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Restructuring of the E-Learning Styles Factors for Technology Training

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Abstract: The introduction of e-training and e-learning in Malaysia was a major step towards the democratisation of many aspects of education for diverse learners. Nevertheless, several surveys of blended or hybrid learning approaches showed some gaps in learning-style research involving the teaching and learning of technology. The initial framework of this study involved the construction of a questionnaire to assess the learning styles of technology trainees who had attended a hybrid e-training course. The questionnaire initially consisted of six factors that assessed learning styles in general. The factors were (i) visual, (ii) kinaesthetic (iii) auditory (iv) tactual, (v) individual and (vi) group-learning styles. The questionnaire was administered to 249 ICT trainers from the Faculty of Education, in one public university in Malaysia. After going through the process of principal-component analysis, learning styles for technology training were eventually classified into five factors with slightly different items and factor names, namely (i) visual, (ii) auditory, (iii) kinaesthetic-tactual, (iv) individual and (v) group. This paper shows how this process was carried out and further discusses the findings.

Key words: E-learning % Technology training % Learning style % Blended learning % Diverse learners

INTRODUCTION

A *blended* teaching and learning program, also known as *hybrid* e-training or hybrid e-learning, has a clear mission to achieve strategic change in education through lifelong learning and the creation of a ‘knowledge society [1]’. The emergence of blended/hybrid learning has paved the way for most higher-education institutions to certify, fund, design and deliver better alternative-education and professional-development programs. The programs help technology trainees develop their professional skills through the direct acquisition of knowledge. The introduction of e-learning in Malaysia is a big step towards the democratisation of education in that country for learners and trainees with various learning-style preferences. Thus, this study aims to provide a highly reliable and valid instrument, the e-Learning Style Preferences (eLSe) questionnaire, to measure learning-style preferences of technology trainers and trainees. In pursuit of this aim, a principal-component analysis was conducted on the eLSe questionnaire (version 8.1) before it underwent a confirmatory factor analysis for the highest level of validity processes, that is, the convergent and discriminant validity process.

Overall reliability analysis using Cronbach’s alpha on pilot data from 213 participants, following the content validity assessment by experts, showed that the questionnaire was reliable and valid in its purpose of measuring e-learning styles in technology learning. The reliability value of the questionnaire as tested in the pilot test was derived from data collected from 213 technology trainers and trainees; the value was ″ =. 89. However, one of the six constructs did not meet the criterion of ″ >. 0.7 [2]. Thus, the Rasch model was applied using Winsteps, version 3.68.2 to obtain the test’s item and person reliability [3], which were. 94 and. 85 respectively.

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While obtaining item and person reliability using the Rasch model, dimensional analysis [3,4] was also carried out. Through this analysis, learning-style dimensions were discovered that slightly differ from those expected in the underlying theory of previous studies [5-9]. Thus, another field study was carried out to verify the validity of the reshuffled items with corrected sentence structures. At this time, sufficient data were collected to do principal-component analysis (PCA).

In the PCA, data were collected from the items, which had been restructured and grouped into the components of the eLSe questionnaire. PCA was not performed on the pilot data. At that time, only a confirmatory factor analysis [11, 12] was performed, on the basis of the underlying theories governing the construction of eLSe version 5.1, which had been named 'learning style-preference (LSP) inventory' at the time [9]. The number of respondents was increased for the second field test using eLSe version 8.1. The next objective was then to obtain sufficient evidence to show the construct validity of eLSe 8.1.

The aim was to produce a new, highly reliable and valid version of the e-learning-style questionnaire. To achieve the aim of the study, several research objectives have been determined. The following sections will discuss the principal component-analysis procedure to verify the key components that represent e-learning styles or technology-learning style preferences.

MATERIALS AND METHODS

The survey method was used in this study, which involved 249 ICT trainers from the Faculty of Education, in one public university in Malaysia. The aim is to produce a new version of a highly reliable and valid e-learning style-preference questionnaire. To achieve this aim, several research objectives have been determined and phrased in the form of research questions, as follows:

- Is the sample size adequate to perform principal-component analysis?
- Are there overlapping measurements (multicollinearity) among the reshuffled items?
- What are the factors derived from the principal-component analysis?

Principal Component-Analysis Procedure: PCA is an exploratory factor analysis (EFA) technique used to determine the dimensions or components of items in a questionnaire. This technique is very important to determine the uni or multidimensionality of each of the constructs in the questionnaire. In general, to perform PCA using SPSS software such as the SPSS version 16 [10] used for this study, one first selects the *analyze* function, then choose *data reduction*. A dialogue box will appear. In the *factor* selection section of the dialogue box, constructs to be analysed are then entered. In the case of this study, the data to be used are those collected using the eLSe questionnaire.

Subsequently in the present analysis, under the (i) *descriptive* option, three selections were made - the *easy image*, *KMO* and *determination* options. Next under the (ii) *extraction* option, two areas were selected—*correlation* and *scree plot*. For the (iii) *eigenvalues* option, the value '*1*' was selected, with a maximum iteration of '*25*'. For the (iv) *rotation* option, two points were selected—*varimax* and *oblimin data*. Next on the (v) *display* option, *rotated solution* was checked, still with a maximum iteration of '*25*'. Finally, the (vi) *continue* button was clicked to start the process of principal-component analysis.

The next step was to notify the system to store the input analysis by clicking on the *save as a variable* option. Finally, in the *method* section, (vii) *regression* and *display factor score* were selected. These procedures gave an output able to answer the research questions. The results of data analysis are reported in the *results* section. The first research question of this study is whether PCA can be implemented, based on two types of test - the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) and the anti-image correlation. The second and third research questions relate to factors derived from the restructuring process using the PCA factors.

RESULTS AND DISCUSSION

The results of data analysis will be reported in this section, with an eye to answering research questions. The first question is to determine whether PCA can be implemented, based on the KMO and anti-image-correlation tests, as mentioned above. The second and third questions relate to the factors derived from the restructuring process using the PCA.

Adequacy of Sampling According to the Kaiser-Meyer-Olkin Measure of Sampling Adequacy: Table 1 shows the KMO in order to answer the first research question, 'Is the sample size adequate to perform principal-component analysis?' To conduct PCA, the minimum value of KMO must not be less than .50, and a

Table 1: KMO dan Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.835	
Bartlett's Test of Sphericity	Approx. Chi-Square	3.459E3
	Df	435
	Sig.	.000

Table 2: Anti Image Correlation

dv01	.724a	(0.19)	(0.23)	(0.10)	(0.09)	0.06	(0.08)	(0.19)	(0.07)	0.17	0.12	(0.16)	0.01	(0.26)	(0.21)	0.09	0.12	(0.29)	0.14	0.04	(0.10)	0.13	(0.07)	0.24	0.04	(0.06)	0.09	(0.04)	0.08	(0.10)
dv02	(0.19)	.859a	(0.40)	0.02	0.05	(0.02)	0.08	(0.03)	0.14	(0.09)	(0.03)	0.10	0.03	(0.04)	0.01	(0.08)	(0.10)	(0.06)	(0.03)	(0.04)	(0.01)	0.06	(0.12)	-	0.06	(0.14)	0.02	(0.06)	0.08	(0.04)
dv03	(0.23)	(0.40)	.794a	-	(0.03)	0.03	(0.21)	0.13	(0.03)	(0.11)	0.03	(0.08)	(0.03)	0.02	0.09	(0.12)	0.02	0.06	(0.01)	0.11	0.02	(0.17)	0.13	(0.15)	(0.04)	0.14	(0.26)	0.07	(0.11)	0.12
dv04	(0.10)	0.02	-	.802a	(0.36)	(0.25)	0.02	0.26	(0.03)	0.06	(0.03)	(0.03)	(0.19)	0.02	0.03	(0.12)	0.09	0.03	(0.05)	(0.06)	0.06	(0.05)	(0.04)	0.06	(0.02)	0.03	(0.24)	0.03	(0.02)	0.05
dv05	(0.09)	0.05	(0.03)	(0.36)	.752a	0.07	(0.02)	(0.10)	0.31	(0.20)	(0.13)	0.16	(0.06)	0.06	0.07	(0.17)	0.15	0.04	(0.06)	0.12	(0.22)	0.07	0.03	(0.16)	0.07	(0.18)	0.01	(0.17)	(0.12)	0.00
da01	0.06	(0.02)	0.03	(0.25)	0.07	.775a	(0.27)	(0.33)	(0.01)	0.17	0.05	(0.25)	0.22	(0.15)	(0.15)	0.05	0.03	0.01	(0.03)	-	0.18	(0.10)	(0.15)	0.03	(0.01)	0.02	(0.03)	0.03	(0.06)	(0.01)
da02	(0.08)	0.08	(0.21)	0.02	(0.02)	(0.27)	.842a	(0.07)	(0.19)	(0.03)	(0.11)	0.06	(0.01)	(0.09)	0.04	0.03	(0.02)	0.06	(0.03)	(0.13)	0.01	0.13	(0.14)	0.02	0.08	(0.06)	0.07	(0.03)	0.12	(0.07)
da03	(0.19)	(0.03)	0.13	0.26	(0.10)	(0.33)	(0.07)	.700a	(0.03)	(0.25)	0.11	0.04	(0.17)	0.20	0.08	(0.17)	(0.04)	(0.01)	0.10	0.03	(0.04)	(0.01)	0.05	(0.22)	(0.09)	0.06	0.01	0.00	(0.16)	0.02
da04	(0.07)	0.14	(0.03)	(0.03)	0.31	(0.01)	(0.19)	(0.03)	.764a	(0.35)	(0.24)	0.19	(0.02)	0.07	(0.04)	(0.09)	(0.03)	(0.01)	(0.15)	0.13	(0.01)	(0.03)	(0.06)	(0.03)	0.10	(0.02)	(0.12)	(0.11)	0.02	0.03
da05	0.17	(0.09)	(0.11)	0.06	(0.20)	0.17	(0.03)	(0.25)	(0.35)	.787a	0.01	(0.26)	0.16	(0.20)	(0.02)	0.09	0.11	0.01	(0.05)	(0.15)	0.00	0.01	(0.05)	(0.03)	0.01	0.03	0.04	0.05	(0.06)	(0.04)
dt01	0.12	(0.03)	0.03	(0.03)	(0.13)	0.05	(0.11)	0.11	(0.24)	0.01	.869a	(0.40)	(0.01)	0.01	(0.04)	0.08	(0.12)	(0.14)	0.10	(0.05)	(0.12)	0.02	(0.04)	(0.01)	(0.05)	0.01	(0.01)	0.03	(0.00)	(0.03)
dt02	(0.16)	0.10	(0.08)	(0.03)	0.16	(0.25)	0.06	0.04	0.19	(0.26)	(0.40)	.802a	(0.13)	0.04	(0.11)	(0.11)	(0.02)	(0.04)	(0.04)	0.03	(0.02)	0.13	(0.04)	(0.06)	0.15	(0.12)	0.13	(0.11)	(0.05)	0.09
dt03	0.01	0.03	(0.03)	(0.19)	(0.06)	0.22	(0.01)	(0.17)	(0.02)	0.16	(0.01)	(0.13)	.784a	(0.29)	(0.02)	0.17	(0.10)	(0.01)	(0.05)	(0.19)	0.23	(0.11)	(0.09)	(0.00)	0.00	(0.03)	(0.09)	0.10	(0.03)	(0.04)
dt04	(0.26)	(0.04)	0.02	0.02	0.06	(0.15)	(0.09)	0.20	0.07	(0.20)	0.01	0.04	(0.29)	.860a	0.01	(0.08)	(0.19)	0.15	(0.10)	0.04	(0.02)	(0.23)	0.09	(0.07)	0.00	0.02	(0.02)	(0.09)	(0.03)	0.02
dt05	(0.21)	0.01	0.09	0.03	0.07	(0.15)	0.04	0.08	(0.04)	(0.02)	(0.04)	(0.11)	(0.02)	0.01	.915a	(0.22)	(0.03)	(0.13)	(0.10)	(0.08)	0.07	(0.19)	0.09	(0.07)	(0.10)	0.07	(0.07)	0.07	(0.06)	0.03
dk01	0.09	(0.08)	(0.12)	(0.12)	(0.17)	0.05	0.03	(0.17)	(0.09)	0.09	0.08	(0.11)	0.17	(0.08)	(0.22)	.857a	(0.44)	0.02	(0.11)	(0.14)	0.11	(0.04)	(0.04)	0.04	(0.06)	0.09	0.07	0.05	0.02	(0.01)
dk02	0.12	(0.10)	0.02	0.09	0.15	0.03	(0.02)	(0.04)	(0.03)	0.11	(0.12)	(0.02)	(0.10)	(0.19)	(0.03)	(0.44)	.863a	(0.18)	0.04	(0.01)	(0.09)	0.12	0.01	(0.02)	(0.04)	(0.04)	(0.04)	(0.07)	(0.06)	0.01
dk03	(0.29)	(0.06)	0.06	0.03	0.04	0.01	0.06	(0.01)	(0.01)	0.01	(0.14)	(0.04)	(0.01)	0.15	(0.13)	0.02	(0.18)	.897a	(0.31)	(0.09)	(0.04)	(0.06)	0.04	(0.04)	(0.14)	0.07	(0.06)	0.02	0.06	(0.02)
dk04	0.14	(0.03)	(0.01)	(0.05)	(0.06)	(0.03)	(0.03)	0.10	(0.15)	(0.05)	0.10	(0.04)	(0.05)	(0.10)	(0.10)	(0.11)	0.04	(0.31)	.910a	(0.14)	(0.18)	0.09	(0.02)	(0.06)	(0.00)	(0.06)	0.02	0.06	0.05	(0.14)
dk05	0.04	(0.04)	0.11	(0.06)	0.12	-	(0.13)	0.03	0.13	(0.15)	(0.05)	0.03	(0.19)	0.04	(0.08)	(0.14)	(0.01)	(0.09)	(0.14)	.909a	(0.20)	(0.03)	0.05	(0.04)	0.02	(0.09)	(0.01)	(0.05)	0.01	0.07
dg01	(0.10)	(0.01)	0.02	0.06	(0.22)	0.18	0.01	(0.04)	(0.01)	0.00	(0.12)	(0.02)	0.23	(0.02)	0.07	0.11	(0.09)	(0.04)	(0.18)	(0.20)	.842a	(0.33)	(0.11)	(0.05)	(0.12)	0.05	(0.07)	0.18	(0.12)	0.09
dg02	0.13	0.06	(0.17)	(0.05)	0.07	(0.10)	0.13	(0.01)	(0.03)	0.01	0.02	0.13	(0.11)	(0.23)	(0.19)	(0.04)	0.12	(0.06)	0.09	(0.03)	(0.33)	.838a	(0.40)	(0.08)	0.03	(0.03)	0.15	(0.10)	0.08	(0.03)
dg03	(0.07)	(0.12)	0.13	(0.04)	0.03	(0.15)	(0.14)	0.05	(0.06)	(0.05)	(0.04)	(0.04)	(0.09)	0.09	0.09	(0.04)	0.01	0.04	(0.02)	0.05	(0.11)	(0.40)	.877a	(0.21)	(0.26)	0.08	(0.00)	0.03	0.03	0.03
dg04	0.24	-	(0.15)	0.06	(0.16)	0.03	0.02	(0.22)	(0.03)	(0.03)	(0.01)	(0.06)	(0.00)	(0.07)	(0.07)	0.04	(0.02)	(0.04)	(0.06)	(0.04)	(0.05)	(0.08)	(0.21)	.891a	(0.12)	(0.10)	0.06	(0.05)	0.22	(0.11)
dg05	0.04	0.06	(0.04)	(0.02)	0.07	(0.01)	0.08	(0.09)	0.10	0.01	(0.05)	0.15	0.00	0.00	(0.10)	(0.06)	(0.04)	(0.14)	(0.00)	0.02	(0.12)	0.03	(0.26)	(0.12)	.858a	(0.14)	0.16	(0.14)	(0.21)	0.15
di01	(0.06)	(0.14)	0.14	0.03	(0.18)	0.02	(0.06)	0.06	(0.02)	0.03	0.01	(0.12)	(0.03)	0.02	0.07	0.09	(0.04)	0.07	(0.06)	(0.09)	0.05	(0.03)	0.08	(0.10)	(0.14)	.840a	(0.40)	0.04	(0.06)	(0.01)
di02	0.09	0.02	(0.26)	(0.24)	0.01	(0.03)	0.07	0.01	(0.12)	0.04	(0.01)	0.13	(0.09)	(0.02)	(0.07)	0.07	(0.04)	(0.06)	0.02	(0.01)	(0.07)	0.15	(0.00)	0.06	0.16	(0.40)	.814a	(0.33)	0.01	(0.10)
di03	(0.04)	(0.06)	0.07	0.03	(0.17)	0.03	(0.03)	0.00	(0.11)	0.05	0.03	(0.11)	0.10	(0.09)	0.07	0.05	(0.07)	0.02	0.06	(0.05)	0.18	(0.10)	0.03	(0.05)	(0.14)	0.04	(0.33)	.862a	(0.27)	(0.17)
di04	0.08	0.08	(0.11)	(0.02)	(0.12)	(0.06)	0.12	(0.16)	0.02	(0.06)	(0.00)	(0.05)	(0.03)	(0.03)	(0.06)	0.02	(0.06)	0.06	0.05	0.01	(0.12)	0.08	0.03	0.22	(0.21)	(0.06)	0.01	(0.27)	.780a	(0.61)
di05	(0.10)	(0.04)	0.12	0.05	0.00	(0.01)	(0.07)	0.02	0.03	(0.04)	(0.03)	0.09	(0.04)	0.02	0.03	(0.01)	0.01	(0.02)	(0.14)	0.07	0.09	(0.03)	0.03	(0.11)	0.15	(0.01)	(0.10)	(0.17)	(0.61)	.802a

Table 3: Total Variation Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings	
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance
1	7.96	26.52	26.52	7.96	26.52	26.52	3.98	13.27
2			3.99	3.99	13.30	39.82	3.70	12.32
3	1.68	5.60	45.42	1.68	5.60	45.42	3.47	11.57
4	1.48	4.95	50.37	1.48	4.95	50.37	2.19	7.29
5	1.35	4.48	54.85	1.35	4.48	54.85	2.14	7.13
6	1.28	4.26	59.12	1.28	4.26	59.12	1.79	5.95
7	1.17	3.89	63.00	1.17	3.89	63.00	1.64	5.47
8	0.98	3.28	66.29					
9	0.84	2.78	69.07					
10	0.82	2.74	71.81					
11	0.80	2.66	74.47					
12	0.74	2.48	76.95					
13	0.64	2.15	79.09					
14	0.63	2.11	81.21					
15	0.55	1.83	83.04					
16	0.53	1.78	84.82					
17	0.52	1.73	86.55					
18	0.48	1.60	88.16					
19	0.43	1.44	89.60					
20	0.42	1.39	90.99					
21	0.40	1.32	92.31					
22	0.36	1.19	93.50					
23	0.32	1.07	94.57					
24	0.32	1.05	95.63					
25	0.28	0.92	96.55					
26	0.27	0.90	97.44					
27	0.24	0.81	98.26					
28	0.20	0.67	98.92					
29	0.18	0.59	99.51					
30	0.15	0.49	100.00					

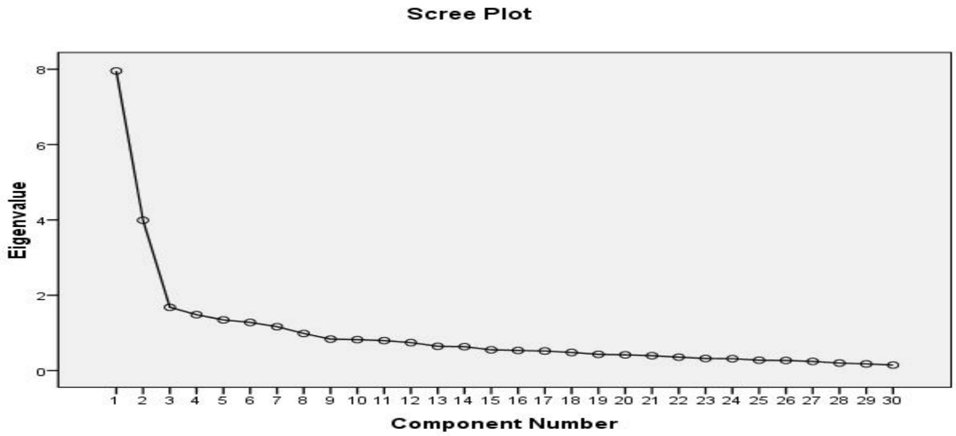

Fig. 1: Determination of Total Factor Through the Scree Plot

Table 4: Determining Factors Using Rotated Component Matrix

	1	2	3	4	5	6	7
dv01	0.14	0.22	(0.05)	0.68	(0.03)	0.14	0.22
dv02	0.14	0.25	0.16	0.77	0.05	(0.00)	(0.04)
dv03	0.16	0.08	0.12	0.78	0.24	0.11	0.02
dv04	0.35	0.04	0.10	0.17	0.01	0.69	0.11
dv05	0.66	(0.12)	0.30	0.16	(0.01)	0.22	(0.10)
da01	0.08	0.19	0.15	0.08	0.15	0.16	0.78
da02	(0.01)	0.03	0.09	0.26	0.55	0.17	0.43
da03	0.29	0.12	0.33	0.07	0.12	(0.45)	0.49
da04	0.01	0.22	0.07	0.05	0.74	(0.01)	0.11
da05	0.22	0.09	0.33	0.14	0.67	(0.20)	0.00
dt01	0.08	0.46	0.18	(0.05)	0.52	0.21	(0.01)
dt02	0.05	0.50	0.03	0.07	0.37	0.17	0.27
dt03	0.22	0.23	0.12	0.09	0.02	0.57	0.13
dt04	0.16	0.32	0.20	0.34	0.12	0.35	0.26
dt05	(0.06)	0.67	0.23	0.13	0.08	0.12	0.24
dk01	0.05	0.68	0.25	0.21	0.04	(0.05)	0.16
dk02	0.13	0.77	0.10	0.13	0.06	(0.04)	0.07
dk03	(0.02)	0.69	0.28	0.20	0.12	0.05	(0.05)
dk04	0.10	0.53	0.36	0.09	0.29	0.19	(0.10)
dk05	0.01	0.50	0.38	0.01	0.22	0.25	(0.09)
dg01	(0.02)	0.27	0.72	0.10	0.16	0.02	(0.20)
dg02	(0.17)	0.20	0.73	0.12	0.08	0.19	0.19
dg03	(0.16)	0.18	0.73	0.09	0.17	0.14	0.28
dg04	0.05	0.20	0.70	0.06	0.24	(0.01)	0.10
dg05	0.16	0.35	0.63	(0.03)	(0.13)	(0.11)	0.13
di01	0.62	0.05	0.04	0.13	0.12	0.31	(0.15)
di02	0.70	0.03	(0.15)	0.23	0.15	0.35	(0.08)
di03	0.82	0.07	(0.05)	0.10	0.08	0.06	0.13
di04	0.88	0.11	(0.02)	0.00	(0.02)	(0.07)	0.14
di05	0.84	0.06	(0.11)	0.03	0.03	(0.03)	0.12

Rotation method: Varimax with Kaiser normalisation

significantly small result of < 0.05 [13] is required. By mapping these requirements to the output of the analysis, it can be concluded that the eLSe questionnaire meets the first requirement for the implementation of PCA.

Implementing PCA According to Anti Image Correlation Analysis: To fulfill the prerequisite for implementation of PCA, Anti-image correlation test (Table 2) was carried out. In the output for this test, one point to note is the figures that form a diagonal line, where the figures should be valued at 0.5 or above [13]. By mapping these requirements to the output of the analysis in Table 2, it can be concluded that the learning style-preferences questionnaire met the correlation requirement for the implementation of PCA.

Structuring Factors using Principal-Component Analysis: Table 3 explains the total variance. Only total initial eigenvalues of above 1.0 or cumulative values above 60% were considered [13]. For the e-learning style-preferences questionnaire (eLSe, version 8.1), there were only seven values greater than 1.0. Thus, we conclude that there are seven constructs in this questionnaire. This is also supported by the findings of the scree plot, as shown in Figure 1.

Analysis by rotated component matrix table stipulates that only values which have the capacity for loading of .40 and above will be accepted as items for the respective construct. Based on these requirements, it can be concluded that the research instrument consists of seven different e-learning-style preferences at this stage

Table 5: Separation of 7 Rotated Component Factor Using Matrixa

	1	2	3	4	5	6	7
dv01				0.68			
dv02				0.77			
dv03				0.78			
dv04						0.69	
dv05	0.66						
da01							0.78
da02					0.55		0.43
da03							0.49
da04					0.74		
da05					0.67		
dt01		0.46			0.52		
dt02		0.50					
dt03						0.57	
dt04							
dt05		0.67					
dk01		0.68					
dk02		0.77					
dk03		0.69					
dk04		0.53					
dk05		0.50					
dg01			0.72				
dg02			0.73				
dg03			0.73				
dg04			0.70				
dg05			0.63				
di01	0.62						
di02	0.70						
di03	0.82						
di04	0.88						
di05	0.84						

Table 6: Summary of Constructs after the PCA and Expert Judgement

Construct	Item	Total Item
First	di01, di02, di03, di04, di05 dan dv05 (main-individual)	6
Second	dt01, dt02, dt05, dk01, dk02 dan dk03, dk04, dk05. (main-kinesthetic)	8
Third	dg01, dg02, dg03, dg04 dan dg05 (main-group)	5
Fourth	dv01, dv02, dv03 (main-visual)	3
Fifth	da02, da04, da05, dt01, (auditory)	4
Sixth	dv04, dt03	2
Seventh	da03 dan da04	3
	Total Item	30

of the analysis. Therefore, it can be concluded that eLSe's factors are as shown in Tables 4 and 5. After going through the process of grouping, the constructs for each item are formulated as in Table 6. In addition, after expert judgement, item da2 has been moved from the seventh to the fifth construct.

Overlapping Measurement (Multicollinearity): As shown in Table 5, the overlap in items indicates the existence of multicollinearity. This overlap shows that the respective items measure more than one construct. Thus, the analysis and evaluation of the items was performed to determine where the respective items belonged, in addition to taking into account the value of the items that were loaded on both constructs. This process was intended to elicit an answer for the second research question, as seen in Tables 5 and 6. The research question, again, was 'Is there duplication of measurements (multicollinearity) among the items that measure e-learning-style preferences'? Based on the rotated component matrix, it could be concluded that preferences questionnaire (eLSe, version 8.1) still contained multicollinear items that were cross-loaded with other constructs. This was evident with items dt04, dt01 and da02. Thus, these three items could be specified as not valid to measure the problem of learning styles. This finding may also be evidence to show that a person might employ more than one learning style at a time. One might employ a particular dominant learning style but also another almost equal, slightly less used, or little to negligibly used learning style [9]. If this instrument has six constructs, meaning there are six different styles of learning technology, then the PCA indicates that there are actually seven constructs, which means there are some individuals who have a combination of learning styles.

The findings discussed earlier can be used to answer the last research question, 'What are the factors derived from the restructuring of the PCA factors?' The findings revealed roughly seven factors derived from the restructuring of the PCA factors. These factors were (i) individual, (ii) kinaesthetic-tactual, (iii) group, (iv) visual, (v) auditory and two new components or factors, currently cited as factor X and factor Y. Factor X contains two items, while factor Y contains three items.

Table 7: Items and Loading

Item	YFactor	Auditory Factor
A1 *When the teacher tells me the instructions I understand better..*	0.78	
A2 *When someone tells me how to do something in class, I learn it better.*		0.55 (audio)
A3 *I remember things I have heard in class better than things I have read.*	0.49	-

Furthermore, a few items have now been added to the kinaesthetic factor from the tactual factor, during the PCA process. Thus, the kinaesthetic factor will now be known as the kinaesthetic-tactual factor.

Since factor X contains only two items, the writer does not intend to take it into account, meaning that factor X will not be accepted as a new factor. Moreover, the first item for factor X, derived from the *visual* factor, contained a vague phrase, 'I learn better by reading than by listening to someone'. Having examined the items closely, the writer decided not to drop the item or create a new factor X for this instrument. Instead the writer will improve the clarity of the expression of this item and will collect new data to be tested in the next PCA. Similarly, the next item in factor X was derived from the *tactual* factor. This item has been rephrased and will be tested in another field study and again analysed using PCA and confirmed using confirmatory-factor analysis with AMOS [14]. Table 7 shows the items and the loading on load factor Y as well as factors which are higher than 0.3. Since the capacity of item A2 on the *auditory* factor is higher (0.55) than is its capacity on factor Y (0.43), A2 was listed under *auditory*. Since there were only two items left to form a new factor Y, the writers decided not to create the new factor but to rephrase and test the items again in another field study.

CONCLUSION

Based on the findings obtained, it would be interesting to study further how to isolate respondents with more than one learning-style preference (dominant or otherwise). A more sensitive measuring instrument to measure the ability of respondents in terms of the items provided will be needed. Rasch Modeling method might be able to address this issue, due to its ability to measure both the items and the respondents' ability. Therefore, a follow-up study with new methods of data analysis such as those employed in modern psychometrics (e.g. Rasch modelling) will be needed in future studies.

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