 are classified in the "high" category, and values of 0.90 and above are classified in the "excellent" category (Field, 2009; Nikkhah et al., 2018). The lowest KMO value calculated for each item was 0.941, confirming that the sample was adequate. Furthermore, Bartlett's test found $\chi^2(561) = 11048.951$; $p < .05$, demonstrating that inter-item correlations were adequate for EFA.

Cronbach's alpha was 0.973. This indicates that the 34 items of the scale are highly consistent with each other and that the scale is a reliable measurement tool. In this respect, the value of 0.973 indicates that the scale has excellent internal consistency and that all items are compatible with the overall structure. All values, such as Cronbach's alpha, Spearman-Brown coefficient, and Guttman split-half coefficient, confirmed that the scale provided consistent and reliable results when divided into parts and as a whole. In the social sciences, the reliability score measured by Cronbach's alpha is considered acceptable when the threshold of .70 is exceeded (Hair et al., 2014; DeVellis, 2012), the value between 0.80–0.89 is considered good, and it is considered excellent when it takes the value between 0.90–1.00 (Sarmento & Costa, 2017). These results support that the scale is a valid and reliable measurement tool.

The EFA determined that the 34-item Data Literacy Scale has three subdimensions (factors). Components 1, 2, and 3 had eigenvalues of 18.388, 2.047, and 1.344, respectively, and, according to the Kaiser criterion, factors with eigenvalues greater than 1 were considered significant (Braeken & Van Assen, 2017). These components explained 64.056% of the total variance and represented a significant portion of the dataset. Additionally, it was found that the first sub-dimension explained 54.083% of the variance, the second 60.104%, and the third 64.056%. Accordingly, we concluded that the "Data Literacy Scale" was valid.

Furthermore, the CFA shows that the model's fit indices represent the three sub-dimensions of data literacy (collection, processing, and ethics). High RMSEA, CFI, IFI, and RFI values indicate that the model provides a very good fit compared with the independent model. A χ^2/df value ≤ 2 indicates a good fit (Cole, 1987, as cited in Karaman, 2023). It is stated that if this coefficient falls between 2 and 5, it is an acceptable level (Hu & Bentler, 1999; Kline, 2016). An RMSEA value between 0.08 and 0.10 is considered a mediocre fit (MacCallum et al., 1996), a value of 0.07 or below is considered an acceptable-reasonable fit (Steiger, 2007), and a value equal to or lower than 0.05 is considered a very good fit (Sarmento & Costa, 2019). Brown (2015) reported that fit indices are divided into three groups: absolute fit indices (χ^2, SRMR, and RMR), parsimony fit indices (RMSEA), and comparative fit indices (CFI-IFI, TLI), and suggested using at least one index from each group in reporting (as cited in Koyuncu & Kılıç, 2019).

Exploratory factor analysis (EFA) revealed that the scale comprises three sub-dimensions, which explain a significant portion of the total variance. All items exceeded the determined minimum factor loading, and high Cronbach's alpha values strongly supported the scale's internal consistency and reliability. The results of the confirmatory factor analysis (CFA) demonstrate that the scale has a high model fit and successfully represents the three sub-dimensions of data literacy. These findings confirm that the data-literacy scale is a valid and reliable measurement tool. In its current form, this model provides a solid foundation for research on data literacy.

The Data Literacy Scale developed in the current study was meticulously evaluated for validity and reliability and demonstrated strong performance. These results reveal important similarities and differences when compared with the scales available in the literature. For instance, Kim et al. (2023) showed that the three-factor, 24-item Data Literacy Scale, developed for university students, demonstrated high reliability and construct validity. Likewise, the "NU Data Knowledge Scale (NUDKS)", developed by Trantham et al. (2021), was designed to reliably evaluate educators' data literacy and data usage skills, and was tested for its suitability to the Rasch model. Although both scales were evaluated as valid and reliable, they differ from this study in terms of purpose, scope, and items. In particular, while studies by Evans and Trantham address data literacy within a general framework, the scale developed in the current study aims to measure data literacy in the context of social sciences.

4.1. Implementing the Scale in Different Cultural Contexts

Examining the scale's validity and reliability across culturally diverse contexts (countries or cultures) will support its international use. Cross-cultural validity tests can reveal whether a scale works similarly in different cultural groups.

4.2. Use for Practical Applications and Training Programs

The results obtained can be used to develop data literacy training programs. This scale can be used to measure the effects of training programs and assess participants' progress.

5. Declarations

5.1. Author Contributions (CRediT)

Çağrı Demirtaş: Conceptualization, Methodology, Investigation, Formal Analysis, Data Curation, Writing – Original Draft, Writing – Review & Editing, Visualization, Project Administration.

5.2. Conflict of Interest

The author declares no financial, commercial, or personal conflicts of interest related to this study.

5.3. Funding Statement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. The study was not supported by any institutional research program, foundation, or ministry.

5.4. Data Availability Statement

The data related to the study can be accessed via the links given below.

EFA:
https://docs.google.com/spreadsheets/d/17r33zkIzZ3xHO7NFZoPRhwO5s00xtzyiWMiZKUhJzNk/edit?usp=sharing

CFA:

https://docs.google.com/spreadsheets/d/13RTYYMR5ihpa7OH_CqJ3NRxaZge-zOjIDgymkkiofaU/edit?usp=sharing

5.5. Ethics Approval

Ethical approval for this study was granted by the Adıyaman University Social and Humanities Ethics Committee (Approval No: 53; Approval Date: 14.05.2024). The purpose of the study is to develop a data literacy scale for use in the social sciences field. Participation was entirely voluntary, and no personally identifiable information was requested from participants. All responses were kept strictly confidential and evaluated solely by the research team. The data obtained will be used exclusively for scientific publications.

5.6. Use of Artificial Intelligence (AI) Tools

The authors disclose the use of AI-assisted tools in the preparation of this manuscript. During the preparation of this study, the authors used ChatGPT for language editing and reference ordering purposes. After using this tool, the authors revised and organized the content and references as needed; the AI tool used has been included in the reference list. AI tools were not used to generate or alter empirical data, produce analytical results, or shape the study's core findings and conclusions. All AI outputs were reviewed and verified by the authors, who take full responsibility for the integrity, originality, and accuracy of the content.

5.7. Acknowledgements

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6. Appendix: Data Literacy Scale Items

Table A1 presents all 34 items of the Data Literacy Scale in Social Sciences, organized by sub-dimension.

Table A1 ***Data Literacy Scale — Items by Sub-Dimension***

Dimension	Items
Data Collection	i1. I know that there are different types of data.
	i2. I know that everything that exists in nature can be data.
	i3. I know that for something to be data, it must be processed.
	i4. I know that verbal expressions can be data.
	i5. I know that data existed before the invention of computers.
	i6. I know that data will not end when computers disappear.
	i7. I know that sounds can be data.
	i8. I know that data exist in nature by itself.
	i9. I know where I can access the data I need.
Data Processing	i10. I know that data can be collected from people.
	i11. I know that data can be collected from animals.
	i12. I know that data should be collected in line with the purpose.
	i13. I know that data can be collected from everything in nature.
	i14. I know how to access the needed data.
	i15. I know that data can be collected without the help of a technological tool.
	i16. I know that data are meaningful when collected in line with a purpose.
	i17. I know that even a pen and paper will be enough as a data collection tool.
	i18. I know that it is not necessary to be an expert to collect data.
	i19. I know that data such as symbols, numbers, images, sounds, etc. can be processed by bringing them together.
	i20. I know that data turn into information when processed.
	i21. I know that data processing increases the usability of that data.

Dimension	Items
	i22. I know that data can be formed from information again.
	i23. I know that data are also used outside of scientific research.
	i24. I know that it is impossible to use all the data that exist in nature nowadays.
	i25. I know that data can be used multiple times.
	i26. I know that everyone uses data in their daily lives.
	i27. I know that the use of data makes it easier to understand a situation.
	i28. I know that data will not lose its function when used.
Ethics	i29. I know that it is necessary to inform participants to collect data.
	i30. I know that the actual purpose should be disclosed when collecting data.
	i31. I know that it is illegal to share the data of the person(s) from whom the data were collected with others without their permission.
	i32. I know that it is necessary to receive permission from individuals to collect data from them.
	i33. I know that the data should not be used for any purpose other than the purpose for which it was collected.
	i34. I know that legal permissions received to collect data must be presented to the participant.