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An Instrument to Measure Perceived Cognitive, Affective, and Psychomotor (CAP) Learning for Online Laboratory in Technology and Engineering Courses

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ABSTRACT

The effectiveness of student learning in an online laboratory environment requires appropriate measurements from the cognitive, affective, and psychomotor (CAP) domains. However, current self-reporting perceived CAP instruments are general and focused on non-technical fields, hence unsuitable for comprehensively measuring and evaluating technology and engineering (TE) online laboratory courses. This work aims to develop and validate a new instrument to measure perceived CAP learning domains in technology and engineering (TE) online laboratory courses. An initial instrument with 22 questions to assess CAP attributes was developed based on adaptation and expert consultation. About 1414 questionnaires were deployed and obtained a response rate of 25%, which meets the requirement of a confidence level of 90% with a 5% error. Principal Component Analysis (PCA) and Exploratory Factor Analysis (EFA) were used to further reduce the items to 13. Items reliability was verified using Cronbach Alpha. The finalized items consist of 5 cognitive, 4 affective, and 4 psychomotor items. For cognitive, the five items relate to students' perception of self-directed learning, reproducing study guides

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for future students, organizing their tasks and solving problems, relating lab works with fundamental concepts and theories, and completing all tasks. The four affective items are associated with students' perception of active involvement in learning, communication of findings, collaboration with team members, and awareness of safety and requirements. The four psychomotor items are linked to students' perceived attainment in performing the experiment, visualizing the procedure, demonstrating technical skills, and operating the equipment. The tool is verified to self-measure CAP attainment for online laboratories.

Keywords: Affective, bloom taxonomy, cognitive, instrument validation, learning domains, learning measurement, online laboratory, psychomotor

INTRODUCTION

A deadly virus (known as COVID-19), which started in Wuhan, China, has caused a worldwide pandemic (Nature News, 2020). The COVID-19 pandemic has led to the closure of many tertiary institutions to prevent the spread of the disease (Murphy, 2020). Many higher learning institutions in Malaysia quickly adopt e-learning under the online distance learning (ODL) mode (Tan, 2021). The ODL also includes laboratory courses using the traditional model of face-to-face instruction. In an online setting, some institutions have conducted laboratory courses via virtual labs, remote control labs, or video-based labs (Zhai et al., 2012). Virtual labs adopt the use of simulation tools and virtual reality. Remote laboratories enable students to access and perform experiments in the lab from remote areas. In contrast, video-based labs provide an overview of a physical lab for the students to visualize the whole experimental process and its outputs through a video demonstration. These methods were widely adopted during the pandemic period.

The emergence of any methods in teaching and learning, whether offline or online, places the need to evaluate student learning outcomes to evaluate the impact on learning. Hence, online laboratories may impact the learning outcomes and experiences that must be evaluated comprehensively. Chan and Fok (2009) measured students' perception of traditional and virtual laboratories on whether the laboratories are easy to understand, operate, flexible, stimulating, and satisfying. Kapilan et al. (2021) distributed a perception survey on mechanical engineering students' learning experiences in fluid mechanics virtual laboratories during the pandemic to gauge students' experience and cognitive learning, such as improvement in knowledge or skill set, the effectiveness of the virtual laboratories, the flow and usefulness of the course. Chowdury et al. (2019) developed nine questions to obtain students' feedback on the effectiveness of the delivery and students' learning experience for the online laboratory conducted via video demonstration and computer simulations.

One of the immediate challenges with online laboratories is the difficulty of achieving hands-on practical skills effectively (Gamage et al., 2020; Lewis, 2014). In addition, other learning attributes need to be measured and evaluated, such as integrating theory with practice, experimental design and problem-solving skills, data recording and analysis; communication and interpersonal skills; technical judgment, and professional ethics (Davies, 2008). From a pedagogical perspective, these attributes can be categorized into cognitive, affective, and psychomotor (CAP) learning domains. These categories of learning in the cognitive, affective, and psychomotor domains were introduced by Bloom et al. (1956). A well-known definition of cognitive learning derived from Bloom et al. (1956) is "recall or recognition of knowledge and the development of intellectual abilities and skills." The cognitive domain includes knowledge, comprehension, application of knowledge to solve a problem, analysis; evaluation; and knowledge creation (Anderson et al., 2001). Affective learning is "an increasing internalization of positive attitudes toward the content or subject matter" (Kearney, 1994). The affective domain focuses on developing attitudes and behavior, consisting of five attributes: interests, opinions, emotions, attitudes, and values (Anderson et al., 2001; Krathwohl et al., 1964). Simpson (1974) defined the psychomotor domain as having five attributes: detecting cues to response (perception), performing a specific act under guidance (guided response); performing a learned task independently (a mechanism); performing a complex action; altering an act to respond to a new situation (adaptation), and the developing new acts (origination).

The immediate challenge is measuring CAP learning independent of the course content, instructor, student grades, institution, academic level, and other limiting factors. Rovai et al. (2009) developed a self-reporting instrument to measure perceived CAP learning that gathers student perception on these domains to address this. It is measured from the student's viewpoint, independent of course content and academic assessments. Perceived CAP was implemented to compare online and offline courses (Carpenter-Horning, 2018). Kawasaki et al. (2021) conducted perceived CAP learning on fifty-six third-year nursing students who took emergency remote teaching during the pandemic. Like Rovai et al. (2009), the authors developed a 9-item self-reporting instrument that explicitly measures CAP in nursing skills. In another work, Rachmawati et al. (2019) developed questionnaires to measure students' cognitive, affective, and psychomotor learning in the bakery industry. There was other research on evaluating the learning outcome, but questionnaires were not shared (Triyanti et al., 2021).

Based on the literature reviewed, a comprehensive instrument to measure perceived CAP learning for online laboratory courses in technology and engineering major (TE) has not yet been developed. Some instruments that measure the effectiveness of online laboratories have been developed (Chan & Fok, 2009; Chowdury et al., 2019; Kapilan et al., 2021) but mainly focus on the student learning experiences and feedback and do not assess the CAP achievements. Besides, the authors did not provide evidence that these instruments were validated. Although the instrument from Rovai et al. (2009) can be used to evaluate any course, it could only provide a general achievement of CAP. The instrument cannot scrutinize some important attributes of learning related to online laboratories, whereas other CAP instruments focus on non-technical fields (Kawasaki et al., 2021; Rachmawati et al., 2019). Therefore, a comprehensive instrument may help practitioners evaluate CAP attributes of TE online labs, such as knowledge of the subject matter, experimental design, problem-solving skills, hands-on competencies, valuing of occupational safety and health, professional attitudes, and ethics. These are some detailed attributes not measured comprehensively by currently available instruments.

Given the need to comprehensively measure CAP's effectiveness in TE online laboratory courses, this work aims to develop and validate an instrument to collect perceived CAP domains of learning in TE online laboratory courses. Based on the existing self-reporting instrument for CAP and consultation with experts, this research developed and validated an extended self-reporting instrument suitable to measure CAP learning in TE online labs. The methodology implemented in this research includes cleaning the data, validating the questions' reliability, and finalizing the instrument (MacLeod et al., 2018; Martin et al., 2020). The results and discussions highlight findings from the data analysis and the instrument's limitations.

METHODS

Development of Self-Reporting Instrument to Measure Perceived CAP Domains

Table 1 lists the attributes of the abilities under each CAP area by referring to Davies (2008) and Rovai et al. (2009). New attributes were added based on consultation with experts. The items developed for the instrument are then compared against the list of abilities to determine the suitable CAP category.

Table 1
Attributes of cognitive, affective, and psychomotor (CAP) learning

Cognitive	Affective	Psychomotor
● Ability to relate theory and practice* ● Ability to collect and analyze data* ● Ability to analyze and solve problems* ● Ability to understand and apply knowledge independently** ● Ability to organize knowledge**	● Ability to regulate attitude of learning* ● Ability to collaborate with others* ● Ability to communicate results and findings* ● Ability to communicate effectively with instructor/peers* ● Ability to evaluate the learning experience* ● Ability to value safety and ethic***	● Ability to demonstrate the practical skills learned** ● Ability to perform laboratory work safely*** ● Ability to handle actual equipment after learning stimulated/video-based experiments*** ● Ability to conduct experiments via guided responses*

*(Davies, 2008), ** (Rovai et al., 2009), *** New attributes

Instrument Development

The items in the instrument for this research are selected and modified based on previous research (Chowdury et al., 2019; Chan & Fok, 2009; Kapilan et al., 2021; Rachmawati et al., 2019; Rovai et al., 2009). In addition, some items are developed based on consultations with subject matter experts. The newly developed instrument for verification has 22 items, as shown in Table 2. Each item was developed to measure targeted attributes in Table 1 and categorized into CAP domains. Some items may be interpreted for two different areas and later would be verified statistically on the more suitable category (refer to column 1 of Table 2). There were five cognitive items, eleven for affective, and six for psychomotor. The fourth column of Table 2 indicates that the item was developed based on adaptation and improvising (AI) from related sources. New items were developed based on consultation with experts. The previous research shows that most items measure cognitive and psychomotor perspectives. Therefore, more affective items were developed for this instrument.

Table 2
Twenty-two (22) cognitive, affective, and psychomotor (CAP) items to measure perceived student learning (original questionnaire)

CAP Area	Label	Items Description	Source
C	C1	I can organize course material into a logical structure	AI Rv
C	C2	I cannot produce a course study guide (compilation of topics, exercises, learning activities) for future students	AI Rv
C	C3	I can self-learn, understand and apply the lessons and concepts in this course	AI Rv
C	C4	I cannot organize my tasks, apply appropriate methods and solve related problems to achieve the desired outputs	AI Chdh
C	C5	I cannot relate the online lab experiments to fundamental concepts and theories	AI Chdh
A	A1	I changed my attitude about the course subject matter as a result of this course.	AI Rv
A, P	A2	I am actively involved in the learning process through the online lab.	AI Chdh
A	A3	I prefer hands-on experiments compared to online lab	AI Chan
A	A4	I can communicate my findings and results through reports and oral presentations	AI Rchw
A	A5	I can collaborate well with others in my group	AI Rchw
A	A6	I feel that tasks can be assigned effectively during an online lab	AI Rchw
C, A, P	A7	I cannot complete all the required group tasks effectively and timely	AI Rchw
A, P	A8	I am aware of the safety requirements when working in a physical lab compared to an online lab	New Items
A	A9	I cannot discuss and clarify issues effectively with my instructor via the available communication platform	New Items

Table 2 *(continue)*

CAP Area	Label	Items Description	Source
A	A10	I can discuss and clarify issues effectively with my peers via the available communication platform	New Items
A	A11	I believe computer simulation can replace actual experiments.	AI Chdh
A, P	P1	I can perform the online lab experiments multiple times, unrestricted by laboratory space, rules, and safety concerns	New Items
C, P	P2	I cannot complete the online lab independently	AI Rchw
P	P3	I cannot handle the lab's equipment without the lab supervisor's assistance through the online lab videos	AI Chdh
P	P4	I can visualize the procedure for using the lab's equipment through the online lab videos	AI Chdh
P	P5	I can demonstrate to others the physical/technical skills learned in this course	New Items
P	P6	I can operate actual equipment confidently after conducting online lab experiments using simulated/virtual equipment	AI Chdh

Notes. Rchw (Rachmawati et al., 2019), Chdh (Chowdhury et al., 2019), Rv (Rovai et al., 2009), and Chan (Chan & Fok, 2009)

The developed items are a combination of positive statements and negative statements. It is to ensure that the participants are paying attention and alert when doing the survey. The respondent then chooses the option of a 5-point Likert scale answer, with one representing strongly disagree and five representing strongly agree. Questions with inconsistent responses will be eliminated during the statistical validation process.

Data Collection

The survey instrument was deployed via Google Forms across four public/private higher learning institutions in Malaysia on multiple courses and cohorts of online laboratories. These courses include programming for Year 1 Computer Science students (to represent Technology fields) and engineering labs for Year 1 to Year 3 Electrical/Electronic Engineering students. Due to the pandemic, all these courses were delivered online. A total of 1414 surveys were sent, and 349 responded to the survey. The response rate of 25% is within the typical response rate of 5% and 30%. Participation is voluntary, and there is no reward for completing the survey. Using a sample size calculator (https://www.calculator.net/sample-size-calculator.html; https://www.surveysystem.com/sscalc.html; https://www.qualtrics.com/au/experience-management/research/determine-sample-size/; https://select-statistics.co.uk/calculators/sample-size-calculator-population-proportion/), it is safe to conclude that the sample size of 300 participants and above qualifies for the confidence level of 90%, with a 5% error margin.

Validation of the Instrument

The following steps were taken to analyze the data:

1. Cleaning the data,
2. Performing Exploratory Factor Analysis (EFA) to identify the groupings of the items and the possible elimination of unrequired items,
3. Performing Cronbach Alpha Analysis (CAA) to ascertain internal reliability and consistency of items within the same group, and
4. Performing Inter-Item Correlation to identify whether a group's items are repetitive or redundant.

Cleaning the Data

All 349 respondents should and had answered all the questions. Out of the 349 respondents, six (6) respondents disagreed with the data to be used in the research. Therefore, their responses were excluded for further analysis, resulting in the total number of respondents for statistical analysis being 343. As the questions were all set as compulsory, all respondents answered all the questions. There were no outliers in the responses, as the answers are in the Likert scale range (1–5). Therefore, it was not required to remove outliers' data before the analysis.

Next, the negatively stated items need to be reverse-coded. The negative statement items with the keyword "cannot" in Table 2, i.e., items labeled C2, C4, C5, A7, A9, P2, and P3, were reverse coded. It is done by reversing the value of the response for negative statement items. The value for one is reverse-coded to five; two is reverse-coded to four, and three remains, four is reverse-coded to two, and five is reverse-coded to one, using the SPSS software.

Performing Exploratory Factor Analysis (EFA). Exploratory factor analysis (EFA) is one of the factor reduction methods. Under SPSS, the Principal Component Analysis (PCA) is conducted as part of the EFA process. The PCA calculates the inter-correlation among the items, which will cause the items to be clustered into principal components. Hence, PCA can reduce items to category areas that account for the most variance. The PCA process identifies the number of relevant components. Each set of components is known as the principal component. It also means that each component is distinctively different from another. The initial number of principal components is identified using the Eigenvalues of the covariance matrix greater than one. For example, if three Eigenvalues of the covariance matrix are greater than one, then there are three principal components for the items. Assuming that the items in Table 2 are distinctively different for this research, the PCA will cluster the items into three components, each representing the cognitive, affective, and psychomotor domains, respectively. Hence, the items should converge to three components: cognitive, affective, and psychomotor, after the items are reduced using

PCA. The PCA results will also reveal whether it passes the Kaiser-Meyer-Oikin (KMO) sampling adequacy above 0.5 and the commonality of each item above 0.3.

Factor rotation is part of the step in EFA to arrive at the rotated component matrix. There are two ways to do the factor rotation, i.e., oblique or orthogonal. The orthogonal rotation requires the factors to be uncorrelated, while the oblique rotation allows the factors to correlate. It is necessary to explore the oblique rotations first to get a correct factor structure (Jolliffe, 2014). Therefore, the oblique rotation test, i.e., the Oblimin test in SPSS, was conducted. The choice between using the oblique or orthogonal depends on the values in the Principal Component Correlation Matrix (PCCM) produced by the oblique rotation. Absolute values in PCCM closer to one indicate that the factors are correlated; hence, the oblique rotation is suitable for implementation. Values closer to zero indicate that the factors are unrelated, so the orthogonal rotation is suitable. The threshold for this research is 0.5. The oblique rotation method will be used if any of the absolute PCCM values is 0.5 or greater. Otherwise, the orthogonal rotation should be used. An example of orthogonal rotation in SPSS is the Varimax rotation. The rotated component matrix will display the factor loading value for each item. If an item has values for two components, the higher factor loading above 0.5 will be considered.

Performing Cronbach Alpha (CA) Analysis and Inter-Item Correlation. Cronbach alpha (CA) analysis measures the consistency within a component or group. This step is done after all items are grouped into the same component in the EFA. Each item within each component is analyzed using CA. The reliability coefficient of 0.70 is considered reliable and will be used as the baseline for measurement. The CA value of 0.70 is reliable, and values lower will require justification (Waltner et al., 2019). Next, an inter-item correlation was conducted to evaluate the correlation across all items—the inter-item correlation matrix measures if the questions measure the same aspect. Acceptable inter-item is between 0.2 and 0.5, a value greater than 0.7 is very similar, and a value of 1.0 is the same question.

RESULTS AND DISCUSSION

Exploratory Factor Analysis (EFA)

Six of the 349 respondents disagreed with the data used in the analysis. Therefore, only 343 responses were analyzed. The PCA revealed that the KMO measurement of sampling adequacy is at 0.889. This sampling adequacy is good as it exceeds the required minimum of 0.50. According to Bartlett's test of sphericity, the significance is at 0.000. It means at least one correlation exists between the 22 items analyzed. The extraction of commonalities indicated that all 22 items have a value greater than 0.30. Therefore, we do not need special consideration to eliminate questions at this initial analysis stage.

Based on the PCA result, the number of components is indicated by eigenvalues greater than one. The rotation method was then applied to identify the items related to each component, using either the oblique or orthogonal method. As all the absolute values for the PCCM are less than 0.5, the orthogonal rotation method was applied to derive the rotated component matrix. The PCA and rotation method will be repeated after each round of item elimination to obtain the final validated instrument that converges into three CAP components.

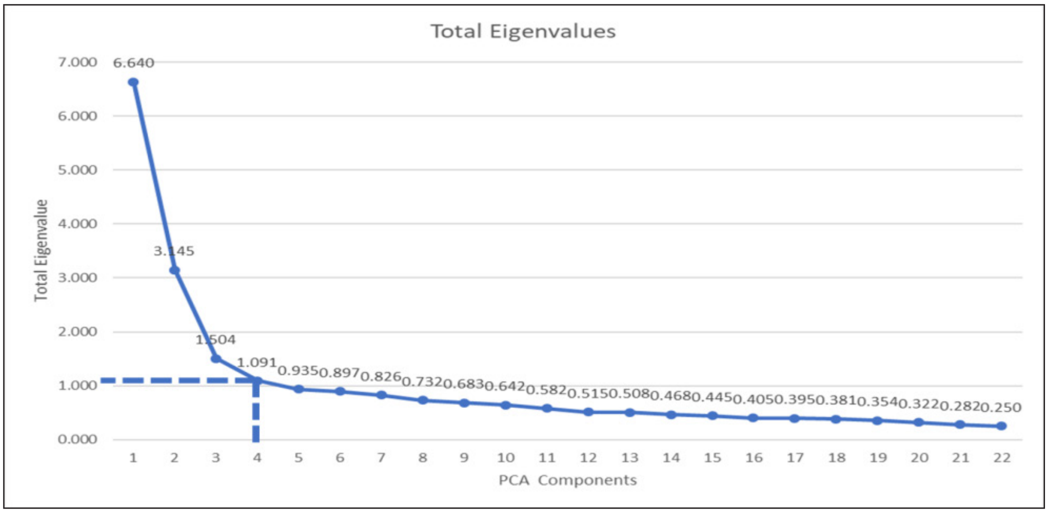

Figure 1. Scree plot from PCA

Based on Figure 1, there are four components with Eigenvalues greater than one. However, the fourth component just slightly exceeded one. Figure 2(a) shows that the fourth component has only two items. According to (Laerd Statistics, 2018), each component should not be fewer than three items. A component with fewer than three items is weak and unstable. Hence, the fourth component is insignificant. As the fourth component has less than three items, the two items (i.e., A1 and A3) were eliminated from the following rotation list. With the elimination of these two items, PCA and orthogonal rotation were conducted for the remaining 20 items.

Figure 2(b) shows the orthogonal rotated component matrix for 20 items. The results show that items C1, A10, A2, and A4 have factor loadings across two components. The four items can potentially be measured in two components. Higher factor loading signifies a stronger relationship between the items and the component. Therefore, factor loadings with a higher value will be considered. It means C1 and A10 will be considered under component 1, not component 3. A2 and A4 will be considered under component 3 and not component 1. Component 1 has more psychomotor items; component 2 has more cognitive items, whereas all affective items were successfully grouped in component 3.

Rotated Component Matrix[a]

	Component 1	2	3	4
P6	.787			
P5	.743			
P4	.711			
C3	.707			
A6	.692			
P1	.655			
C1	.643			
A11	.605			
A10	.553		.482	
A2	.550		.427	
A4	.542		.401	
C4		.793		
A7		.722		
C5		.705		
P2		.698		
C2		.680		
A9		.632		
P3		.547	-.415	
A5			.734	
A8			.488	
A3				.681
A1	.427			.553

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 16 iterations.

(a)

Rotated Component Matrix[a]

	Component 1	2	3
P6	.811		
P5	.740		
P4	.737		
C3	.653		
A6	.653		
A11	.612		
P1	.572		
C1	.560		.419
A10	.526		.460
C4		.791	
C5		.727	
P2		.714	
A7		.695	
C2		.685	
A9		.666	
P3		.559	
A5			.752
A8			.638
A2	.463		.550
A4	.463		.547

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

(b)

Rotated Component Matrix[a]

	Component 1	2	3
C4	.824		
C5	.757		
C2	.725		
A7	.711		
P2	.679		
P6		.831	
P4		.797	
P5		.796	
P1		.532	
A5			.752
A8			.727
A4		.400	.610
A2		.446	.555

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

(c)

Figure 2. Rotated component matrix for (a) 22 items, (b) 20 items, and (c) 13 items

The next step is excluding items in Figure 2(b) that do not belong to the same component. It is done by comparing with the items in Table 2. Component 1 is considered a psychomotor component as it contains more psychomotor items. Based on Table 2, items C1, C3, A6, A10, and A11 were removed from the list in component 1 as these items did not measure psychomotor attributes. Component 2 is considered a cognitive component as it has more cognitive items. Hence, items with labels from psychomotor and affective such as A7, A9, P2, and P3, are considered for removal. Based on Table 2 (refer to labels in column 1), the authors opined that "complete tasks" in A7 and P2 can be considered a problem-solving process involving psychomotor, affective, or cognitive processes in A7 cognitive or psychomotor process in P2. Hence, these two items can be considered in any one of these learning domains. Figure 2(b) results grouped A7 and P2 with cognitive items. Therefore, "completing the tasks" is categorized as a cognitive process. It is supported by literature gathered in Elif (2018), where scientists agreed that problem-solving is an activity that requires domain knowledge and appropriate cognitive strategies. By maintaining items A7 and P2, only A9 and P3 were eliminated from component 2.

After eliminating seven items in the previous step, the orthogonal rotation matrix for the new list is shown in Figure 2(c). Figure 2(c) shows the orthogonal rotated component matrix for 13 items. Only A2 and A4 have factor loading for two components. Both items have higher factor loading values in component 3, so A2 and A4 will be categorized under component 3. Finally, after three iterations, the original list of 22 items was reduced to 13 and successfully grouped in the respective CAP components using the EFA.

Cronbach Alpha Analysis (CAA)

Cronbach Alpha Analysis was conducted on component 1 (cognitive) with C4, C5, C2, A7, and P2. The Cronbach Alpha Analysis generated a value of 0.803. Therefore, all five items are relevant to component 1. Figure 3 shows items-total statistics and inter-items correlation matrix for component 1. The inter-item correlation matrix shows that each question measures independent yet related aspects.

The second component (psychomotor) is P6, P4, P5, and P1. The Cronbach's Alpha (CA) value is 0.802. At this stage, the best practice is to delete items to obtain higher internal reliability (i.e., higher CA value). For example, Figure 4 item-total statistics indicated that deleting the item with the label P1 will increase the reliability value to 0.816. However, this deletion is unnecessary because the current reliability value exceeds 0.70. The inter-item correlation matrix indicates that all items tend to measure similar aspects.

The third component (affective) contains the items containing A2, A4, A5, and A8. The Cronbach Alpha's value for this component slightly exceeded the minimum value of 0.70

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
C4	12.48	11.291	.693	.733
C5	12.68	11.616	.622	.754
C2	12.80	12.418	.527	.783
A7	12.41	11.769	.536	.781
P2	12.59	11.224	.568	.773

Inter-Item Correlation Matrix

	C2	C4	C5	A7	P2
C2	1.000	.532	.437	.339	.349
C4	.532	1.000	.610	.462	.475
C5	.437	.610	1.000	.395	.458
A7	.339	.462	.395	1.000	.466
P2	.349	.475	.458	.466	1.000

Figure 3. Cronbach alpha analysis for component 1 (cognitive)

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
P1	9.77	6.735	.470	.816
P4	10.08	5.797	.650	.735
P5	10.13	5.861	.653	.734
P6	10.38	5.378	.696	.710

Inter-Item Correlation Matrix

	P1	P4	P5	P6
P1	1.000	.408	.388	.411
P4	.408	1.000	.547	.611
P5	.388	.547	1.000	.634
P6	.411	.611	.634	1.000

Figure 4. Cronbach alpha analysis for component 2 (psychomotor)

at 0.702. The item-total statistics in Figure 5 indicate that the reliability can be increased to 0.719 by deleting item A8. However, as the current reliability value is sufficient, the deletion of A8 is insignificant. Hence, A8 is a valid item in the third component. The inter-item correlation matrix in Figure 5 has values between 0.2 and 0.5, indicating that each item measures related yet independent aspects.

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
A2	11.67	4.666	.515	.620
A4	11.74	4.953	.544	.606
A5	11.36	4.747	.548	.600
A8	11.39	5.302	.356	.719

Inter-Item Correlation Matrix

	A2	A4	A5	A8
A2	1.000	.482	.437	.259
A4	.482	1.000	.470	.271
A5	.437	.470	1.000	.326
A8	.259	.271	.326	1.000

Figure 5. Cronbach alpha analysis for component 3 (affective)

Finalized Questionnaire

Upon completing the Exploratory Factor Analysis (EFA) and Cronbach alpha analysis, the finalized questionnaire is shown in Table 3.

Table 3
Thirteen (13) cognitive, affective, and psychomotor (CAP) items to measure perceived student learning (finalized questionnaire)

Questions	Survey Items	Label
I1	I cannot produce a course study guide (compilation of topics, exercises, learning activities) for future students	C1r
I2	I cannot organize my tasks, apply appropriate methods and solve related problems to achieve the desired outputs	C2r
I3	I cannot relate the online lab experiments to fundamental concepts and theories	C3r
I4	I cannot complete the online lab independently	C4r
I5	I cannot complete all the required group tasks effectively and timely	C5r
I6	I am actively involved in the learning process through the online lab.	A1
I7	I can communicate my findings and results through reports and oral presentations	A2
I8	I can collaborate well with others in my group	A3
I9	I am aware of the safety requirements when working in a physical lab compared to an online lab	A4
I10	I can perform the online lab experiments multiple times, unrestricted by laboratory space, rules, and safety concerns	P1
I11	I can visualize the procedure for using the lab's equipment through the online lab demonstration	P2
I12	I can demonstrate to others the physical/technical skills learned in this course	P3
I13	I can operate actual equipment confidently after conducting online lab experiments using simulated/virtual equipment	P4

CONCLUSION

The research successfully developed and validated a 13-item self-reporting instrument of perceived learning according to the CAP domains for technology and engineering online laboratory courses. This instrument was validated and refined statistically using perceived CAP responses from computer science and engineering students. Compared to the previous research instruments, this newly developed instrument has more items covering CAP learning. The items for each area are well balanced, with cognitive having five items, affective having four items, and psychomotor having four items. This study only validates this instrument or questionnaire, which can be used to study the reality of online lab learning. It will be the basis for studying the reality of online labs upon implementation**.** Hence, this instrument can assist practitioners in measuring and analyzing the related attributes of CAP learning in engineering and technology online laboratories.

This pilot study was only conducted with computer science and engineering students. This research can be extended to make this tool suitable for science and mathematics. Hence, future works on the instrument will be conducted in the science and mathematics courses to fine-tune this instrument to be a suitable tool for all science, technology, engineering, and mathematics (STEM) courses. The instrument can be implemented for face-to-face lab sessions by modifying the psychomotor items, as the existing psychomotor items are designed to measure perceived CAP learning for online lab sessions during the COVID-19 pandemic.

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