Journal of Theoretical Educational Science, 18(1), 106-130, January 2025
Kuramsal Eğitimbilim Dergisi, 18(1), 106-130, Ocak 2025
[Online]: http://dergipark.org.tr/akukeg
DOI number: http://doi.org/10.30831/akukeg.1472451

Data Literacy at School: A Scale Development Study

Okulda Veri Okuryazarlığı: Bir Ölçek Geliştirme Çalışması

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Received: 23 April 2024 **Research Article** **Accepted:** 25 January 2025

ABSTRACT: The purpose of this study is to develop a valid and reliable scale to determine and evaluate the different dimensions of data literacy at school. The study is a quantitative descriptive survey model. The sampling for exploratory factor analysis was formed of 307 and confirmatory factor analysis 338 teachers and school administrators who are on active duty in 2023-2024 educational year in Kastamonu. Data was collected through a five item likert data collection tool. A three-dimension structure was formed and it was confirmed by CFA. The dimensions of data culture at school are; “data identification”, “data use” and “data management”. Internal reliability and validity was verified through Cronbach Alpha (Cronbach’s α=.882), split half method (r=.837), Spearman-Brown correlation coefficient (R=.911) and Guttman’s lambda (λ=.904). The external reliability and validity was verified by test-retest technique (first application n=44, second application n=39, r=.800, p≤.05, R=.961, p≤.05, and Kendal’s tau-b is τb=.904, p≤.05). The findings confirmed the validity and reliability of the scale.

Keywords: Data literacy, data identification, data culture, data management.

ÖZ: Bu çalışmanın amacı okulda veri okuryazarlığının farklı boyutlarını ortaya koymak ve bu farklı boyutları değerlendirebilmek adına geçerli ve güvenilir bir ölçek geliştirmektir. Çalışma nicel betimsel tarama modelinde bir araştırmadır. Çalışmanın örneklemini Kastamonu’da 2023-2024 eğitim öğretim yılında aktif görevde olan, açımlayıcı faktör analizi için 307, doğrulayıcı faktör analizi için 338 öğretmen ve okul yöneticisi oluşturmuştur. Veri beşli Likert formunda bir veri toplama aracı ile elde edilmiştir. Analiz sonucunda üç boyutlu bir ölçek geliştirilmiş ve bu ölçek doğrulayıcı faktör analizi ile doğrulanmıştır. Ölçeğin boyutları “verinin tanımlanması”, “verinin kullanılması” ve “veri yönetimi” olarak adlandırılmıştır. Ölçeğin iç tutarlılığı ve geçerliliği Cronbach Alfa (Cronbach’s α=.882), split half yöntemi (r=.837), Spearman-Brown korelasyon katsayısı (R=.911) ve Guttman’s lambda (λ=.904) ile doğrulanmıştır. Ölçeğin dış geçerliğinin test edilmesinde test-tekrar test yönteminden yararlanılmıştır (ilk uygulama n=44, ikinci uygulama n=39, r=.800, p≤.05, R=.961, p≤.05, ve Kendal’s tau-b τb=.904, p≤.05). Bulgular ölçeğin geçerli ve güvenilir olduğunu ortaya koymuştur.

Anahtar kelimeler: Veri okuryazarlığı, verinin tanımlanması, veri kültürü, veri yönetimi.

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Citation Information
Duygulu, A., Doğan, S., & Yıldız, S. (2025). Data literacy at school: A scale development study. *Kuramsal Eğitimbilim Dergisi [Journal of Theoretical Educational Science]*, *18*(1), 106-130.

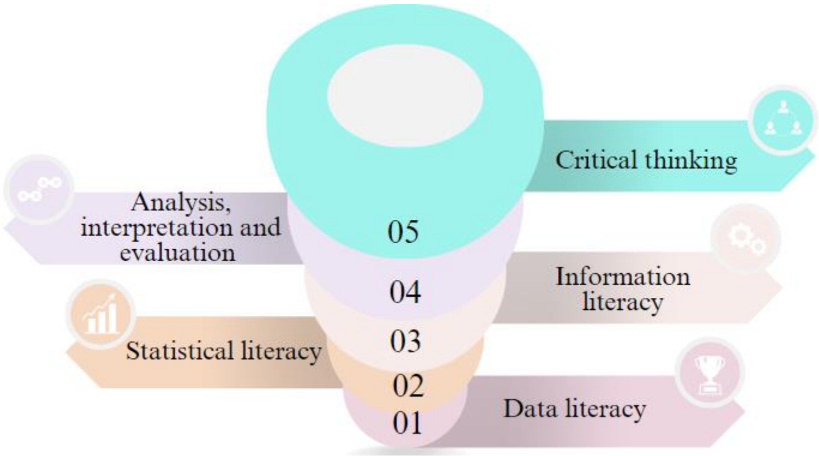
ISSN: 1308-1659

As in all other organizations, data play a key role in the development of and have crucial functions for educational institutions. First of all, student achievement data is one of the key references to assess whether educational institutions' performance comply with the set standards. It is also essential for school administrators and policy makers to have a healthy understanding for the effectiveness of curriculums and educational implementations and improve teaching and learning processes. Data driven assessments for educational implementations are central to justify the decisions (Knapp et al., 2007, p. 77) and thus data are vital assets for decision making processes in educational institutions. In this regard, data also add to the accountability of the educational institutions. Data can also contribute to the allocation of the resources in the right domains in educational institutions by revealing the priority areas (Custer et al., 2018, p. 4). Data based needs analysis could optimize the use of organizational resources. Student achievement data is the key for effective guidance for students as well as the areas of professional development of teachers (Breiter & Light, 2006, p. 213). Performance data form the basis for determining attainable performance standards for educational institutions (Armstrong & Anthes, 2003, as cited in Datnow & Park, 2014, p. 19). Data can also enable the establishment of a data based communication ecosystem at educational institutions (Earl & Katz, 2006, as cited in Datnow & Park, 2014, p. 19). It is important for the mission statement of the educational institutions to be measurable and data in this regard are central to compare and contrast the realized performance of the educational institutions with the goals set in the mission statement (Goldring & Berends, 2009, p. 185). All in all, data is a key component for the development of educational institutions. Despite its significance, members of the educational institutions should have developed a form of data literacy to benefit from data obtained or generated.

Data literacy involves the collection, processing, management, and evaluation of data for the purpose of scientific enquiry and providing access to actionable information (Qin & D'Ignazio, 2010, p. 5). Data literacy is a concept which corresponds to the skills for utilizing data in solving problems related to real life (Wolff et al., 2016, p. 10). Data literacy may be perceived as a discipline which requires less technical skills compared to computer technologies and information management systems. However, data literacy entails having a set of skills related to accessing, processing, analyzing and transforming data into information. Data literacy also forms the basis of critical thinking. The relationship between data literacy and critical thinking can be presented in Figure 1 (Shields, 2005, p. 8).

Figure 1

Critical Thinking Perspective

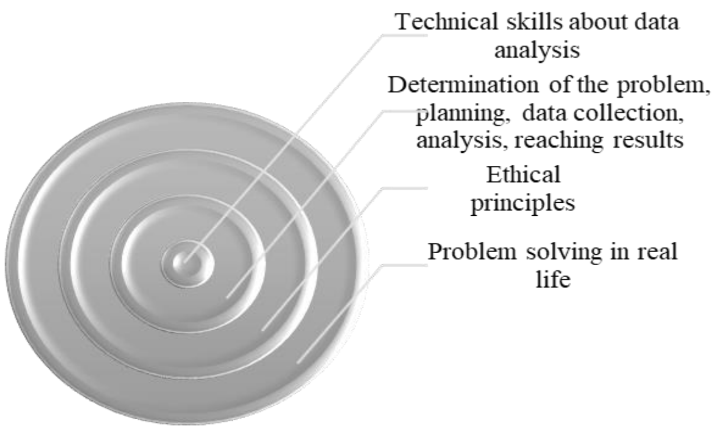


Note. (Shields, 2005, p. 8).

When Figure 1 is analyzed, it can be alleged that data literacy constitutes the basis of critical thinking. Data literacy basically focuses on increasing individuals' understanding and awareness of systems, events and phenomena which can be explained based on data (Pangrazio & Sefton-Green, 2020, p. 213). Data literacy not only affects individuals' questioning processes towards events and phenomena, but also plays a functional role in reaching healthy judgements as a result of questioning (Fontichiaro & Oehrli, 2016, p. 22). Data literacy does not mean collecting, processing, transforming and analyzing data. On the contrary, it is based on having some basic technical skills in the process of accessing information from raw data. Data literacy encompasses also the issues such as considering ethical principles in the process of accessing information from data. Wolff et al. (2016, p. 19) put forward the components of data literacy as shown in Figure 2;

Figure 2

Components of Data Literacy



Note. (Wolff et al., 2016, p. 19)

Data literacy plays an active role in the healthy execution of decision-making processes at both individual and organizational levels. The global economy attaches significance to a structure which is based on information. In this respect, data literacy is regarded as an important dexterity in all sectors and disciplines (Ridsdale et al., 2015, p. 2). Data literacy refers to individuals' conceptual knowledge of data and a set of skills for utilizing data in solving problems (Matthews, 2016, p. 54). Data literacy is composed of skills related with knowledge and skills about data concept and data use (Vanhoof et al., 2013, p. 116). In this respect, it can be claimed that improving data literacy at the organizational level can accelerate the identification of organizational problems via a data-based approach and decision making in management processes.

Considering the organizational value of data and data literacy, it can be argued that educational institutions are no exception to this situation. Improving the knowledge and skills of teachers and school administrators in data literacy can pave the way for the development of strategies which can play an effective role in identifying and solving educational problems. Efforts aimed at increasing the competences of teachers and school administrators for data use in schools can mediate the development of data literacy at the institutional level (Vanhoof et al., 2013, p. 132).

Data literacy is important for both school administrators and teachers as it enables the establishment of a data culture at school (Anderson, 2015, p. 203). It paves the way for an organizational level awareness for the functions of data use. Data literacy could encourage and foster data based decision making in educational institutions. Data use at school is possible only if the teachers and administrators have data literacy to a certain extent. Data play a vital role in school feedback cycle and effective data based feedback could be ensured through data literacy at the school level. Data literacy is crucial for both teachers and administrators to base their assessments on objective, verifiable data rather than subjective personal opinions and judgments. Data literacy can also have a positive impact on the attitudes of the school members towards data use and facilitate and enforce the adoption of data use at school. Data literacy is also significant for establishing a data driven communication ecosystem at school. Both teachers and administrators should have basic skills such as interpreting visual data and making comparisons based on verifiable data to ensure a data informed communication system at school.

Despite the awareness of the significance of data literacy at school, school leaders feel themselves inefficient about the data literacy and data based guidance and this brings about a sense of insecurity among the them (Earl & Fullan, 2003, p. 393). Schildkamp and Poortman (2015, p. 232) also found out that individual teachers lack data literacy skills. Training for data literacy is significant both for all educational professionals, including teachers and school leaders (p. 243). The data based evaluation of the current situation of data literacy level at school could be an important step for a healthy needs analysis for data literacy training. The most fundamental function of data literacy at school is the role it plays in data based decision making processes (van Geel et al., 2017, p. 187). Thus, scales for data based decision making prevail the literature, which are functions of data literacy (Yılmaz & Jafarova, 2022, Doğan & Ottekin Demirbolat, 2021, Bennett et al., 2010).

Though it is one of the most significant pre-requisites of data based decision making, there is only one scale development study in literature about data literacy which was carried out by Abrams et al. (2021), which was also adapted to Turkish culture by Naillioğlu Kaymak and Doğan (2023). The original scale was formed of 18 items five sub-components (identifying problems through data use, converting data to information, decision making based on data and assessing the outcomes) and exploratory and confirmatory factor analyses were not carried out in the creation of the scale. The study group was formed of 28 teachers and 15 administrators who completed a professional development program and provided data about data literacy in groups of nine (Abrams et al., 2021, p. 3). A case study design was applied to explore teachers' data use practices and scale was developed through collecting data from various sources such as individual opinions and team discussions (p. 10). It was observed that the some items concentrated on research skills of teachers and administrators rather than their data literacy competencies (for instance the items "Engage in a cycle of inquiry to continually support learning" and "Communicate to colleagues or communicate to colleagues or supervisors about instructional adjustments"). Moreover, some items focused on teaching and learning processes though the aim is to assess data literacy of both teachers and administrators (For instance items "understand the factors that influence test scores", "diagnose teaching and learning issues using student data" and "plan instruction based on findings from data analysis") (p. 12). In our scale though, we aimed at depicting a true picture of data literacy levels of both teachers and administrators to enable a healthier planning for data literacy training. In the Turkish adaptation of the scale which was carried out by Naillioğlu Kaymak and Doğan (2023), items focused on only teaching and learning processes were omitted, Also the last item which focuses on research skills (Engage in a cycle of inquiry to continually support learning) was omitted as its error variance is high. The final version of the adapted scale though misses an important dimension of data literacy, which is data management. Data management is the coordination and the control of data generation processes, which are targeted to solve a organizational problem (Gordon, 2007, p. 54). The scale in this study was designed to address all integral dimensions of data literacy and thus could enable a more vivid picture of the prevalent situation of data literacy at schools.

Method

The research is a quantitative research in a descriptive survey model. Descriptive research aims at revealing the components and characteristics of the subject in detail (Howitt & Cramer, 2017, p. 29). Researches in descriptive survey model aim at determining issues such as participants' thoughts, attitudes and skills towards a particular subject (Büyüköztürk et al., 2008, p. 226). The aim of this study is to develop a scale of data literacy at school based on the views of teachers and school administrators. The development process of the scale was carried out in three different stages: the development of a draft data collection tool based on the literature and expert opinions, exploratory factor analysis and confirmatory factor analysis. Issues such as population and sample, data collection process, data collection tools and data analysis were discussed separately for each stage.

Ethical Procedures

The ethical commission permission for the research was obtained from Ordu University Ethics Committee for Educational Studies on the date 23.02.2024 with the number 2024-32. The ethical principles were attached significance in all phases of the research, beginning with the data collection and reporting the results. No personal data which will allow to expose the identity of the researcher was collected and informed consent was added to the data collection tools. Permission from the principals of the schools was also obtained before the application of the data collection tool.

Development of the Draft Data Collection Tool

In the process of developing the draft data collection tool, as the initial step, a comprehensive literature review was conducted. As a result of the literature review, a 61-item draft data collection tool was developed. The developed tool was submitted to the experts' opinions. The experts to whose opinions were received are associate professor Ümit Dilekçi Nartgün, Batman University, Dr. Gökhan Savaş, Karabük University, and Dr. Erhan Dolapçı Ministry of National Education. Based on the expert's opinions, items 11, 13, 27, 29, 38 were removed from the draft data collection tool in view of the fact that they were not clear and understandable, and items 46 and 54 were combined into a single item. Similarly, items 20, 21 and 6, 17 were combined into single items. Since item 24 met items 22, 23, 25 and 26 in terms of meaning and scope, the related items were removed from the data collection tool. Since the expression "data storage tools" in item19 covers the concepts of "database", "data warehouse" and "data market" in items 42, 43 and 44, items 42, 43 and 44 were removed from the draft tool. Within the framework of expert opinions, it was concluded that it would be appropriate not to include the items 47, 52 and 53 in the draft tool on the grounds that they are met by item 51 in view of meaning and scope. Items 12, 30, 31, 32, 36, 48, 56, 58 were removed from the draft scale based on expert opinions that they were not directly related to data literacy. Items 5 and 16 were removed on the grounds that they contained more than one concepts. Items 2, 3 and 4 were removed from the draft scale due to the fact that they are not related with data, and item 28 was removed from the draft scale due to referring to a stage of data analysis. Item 60 was removed from the draft tool on the grounds that it did not address both teachers and administrators at the same time in terms of data literacy. Item 40 "I can explain what data management is" was rephrased as "I can list the stages in the data management process". Within the framework of expert opinions, the item "I can explain the concept of knowledge pyramid" was added to the draft data collection tool and the draft data collection tool was finalized before the principal components analysis. The final draft data collection tool was composed of 29 items.

The First Application: Exploratory Factor Analysis

The teachers and school administrators in Kastamonu city center (first educational area) and its three different districts (Tosya, İnebolu and Taşköprü) constituted the population of this research. Sample size of the first application is 307 participants. Hair et al. (2014, p. 100) denote that for factor analysis, sample size should be 100 or over. They also allege that the observations should be at least five times more than the total number of items to be analyzed, which equals to 145 observations. Field (2009, p. 647) denote that sample size for factor analysis should be at least 300. In all cases, the proper number for sample size was attained and sample size was assumed to be appropriate for the factor analysis. Different sampling methods were utilized together in the study. Stratified sampling was applied to represent participants from different subgroups such as different duties and school levels. In the similar way, quota sampling was applied to represent the participants from different sub groups in correlation with their ratio in the population. The demographic data about the participants of the first application are presented in Table 1;

Table 1

Demographic Data About the Participants of the First Application

		n	%
Duty	Teacher	231	75.2%
	Administrator	76	24.8%
Seniority	1-10 Years	51	16.6%
	11-20 Years	124	40.4%
	21-30 Years	122	39.7%
	31 years and over	10	3.3%
School Level	High School	169	55.04%
	Secondary School	78	25.4%
	Primary School	60	19.54%

Data was collected through a google survey. Informed consent was added to the online survey. The participants were warned not to include any details to expose their identity in the form. Moreover, they were assured that they would be mentioned as only the case numbers in the data set and data set will be stored in a computer which can be accessed through a code special to the researchers. The survey is in the form of a five item likert scale, extending alternatives from “totally agree” to “totally disagree”. The school principals were informed before the application and their permission was received. The data on online form were transferred to SPSS program. Before the main analyses, data preparation phase was carried out. Firstly, the data sets were checked by means of observation and then missing value analysis was realized. In none of the data sets, the missing values exceeded the threshold of 5% (Tabachnick & Fidell, 2013, p. 63). The highest percentage for missing values was 0.3% in only seven cases of the data set. The EM statistics value is $p=.158$ and $p\geq.05$. The findings denote that the missing values in the data sets signify a random distribution and mean substitution which is one of the most commonly applied methods to replace missing values (Hair et al., 2014, p. 51) can be applied to replace missing values.

As the second step, outlier analysis was carried out. First of all, Z scores were calculated. The highest Z score has been calculated to be -2,52429. Field (2009, p. 153) allege that values over 3.29 signify the existence of an outlier. Mahalanobis distances were also checked. Tabachnik and Fidel (2013, p. 75) suggest that for a case to be an outlier in terms of Mahalanobis distance, p value should be less than .001 for χ^2 value. In the analysis, it was found out that $p=.000$. Field (2009, p. 218) denote that with samples smaller than 500, values over 15 should be regarded as problematic according to Mahalanobis distance. The highest value for the data set was calculated to be 9.33530, signifying that there are no outliers in the data set. As the final stage for outlier analysis, Cook' distance was calculated, in which a value over 2.5 denotes the existence of an outlier (Hair et al., 2014, p. 64). The highest value for Cook's distance is .03784.

To test normality of distribution, skewness and kurtosis values were checked. In none of the sub groups, skewness and kurtosis values exceeded the threshold values of +1 and -1 (Cohen et al., 2018, p. 736). The highest value is for skewness (-.900) in secondary school group. Normality of distribution was also tested through Kolmogorov-Smirnow and Shapiro Wilk tests. Kolmogorov-Smirnov test indicated abnormal distribution for four groups (high school, p=.019, secondary school, p=.003, 11-20 years of seniority, p=.019 and 21-30 years of seniority p=.012 and teacher, p=.000). The tests denoted a normal distribution for all other groups $p \geq .05$. Kolmogorov Smirnov test is influenced by sample size and might not put forth reliable results with small sample sizes (Engmann & Cousineau, 2011, p. 3). The homogeneity of the variances was tested by Levene test. In duty group, the score was calculated to be p=.985, which can be regarded as the indication of the homogeneity of the variances (Stockemer, 2019, p. 104). In institution and seniority groups, p=.000 and $p \leq .05$, which signify that homogeneity of variances is not met. Nordstokke and Colp (2014, p. 361) denote that Levene test is robust in highly skewed samples. Hatchavanich (2014, p. 191) put forward that Levene test could be affected by the sample size and it might not be the best solution to test homogeneity of variances with all samples. As the result of these analyses, data set was regarded to be ready for the principal component analysis. The results of the principal component analysis are presented under the following heading.

Results

To test sphericity, Bartletts' test was applied. The result (p=.000 and $p<.05$) signified that there is a sufficient correlation between the variables (Bartlett, 1950, p. 112). Field (2009, p. 647) allege that a value close to 1 is as the results of the KMO test, it signifies the adequacy of the sampling. KMO test result is p=.905. As the rotation method, direct oblimin was applied. In the first step of principal component analysis, communalities were checked. Field (2009, p. 638) regards 0.4 as the threshold value for the eligibility of an item. The communality values of five items were calculated to be lower than 0.4, item 8=.395, item 11=.395, item 12=.333, item 20=.389 and item 21=.369. These items were excluded from the data and the analysis was repeated. In the second analysis, item 7 had the communality value of .379 and was omitted from the data set. When the analysis was repeated, the communality value of item 4 dropped to .388 and item 9 to .305. The analysis was repeated omitting these two items. In the analysis, none of the items signified communality values lower than 0.4 and the lowest value was calculated to be .422 (item 26). In this phase, KMO was p=.887 and Bartlett's test of sphericity is p=.000.

In this phase a six-factorial structure was formed. The total variance explained by the factors which have eigenvalues greater than 1 is 53.724%, factor 1=26.598%, factor 2=5.948%, factor 3=5.642%, factor 4=5.529%, factor 5=5.085% and factor 6=4.922%. When pattern matrix was examined, it was found out that some items had close factor loadings under more than one factor, item 17, -.469 for factor 2 and .429 for factor 6, item 28, .366 for factor 2, -.312 for factor 4 and .349 for factor 6 and item 22, .305 under for 1 and .358 for factor 6. These items were regarded to be overlapping and were excluded from the data set. The analysis was repeated omitting these items.

In this phase, a five factor structure was formed. The total variance explained by the five factors is 50.472%. In this phase, item 14 had close factor loadings for factor 1 (.353) and for 5 (.321). In the same way, item 6 had close factor loadings for factor 1 (-.452) and for factor 3 (.417) and factor 4 (.377). Item 2 had factor loadings of .437 for factor 4 and .468 for factor 5. These items were excluded from the data set and the analysis was repeated. In this phase, a four factor structure was observed but item 25 had close factor loadings for factor 1 (.344) and factor 4 (-.321) and item 13 factor 2 (.367) and factor 4 (-.393). They were regarded to be overlapping items and excluded from the data set.

The omitted items were also assessed if they could have an overall impact on the content validity of the draft scale. The analysis results supported the literature as for example item 17, which is about big data, is a domain of expertise in data management. In the same way, item 28 focuses on the role of data in educational management processes, though the school administrators are not the only target group in our scale development study. All in all, it can be alleged that items excluded contributed to the content validity of the scale.

Finally, the analysis was repeated. In this phase a three factor structure was found out and the factors with eigenvalues over 1 explained 44.005% (factor 1=27.092%, factor 2=8.812%, factor 3=8.101%). Hair et al. (2014, p. 107) allege that the percentage of variance explained by a factor should be over 5% of the total variance explained and this verifies that all factors could be independent factors. Çokluk et al. (2018, p. 197) denote that in social sciences, the threshold value for the total variance explained could be 30%. The KMO value of three factorial structure is $p=.845$, $p\geq.05$ and Barttlett's test of sphericity value is $p=.000$, $p\leq.05$. None of the items had close factor loadings for different factors. Results of the principal component analysis are presented in Table 2.

Component correlation matrix was scrutinized to figure out if there is a high correlation among the factors. Values closer to -1 and +1 denote strong association among factors (Heiman, 2011, p. 142). In literature, the shared notion is that correlation coefficient lower than .30 denote weak correlation, values between .30 and .70 signify intermediate correlation and values higher that .71 signals high correlations (Büyüköztürk et al., 2013, p. 92). In the analysis, the correlation between factor 1 and 2 was calculated to be $r=-.359$, factor 1 and 3, $r=.298$ and factor 2 and 3, $r=-.308$. It was concluded that the factors did not have high correlations with each other and can be handled as distinctive and separate variables. For reliability AVE (average variance extracted) and CR (composite reliability) values were calculated for each factor. The online system created by Aydoğdu (2023) was used to calculate AVE and CR values. The values were calculated for factor 1, AVE value is 0.324 which is below the acceptable threshold and CR is 0.733, which denotes that the factor's reliability is high. For factor 2, AVE is 0.438, which is below the threshold value of 0.50 and CR value is 0.756, which refers to the reliability of the test. And AVE for factor 3 is 0.410 and CR value is 0.674, both are below the threshold values. After the analyses, the factors were denominated.

Table 2

The Findings of the Principal Component Analysis for Data Literacy at School Scale

Item	Factor 1	Factor 2	Factor 3
3	.753		
1	.627		
16	.606		
26	.518		
27	.471		
5	.358		
15		-.717	
29		-.712	
23		-.622	
24		-.587	
19			.826
10			.584
18			.486
Eigen value	3.522	1.146	1.053
Variance explained by each factor %	27.092%	8.812%	8.101%
Cumulative variance explained 44.005%			

The factors were denominated based on literature. Pangrazio and Selwyn (2019, p. 420) identify five dimensions for data literacy: 1) data identification, 2) data understandings, 3) data reflexivity, 4) data uses, and 5) data tactics. The ability to identify data sets and form an understanding towards the data collected, its scope and functions could constitute an integral part of data literacy. Wolf et al. (2016, p. 10) define data literacy as “the set of abilities around the use of data as part of everyday thinking and reasoning for solving real-world problems”. Van Audenhove et al. (2020, p. 2) put forward two important components of data literacy: understanding data and using data. It can be alleged that both components entail having knowledge and skills for the term “data” and for making use of them in organizational processes or real life. Mandinach and Gummer (2013, p. 30) define data literacy as “a specific skill set and knowledge base which enables educators to transform data into information and ultimately into actionable knowledge”. This definition refers to the basics of data management, which can be defined as the process of transforming raw data into functional and actionable information (Duygulu, 2023, p. 78). In the light of the literature, factors were denominated as follows; factor 1, data identification, factor 2, data use and factor 3, data management.

Data identification is an integral component of data literacy as it is related with the ability to distinguish various types data. At school context, various data have distinctive functions, so the dexterity to distinguish between the types of data plays a key role in optimizing data use. For data literacy, it is not enough to distinguish between types of data, it is crucial to use it. Data use implicates a number of processes, conditions, and contexts which encompasses interpretive processes carried out using data to construct implications for next steps for an organizational implementation (Coburn & Turner, 2011, p. 173). Data use by educational professionals is a component which constructs and guides institutional structures, processes, and logics (Little, 2012, p. 143) and thus constitutes a significant parameter of data literacy. Data management can be regarded as the highest level of data literacy as it encompasses all processes in which data are handled in an organization (Duygulu, 2023, p. 75). Thus, having a basic knowledge about the data life cycle in an organization is among the basics of data literacy. In this regard, the scale presents a logical order for the various levels of data literacy and can guide the educational leaders with a better understanding for trainings targeted to increase data literacy as it can offer a better professional needs analyses.

The three dimensions discovered in the development of the scale are interrelated concepts and they focus on distinctive components of data literacy. They form a hierarchical structure depending on the extent of the expertise in data literacy. Data identification is an important prerequisite for data use since defining and describing data forms the basis for deciding on the domains and issues for which the available data could be functional to act on. Data use is also a prerequisite for a more comprehensive competence in terms of benefiting from data in organizational level, which is data management. Data management encompasses all processes and procedures in which raw data is transformed into functional information which could guide organizational decision making processes. To sum up, the tree different dimensions of the scale are interconnected based on the extent of expertise and competence in the context of data literacy.

As the final phase of exploratory factor analysis, Cronbach Alpha coefficient was tested. Cronbach's Alpha reliability coefficient was calculated to be .772. A value over .60 denote the reliability of a scale (Hair et al., 2014, p. 90; DeVellis, 1991, Kline, 1986 as cited in McNeish, 2018, p. 423). Kline 1999 (as cited in Field, 2009, p. 675) notes that for ability tests a cut-off point of .7 is suitable. In the light of the findings, the three factorial scale was regarded to be reliable and valid. To confirm the three factorial structure, second application was implemented.

The Second Application: Confirmatory Factor Analysis

The sampling is composed of 338 teachers and school administrators from four different educational areas in Kastamonu; Kastamonu city center (schools in the second educational area), Devrekâni, Daday and İhsangazi. Stratified and quota sampling methods have been utilized together. Maximum variation has been attached importance during the sampling process and various variables such as “duty”, “seniority” and “school level” were taken into consideration to be able to reach the maximum variety. The demographic data about the participants of the second application are presented in Table 3.

Table 3

Demographic Data about the Participants of the Second Application

		n	%
Duty	Teacher	286	84.6%
	Administrator	52	15.4%
Seniority	1-10 Years	61	18%
	11-20 Years	123	36.4%
	21-30 Years	131	38.8%
	31 years and over	23	6.8%
School Level	High School	182	53.8%
	Secondary School	87	25.7%
	Primary School	69	20.4%

Data was collected by means of a google survey questionnaire. Before the implementation, principals of the schools were informed and asked for permission. Informed consent was also included in the questionnaire and participants were assured to keep their data private. Data was transferred to SPSS 20.0 program for preliminary analyses.

As the first stage of data preparation, missing value analysis was carried out. It was found out that in none of the data sets, the missing values are not more than 5%. The highest percentage of the missing values was calculated to be 0.9% for the data set of item 4. The EM statistics is $p=.861$ and $p\geq.05$. As the result of the missing value analysis, it was concluded that data has a random distribution and averaging (series means) has been applied to replace the missing values. For outlier analysis, first of all Z scores were examined. One case (Demographic data about the case excluded, institution=high school, seniority=11-20 years and duty=teacher) exceeded the threshold values of + and -3 with a value of -3,03206 and it was excluded from the data set. Z scores changed between -2,81958 and 1,74867. Mahalanobis distances were also checked and none of the cases were out of the threshold values of +15 and -15. The highest value was calculated to be 12,56280. In the same way, Cook's distance signified no outlier in the data set as the highest value has been .03511.

Skewness and kurtosis values were checked for normality of distribution. Skewness values for all groups were between the threshold values of +3 and -3 (Bai & Ng, 2005, p. 49). For kurtosis, in two of the groups, values were out of +3 and -3. For primary school, it was calculated to be 4.011 and for 31 years and over seniority to be 4.526. The kurtosis values could have been affected by sampling as both groups have fewer participants (primary school n=69, 31 years and over seniority=23). Normality of distribution was also tested by normality tests. The Kolmogorov-Smirnow and Shapiro Wilk tests presented abnormal distribution, $p\leq.05$ in teacher, 11-20 and 21-30 years of seniority and in all sub groups of institution. Homogeneity of variances was tested by Levene test and for institution group $p=.867$, for seniority $p=.106$ and for duty $p=.184$ values were obtained and the homogeneity of variances was attained, $p\geq.05$ for all groups. As the result of these analyses, the data set was regarded to be ready for the confirmatory factor analysis. The results of the confirmatory factor analyses are presented under the following heading.

Results

For confirmatory factor analysis, path diagram has been applied to test the model. First of all, to test the adequacy of the sampling, critical N was calculated and it was found out to be CN=220.85. In view of CN, the sampling size was assumed to be adequate, n=337. As the estimation method, maximum likelihood method was applied as it is a robust estimation method especially when normality of distribution assumption cannot be met (Hair et al., 2014). Asymptotik covariance matrix was applied in the analysis. The results of the analysis were presented in the Table 4.

Table 4

The CFA Results of the Data Literacy at School Scale

Factor 1: Data identification				
Item	t-scores	Error Variance	Standardized Loadings	R^2
1	17.55	.42	.90	.66
2	16.53	.51	.89	.61
3	16.78	.57	.96	.62
4	15.40	.58	.84	.55
5	16.61	.51	.89	.61
6	16.22	.49	.84	.59
Factor 2: Data use				
Item	t-scores	Error Variance	Standardized Loadings	R^2
7	15.00	.42	.72	.56
8	18.35	.31	.95	.75
9	14.98	.55	.83	.55
10	13.83	.63	.78	.49
Factor 3: Data management				
Item	t-scores	Error Variance	Standardized Loadings	R^2
11	16.15	.49	.91	.63
12	14.58	.55	.80	.54
13	13.69	.57	.74	.49

As presented in Table 4, t scores are meaningful ($t>2.56$, $p<.05$) Çokluk et al. (2018) note that t values over 2.56 are significant at the significance level of .05. The lowest standardized factor loading is .72 Hair et al. (2015, p. 115) denote that factor loadings over .30 are considered to meet the minimal level, factor loadings over .50 are practically significant and factor loadings over .70 are regarded as the indication of a well-defined structure. In the light of the findings, it can be alleged that the model is robust. The highest error variance is .58, which is below threshold value of 1 (French & Finch, 2006, p. 383). The goodness of fit statistics for the first order confirmatory factor analysis are presented in Table 5.

Table 5

Goodness of Fit Statistics for the First Order CFA Analysis

Model	X^2	$(X^2$ /sd)*	RMSEA	SRMR	NFI	NNFI	CFI	GFI	AGFI
First Order	137.86	2.224	0.060	0.045	0.97	0.98	0.98	0.94	0.91

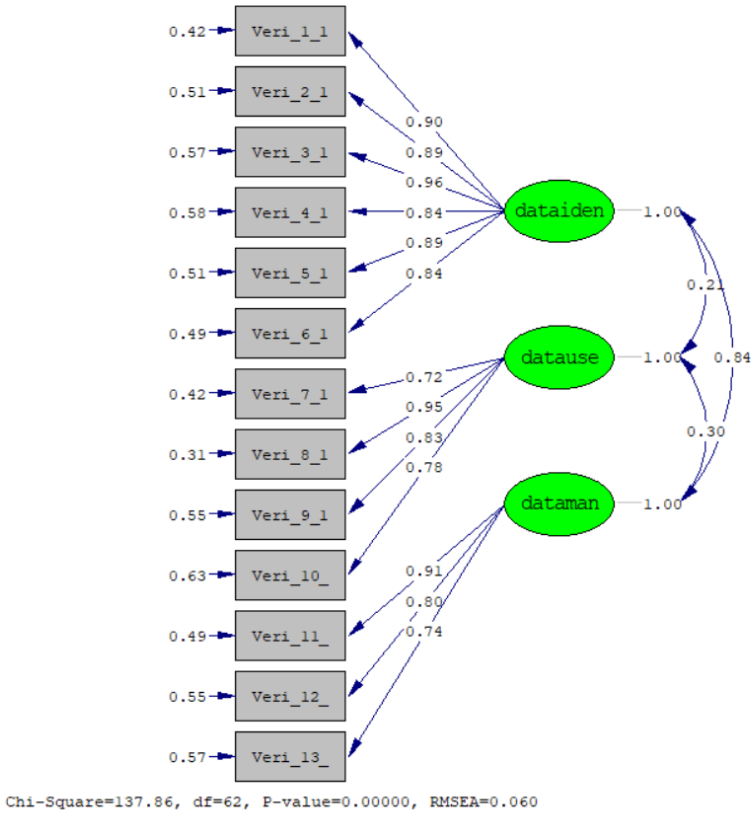
*df=137.86, p=.000

As presented in Table 5, (X^2 /sd) value is lower than 3, which signifies that the model is robust (Prudon, 2015, p. 9), X^2 /sd=2.224. As the value of X^2 could be influenced by the sample size, it should not be regarded as the only indication of good fit (Harrington, 2009, p. 80). A value for root mean square error of approximation close to .00 indicate the existence of a good fit (Brown, 2006, p. 84). The cut-off value for RMSEA is .05 (Browne & Cudeck, 1993, as cited in Li & Bentler, 2011, p. 119). Thus RMSEA score (.0060) verifies the goodness of fit. For standardized root mean square residual (SRMR), a value close to 0 is regarded as the sign of a good fit (Brown, 2006, p. 83). Kline (2016, p. 277) denote that a value over .10 signals as a serious problem. The value could be increased to .12 in smaller than 150 samples (Sivo et al., 2006, p. 276). As a result, it can be alleged that SRMR index proves a good fit (SRMR=.045) The value for NFI should be equal to .90 or over in a good fit model (Shek & Yu, 2014, p. 198). Normed fit index (NFI) denotes a good fit, having the value of .97. In the same way, non-normed fix index (NNFI) should be .90 or over (Obst & White, 2004, p. 699). The value is .98, which verifies the goodness of fit.

The comparative fit index (CFI) has a range of values between 0.0 to 1.0, and values over .90 imply a good model fit (Cheung & Rensvold, 2002, p. 235). The model has a CFI value of .98. Cheung and Rensvold (2002 p. 235) note that a score over .90 for goodness of fit index (GFI) is regarded as the robustness of the model and the value in our model is .94. The adjusted goodness of fit index (AGFI) penalizes more complicated models and favors the ones with a minimum number of free paths. AGFI values are generally lower than GFI values regarding the complexity of the model (Hair et al., 2014, p. 581). Schreiber et al. (2006, p. 330) allege that adjusted goodness of fit index (AGFI) score should be over .90 for a good fit. The score in the model is .91. In the light of the goodness of fit indexes, it can be alleged that the model is robust. The first order path diagram of the model is presented in Figure 3;

Figure 3

The First Order Path Diagram of the Data Literacy at School Scale



To test multi-collinearity, correlations among the factors were checked. Hair et al. (2014, p. 196) allege that for the presence of multi-collinearity, the correlation coefficients should be .90 or over. A correlation value of +1 and -1 refers to singularity (Martin & Bridgmon, 2012, p. 414). Brown (2006, p. 32) denote that an inter-correlation score over .85 imply poor discriminant validity. In the model, the highest correlation coefficient score is .84 between factors 1 and 3. The correlation between factors 1 and 2 is very low; .30 and .21. The findings verify that there is no multi collinearity among factors. Based on the findings, the three-factorial structure formed through exploratory factor analysis was confirmed. The goodness of fit indexes of CFA signify that the three-factorial model established is robust.

As the final stage, reliability tests were carried out. Cronbach Alpha coefficient was tested to find out the internal validity of the scale. Singh (2007, p. 78) suppose that a figure of .75 or more usually is treated as an accepted level of reliability. Cronbach's α was calculated to be .882. The internal validity and reliability were also tested by split-half method. Split-half is a reliability test in which "half of the indicators, tests, instruments, or surveys, are analyzed assuming it to be the whole thing" (Singh, 2007, p. 78). The correlations between the two halves are calculated and high correlations are regarded to be the sign of reliability (Field, 2009, p. 674). Split half method is preferable to Cronbach alpha when the items are in a multi-dimensional form (Thompson et al., 2010, p. 235). A high correlation coefficient must be met in split half reliability test to verify a goodness of fit. In the analysis, the correlation between the two halves is r=.837 and Spearman-Brown coefficient is R=.911. The findings verify that the model is robust. As the last internal validity and reliability technique, Gutman split-half coefficient was calculated and Guttman’s lambda has been found out to be λ=.904, signifying the goodness of fit.

Test-retest technique was applied to examine the external validity of the scale. The scale was applied to the same group of teachers and administrators twice in an interval of two weeks and the correlations between the results of the two applications were calculated. The demographic data about the test-retest are presented in Table 5;

Table 5

Demographic Data about the Participants of the Test-Retest

		n	%
	First	44	53.01
	Second	39	46.99%
Duty	Teacher	71	85.5%
	Administrator	12	14.5%
Seniority	1-10 Years	9	10.8%
	11-20 Years	32	38.6%
	21-30 Years	35	42.2%
	31 years and over	7	8.4%
School Level	High School	51	61.4%
	Secondary School	17	20.5%
	Primary School	15	18.1%

The missing value analysis was carried out and in none of the cases the rate of the missing values exceeded the value of 5%. The EM statistics is $p=.763$ and $p\leq.05$. The Z scores are between the threshold values of +3 and -3. The averaging method was utilized to replace missing values. The skewness and kurtosis values are out of the threshold values only in 31+ years of seniority groups, which consists of six participants, skewness=1.461, kurtosis=3.948. After data cleaning processes, correlations between the two tests were calculated between the two applications. Pearson correlation coefficient is $r=.800$, $p\leq.05$, Spearman-Brown correlation coefficient is R=.961, $p\leq.05$, and Kendal’s tau-b is $\tau_b=.904$, $p\leq.05$. The findings of test-retest technique verified the external validity of the scale. The final scale was sent to language experts for translation and the draft was reviewed by the researchers and the final version of the “data literacy at school scale” was formed. The language experts to whose opinions applied are Dr. Kerem Tekşen, Ministry of National Education, Dr. Gökhan Savaş, Karabük University and Dr. Erhan Dolapçı, Ministry of National Education. The final version of the scale is presented in Appendix 1.

Discussion and Conclusion

Data based decision making is significant for instructional processes and thus, it is crucial for teachers and school leaders to be trained not only for statistical techniques but also for how data should be utilized to inform instruction (Henderson & Corry, 2021, p. 242). Data literacy is a prerequisite for data-based decision making (Kippers et al., 2018, p. 21). Data literacy requires skills related to understand data and its graphical representations (Stephenson & Schifter Caravello, 2007, p. 525). It is vital to improve data literacy both for teachers and school administrators to make use of data in educational and instructional processes. In this context, to put forth a realistic picture of the current situation of data literacy at school could be handled as a significant first step to manage efforts to improve data literacy of school members. Therefore, the scale could be functional in determining the current situation of data literacy at school.

The development of the scale was carried out in four main phases. First of all, an item pool was created and it was revised and improved with the help of the experts. In the second phase exploratory factor analysis was carried out and the draft scale was structured to be applied to confirmatory factor analysis. The confirmatory factor analysis proved that the three dimensional structure formed by the exploratory factor analysis is robust. As the final stage, validity and reliability analyses were carried out. Cronbach's α was calculated to be .882, which denoted the internal validity of the scale. For internal validity, spit half method and Guttman's lambda tests were carried out. The results of the split half test proved the internal validity of the scale; $r=.837$ and Spearman-Brown coefficient is $R=.911$. Moreover, Guttman's lambda was calculated to be $\lambda=.904$, which is the indication of the internal validity. A test-retest technique was applied to test external validity. As the results of the analyses, it has been found out that Pearson correlation coefficient is $r=.800$, $p\leq.05$, Spearman-Brown correlation coefficient is $R=.961$, $p\leq.05$, and Kendal's tau-b is $\tau b=.904$, $p\leq.05$.

The scale has three dimensions, which have different functions. First of all, it can help school leaders form a clear understanding for competencies of school administrators and teachers for data identification. Data identification refers to skills about distinguishing and describing various data types, visualizing data and figuring out their functions in educational and instructional processes. The ability to distinguish among different data types, representing them with visual instruments and discovering their possible functions could be regarded as an integral part of data literacy.

Data use implicates processes, conditions, and contexts in which data are interpreted and next steps are determined based on the implications from data (Coburn & Turner, 2012, p. 99). Data use at school could have positive impact on educational and instructional processes especially when actions are performed through data informed decisions (Anderson et al., 2010, p. 321). The level of data use could be affected by such factors as accessibility and timeliness of data, perceived validity of data and staff capacity and support (Ikemoto & Marsh, 2007, pp. 120-121). Therefore, increasing data literacy capacity of staff at schools could have a positive impact on data use and data use could be regarded as an integral component of data literacy. Data literacy capacity refers to individual skills and competencies of the members of an organization as well as the overall competence of the organization itself to manage data and reach actionable information from raw data. On the organizational level data literacy is the collective ability of school staff to effectively engage with data across its lifecycle, from identification to application.

Data management refers to all processes, procedures and implementations regarding handling data. The final objective of data management is to extract value which can be put to work in organizational processes (Duygulu, 2023, p. 75). Components such as defining a data policy, collection, standardization and documentation of data, data access and data share are involved in data management (Fary & Owen, 2013 as cited in Chigwada et al., 2017, p. 2). When components of data management are scrutinized, it can be alleged that data management and data literacy involve similar skills and thus having an understanding for basics of data management could shed light on the current situation of data literacy levels of schools. Data management at the school context refers to the processes of turning data obtained through such sources as student achievement tests and teacher performance evaluations to actionable information and reflect information on schools' routine implementations to improve teaching and learning as well as to manage change processes.

Depicting the current picture of the data literacy at schools can guide school leaders for providing the teachers with the necessary and appropriate training for data literacy . Filderman et al., 2022, p. 337) found out that trainings on data literacy have a positive impact on teachers' knowledge and skills about data use. Based on the insights obtained from assessing the current situation of data literacy level at schools, school-based training programs could be designed to meet the needs of the teachers and school leaders. For example, based on a meta-analysis carried out on articles about data literacy between 2010-2018, Henderson and Corry (2021, p. 241) have put forth four recommendations for data literacy training for teachers and school leaders; "(1) create more skill-focused educator preparatory programs at colleges and universities, (2) encourage opportunities for collaboration between educators, (3) model and encourage data use from both quantitative and qualitative sources and (4) investigate the role of technology and big data on data literacy".

The scale could realize significant functions at school. To embody the hypothesis, some real life examples from school ecosystem could be given. Performance evaluation constitutes an integral part of instructional processes and it forms the basis for reshaping and redesigning instructional implementations. Teachers are encouraged to carry out process assessments with the rise of the constructivist approach. The teachers can apply to various tolls such as excel and google forms to carry out process assessment activities and these tools provide them with automatically created visuals and data about the assessment. Though, to interpret the data provided in various forms, teachers need to have data literacy to an extent, to interpret the data formed in various types by the software used. The situation is the same for school leaders as they are bombarded by data from various sources during their professional lives. The schools could organize trainings on data literacy though as the data literacy competencies might change drastically for each individual, it requires a healthy needs analyses to discover areas of improvement for each teacher and school leader. The scale in this context could provide the school members with valuable insights to concentrate on the right domains of data literacy for training. Taking the data obtained through the scale, training programs targeted at school members with different levels of data literacy could be designed. In the same way, depending the on the data, topic based training sessions such as data visualization or data tabulating could be designed.

Consequently, the scale could help figure out data literacy competencies and deficiencies of school members. A data based needs analysis could be functional in developing data literacy capacity of schools by shedding light on the areas of development. Data based needs analysis refers to providing feedback for the target group based on objective, verifiable data obtained through scientific measurement instruments. It is a systematic evaluation process to identify gaps in data literacy skills among school staff, informed by objective data. To integrate trainings into the school in-service training activities, it could be essential to develop a healthy understanding towards the data literacy levels of teachers and school administrators. The scale could contribute to the processes of improving data literacy at schools by providing objective data about the areas of improvement with a view to data literacy. The developed scale offers school leaders a practical tool to assess current data literacy levels within their institutions. This assessment provides a foundation for designing targeted strategies to enhance data literacy skills, thereby improving overall competency and capacity in data-informed decision-making. It can also help individualize data literacy trainings at schools, figuring individual needs of the shareholders at school.

Limitations

The study has some limitations. One of the most significant limitation is that owing to the nature of the data literacy, the basic criteria might change drastically depending on the socio-economic structure of the community in which it was evaluated. Though maximal variation in sampling, they are all state schools and new research could also include private schools, which can be sometimes better equipped with information management systems and sometimes employ younger teachers who are more equipped with data analysis tolls and software. Another limitation of the research is the geographical area where data was collected. As socio-economic structure of the society could affect the components of data literacy levels of individuals and organizations, the districts could be varied in a way that it will encompass provinces which are more developed in relation to Kastamonu.

Acknowledgements

Authors are not funded by any institutions.

Statement of Responsibility

Each of the authors of the research contributed equally in the process, extending from literature review to revising the final draft of the article.

Conflicts of Interest

As the authors of the article, we confirm that there are no conflicts of interest in the research.

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Appendix

Appendix 1

Factors and Items of the Data Literacy at School Scale

Items	Factor 1: Data identification
3	I can tabulate textual data
1	I can explain the concept of "data".
16	I can define the concept of "factual data".
26	I can list the types of data used in educational and instructional processes.
27	I can list the functions of data in teaching processes.
5	I can convert textual data into visual tools.
Items	Factor 2: Data use
15	I can explain the concept of "secondary data sources".
29	I can explain the concept of information pyramid.
23	I have knowledge about data storage tools at school.
24	I can benefit from digital data sources at school.
Items	Factor 3: Data management
19	I can list the specific characteristics of data.
10	I have knowledge about data storage tools.
18	I can list the stages in the data management process.