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Development and validation of the digital intelligence diagnostic test using cognitive diagnostic models

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Abstract

Cognitive Diagnostic Models (CDMs) provide separate and multivariate diagnostic feedback on examinees' strengths and weaknesses. This study presents CDMs for assessing psychological variables. The research aimed to (1) develop a digital intelligence diagnostic test using the G-DINA model and validate the quality of the Q-matrix, (2) investigate the components of digital intelligence, and (3) analyze digital intelligence. Participants included 978 junior high school students from various schools in Bangkok, Thailand, enrolled in the academic year 2022. These students were selected through multi-stage random sampling (Ma & De la Torre, 2016). Instruments included a misconceptions questionnaire and diagnostic test. Data analysis involved content validity using Item-Objective Congruence (IOC), construct validity with Confirmatory Factor Analysis (CFA), reliability testing using KR-20, item analysis with the G-DINA model, and validation of the Q-matrix with results illustrated using a Mesa plot (PVAF and EPS indices). Results were as follows: The test consisted of 94 items, which were quality based on the G-DINA model. The confirmatory factor analysis indicated that the model is a good fit with the empirical data. The highest skill mastery probability was digital citizen identity, and the lowest was managing for digital footprints. The study offers guidelines for teachers and parents to use diagnostics to identify individual student deficiencies.

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Introduction

In the era of Digital Transformation, internet user behavior survey results increased threefold from the previous year, particularly noticeable among children and youth (Electronic Transactions Development Agency, 2021). In Thailand it was revealed that 55.9 percent of Thai children aged 12–16 have chatted or met with strangers online (Phonphaphon, 2018). Thai children Stand with online dangers, the most common include cyberbullying, easy access to inappropriate media, gaming addiction, and meeting strangers online, reflecting the digital literacy gaps among children (Digital Economy Promotion Agency [DEPA], 2018). These survey results reflect the weaknesses or deficiencies of Thai children in their media literacy and social network skills. The promotion of digital intelligence (DQ) is defined in the Basic Education Core Curriculum 2008 (Revised 2017) in the Science Learning Group, Content Four: Technology. Most parents rely on schools to tackle these deficiencies. Teachers play a crucial role in alleviating these issues. They need enough information to provide feedback to both students and parents. Instructors can use the concept of diagnosis to assess and identify individual students' weaknesses through a diagnostic test.

Developing a diagnostic test is an instrument for evaluating students' strengths and areas for improvement based on Cognitive Diagnostic Models (CDMs). Diagnostic approach is divided into two categories: deficit measurement, which seeks to uncover knowledge gaps or skill deficiencies, and error analysis, which looks into the characteristics and patterns of students' mistakes (Lee & Corter, 2003). Currently, cognitive assessment models are the G-DINA and DINA models, which are popularly used to classify test takers' skills in conceptual diagnostic tests (Najera et al., 2019). Suphamon and Sukanya (2017) found that the G-DINA model indicates better efficiency in relative diagnostic assessment compared to the DINA model. To validate diagnostic assessment tests, it is essential to develop a Q-matrix that illustrates the relationship between test items and the specific students' skills. The validation process in previous research frequently utilized expert judgment and the think-aloud technique. Nonetheless, these approaches are abstract and lack statistical evidence to confirm their precision, which may result in errors in developing the Q-matrix (De la Torre & Chiu, 2016; Ma & De la Torre, 2020; Najera et al., 2019). The Proportion of Variance Accounted For (PVAF) index effectively distinguishes the specific student's skills, providing empirical evidence to validate the quality of the Q-matrix (De la Torre & Chiu, 2016).

Based on the previous reasons, the researcher intends to assess strengths and areas for improvement in essential digital cognition, attitudes, and skills among students in lower secondary education. This assessment will involve developing a diagnostic test to evaluate Digital Intelligence Quotient (DQ) in essential attributes. The research aimed to (1) develop a digital intelligence diagnostic test using the G-DINA model and validate the quality of the Q-matrix through expert judgment and the Proportion of Variance Accounted For (PVAF) index. The PVAF index will provide statistical support for the Q-matrix validation alongside expert judgment (Ma & De la Torre, 2020), (2) investigate the components of digital intelligence, and (3) analyze the strengths and weaknesses of students in digital intelligence.

Literature Review

Digital Intelligence Quotient (DQ) encompasses the ability to perceive, along with social and emotional adaptability essential for thriving in the digital era. It involves the capacity to confront challenges, adapt to various situations, and utilize digital technology judiciously and responsibly. DQ comprises a combination of knowledge, skills, and values. (Yuhyun, 2016; Gardner, 1983) These components align with the DQ concept consisting of digital citizen identity, balanced technology use, behavioral cyber risk management, personal cyber security management, digital empathy, digital footprint management, media and information literacy, and privacy management. (Jurairat, 202; Teerawat, 2017; Wannakorn et al., 2020; Yuhyun, 2016)

The Cognitive Diagnostic Models (CDMs) have received increasing attention after "No Child Left Behind" Act of 2001 in the USA. The main objective of this approach is to provide cognitive feedback to students, teachers, and families. (Embretson, 1998). CDMs are multidimensional models of latent variables represented as vectors, called Attributes, consisting of examinees' strengths and areas for improvement. CDMs rely on a Q-matrix, which is of size J x K dimensions, where K represents the number of attributes and J represents the number of test items. Attributes are assigned values of 1 when examinees have mastery in that area and 0 when they need improvement. This enables the classification of examinees into 2^k groups, with each group having different attribute patterns, written in the form (pattern, α where $\alpha = [\alpha_1, \alpha_2, \dots, \alpha_k]$), representing a vector of latent attributes. The Q-matrix indicates examinees' skills based on their responses to each test item, with 0–1 dichotomous attributes. (Tatsuoka, 1990).

The Performance comparison of Cognitive Diagnostic Models (CDMs) between DINA and G-DINA shows that the

G-DINA model has better fit results than the DINA model. Basokcu et al., (2013) compared these CDMs using fit indices (2LL, AIC and BIC). The analysis confirmed that the G-DINA model outperformed the DINA model. In the DINA model, the values range from .00 to .08, while in the G-DINA model, the values range from .00 to .01. A comparison of the residual means associated with correct guessing in both models reveals values of .011 for the DINA model and .003 for the G-DINA model. Suphamon and Sukanya (2017) examined the efficiency of G–DINA and DINA models by considering the absolute fit indices and the relative fit indices. They found that the G-DINA model has a higher relative diagnostic evaluation efficiency than the DINA model.

The G-DINA model (generalized deterministic inputs, noisy "and" gate) model is generalization of the DINA model with more flexible assumptions. Basokcu et al. (2013) found that the G-DINA model provides a more compensatory estimation than the DINA model. The G-DINA model is similar to other general models for cognitive diagnosis, utilizing alternative link functions. When appropriate constraints are applied, several commonly used cognitive diagnosis models are shown to be specific cases of the general models. This model also utilizes *JxK* Q matrix. The G-DINA model distinguishes latent classes into $2^{K_j^*}$ latent groups. Every latent group is reduced to an attribute vector represented by α_{lj}^*. Every latent group is probability of correct answering represented by $P(\alpha_{lj}^*)$ (De la Torre, 2011). The probability formula for the G-DINA model is:

$$P(\alpha_{lj}^*) = \delta_{j0} + \sum_{k=1}^{K_j^*} \delta_{jk}\,\alpha_{lk} + \sum_{k'=k+1}^{K_j^*} \sum_{k=1}^{K_j^*-1} \delta_{jkk'}\alpha_{lk}\alpha_{lk'} + \cdots + \delta_{j12\ldots K_j^*} \prod_{k=1}^{K_j^*} \alpha_{lk} \quad (1)$$

Where δ_{j0} represents the intercept for item j, δ_{jk} represents the main effect of attribute *K*, $\delta_{jkk'}$ represents the interaction effect of attributes K and K' ,and $\delta_{j12\ldots K_j^*}$ represents the interaction effect of attributes 1 to K_j^*.

Q-Matrix Validation: According to Najera et al. (2019), the current approach to Q-matrix validation depends on the experts' assessments, which are relatively abstract and may have errors in the Q-matrix construction process. They introduced a validation method that can identify error Q-vectors based on the discrimination index. The results indicate that with an increase in the variance in the probability of correct responses associated with a constructed Q-vector, the more accurate the Q-vector is in identifying individuals' abilities. Furthermore, they emphasized the importance of the parsimony principle, which suggests that when various Q-vectors demonstrate equivalent variance in the probability of accurate responses, the simpler model should be preferred as it is more appropriate. The G-DINA model characterizes the discrimination index as the variance in the probability of accurate responses among various latent groups, which is adjusted according to the posterior distribution of latent groups, as the following equation:

$$\varsigma_j^2 = \sum_{l=1}^{2^{k^*}} \omega(\alpha_{lj}^*)\left[P(\alpha_{lj}^*) - \bar{P}(\alpha_{lj}^*)\right]^2 \quad (2)$$

Where $\omega(\alpha_{lj}^*)$ represents the posterior probability of a correct answer to item *j* for all examinees in the groupα_{lj}^*, $P(\alpha_{lj}^*)$ represents the probability of a correct answer of examinees in the group α_{lj}^*, and $\bar{P}(\alpha_{lj}^*)$ represents the probability of a correct answer to item *j* of all skill groups.

An increase in the number of skills necessary for correctly answering leads to differences in response probabilities, which affects the variance of the probability of correct responses. Development of an optimal Q-vector should be both parsimonious and demonstrate the highest possible variance, which can be measured using the Proportion of Variance Accounted For (PVAF) for each possible Q-vector. PVAF is $\varsigma_j^2/\varsigma_{j1:K}^2$ and using the Epsilon (∈, EPS) value represents a threshold. Consideration of appropriate PVAF values: When PVAF > EPS, the Q-vector is the most parsimonious. In cases of two Q-vectors satisfying PVAF > EPS and having the same number of assigned skills, the Q-vector with the higher PVAF is considered more optimal.

Methodology

This research uses research and development (R&D) methods. The research process consists of: (1) investigating the elements of the digital intelligence, (2) developing a digital intelligence diagnostic test using the G-DINA model, (3) validating the quality of the matrix of test characteristics (Q-matrix), and (4) analyzing the digital intelligence.

Participants

Participants involved 978 junior high school students from various schools in Bangkok, Thailand, enrolled in the academic year 2022. These students were selected using a multi-stage random sampling method (Ma & De la Torre, 2016).

Data Collection

This study process involved: (1) reviewing literature, concepts, theories, and related research. The researcher determined the content and indicators based on the Basic Education Core Curriculum 2008 (revised edition 2017) in the science and technology learning subject group, specifically subject 4, technology, (2) a focus group discussion was conducted with 20 stakeholders, including educational institution administrators, teachers, psychologists, behavioral scientists, and academics in educational measurement and evaluation. Finally, (3) a survey on digital misconceptions was carried out using an online questionnaire collected from junior high school students. This research received ethical approval from the Ethics Committee at Kasem Bundit University, approval number R001/67P., (4) defining the specific skills of students to create the matrix of test characteristics (Q-matrix) consisting of: A1 digital citizen identity, A2 balanced use of technology, A3 behavioral cyber-risk management, A4 personal cyber security management, A5 digital empathy, A6 digital footprint management, A7 media and information literacy, and A8 privacy management. In the Q-matrix, a value of 1 indicates that the item requires students to have that skill as a strength to answer, while a value of 0 means that the item does not require that skill as a strength to answer. Shown in Figure 1. (5) establishing a test specification for test, as shown in Table 1.

Item	A1	A2	A3	A4	A5	A6	A7	A8	Item	A1	A2	A3	A4	A5	A6	A7	A8	Item	A1	A2	A3	A4	A5	A6	A7	A8
1	1	0	0	0	0	0	0	0	46	1	0	0	0	0	0	0	1	91	1	0	0	0	0	0	0	1
2	1	0	0	0	0	0	0	0	47	1	0	0	0	0	0	0	0	92	1	0	1	0	0	0	0	0
3	1	0	0	0	0	0	0	0	48	1	0	0	0	0	0	0	1	93	1	0	0	0	0	0	0	0
4	1	0	1	0	0	0	0	0	49	0	1	0	0	0	0	0	0	94	1	0	1	0	0	0	0	0
5	0	0	0	1	0	0	0	0	50	1	0	0	0	0	0	0	1	95	1	0	0	1	1	1	0	0
6	0	1	0	0	0	0	0	0	51	0	1	0	0	0	0	0	0	96	0	1	0	0	0	0	0	0
7	0	1	0	0	0	0	0	0	52	1	1	0	0	0	0	0	0	97	0	1	0	0	0	0	0	0
8	0	1	0	0	0	0	0	0	53	0	1	0	0	0	0	1	0	98	0	1	0	0	0	0	0	0
9	0	1	0	0	0	0	0	0	54	0	1	0	0	0	0	0	0	99	1	1	0	0	0	0	0	0
10	0	0	1	0	0	0	0	0	55	0	1	0	0	0	0	0	0	100	0	0	1	0	0	0	0	0
11	0	0	1	0	0	0	0	0	56	0	0	1	0	0	0	0	0	101	0	0	1	0	0	0	0	0
12	0	0	1	0	0	0	0	0	57	1	0	1	0	0	0	0	0	102	1	0	1	0	0	0	0	0
13	0	0	1	1	0	0	0	0	58	0	0	1	1	0	0	0	0	103	0	0	1	1	0	0	0	0
14	0	0	1	0	0	0	0	0	59	0	0	1	0	0	0	0	0	104	0	0	1	0	0	0	0	0
15	0	0	1	1	0	0	0	0	60	0	0	1	0	1	0	0	0	105	0	0	1	0	0	0	0	0
16	0	0	0	1	0	0	0	0	61	0	0	0	1	0	0	0	1	106	1	0	0	1	0	0	0	0
17	0	0	0	1	0	0	0	0	62	0	0	0	1	0	0	0	0	107	0	0	0	1	0	0	0	1
18	0	0	0	1	0	0	0	1	63	0	0	0	1	0	0	0	0	108	0	0	0	1	0	0	0	0
19	1	0	0	1	0	0	0	0	64	0	0	0	1	0	0	0	0	109	0	0	0	1	0	0	0	0
20	0	0	0	1	0	0	0	0	65	0	0	0	1	0	0	0	0	110	0	0	0	1	0	0	0	0
21	0	0	0	0	1	0	0	0	66	1	0	0	0	1	0	0	0	111	0	0	0	0	1	0	0	0
22	0	0	0	0	1	0	0	0	67	0	0	0	0	1	0	0	0	112	0	0	0	0	1	0	0	0
23	0	0	0	0	1	0	0	0	68	0	0	0	0	1	0	0	0	113	0	0	0	0	1	0	0	0
24	0	0	0	0	1	0	0	0	69	0	0	0	0	1	0	0	0	114	0	0	0	0	1	0	0	0
25	0	0	0	0	1	0	0	1	70	0	0	0	1	1	0	0	0	115	0	0	0	0	1	0	0	0
26	0	0	0	0	1	0	0	1	71	0	0	0	1	1	0	0	0	116	0	0	0	0	1	0	0	0
27	0	0	0	0	1	0	0	0	72	0	0	0	0	1	0	0	0	117	0	0	0	0	1	0	0	0
28	0	0	0	0	0	1	0	0	73	0	0	0	0	0	1	0	1	118	0	0	0	0	1	1	0	0
29	0	0	0	0	0	1	0	0	74	0	0	0	0	0	1	0	0	119	0	0	0	0	0	1	0	0
30	0	0	0	0	0	1	0	0	75	0	0	0	0	0	1	0	0	120	0	0	0	0	0	1	0	0
31	0	0	0	0	0	1	0	0	76	0	0	0	0	0	1	0	0	121	0	0	0	0	0	1	0	0
32	0	0	0	0	0	1	0	0	77	0	0	0	0	0	1	0	0	122	0	0	0	0	0	1	0	0
33	0	0	0	0	0	0	1	0	78	0	0	0	0	0	0	1	0	123	0	0	0	0	0	0	1	0
34	0	0	0	0	0	0	1	0	79	0	0	0	0	0	0	1	0	124	0	0	0	0	0	1	1	0
35	0	0	0	0	0	0	1	0	80	0	0	0	0	0	0	1	0	125	0	0	0	1	0	0	1	0
36	0	0	0	1	0	0	1	0	81	0	0	0	1	0	0	1	0	126	1	0	0	0	0	0	0	1
37	0	0	0	0	0	0	1	0	82	0	0	0	0	0	0	1	0	127	0	0	0	0	0	0	1	0
38	0	0	0	0	0	0	1	0	83	0	0	0	0	0	0	1	0	128	1	0	0	0	0	0	1	0
39	0	0	0	1	0	0	0	1	84	0	0	0	0	0	0	0	1	129	1	0	0	0	0	0	1	1
40	0	0	0	1	0	0	0	1	85	0	0	0	0	0	0	0	1	130	0	0	0	0	0	0	0	1
41	0	0	0	0	0	0	0	1	86	0	0	0	0	1	0	0	1	131	0	0	0	0	0	0	1	1
42	0	0	0	0	0	0	0	1	87	1	0	1	0	1	0	0	1	132	0	0	0	0	1	0	0	1
43	1	0	0	0	0	0	0	1	88	0	0	0	0	0	0	0	1	133	1	0	0	0	0	0	0	1
44	0	0	0	0	1	0	0	1	89	0	0	0	0	0	0	1	1	134	1	0	0	0	0	0	0	1
45	0	0	0	1	0	0	0	1	90	0	0	0	1	0	0	0	1	135	0	0	0	0	1	0	0	1

Figure 1 The matrix of test characteristics (Q-matrix)

Table 1 Test specification in diagnostic test for junior high school students

Element of DQ	Contents	Item
1. Digital citizen identity	1. Understanding basics of digital citizenship, Digital self-identity, and interpret human right.	1–5
	2. Have appropriate behaviour when using technology.	46–50
	3. Be mindful of the public peace.	91–95
2. Balance use of technology	4. Understanding impact of technology on health.	6–9
	5. Able to assess health risks.	51–54
	6. Be honest and have positive relationships online.	96–99
3. Behavioral cyber-risk management	7. Understanding about cyber risks, copyright and computer security.	10–16
	8. Choose safe manage cyber risk behavior.	55–60
	9. Be aware of safety.	00–105
4. Personal cyber security management	10. Explain personal cyber security and cyber threats	17–20
	11. Skills in preventing cyber threats.	61–65
	12. Be careful about personal data security.	06–110
5. Digital empathy	13. Understanding the emotional impact of actions on others and be reasonable online.	21–27
	14. Manage emotions in response to cyberbullying.	66–72
	15. Respect privacy and empathize with online victims.	111–117
6. Digital footprint management	16. Understand the meaning of digital footprint.	28–32
	17. Manage digital footprint using.	73–77
	18. Be mindful of leaving a digital footprint.	118–122
7. Media and information literacy	19. Distinguish between facts, opinion, and fake news.	33–38
	20. Have online skills to find reliable information.	78–83
	21. Consider the impact of media literacy.	123–128
8. Privacy management	22. Understand privacy, personal data.	39–45
	23. Use standard rules and prevent rights breaches.	84–90
	24. Respect personal data of yourself and others.	129–135

(6) The researcher developed a digital intelligence diagnostic test based on a test specific. It includes 135 multiple-choice questions. The scoring format is dichotomous, where a correct answer earns 1 point and an incorrect answer earns 0 points., (7) the content validity of the digital intelligence diagnostic test by seven experts using the Item Objective Congruence (IOC) method (Rovinelli & Hambleton, 1977)., (8) the quality of the Q-matrix was validated with nine experts' consideration of Mesa plots to visualize the Percent Variance Accounted For **(**PVAF**)** of q-vectors and EPS indices set at .95 (De la Torre & Chiu, 2016).

Finally, (9) the researcher revised the digital intelligence diagnostic test and the Q-matrix and then tested them with a sample group.

Data Analysis

Descriptive Statistics, the KR-20 method (Taber, 2018), confirmatory factor analysis (CFA) (Hair et al., 2006), cognitive diagnostic model analysis using the G-DINA model (Ma & De la Torre, 2020), validation of a Q-matrix, with results explained using Mesa plot (PVAF and EPS indices) (Ma & De la Torre, 2020).

Results

Result of Developing a Digital Intelligence Diagnostic Test Using the G-DINA Model and Validating the Quality of the Q-matrix.

The DQ diagnostic test was developed based on the test specification from Table 1, which consisted of 24 contents, 135 items. Each item aimed to measure strengths and areas for improvement in three dimensions: cognition, skills, and values, as defined in the Q-matrix. The validation of content validity involves four issues: item and content, item and attribute, item and learning behaviour, and item and the Q-matrix. This is based on the criteria of more than .5 (Rovinelli & Hambleton, 1977), with the IOC index ranging from 0.78 to 1.

The consistency validation between the items and the Q matrix of the test used the Hull method with PVAF (Najera et

al., 2019). The suggested Q-matrix, was based on the stepwise Wald test. The validation results found that the q-vector of 11 items were suggested to be modified. Additionally, the mesa plots were drawn to visualize the PVAF of q-vectors. In mesa plots, the x-axis represents the q-vectors and the y-axis shows their corresponding PVAF values. The default cutoff value for PVAF (eps) is set to .95, ranging from 0 to 1 (Ma & De la Torre, 2016) In these mesa plots, the red dots were the original q-vectors. The plots of items 14, 20, 21, 27, 38, 46, 53, 66, 91, 93, and 94 were suggested to be the correct ones instead of the q-vectors [00010000], [00000001], [10000000], [00000010], [01000000], [00100000], [00010000], [00000001], [00010001], [00000001], and [00000001] in the modified Q-matrix, as shown in Figure 2.

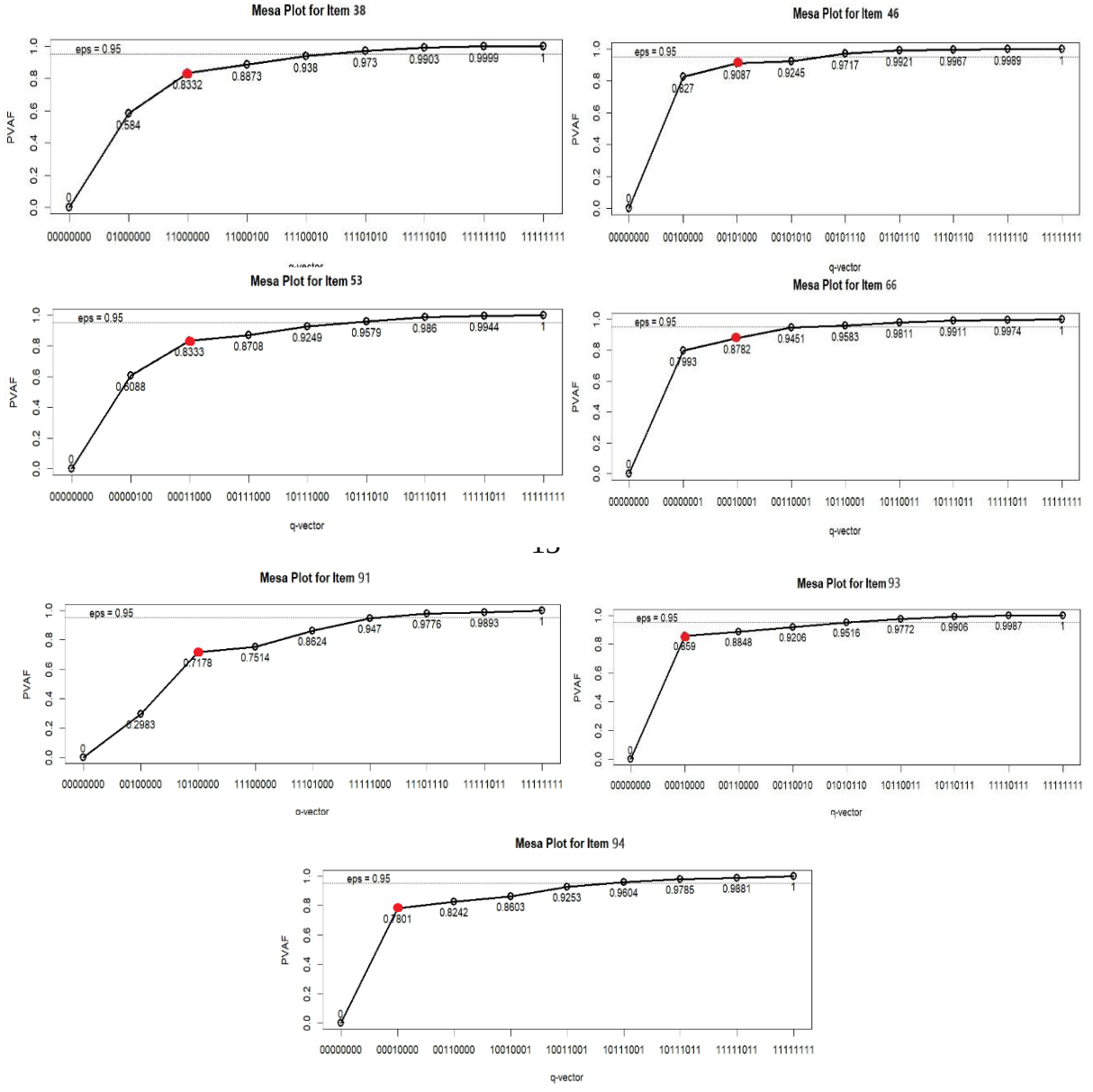


Figure 2 Mesa plot

Validation to select items of the DQ diagnostic test using the G-DINA Discrimination Index (GDI) coordinating the Q matrix with the PVAF method, found that a total of 135 test items were investigated, of which 94 items (69.6%) passed the selection criteria, while 41 items (30.4%) did not, as presented by the asterisk in Table 2 (De la Torre & Chiu, 2016; Williamson, 2023). The passed items were categorized based on the components of DQ as follows: (1) 32 items of cognitive domain, (2) 34 items of skill domain, and (3) 28 items of value domain.

Investigation of the item parameters of the DQ diagnostic test (94 items) in the G-DINA model involved guessing, slipping, probability, and the item discrimination index (IDI) (De la Torre & Chiu, 2016). The DQ diagnostic test featured guessing values ranging from 0.01 to 0.60, with items 3 and 89 exceeding 0.50. This suggests that students with lower digital skills might successfully guess the correct responses for those questions. The slipping values ranged from 0.01 to 0.56, with values greater than 0.50 corresponding to items 5, 52, and 87. This suggests that students with high digital ability levels answered those items incorrectly.

Table 2 Consistency validation of the items and the Q-matrix

Item	Cognition (45 items)			Item	Skill (45 items)			Item	Value (45 items)		
	GDI	PVAF	Result		GDI	PVAF	Result		GDI	PVAF	Result
1	0.42	Identified	Retained	46	0.51	ERROR	Rechecked	91	0.33	Not Identified	Removed*
2	0.40	Identified	Retained	47	0.33	ERROR	Rechecked	92	0.59	Identified	Retained
3	0.40	Identified	Retained	48	0.42	Identified	Retained	93	0.27	Not Identified	Removed*
4	0.50	Not Identified	Removed*	49	-0.05	ERROR	Removed*	94	0.68	Identified	Retained
5	0.30	Not Identified	Removed*	50	0.82	Identified	Retained	95	-0.28	Identified	Removed*
6	0.61	Not Identified	Retained	51	0.35	ERROR	Rechecked	96	0.06	ERROR	Removed*
7	0.25	ERROR	Rechecked	52	0.46	Identified	Retained	97	0.62	Identified	Retained
8	0.35	ERROR	Rechecked	53	0.46	ERROR	Rechecked	98	1.00	Identified	Removed*
9	0.35	ERROR	Rechecked	54	0.53	Identified	Retained	99	0.64	Identified	Retained
10	0.09	ERROR	Removed*	55	0.22	ERROR	Rechecked	100	0.68	Identified	Retained
11	0.23	ERROR	Rechecked	56	0.54	Identified	Retained	101	0.31	Not Identified	Removed*
12	0.39	Identified	Retained	57	0.86	Identified	Retained	102	0.58	ERROR	Rechecked
13	-0.10	ERROR	Removed*	58	0.66	Identified	Retained	103	0.34	Not Identified	Removed*
14	0.32	Not Identified	Removed*	59	0.58	ERROR	Rechecked	104	0.07	Not Identified	Removed*
15	0.64	Identified	Retained	60	0.55	Identified	Retained	105	0.53	ERROR	Rechecked
16	0.39	ERROR	Rechecked	61	0.55	Identified	Removed*	106	0.67	Identified	Retained
17	0.34	ERROR	Rechecked	62	0.65	Identified	Removed*	107	0.66	ERROR	Rechecked
18	0.65	Identified	Retained	63	0.65	Identified	Retained	108	0.60	ERROR	Rechecked
19	0.56	Identified	Retained	64	0.61	Identified	Retained	109	0.57	ERROR	Rechecked
20	0.58	Identified	Retained	65	0.41	ERROR	Rechecked	110	0.60	ERROR	Rechecked
21	0.41	ERROR	Rechecked	66	0.10	Not Identifie	Removed*	111	0.42	ERROR	Rechecked
22	0.54	Identified	Retained	67	0.64	Identified	Retained	112	0.28	ERROR	Rechecked
23	0.62	Identified	Retained	68	0.51	Identified	Retained	113	0.55	ERROR	Rechecked
24	0.45	Identified	Retained	69	0.29	ERROR	Rechecked	114	0.38	ERROR	Rechecked
25	0.44	Identified	Retained	70	0.36	Identified	Retained	115	0.15	Not Identified	Removed*
26	0.53	Identified	Retained	71	0.92	Identified	Removed*	116	0.34	ERROR	Rechecked
27	0.07	Not Identified	Removed*	72	0.29	ERROR	Rechecked	117	0.28	ERROR	Rechecked
28	-0.13	ERROR	Removed*	73	0.57	Identified	Retained	118	0.47	ERROR	Rechecked
29	0.41	Identified	Retained	74	0.34	ERROR	Rechecked	119	0.46	ERROR	Rechecked
30	0.30	ERROR	Retained	75	0.27	Not Identifie	Removed*	120	0.48	Identified	Retained
31	0.50	Identified	Retained	76	-0.10	Not Identifie	Removed*	121	0.13	Not Identified	Removed*
32	-0.17	ERROR	Removed*	77	0.79	Identified	Retained	122	0.38	Not Identified	Removed*
33	-0.03	Not Identified	Removed*	78	0.66	Identified	Removed*	123	0.55	ERROR	Rechecked
34	0.65	Identified	Retained	79	0.58	Not Identifie	Removed*	124	0.31	ERROR	Rechecked
35	0.38	Identified	Retained	80	0.55	Identified	Retained	125	0.55	ERROR	Removed*
36	0.58	Identified	Retained	81	0.13	Not Identifie	Removed*	126	0.46	Identified	Removed*
37	0.17	Not Identified	Removed*	82	0.45	ERROR	Rechecked	127	0.48	Identified	Retained
38	0.52	ERROR	Rechecked	83	0.66	Identified	Retained	128	0.63	Identified	Removed*
39	0.65	Not Identified	Removed*	84	0.64	Identified	Retained	129	0.56	Not Identified	Removed*
40	0.47	Identified	Retained	85	0.47	Identified	Retained	130	0.76	Identified	Removed*
41	0.67	Identified	Retained	86	0.67	Identified	Retained	131	0.68	Identified	Retained
42	0.20	ERROR	Rechecked	87	0.03	Identified	Removed*	132	0.60	ERROR	Removed*
43	0.19	ERROR	Rechecked	88	0.51	Identified	Retained	133	0.52	ERROR	Rechecked
44	0.04	Not Identified	Removed*	89	0.47	Identified	Retained	134	0.78	Identified	Retained
45	0.14	Not Identified	Removed*	90	0.65	Identified	Retained	135	0.66	Identified	Retained

Note: Items marked with an asterisk (*) were removed due to failing to criteria for discrimination index and PVAF.

The probability correct response was between 0.43 to 0.99. Item Discrimination Index (IDI) was between 0.15 to 0.99, with an IDI that should exceed 0.50. However, items 3, 5, 6, 8, 12, 22, 39, 49, 52, 87, and 89 did not meet this acceptable threshold, as shown in Table 3.

The reliability results of the DQ test for lower secondary school students, using the Kuder-Richardson 20 (KR-20) method, indicated a high level of reliability, with a coefficient exceeding the threshold of 0.70, as suggested by Quaigrain and Arhin (2017) suggest that KR-20 value of < 0.3 is considered poor, and a value of ≥ 0.7 is considered acceptable. The reliability of the DQ test was 0.90, as shown in Table 4.

Result of Investigating the Components of Digital Intelligence.

The confirmatory factor analysis (CFA) of the digital intelligence model provides the following analytical evidence: Pearson's correlation revealed that most observed variables were significantly correlated at the 0.05 and 0.01 levels. The Bartlett's test of sphericity found a value of 713.28 ($p < .000$), indicating that the correlation matrix significantly differs from the identity matrix, which aligns with the Kaiser-Meyer-Olkin (KMO) index of 0.856. These results indicate that the variables are interrelated and suitable for factor analysis.

Table 3 Item parameters on the G-DINA model

Item	Cognition (32 items)				Item	Skills (34 items)				Item	Values (28 items)			
	Guess	Slip	Prob	IDI		Guess	Slip	Prob	IDI		Guess	Slip	Prob	IDI
1	.22	.32	.68	.50	33	.33	.21	.79	.50	67	.30	.13	.90	.57
2	.12	.25	.75	.63	34	.23	.25	.45	.52	68	.28	.08	.94	.64
3	.60	.08	.92	.32	35	.14	.23	.77	.63	69	.00	.00	.96	.99
4	.29	.19	.81	.52	36	.01	.01	.99	.98	70	.27	.01	.99	.72
5	.23	.52	.48	.25	37	.08	.33	.67	.59	71	.33	.05	.95	.62
6	.40	.30	.70	.30	38	.28	.07	.93	.65	72	.17	.32	.67	.51
7	.13	.23	.77	.64	39	.36	.24	.77	.40	73	.31	.12	.88	.57
8	.21	.49	.51	.30	40	.21	.27	.73	.52	74	.26	.01	.99	.73
9	.12	.36	.64	.52	41	.15	.32	.68	.53	75	.03	.24	.75	.73
10	.42	.08	.92	.50	42	.30	.15	.85	.55	76	.37	.01	.99	.62
11	.24	.16	.84	.60	43	.09	.12	.88	.79	77	.28	.20	.80	.52
12	.23	.43	.57	.34	44	.33	.06	.94	.61	78	.30	.09	.91	.61
13	.37	.04	.96	.59	45	.36	.05	.95	.59	79	.18	.33	.67	.50
14	.16	.26	.74	.58	46	.44	.06	.94	.50	80	.19	.22	.78	.59
15	.31	.10	.90	.59	47	.32	.08	.92	.60	81	.12	.09	.91	.79
16	.36	.21	.79	.50	48	.35	.05	.95	.60	82	.10	.45	.55	.50
17	.28	.18	.82	.54	49	.42	.22	.78	.36	83	.16	.21	.79	.63
18	.25	.17	.83	.58	50	.31	.14	.86	.55	84	.22	.25	.75	.53
19	.10	.42	.58	.50	51	.22	.33	.67	.50	85	.01	.24	.74	.75
20	.12	.21	.79	.67	52	.21	.22	.49	.28	86	.24	.12	.90	.64
21	.29	.14	.86	.57	53	.23	.28	.78	.55	87	.17	.56	.43	.27
22	.36	.36	.64	.28	54	.15	.48	.72	.57	88	.20	.15	.85	.65
23	.23	.21	.79	.56	55	.27	.18	.82	.55	89	.50	.35	.63	.15
24	.16	.16	.85	.68	56	.25	.21	.79	.54	90	.17	.31	.63	.52
25	.18	.12	.88	.70	57	.30	.11	.89	.59	91	.12	.15	.84	.73
26	.13	.22	.78	.65	58	.25	.17	.83	.58	92	.01	.30	.70	.69
27	.23	.20	.82	.57	59	.28	.27	.73	.50	93	.29	.01	.99	.70
28	.22	.29	.71	.50	60	.27	.07	.93	.66	94	.25	.09	.86	.66
29	.23	.31	.69	.50	61	.22	.16	.84	.62					
30	.22	.11	.89	.67	62	.28	.19	.81	.53					
31	.25	.15	.85	.60	63	.28	.08	.92	.64					
32	.17	.26	.74	.57	64	.27	.25	.75	.50					
					65	.19	.24	.76	.57					
					66	.36	.08	.92	.56					

Table 4 Reliability of the test

	KR-20								
	A1	A2	A3	A4	A5	A6	A7	A8	Total
Cognition	.72	.72	.74	.74	.70	.73	.70	.75	.86
Skill	.77	.71	.75	.78	.78	.78	.75	.73	.86
Value	.76	.77	.78	.78	.71	.88	.74	.77	.88
DQ test					.90				



Figure 3 The digital intelligence model

Table 5 Confirmatory factor analysis of the digital intelligence model

Factor	Indicators	Factor loading	S.E.	*t*	R^2
1. Cognition	CA1	.62			.38
	CA2	.52	.11	7.56**	.28
	CA3	.33	.12	4.92**	.11
	CA4	.78	.12	10.23**	.61
	CA5	.84	.12	10.64**	.70
	CA6	.42	.12	6.27**	.18
	CA7	.70	.14	9.46**	.49
	CA8	.60	.11	8.42**	.36
2.Skills	SA1	.46			.21
	SA2	.54	.18	6.01**	.29
	SA3	.75	.23	6.98**	.56
	SA4	.66	.27	6.67**	.44
	SA5	.65	.21	6.61**	.42
	SA6	.76	.31	6.68**	.58
	SA7	.59	.28	6.36**	.35
	SA8	.67	.26	6.71**	.45
3. Values	VA1	.50			.25
	VA2	.60	.15	7.99**	.37
	VA3	.63	.18	7.33**	.40
	VA4	.82	.20	8.22**	.66
	VA5	.64	.15	7.46**	.41
	VA6	.62	.19	7.24**	.38
	VA7	.60	.19	6.96**	.36
	VA8	.64	.20	7.40**	.40
	Cog	.51			.46
	Ski	.37	.27	3.92**	.38
	Val	.42	.38	4.89**	.58
Chi-square = 235, df = 232, *p*-value = .433, χ^2/df = 1.013, CFI = .999, TLI = .998, RMSEA = .008, SRMR = 0.032					

Note: ** $p < .01$

The confirmatory factor analysis indicated that the model is a good fit with the empirical data ($\chi^2 = 235$, $p < .01$, df = 232, $\chi^2/df \leq 2$). The goodness-of-fit indices were more than .90 (CFI = .999, TLI = .998), and the error indices were less than 0.05 (RMSEA = .008, SRMR = 0.032). The factor loadings ranged from 0.33 to 0.84, and all factor loadings were statistically significant. ($p < .01$). The percentage of variance explained did not exceed 60 percent (Hair et al., 2006) as shown in Figure 3, and Table 5.

Result of Analyzing the Digital Intelligence.

Analyzing the digital intelligence consists of the latent class proportions and attribute prevalence, which found that (1) the content of the DQ included 8 attributes. Calculating the response pattern profile were 256 latent classes (2^K, where K is the number of attributes, in this case, 2^8). The response pattern found 35 respondents format. The most common response format is "11111111," indicating that respondents were well-versed in all characteristics, representing 34.4 percent. This is followed by the response format "00000000," with 16.7 percent of respondents, and the response format "01011000" had the lowest proportion of respondents at .10 percent, as shown in Figure 4.

(2) Considering the attributes analyzed by the G-DINA model, it was found most skill mastery probability in attribute 1 (A1) digital citizen identity, at 79.9 percent. This was followed by attribute 5 (A5) digital empathy at 75.5 percent, attribute 2 (A2) balance and use of technology at 74.9 percent, attribute 4 (A4) personal cyber security management at 73.8 percent, attribute 3 (A3) behavioral cyber-risk management at 69.2 percent, attribute 7 (A7) media and information literacy at 67.6 percent, attribute 8 (A8) privacy management at 65.6 percent, and attribute 6 (A6) digital footprint management at 59.2 percent, as Figure 5.

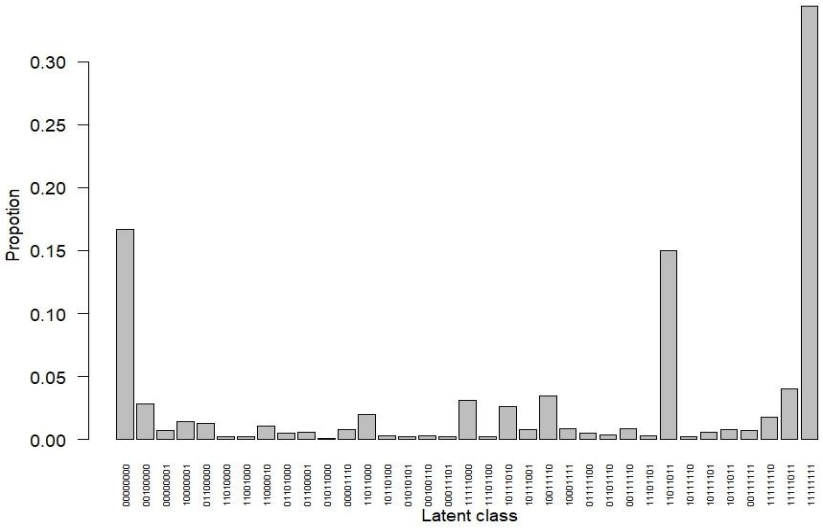


Figure 4 The latent class proportions

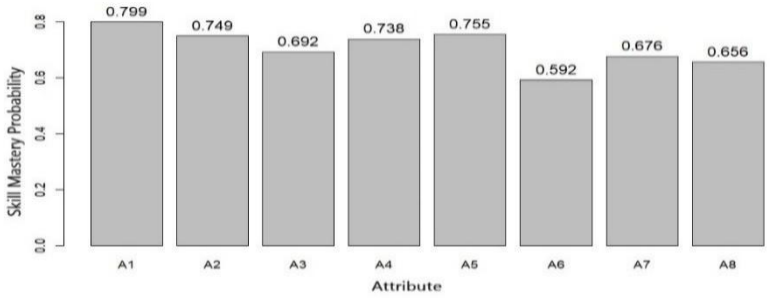


Figure 5 The attribute prevalence

Discussion

The study's results indicate that the strongest attribute was digital citizen identity, while the weakest attribute was digital footprint management. Digital footprint management involves understanding what a digital footprint is, utilizing technological skills to manage it, and being aware of the digital footprint we leave behind. These findings align with Phonphaphon (2018), who reported that 55.9 percent of Thai children aged 12 to 16 gave personal data to strangers online. Most students frequently share, post, or tell personal stories online, such as their travel experiences, food, family, residence, and even personal information. These details are often stored in open online databases, which creates opportunities for criminals to steal or deceive, potentially causing harm to the information owner. Therefore, educational institutions should educate students about online data management, digital footprint management, and the importance of disclosing personal information online only when necessary. This will help protect students from becoming victims to cyber threats.

The digital intelligence diagnostic test consists of eight attributes, three domains of learning, and 94 items (all 135 items) using the G-DINA, with GDI coordinating the Q matrix with the PVAF. This research validates the Q matrix using expert and statistical evidence with PVAF. According to Ma and De la Torre (2020), the validation of the quality of the Q-matrix using the Proportion of Variance Accounted For (PVAF) index will provide statistical support for the Q-matrix validation alongside expert judgment. Najera et al., (2019) found that most of the Q-matrix was correct for the items. This diagnostic test is a good fit for the G-DINA mode, with correspondence between the items and the Q-matrix by the expert judgment method and the PVAF index (mesa plot), which is a popular and reliable method (De la Torre & Chiu, 2016). These had a PVAF lower than the cutoff value (eps = .95). However, when considering the number of attributes, each item had only 1 attribute. Najera et al. (2019) stated that a good Q-matrix must consider the parsimony principle. (If there are different Q-matrix results in the same variance in the probability of correct answers, a simpler model is more appropriate). Najera et al. (2019) suggested that the appropriate EPS value depends on the number of test takers. For a sample size of 1,000 people, the EPS values are around .90 and .95, yielding good analytical results. However, if the number of test takers is smaller (500 people), the appropriate EPS values are .85 and .90, depending on whether the test's discriminatory power is medium or high, respectively.

For the attribute prevalence in DQ, the student's highest skill mastery probability was in attribute 1(A1), digital citizen identity. The elements digital citizen identity includes constructing required personal data, displaying digital self-identity, understanding equality and human rights, using licensed products, and respecting social rules and law. This aligns with Kanyaporn et al. (2021), who found that Mathayom 6 students had digital survival skills, with an overall score exceeding 80 percent. Therefore, it can be said that Thai students have a high level of DQ in digital citizen identity.

Conclusion and Recommendation

This digital intelligence diagnostic test is suitable for lower secondary students. The diagnostic questions are based on cognition, skills, and values related to digital competence as defined by Yuhyun (2016), Gardner's theory (1983), and the Basic Education Core Curriculum B.E. 2551 (revised edition B.E. 2560). The test meets quality standards according to the G-DINA diagnostic model, making it appropriate for classroom use. In addition, we found that the attribute with the lowest score is digital footprint management. Teachers can develop information media and content in related subjects to enhance students' knowledge, skills, and attitudes regarding their digital footprint. This research also developed a diagnostic testing system with automated feedback. This system can be utilized by schools, teachers, parents, and students to identify any misconceptions in digital skill. Teachers can use this digital intelligence diagnostic test to assess digital competency across three learning behaviors (Cognitions, Skills, and Values). The online system can be accessed anytime and anywhere via screens, including computers, smartphones, and tablets. Developing digital intelligence will help build cyber safety resilience, promote digital literacy, and facilitate safe engagement in online communities. For future research, it is advisable to delve into higher-level digital skills, including digital creativity and digital entrepreneurship, to guide the development of digital intelligence in line with advancements in modern technology. Additionally, the research should consider utilizing the general diagnostic model and regularized latent class model for polytomous attributes and responses.

Conflict of Interest

The authors declare that there is no conflict of interest.

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