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Validating Instructional Practice Scale For Instructors In Some Selected Ethiopian Public Universities

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Abstract: The primary aim of this study was to validate the Instructional Practice Scale (IPS) for university instructors in the context of Ethiopian public universities. Recognizing the importance of reliable and contextually appropriate measurement instruments for effective instructional methods, we sought to ensure the IPS was both valid and reliable. The study employed a descriptive survey methodology, gathering data from 1,254 instructors across four public universities. The Smart-PLS were used to analyse the data. The findings provide a robust and reliable instrument for evaluating instructional practices among university instructors. The validated IPS can be effectively used for evaluating and enhancing instructional methods and training programs. Future research should consider adapting and validating the instrument for specific disciplines to further ensure its applicability and accuracy across various educational contexts.

Keywords: Instructional practice, public university instructors, validation, factor analysis, Ethiopian Public Universities

1. Introduction

One of the most important factors in encouraging students to learn and succeed better is instructional practice. In a transmission model of teaching, a teacher imparts knowledge, and students absorb it passively (Emaliana, 2017). Traditionally, instructional practice also referred to as teacher-centred practice is a formal and controlled instructional method where the instructor plans what, when, and how students learn (Horvat-Samardžija, 2011). An alternative view of instructional practice highlights the needs and viewpoints of pupils. How, what, and when learning occurs is set by both the instructor and the pupils (Horvat-Samardžija, 2011). Additionally, Saleh and Jing (2020) stated that teachers were the ones who created the lesson in the classroom. Similarly, Bibon (2022) addresses it from the standpoint of how educational institutions organize, plan, implement, deliver, and evaluate or assess their students' learning.

Research indicates that teachers, a lack of course materials, students' disinterest in the subject, and ineffective teaching strategies are all important factors influencing students' performance (Majo, 2016). In fact, significant funds are allocated to enhancing institutions and developing educational materials to augment students' performance (Barrett, 2018). Nonetheless, there have been initiatives to deliver education; Open University (2018) and Iglesias (2016), for instance, modified the science curriculum to provide instruction that enhances student learning. This generally suggests that instrument validation intended to evaluate one of the essential components of success—that is, instructional practice—is either not prioritized or not given enough weight. Competency-based assessments utilizing instruments that have been contextually validated have lagged despite the amplification of the instruction issue.

Many academics evaluate teaching or instructional practices from diverse angles. Learner-centred teaching practices, such as those found in Sarwar, Zerpa, Hachey, Simon, & Barneveld (2012); classroom organization, student orientation, and enhanced activities-based measures adapted from the Organization for Economic Co-operation and Development (OECD) (2009); high school instructional practice measures that emphasize a focus on people (Fischer, Fishman, Dede, Eisenkraft, Frumin, Foster, & McCoy, 2018); performance criteria-based measures (Ahmad et al., 2023; Mehmood et al., 2023); teaching for conceptual understanding measures (Mullis, Martin, Gonzalez, Gregory, Garden, O'Connor, & Smith, 2000); and observations (Saleh & Jing, 2020). None of these speak to every stage of instructional practice, from preparation to evaluation. By assessment, Bibon (2022) addresses these kinds of problems. Collecting the items from (Ahmad et al., 2024; Ahmad et al., 2023; Alamanda et al., 2024; and Mehmood et al., 2023) into components related to

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instructional planning, delivery, and assessment, Bibon (2022) addresses these kinds of problems.

In general, we validated the instructional practice scale to more accurately assess the construct in the context of Ethiopian university instructors, presuming that the Ministry of Education would provide freshman students with uniform learning modules. Measuring this construct using a validated instrument is essential to gaining knowledge of it, effectively conveying that to others, and making necessary corrections. A construct needs to be evaluated using a reliable and appropriate in-context tool to obtain its images. In light of this, the following goals of the study were set:

- Investigate the fundamental factor structures in instructional practice in EFA.
- Verify the structures discovered using exploratory factor analysis.
- Assess the tool's psychometric qualities, such as validity and reliability, in the setting of Ethiopian public university instructors.

2. Methods and Materials

2.1. Study design and setting

The purpose of this study was to validate the instructional practice tool in the context of Ethiopian public university instructors. Hence, we employed a descriptive survey method to gather data from the target population at certain points in time. We randomly selected the southern part of the country. All eight universities identified in it are categorized based on generation (year of establishment). Four public universities—Arbaminch, Dilla, Wachamo, and Jinka—representing the first, second, third, and fourth generations, respectively, were utilized to select participants.

2.2. Population (or participants and sampling)

The study's target population consisted of instructors at Arbaminch, Dilla, Wachamo, and Jinka universities. Various sample sizes have been suggested to perform factor analysis. For instance, the following criteria are deemed excellent: at least ten times as many subjects as variables (Everitt, 1975; Nunnally, 1978); at least 100 subjects (Gorsuch, 1987; Kline, 1994); sample size to the number of variables (e.g., three to six subjects per variable) (Cattell, 1978); sample size-to-parameter ratio of 20:1 (Jackson, 2003); and 50 - Very poor, 100 - poor, 200 - fair, 300 - good, 500 - very good, and 1,000 or more scale of sample adequacy are excellent (Comrey & Lee, 1992). According to Comrey and Lee, a total of 1,300 individuals were chosen to detect structures, representing an excellent sample size (1,000), accounting for a maximum response error of 30%.

Kothari's (2004) stratified proportional sample size formula, nh = (Nh/N)*n, was employed to draw participants proportionally from the four universities. Where N represents the entire population size, Nh represents the sample size for the hth stratum, nh represents the sample size, and n is the sample size. Therefore, nh was calculated as follows: 432 for Arbaminch University out of 1,720 instructors, 318 for Dilla University out of 1,263 instructors, 281 for Wachamo out of 1,119 instructors, and 269 for Jinka University out of 1,069 instructors, assuming N = 5,171 and n = 1,300.

Since they were either inadequately completed, incomplete, or not returned, 46 response papers were removed. The 1,254-participant data were randomly divided into two groups, 627 participants in each group. The data was then utilized to find patterns of structure and confirm them using confirmatory factor analysis (627).

2.3. Measure

Bibon (2022) refined the instructional practice measure, which was derived from research by Ahmad et al. (2024), and Alamanda et al. (2024). Concerning the three subsections of instruction—planning (8 indicators), delivering (9 indicators), and assessing (8 indicators)—the scale is meant to measure the instructions used by scientific teachers. There were five alternative responses to the questions: never, rare, sometimes, frequently, and always. In his study, the scale's Cronbach's alpha of .86 indicated better internal consistency when assessing the construct.

2.4. Procedures

2.4.1. Content Validity Evaluation

According to Almahanna, Almohanna et al. (2022) reliable instruments yield reliable data. Lewashe's (1975) content validity quantitative evaluation method was used to evaluate each item by nine experienced subject matter experts (SMEs) from the following fields: social psychology, educational planning and management, curriculum and instructional provision, educational measurement and evaluation, and so on. The formula for computation is displayed as follows:

CVR=(ne−N/2)N/2CVR = \frac{(ne - N/2)}{N/2}CVR=N/2(ne−N/2)

Where:

- CVR = content validity ratio
- ne = number of panellists pointing to the item as 'essential'
- N = total number of panellists

A three-point rating system was used to rank each item on the draft data-gathering tool (1 not essential, 2 useful but not essential, and 3 essential). CVR has a value between -1 and +1. The item is deemed acceptable and clear if the value is positive; it should be reworded, modified, or rejected if the value is negative; and it is deemed necessary and legitimate if 50% of the panellists in the N size assess the item as essential. In general, every item satisfies the acceptable standard of ≥ .75 (Lewashe, 1975), suggesting that the items are extremely important.

Table 1: Instructors' instructional practice tool content validity ratings

Item	Panelists									CVR	Decision
	1	2	3	4	5	6	7	8	9		
1	3	3	3	3	3	3	3	2	3	.77	Appropriate
2	3	3	3	3	3	3	3	3	3	1	Appropriate
3	3	3	3	3	3	3	3	3	3	1	Appropriate
4	3	3	3	2	3	3	3	3	3	.77	Appropriate
5	3	3	3	3	3	3	3	3	3	1	Appropriate
6	3	3	3	3	3	3	3	3	3	1	Appropriate
7	3	3	3	2	3	3	3	3	3	.77	Appropriate
8	3	3	3	3	3	3	3	3	3	1	Appropriate
9	3	3	3	3	3	3	3	2	3	.77	Appropriate
10	3	3	3	3	3	3	3	3	3	1	Appropriate
11	3	3	3	3	3	3	3	3	2	.77	Appropriate
12	3	3	3	3	3	2	3	3	3	.77	Appropriate
13	3	3	3	3	3	3	3	3	3	1	Appropriate
14	3	3	3	3	3	3	3	3	3	1	Appropriate
15	3	3	3	3	3	3	3	2	3	.77	Appropriate
16	2	3	3	3	3	3	3	3	3	.77	Appropriate
17	3	3	3	3	3	3	3	3	3	1	Appropriate
18	3	3	3	3	3	3	3	2	3	.77	Appropriate
19	3	3	3	3	3	3	3	3	3	1	Appropriate
20	3	2	3	3	3	3	3	3	3	.77	Appropriate
21	3	3	3	3	3	3	3	3	3	1	Appropriate
22	3	3	3	3	3	3	3	3	3	1	Appropriate
23	3	3	3	2	3	3	3	3	3	.77	Appropriate
24	3	3	2	3	3	3	3	3	3	.77	Appropriate
25	3	3	3	3	3	2	3	3	3	.77	Appropriate
S-CVI/Ave	.92	.92	.92	.76	1	.84	1	.68	.92	.88	Appropriate

CVI and S-CVI/Ave = Score Content Validity Index average proportion of relevance of items across experts

2.4.2 Data Collection

We gathered an endorsement letter and reached out to department heads and deans of colleges and institutes. They were given a brief overview of the study's objectives, the possible participants, the type of data collection tool, and the typical amount of time needed to complete the questionnaire. By establishing a communication channel with these high-ranking officials at various stages, a survey was dispersed around departmental offices. After that, it was distributed at random among instructors who provided consent until the target number of participants was attained.

2.4.3 Data Analysis

Data cleansing was done before data analysis. As a result, eight response sheets that were improperly filled out and three that were not returned were excluded. SPSS version 23 and SmartPLS version 3.2.9 were utilized for the data analysis. SmartPLS was used to investigate confirmatory factor analysis, and descriptive statistics and exploratory factor analysis were carried out using SPSS.

2.5. Ethical Consideration

The Office of Research and Dissemination at Dilla University, along with the Office of Vice President for Research and Technology Transfer, ensured that the issue under investigation complies with academic research criteria and ethical standards. Potential participants received brief instructions regarding the study's overall goal and the characteristics of the data collection instrument. We obtained informed consent, and the confidentiality of the participants was greatly protected.

3. Result and Discussion

3.1. Socio-Demographic Characteristics

Table 2 indicates that 1,254 instructors took part. Approximately 956 (76.2%) participants were male, and 298 (23.8%) participants were female, making up around three-fourths and one-fourth of the total, respectively. The age distribution has a mean of 34.16 years and a standard deviation of 4.37, falling between the minimum age of 28 and the maximum age of 45. This number appears to be in line with the distributions of work experiences and academic ranks. There were 1,186 (94.6%) master's degree holders, 50 (4%) PhD holders, and 18 (1.4%) assistant lecturers as the final minimum size. This means that the instructors in the minimum, maximum, and average age groups were covered, accordingly. One year of work experience at a university is the minimum, while sixteen years is the maximum. Ultimately, 852 (67.9%) participants, or the higher two-thirds, underwent training for higher education teaching under the Higher Diploma Program (HDP). In contrast, approximately one-fourth of instructors did not.

Table 2: Sociodemographic characteristics of participants (*N = 1,254*)

Variables	Attribute	Frequency (%)
Sex	Male	956 (76.2)
	Female	298 (23.8)
Age (years)	Min.	28
	Mean(SD)	34.16 (4.37)
	Max.	45
Academic rank	Assistant lecturer	18 (1.4)
	Lecturer	1186 (94.6)
	PhD	50 (4)
Work experience (university, years)	Min.	1
	Mean(SD)	5.11 (3.06)
	Max.	16
Higher Diploma Program	Yes	852 (67.9)
	No	402 (32.1)

Source: Calculated by the Author

3.2. Exploratory Factor Analysis (EFA)

We employed the Varimax with Kaiser Normalization Rotation Method, a Maximum Likelihood (ML) Extraction Method, an Eigenvalue exceeding one, and a factor loading cut-off value of .5 (greater than the default criteria, i.e., .3). By assuming that the observed variables are normally distributed, ML produces factor structures with high correlations of indicators. With large sample sizes, ML yields estimates that are effective, less skewed, and less variable.

3.2.1. Assumption Test Result

To move forward with EFA, multiple assumptions were examined. According to George and Mallery (2019) and Hair, Hult, Ringle, and Sarstedt (2022), the data distribution resulted in a relatively normal distribution, falling within the range of ±1, with -0.394 for skewness and 0.014 for kurtosis. Other tests, such as the Kolmogorov-Smirnov, Shapiro-Wilk, and Z values or critical ratios for normalcy, showed minor violations (skewed to negative).

Variance Inflation Factor (VIF) results for instructional planning, delivery, and assessment were 1.052, 1.049, and 1.004, respectively. Tolerance values were .95 for instructional planning, .954 for instructional delivery, and .996 for instructional assessment sub-scales. As indicated in the literature, both tests verified that there was no issue with multicollinearity with this set of data. For example, a VIF higher than 5 to 10 (Kim, 2019), a VIF greater than 10, and a tolerance value < 0.10 (Hair, Black, Babin, & Anderson, 2010) indicate a potential problem of multicollinearity, while a VIF < 5 (Ringle, Da Silva, & Bido, 2014; Rogerson, 2001) and even 4 (Pan & Jackson, 2008) are considered acceptable.

The internal consistency of the overall and subscale items was checked using Cronbach's alpha, resulting in .874, .928, .886, .786 for instructional planning, delivery, assessment subscales, and overall scale, respectively (Table 1). As stated by Sarstedt (2019), this guarantees the measurement's unidimensionality and sub-dimensionality nature and satisfies the need for EFA analysis (.7 minimum criteria). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is .846, which is around the desired (≥ .70) category, according to Kaiser (1974), Hoelzle & Meyer (2013), and Ferreres, Hernandez, & Tomas (2017). Bartlett's Test of Sphericity, 7921.264 (p = .00), further confirms that the data are suitable for EFA analysis (Table 2).

Table 2: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.818
Bartlett's Test of Sphericity	Approx. Chi-Square	7921.264
	df	300
	Sig.	.000

Source: Calculated by the Author

3.2.2. Exploratory Factor Analysis Result

Six factors were obtained by rotating the matrix. However, there wasn't a single item loaded in the sixth factor. In the fourth factor, only two items (items 5 and 6) and in the fifth factor, only one item (item 16) were loaded. Therefore, the last three factors were eliminated since they did not meet the criteria for having three to five items in each component and were not appropriate for conducting confirmatory factor analysis, as stated by MacCallum, Widaman, Zhang, & Hong (1999) and Raubenheimer (2004). Additionally, there was no loading in any factor for items 8, 13, 14, 15, and 17, meaning that items were loaded below the given threshold (.50). Eight items were eliminated overall.

Table 3 illustrates the rotation of eight items to the instructional assessment (IA) subscale (loading .573 to .821), four items to the instructional delivery (ID) subscale (loading .854 to .892), and five items to the instructional planning (IP) subscale (loading .569 to .874). For IA, ID, IP, and the overall scale, the internal consistency or reliability values of .886, .928, .874, and .806 exhibit robust (Taber, 2018) and good dependability (Salkind, 2015; Tavakol and Dennick, 2011; Lavrakas, 2008).

Table 3: Summary of descriptive statistics, rotated factor matrix, and alpha value of instructional practice (N = 627)

Factor	Item Code	Items	Loading	Uniqness	Alpha
Instructional Assessment (8 items)	IA21	Uses multiple assessment methods, including adjusted pacing and flexible grouping, to engage learners in active learning opportunities that promote the development of critical and creative thinking, problem-solving, and performance capabilities	.821	.344	.886
	IA25	Creates assessment method that is sustainable and with continuity to trace behavioral and cognitive changes of learners through time	.768	.435	
	IA24	Uses learning materials like module, activity sheets, SIM etc. that evaluates learning inside and outside the school	.749	.410	
	IA19	Provides opportunities for the development of performance-based assessment	.743	.401	
	IA23	Provides assessment that allows learners to work individually or in groups through independent/cooperative learning	.701	.495	
	IA22	Provides multiple assessment strategies for the differentiation and accommodation of individual differences	.664	.499	
	IA20	Shows relevance and connection between topic discussed vis-à-vis assessment strategy	.601	.629	
	IA18	Provides opportunities for the development of product-based assessment	.573	.532	
Instructional Delivery (4 items)	ID11	Facilitates a learning environment where sense of belonging of learners through individual differences is respected	.892	.205	.928
	ID10	Connects prior knowledge of the learners to the new information of the lesson	.871	.226	
	ID9	Discusses lessons in increasing levels of complexity and difficulty	.870	.234	
	ID12	Uses varying perspectives, theories and methods of investigation and inquiry in instructing the concept of the lesson	.854	.266	
Instructional Planning (5 items)\	IP4	Creates and plans strategies that allow multiple learning areas to be integrated in the lesson	.874	.207	.874
	IP2	Assesses teaching materials for its relevance to the learning competency attainment and needs of learners.	.872	.232	
	IP1	Uses and analyzes information of learners to design instruction that meets the diverse needs of learners and leads to ongoing growth and achievement	.749	.429	
	IP3	Uses present data of learners to design instruction that is differentiated on the individual learning needs of learners.	.738	.458	
	IP7	Uses sociodemographic information regarding learners' background like culture, family structure and status, and communities in planning instruction suited to the needs of the learners	.569	.634	

Note, IA = instructional assessment, ID = instructional delivery, IP = instructional planning, CoV=Construct Validity, CV = Convergent Validity, DV = Discriminant Validity, Source: Calculated by the Author

According to the total variance explained analysis, the three components collectively account for 60.95% of the variance in instructional practice. This demonstrates that irrespective of rotation methods and disciplines, 50% explained variance is sufficient (Sürücü, Şeşen, & Maslakçı, 2021; Beavers, Lounsbury, Richards, Huck, Skolits, & Esquivel, 2013; Hair, Sarstedt, Pieper, & Ringle, 2012; Pett, Lackey, & Sullivan, 2003). Furthermore, instructional delivery and instructional planning variables accounted for roughly comparable variances (18.51 %

and 18.47 %), respectively. Whereas the instructional evaluation factor explains the relatively highest share of variance (23.97 %) (Table 4).

Table 4: Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.678	27.518	27.518	3.326	19.563	19.563	4.075	23.973	23.973
2	3.672	21.597	49.116	3.796	22.332	41.895	3.147	18.513	42.486
3	3.070	18.059	67.174	3.240	19.060	60.955	3.140	18.470	60.955

Extraction Method: Maximum Likelihood, Source: Calculated by the Author

When the sample size is 200 or higher, Cattell's Scree Plot test is still another trustworthy method to ascertain the number of components (Sürücü, Yikilmaz, & Maslakci, 2022). Starting with the fourth component indicates a notable linear trend in the eigenvalue pattern (Figure 1). We reasonably retained the three factors at 60.95 per cent.

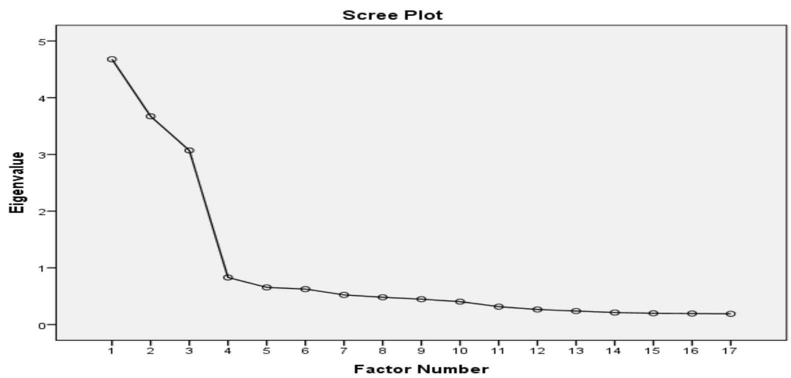

Figure 1: Scree plot factor

3.3. Confirmatory Factor Analysis (CFA) Result

3.3.1. Common Method Bias (CMB)

CMB analysis is advised as the data samples were obtained by a questionnaire and/or all variables were obtained from the same individuals (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). As a result, we used Harman's single-factor test to assess CMB, and the results showed that it explains 24.284% of the variation, which is lower than the 50% acceptable limit.

3.3.2. Measurement Model

Convergent validity, internal consistency reliability, and discriminant validity were examined using a reflective measurement approach. The extent to which a component is positively correlated with another factor that assesses the same construct is known as convergent validity. Factor loadings and average variance extraction were used for testing it. As a result, Items 22, 20, 23, and 25 in the instructional assessment factor and Item 1 in the instructional planning factor were loaded .398, .582, .606, .694, and .698 respectively (Figure 2).

According to Hair, Hult, Ringle, and Sarstedt (2016), Henseler, Ringle, & Sarstedt (2014), and Hair, Black, and Babin (2010), this indicates below the threshold (≥ .7). Following a sequential removal and reanalysis of the first three relatively low-loaded items (items 22, 20, and 23), item 25 improved from .694 to .723, satisfying the threshold. As a result, according to Sarstedt, Ringle, and Hair (2017), Henseler et al. (2014), and Hair et al. (2010), the Average Variance Explained (AVE) in instructional assessment also improved from .476 (Figure 2) to .607 (Figure 3), meeting the minimum acceptable criterion (>.5). To satisfy the minimally acceptable standards of item loading values and AVE values, four items—three from the instructional assessment and one from the instructional planning—were generally removed.

Raykov's rho coefficient, composite reliability (CR), and Cronbach's alpha were employed to assess the construct validity and reliability (Table 2). As per Hair, Hult, Ringle, & Sarstedt (2017) and Hair, Black, Babin, & Anderson (2010), the outcome satisfies the acceptable criterion for all (.7 to .95).

The degree of differentiation between a component and another component is known as discriminant validity. The results of the tests on the heterotrait–monotrait (HTMT) ratio of correlations between constructs and the Fornell-Larcker criterion are displayed in Table 3 and fall within an acceptable range. According to Hair, Risher, Sarstedt, & Ringle (2019); Henseler, Ringle, & Sarstedt (2014); and Fornell & Larcker (1981), this indicates that each construct's square root of the AVE (all bold crossing values) in the Fornell-Larcker criterion exceeds its intercorrelations with other constructs or is greater than the absolute measure of any correlation. Henseler et al. (2014) criticized the Fornell and Larcker test for not consistently detecting the absence of discriminant validity in some study scenarios.

To evaluate discriminant validity, we thus looked at an alternative set of HTMT criteria. The results indicate that there is no discriminant validity issue, according to Hair et al. (2019) and Henseler et al. (2014). Because there is a positive correlation between IP and IA ($r = .242$, $p = .00$), IP and ID ($r = .1$, $p = .00$), and IA and ID ($r = .137$, $p = .000$), the ratio of correlations is also getting closer to zero. The two-tailed confidence interval at the .05 significance level does not include one.

3.3.3. Structural Model

We checked the estimated model's goodness-of-fit. There was a .08 marginal standard root mean square residual (SRMR). Based on Brown's (2015) analysis, the model is appropriate if ≤ 0.08. We also used the variance inflation factor (VIF) to assess for multicollinearity amongst the latent components. Multicollinearity problems are indicated by a VIF of greater than five (Hair, Risher, Sarstedt, & Ringle, 2019; Sarstedt, Ringle, & Hair, 2017). Since all of the numbers in Table 4 are ≤ 3.529, multicollinearity is not an issue for the model.

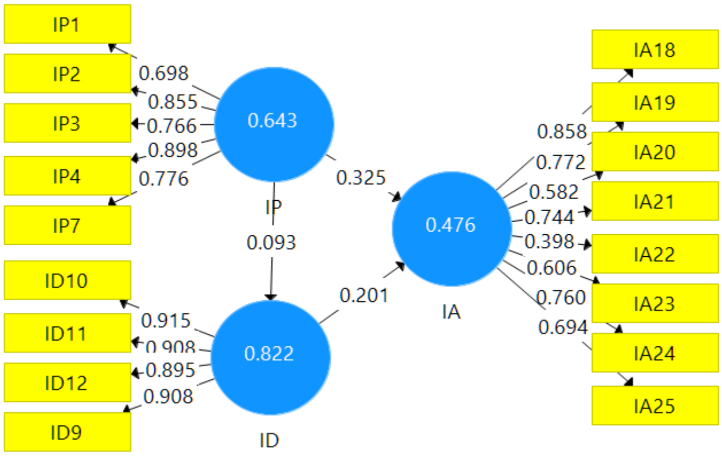

Figure 2: Outer loading and AVE values before modification

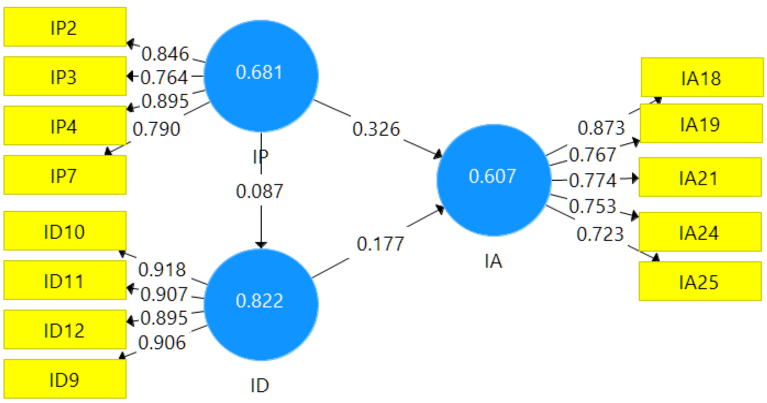

Figure 3: Outer loading and AVE values after modification

Table 5: Construct Reliability and Validity test

Constructs	*n* items	Cronbach alpha (>.7)	rho_A (>.7)	CR (>.7)	AVE (>.5)
IA	5	0.861	1.046	0.884	0.607
ID	4	0.928	0.937	0.949	0.822
IP	4	0.849	0.891	0.895	0.681

n items = number of items, CR=Composite Reliability, AVE=Average Variance Explained

Table 6: Discriminant Validity

	Fornell-and-Larcker test				Heterotrat-Monotrait Ratio (HTMT)		
	IA	ID	IP		IA	ID	IP
IA	**0.779**			IA			
ID	0.149	**0.907**		ID	0.137		
IP	0.310	0.087	**0.825**	IP	0.242	0.100	

IA = Instructional assessment, ID = Instructional delivery, IP = Instructional planning

Table 7: Items loading, mean, standard deviation, and variance inflation

Constructs	Indicators	Loading	Mean	Sd	VIF (≤5)
IA	IA18	0.873	2.824	1.123	1.580
	IA19	0.767	2.478	1.071	1.730
	IA21	0.774	2.492	1.103	2.644
	IA24	0.753	2.625	1.049	1.844
	IA25	0.723	2.639	1.081	2.368
ID	ID10	0.918	3.577	1.036	3.327
	ID11	0.907	3.555	1.007	3.529
	ID12	0.895	3.558	1.005	3.017
	ID9	0.906	3.507	1.036	3.179
IP	IP2	0.846	3.449	1.005	2.726
	IP3	0.764	3.465	1.029	1.980
	IP4	0.895	3.397	1.033	2.672
	IP7	0.790	3.344	1.018	1.445

VIF= Variance Inflation Factor, Source: Calculated by the Author

4. Conclusion and Future Research

Success depends on validating the instrument according to the demands of a particular context, including people, culture, time, and setting. An instructional practice scale for Ethiopian public university lecturers was validated in this study. A total of twenty-five items—eight IPs, nine IDs, and eight IAs—were reduced to seventeen powerful items loaded in the three primary factors (five IPs, four IDs, and eight IAs) using EFA. A final 13 items (4 IPs, 4 IDs, and 5 IAs) were confirmed in the CFA analysis.

We offered an effective and dependable instrument for evaluating university-level instructors' instructional practices. The tool can be used for a variety of tasks, such as investigating and assessing training for promotion. The instrument is approved, nevertheless, for use in general-level university courses. We were aware that the type of instruction should vary according to the disciplines or subject areas. Therefore, it is advised that future researchers build and validate instruments that are unique to their respective specialities.

The self-report measure served as the sole basis for the study. In this specific context, what is actually done prior to, during, and after class practice is not investigated. Potential biases (e.g., socially desirable outcomes) may result from this. Future researchers can therefore complement it (e.g., with observational data and peer ratings) to maximize its robustness.

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